Dissertation

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Dissertation markdown script:

This is the R markdown for my dissertation titled: Psychological Borders: Exploring Attitudes Towards Migrants in the UK from a Psychological Perspective. I have made this (in conjunction with making all my code publicly available) with the intent of making my research more transparent and reproducible.

All of the data used was downloaded from the original source and has not been re-uploaded here. To gain access to it please visit: https://www.sheffield.ac.uk/psychology-consortium-covid19

Packages:

Below is a list of all packages used:

```
library(haven)
library(ggplot2)
library(stargazer)

##
## Please cite as:

##  Hlavac, Marek (2022). stargazer: Well-Formatted Regression and Summary Statistics Tables.

##  R package version 5.2.3. https://CRAN.R-project.org/package=stargazer

library(ltm)

## Loading required package: MASS

## Loading required package: msm

## Loading required package: polycor

library(psych)

##
## Attaching package: 'psych'

## The following object is masked from 'package:ltm':
##
##     factor.scores
```

```
## The following object is masked from 'package:polycor':
##
##     polyserial

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha

library(dplyr)

##
## Attaching package: 'dplyr'

## The following object is masked from 'package:MASS':
##
##     select

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(car)

## Loading required package: carData

##
## Attaching package: 'car'

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

## The following object is masked from 'package:psych':
##
##     logit

library(corrplot)

## corrplot 0.92 loaded

library(summarytools)
```

Importing, filtering and merging the data:

Not all of the measures used in this paper were available in the same wave of the survey. This is due to certain metrics only being asked to new respondents in wave 4 (such as educational level and political scale). Therefore, we need to merge this missing data from previous waves when these respondents answered these exact same questions as posited in wave 4. Below is the code we used to do this.

```r
# Loading in main W4 Data:
original_df<-read_sav("C19PRC_UK_W4_archive_final.sav")

# Loading in previous waves data with the anwsers to the missing W4 data
edudf<-read_sav("C19PRC_UKW1W2_archive_final.sav")
edudf1<-read_sav("C19PRC_UK_W3_archive_final.sav")

# Filtering dataframes to contain only the variables we wish to merge
ldf1<-as.data.frame(cbind(edudf$pid,edudf$W1_Education,
edudf$W1_Political_Scale))
colnames(ldf1)<-c("pid","W1_Edu", "W1_Political_Scale")

ldf2<-as.data.frame(cbind(edudf1$pid,edudf1$W3_Education,
edudf1$W3_Political_Scale))
colnames(ldf2)<-c("pid","W2_Edu","W3_Political_Scale")

# Merging all of the data into a single dataframe
mdf1<-merge.data.frame(original_df,ldf1, by ="pid", all = T)
mdf2<-merge.data.frame(mdf1,ldf2, by ="pid", all = T)


# Replace missing values in W4_Education using responses from W1 or W2
mdf2 <- mdf2 %>%
  mutate(W4_Education = ifelse(is.na(W4_Education), ifelse(W4_Type == 1,
coalesce(W1_Edu, W2_Edu), NA), W4_Education))

# Merge W1_Edu and W2_Edu into W4_Education based on conditions
mdf2 <- mdf2 %>%
  mutate(W4_Education = ifelse(W4_Type == 1 & is.na(W4_Education),
coalesce(W1_Edu, W2_Edu), W4_Education)) # Filter out rows where W4_Type is
NA

# Remove the added variables from previous waves which are no longer needed
mdf2 <- mdf2 %>%
  select(-W1_Edu, -W2_Edu)
mdf2$W4_Education <- as.numeric(as.character(mdf2$W4_Education))

# Replace missing values in W4_Political_Scale using responses from W1 or W2
mdf2 <- mdf2 %>%
  mutate(W4_Political_scale = ifelse(is.na(W4_Political_scale),
ifelse(W4_Type == 1, coalesce(W1_Political_Scale, W3_Political_Scale), NA),
W4_Political_scale))

# Merge W1_Political_Scale and W3_Political_Scale into W4_Political_scale
based on conditions
mdf2 <- mdf2 %>%
  mutate(W4_Political_scale = ifelse(W4_Type == 1 &
is.na(W4_Political_scale), coalesce(W1_Political_Scale, W3_Political_Scale),
W4_Political_scale)) %>%
```

```r
  filter(!is.na(W4_Type))

# Remove the added variables from previous waves which are no longer needed
mdf2 <- mdf2 %>%
  select(-W1_Political_Scale, -W3_Political_Scale)
mdf2$W4_Political_scale<- as.numeric(as.character(mdf2$W4_Political_scale))

# Rename dataframe for ease of use
df<-mdf2

# Remove anyone who isn't born in the UK
df<- subset(df,df$W4_WhereBorn != 5)
```

Coding dependent variable:

In order to create our dependent variable we first need to re-scale some of measures and then add them into an additive scale

```r
# Table of 1st dependent measure before re-scaling
table(df$W4_MigrantAttitudes1)

##
##   1   2   3   4   5   6   7   8   9  10
## 303 108 232 280 586 475 614 525 169 320

# Define the transformation function used for re-scaling
transform_likert <- function(x) {
  transformed_value <- ceiling(x / 2)
  return(transformed_value)}

# Apply the transformation function to the measure
df$W4_MigrantAttitudes1_rescaled <- transform_likert(df$W4_MigrantAttitudes1)

# Print the transformed data to ensure it worked
table(df$W4_MigrantAttitudes1_rescaled)

##
##    1    2    3    4    5
##  411  512 1061 1139  489

# Table of 2nd dependent measure before re-scaling
table(df$W4_MigrantAttitudes2)

##
##   1   2   3   4   5   6   7   8   9  10
## 374 134 246 298 586 459 508 443 191 373

# Apply the transformation function to the measure
df$W4_MigrantAttitudes2_rescaled <- transform_likert(df$W4_MigrantAttitudes2)
```

```r
# Print the transformed data to ensure it worked
table(df$W4_MigrantAttitudes2_rescaled)

##
##    1    2    3    4    5
##  508  544 1045  951  564

# Create additive Dependent variable

df$W4_TotalMigrantAttitudes <- rowSums(df[,
c("W4_MigrantAttitudes1_rescaled",
                                 "W4_MigrantAttitudes2_rescaled",
                                 "W4_Immigration_1",
                                 "W4_Immigration_1")])

summary(df$W4_TotalMigrantAttitudes)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    4.00   11.00   14.00   13.46   16.00   20.00

# Calculate cronach alpha

dependent_data<-data.frame(df[, c("W4_MigrantAttitudes1_rescaled",
                               "W4_MigrantAttitudes2_rescaled",
                               "W4_Immigration_1",
                               "W4_Immigration_1")])
cronbach.alpha(dependent_data)

##
## Cronbach's alpha for the 'dependent_data' data-set
##
## Items: 4
## Sample units: 3612
## alpha: 0.92
```

Calculating cronbach alpha for independent variables:

```r
Extraversion_data<-data.frame(df[, c("W4_Personality1R",
                                     "W4_Personality6")])
cronbach.alpha(Extraversion_data)

##
## Cronbach's alpha for the 'Extraversion_data' data-set
##
## Items: 2
## Sample units: 3612
## alpha: 0.609

Agreeableness_data<-data.frame(df[, c("W4_Personality2",
                                     "W4_Personality7R")])
cronbach.alpha(Agreeableness_data)
```

```
##
## Cronbach's alpha for the 'Agreeableness_data' data-set
##
## Items: 2
## Sample units: 3612
## alpha: 0.359

Conscientiousnes_data<-data.frame(df[, c("W4_Personality3R",
                                      "W4_Personality8")])
cronbach.alpha(Conscientiousnes_data)

##
## Cronbach's alpha for the 'Conscientiousnes_data' data-set
##
## Items: 2
## Sample units: 3612
## alpha: 0.537

Neuroticism_data<-data.frame(df[, c("W4_Personality4R",
                                    "W4_Personality9")])
cronbach.alpha(Neuroticism_data)

##
## Cronbach's alpha for the 'Neuroticism_data' data-set
##
## Items: 2
## Sample units: 3612
## alpha: 0.707

Openness_data<-data.frame(df[, c("W4_Personality5R",
                                    "W4_Personality10")])
cronbach.alpha(Openness_data)

##
## Cronbach's alpha for the 'Openness_data' data-set
##
## Items: 2
## Sample units: 3612
## alpha: 0.237

Depression_data<-data.frame(df[, c("W4_Dep1",
                                   "W4_Dep2",
                                   "W4_Dep3",
                                   "W4_Dep4",
                                   "W4_Dep5",
                                   "W4_Dep6",
                                   "W4_Dep7",
                                   "W4_Dep8",
                                   "W4_Dep9")])
cronbach.alpha(Depression_data)
```

```
##
## Cronbach's alpha for the 'Depression_data' data-set
##
## Items: 9
## Sample units: 3612
## alpha: 0.936
```

```
Paranoia_data<-data.frame(df[, c("W4_Paranoia1",
                                  "W4_Paranoia2",
                                  "W4_Paranoia3",
                                  "W4_Paranoia4",
                                  "W4_Paranoia5")])
cronbach.alpha(Paranoia_data)
```

```
##
## Cronbach's alpha for the 'Paranoia_data' data-set
##
## Items: 5
## Sample units: 3612
## alpha: 0.872
```

```
Conspiracy_data<-data.frame(df[, c("W4_Conspiracy_1",
                                  "W4_Conspiracy_2",
                                  "W4_Conspiracy_3",
                                  "W4_Conspiracy_4",
                                  "W4_Conspiracy_5")])
cronbach.alpha(Conspiracy_data)
```

```
##
## Cronbach's alpha for the 'Conspiracy_data' data-set
##
## Items: 5
## Sample units: 3612
## alpha: 0.888
```

Re-code independent variables:

We need to re-format our variables to make them conducive for our descriptive statistics and OLS regression

```
# Making Gender into a binary
table(df$W4_Gender)
```

```
##
##    1    2    3    4    5
## 1763 1835    8    5    1
```

```
df$W4_Gender_Binary<- NA
df$W4_Gender_Binary[df$W4_Gender == 1] <- 1
df$W4_Gender_Binary[df$W4_Gender == 2] <- 0
table(df$W4_Gender_Binary)
```

```
##
##    0    1
## 1835 1763

# Making visiable minority ino a binary
table(df$W4_Ethnicity)

##
##    1    2    3    4    5    6    7    8    9   10   11
## 3411   35   35   24   25   17   12    3    9    4   37

df$W4_Visible_minority<- NA
df$W4_Visible_minority<-ifelse(df$W4_Ethnicity == 1 | df$W4_Ethnicity == 2,
0,1)
table(df$W4_Visible_minority)

##
##    0    1
## 3446  166

# Re-coding education into a catagorical variable
table(df$W4_Education)

##
##   1   2   3   4   5   6   7   8
## 156 762 653 394 926 163 491  67

df$W4_Education_categories<-NA
df$W4_Education_categories[df$W4_Education == 1] <- "No Qualifications"
df$W4_Education_categories[df$W4_Education == 2] <- "O-Level/GCSE or A-Level
or Technical qualification"
df$W4_Education_categories[df$W4_Education == 3] <- "O-Level/GCSE or A-Level
or Technical qualification"
df$W4_Education_categories[df$W4_Education == 4] <- "O-Level/GCSE or A-Level
or Technical qualification"
df$W4_Education_categories[df$W4_Education == 5] <- "Undergraduate degree or
Diploma"
df$W4_Education_categories[df$W4_Education == 6] <- "Undergraduate degree or
Diploma"
df$W4_Education_categories[df$W4_Education == 7] <- "Postgraduate degree"
df$W4_Education_categories[df$W4_Education == 8] <- "Other"
df$W4_Education_categories<- factor(df$W4_Education_categories, levels =
c("No Qualifications", "O-Level/GCSE or A-Level or Technical qualification",
"Undergraduate degree or Diploma","Postgraduate degree", "Other"))
table(df$W4_Education_categories)

##
##                                   No Qualifications
##                                                 156
## O-Level/GCSE or A-Level or Technical qualification
##                                                1809
##                    Undergraduate degree or Diploma
```

```
##                                                            1089
##                                              Postgraduate degree
##                                                             491
##                                                           Other
##                                                              67
```

```r
# Re-coding education into a numerical catagorical variable
table(df$W4_Education)
```

```
##
##   1   2   3   4   5   6   7   8
## 156 762 653 394 926 163 491  67
```

```r
df$W4_Education_categories_Num<-NA
df$W4_Education_categories_Num[df$W4_Education == 1] <- "1"
df$W4_Education_categories_Num[df$W4_Education == 2] <- "2"
df$W4_Education_categories_Num[df$W4_Education == 3] <- "2"
df$W4_Education_categories_Num[df$W4_Education == 4] <- "2"
df$W4_Education_categories_Num[df$W4_Education == 5] <- "3"
df$W4_Education_categories_Num[df$W4_Education == 6] <- "3"
df$W4_Education_categories_Num[df$W4_Education == 7] <- "4"
df$W4_Education_categories_Num[df$W4_Education == 8] <- "5"
df$W4_Education_categories_Num<- factor(df$W4_Education_categories_Num,
levels = c(1, 2, 3, 4, 5))
table(df$W4_Education_categories_Num)
```

```
##
##    1    2    3    4    5
##  156 1809 1089  491   67
```

```r
# Re-coding education into a numerical catagorical variable without other
group
table(df$W4_Education)
```

```
##
##   1   2   3   4   5   6   7   8
## 156 762 653 394 926 163 491  67
```

```r
df$W4_Education_categories_Num1<-NA
df$W4_Education_categories_Num1[df$W4_Education == 1] <- "1"
df$W4_Education_categories_Num1[df$W4_Education == 2] <- "2"
df$W4_Education_categories_Num1[df$W4_Education == 3] <- "2"
df$W4_Education_categories_Num1[df$W4_Education == 4] <- "2"
df$W4_Education_categories_Num1[df$W4_Education == 5] <- "3"
df$W4_Education_categories_Num1[df$W4_Education == 6] <- "3"
df$W4_Education_categories_Num1[df$W4_Education == 7] <- "4"
df$W4_Education_categories_Num1<- factor(df$W4_Education_categories_Num1,
levels = c(1, 2, 3, 4))
table(df$W4_Education_categories_Num1)
```

```
##
##    1    2    3    4
##  156 1809 1089  491

# Re-coding employment into a catagorical variable
table(df$W4_Employment)

##
##    1    2    3    4    5    6    7    8    9   10
## 1413  477   99   83  171  205  211   33  820  100

df$W4_Employment_categories<-NA
df$W4_Employment_categories[df$W4_Employment == 1] <- "Employed"
df$W4_Employment_categories[df$W4_Employment == 2] <- "Employed"
df$W4_Employment_categories[df$W4_Employment == 3] <- "Employed"
df$W4_Employment_categories[df$W4_Employment == 4] <- "Employed"
df$W4_Employment_categories[df$W4_Employment == 5] <- "Unemployed"
df$W4_Employment_categories[df$W4_Employment == 6] <- "Unemployed"
df$W4_Employment_categories[df$W4_Employment == 7] <- "Unemployed"
df$W4_Employment_categories[df$W4_Employment == 8] <- "Other Situations"
df$W4_Employment_categories[df$W4_Employment == 9] <- "Other Situations"
df$W4_Employment_categories[df$W4_Employment == 10] <- "Student"
df$W4_Employment_categories<- factor(df$W4_Employment_categories, levels =
c("Unemployed", "Employed", "Other Situations", "Student"))
table(df$W4_Employment_categories)

##
##       Unemployed         Employed Other Situations          Student
##              587             2072              853              100

# Re-coding employment into a numerical catagorical variable
table(df$W4_Employment)

##
##    1    2    3    4    5    6    7    8    9   10
## 1413  477   99   83  171  205  211   33  820  100

df$W4_Employment_categories_Num<-NA
df$W4_Employment_categories_Num[df$W4_Employment == 1] <- "1"
df$W4_Employment_categories_Num[df$W4_Employment == 2] <- "1"
df$W4_Employment_categories_Num[df$W4_Employment == 3] <- "1"
df$W4_Employment_categories_Num[df$W4_Employment == 4] <- "1"
df$W4_Employment_categories_Num[df$W4_Employment == 5] <- "2"
df$W4_Employment_categories_Num[df$W4_Employment == 6] <- "2"
df$W4_Employment_categories_Num[df$W4_Employment == 7] <- "2"
df$W4_Employment_categories_Num[df$W4_Employment == 8] <- "2"
df$W4_Employment_categories_Num[df$W4_Employment == 9] <- "3"
df$W4_Employment_categories_Num[df$W4_Employment == 10] <- "4"
df$W4_Employment_categories_Num<- factor(df$W4_Employment_categories_Num,
levels = c(2, 1, 3, 4))
table(df$W4_Employment_categories_Num)
```

```
##
##    2    1    3    4
##  620 2072  820  100
```

```
## Re-coding Income into a  catagorical variable
table(df$W4_Income_2019)
```

```
##
##   1   2   3   4   5
## 798 767 813 724 510
```

```
df$W4_Income_2019_categories<-NA
df$W4_Income_2019_categories[df$W4_Income_2019 == 1] <- "£0-15,490 per year"
df$W4_Income_2019_categories[df$W4_Income_2019 == 2] <- "£15,491-£25,340 per
year"
df$W4_Income_2019_categories[df$W4_Income_2019 == 3] <- "£25,341-£38,740 per
year"
df$W4_Income_2019_categories[df$W4_Income_2019 == 4] <- "£38,741-£57,930 per
year"
df$W4_Income_2019_categories[df$W4_Income_2019 == 5] <- "£57,931 or more per
year"
df$W4_Income_2019_categories<- factor(df$W4_Income_2019_categories)
table(df$W4_Income_2019_categories)
```

```
##
##       £0-15,490 per year £15,491-£25,340 per year £25,341-£38,740 per year
##                      798                      767                      813
## £38,741-£57,930 per year £57,931 or more per year
##                      724                      510
```

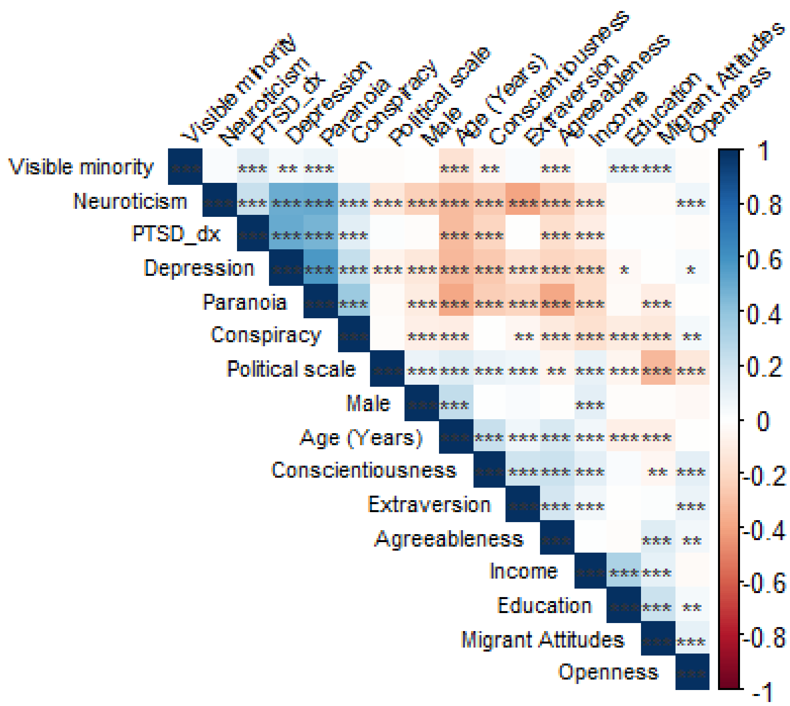
Descriptive statistics:

Now we need to create our descriptive statistics, we made a descriptive table and a correlation matrix

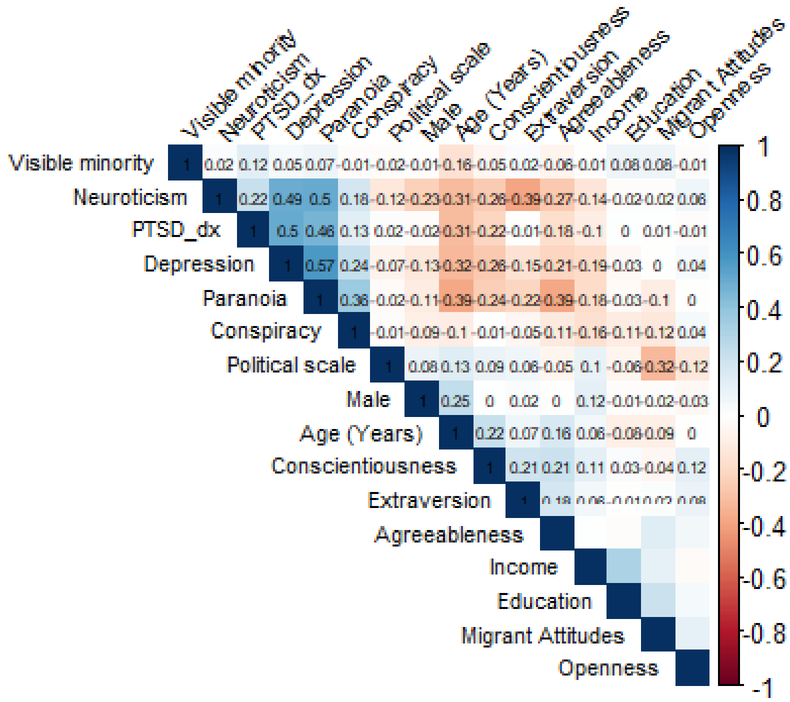
```
# Create a df for variables in descriptive statistics table
cor_df<-data.frame(df[, c("W4_Age_year",
                          "W4_Gender_Binary",
                          "W4_Visible_minority",
                          "W4_Education_categories_Num",
                          "W4_Employment_categories_Num",
                          "W4_Income_2019",
                          "W4_Political_scale",
                          "W4_Extraversion_Total",
                          "W4_Agreeable_Total",
                          "W4_Conscientious_Total",
                          "W4_Neuroticism_Total",
                          "W4_Openness_Total",
                          "W4_Dep_Total",
                          "W4_PTSDdx",
                          "W4_Paranoia_Total",
```

```
                              "W4_Conspiracy_Total",
                              "W4_TotalMigrantAttitudes")])
# Give them df new lables
new_names <- c("Age (Years)", "Male", "Visible minority", "Education",
"Employment", "Income", "Political scale", "Extraversion", "Agreeableness",
"Conscientiousness", "Neuroticism", "Openness", "Depression", "PTSD_dx",
"Paranoia", "Conspiracy", "Migrant Attitudes")
names(cor_df) <- new_names


### create Descriptive Stats and export to CSV:
comprehensive_summary <- describe(cor_df, na.rm = T)
write.csv(comprehensive_summary, "comprehensive_summary.csv")

# Create a df for variables in correlation matrix table
cor_df1<-data.frame(df[, c("W4_Age_year",
                              "W4_Gender_Binary",
                              "W4_Visible_minority",
                              "W4_Education_categories_Num1",
                              "W4_Income_2019",
                              "W4_Political_scale",
                              "W4_Extraversion_Total",
                              "W4_Agreeable_Total",
                              "W4_Conscientious_Total",
                              "W4_Neuroticism_Total",
                              "W4_Openness_Total",
                              "W4_Dep_Total",
                              "W4_PTSDdx",
                              "W4_Paranoia_Total",
                              "W4_Conspiracy_Total",
                              "W4_TotalMigrantAttitudes")])

# Convert 'W4_Education_categories_Num1' from factor to numeric
cor_df1$W4_Education_categories_Num1 <-
as.numeric(as.character(cor_df1$W4_Education_categories_Num1))

# Convert 'W4_Income_2019' from labelled variable to numeric
cor_df1$W4_Income_2019 <-
as.numeric(labels(cor_df1$W4_Income_2019)[cor_df1$W4_Income_2019])

# Convert 'W4_PTSDdx' from labelled variable to numeric
cor_df1$W4_PTSDdx <- as.numeric(as.character(cor_df1$W4_PTSDdx))

# Give df new lables
new_names1 <- c("Age (Years)", "Male", "Visible minority", "Education",
"Income", "Political scale", "Extraversion", "Agreeableness",
"Conscientiousness", "Neuroticism", "Openness","Depression", "PTSD_dx",
"Paranoia", "Conspiracy", "Migrant Attitudes")
names(cor_df1) <- new_names1
```

```r
# Create correlation matrix
cor_matrix1 <- cor(cor_df1, use = "pairwise.complete.obs")
# Calculate p-values for correlations
p_values <- cor.mtest(cor_df1, conf.level = 0.95)$p

# Create a correlation plot with colors, highlighting significant
correlations
corrplot(cor_matrix1, method = "color", type = "upper", tl.col = "black",
tl.srt = 45, p.mat = p_values,sig.level = c(0.001, 0.01, 0.05), pch.cex =
0.9, insig = 'label_sig', pch.col = 'grey20', order = "AOE",number.cex = 0.7,
tl.cex = 0.7, mar = c(0,0,2,0))
```




```r
# Create a correlation plot with colors, highlighting  correlations
coefficients
corrplot(cor_matrix1, method = "color", type = "upper", tl.col = "black",
tl.srt = 45,order = "AOE",number.cex = 0.7, tl.cex = 0.7,mar =
c(0,0,2,0))$corrPos -> p1
text(p1$x, p1$y, round(p1$corr, 2), cex = 0.5)
```



Create models:

```
### Linear models:

m1<-lm(df$W4_TotalMigrantAttitudes ~ df$W4_Age_year + df$W4_Gender_Binary +
df$W4_Visible_minority + df$W4_Education_categories +
df$W4_Employment_categories + df$W4_Income_2019_categories +
df$W4_Political_scale)
summary(m1)

##
## Call:
## lm(formula = df$W4_TotalMigrantAttitudes ~ df$W4_Age_year +
df$W4_Gender_Binary +
##     df$W4_Visible_minority + df$W4_Education_categories +
df$W4_Employment_categories +
##     df$W4_Income_2019_categories + df$W4_Political_scale)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.9343  -2.4271   0.3574   2.7094  11.8953
##
## Coefficients:
##
Estimate
## (Intercept)
15.680571
```

```
## df$W4_Age_year
-0.012164
## df$W4_Gender_Binary
0.090658
## df$W4_Visible_minority
1.125116
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical
qualification  0.708975
## df$W4_Education_categoriesUndergraduate degree or Diploma
1.932588
## df$W4_Education_categoriesPostgraduate degree
2.233461
## df$W4_Education_categoriesOther
1.322678
## df$W4_Employment_categoriesEmployed
0.024191
## df$W4_Employment_categoriesOther Situations
0.404731
## df$W4_Employment_categoriesStudent
0.605688
## df$W4_Income_2019_categories£15,491-£25,340 per year
0.555410
## df$W4_Income_2019_categories£25,341-£38,740 per year
0.904998
## df$W4_Income_2019_categories£38,741-£57,930 per year
1.102986
## df$W4_Income_2019_categories£57,931 or more per year
1.113761
## df$W4_Political_scale
-0.716225
##
Std. Error
## (Intercept)
0.451494
## df$W4_Age_year
0.005518
## df$W4_Gender_Binary
0.132631
## df$W4_Visible_minority
0.309555
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical
qualification   0.324065
## df$W4_Education_categoriesUndergraduate degree or Diploma
0.338290
## df$W4_Education_categoriesPostgraduate degree
0.366138
## df$W4_Education_categoriesOther
0.561235
## df$W4_Employment_categoriesEmployed
0.196164
```

```
## df$W4_Employment_categoriesOther Situations
0.245809
## df$W4_Employment_categoriesStudent
0.437372
## df$W4_Income_2019_categories£15,491-£25,340 per year
0.201663
## df$W4_Income_2019_categories£25,341-£38,740 per year
0.203382
## df$W4_Income_2019_categories£38,741-£57,930 per year
0.212903
## df$W4_Income_2019_categories£57,931 or more per year
0.239265
## df$W4_Political_scale
0.035324
##
t value
## (Intercept)
34.730
## df$W4_Age_year
-2.204
## df$W4_Gender_Binary
0.684
## df$W4_Visible_minority
3.635
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical
qualification   2.188
## df$W4_Education_categoriesUndergraduate degree or Diploma
5.713
## df$W4_Education_categoriesPostgraduate degree
6.100
## df$W4_Education_categoriesOther
2.357
## df$W4_Employment_categoriesEmployed
0.123
## df$W4_Employment_categoriesOther Situations
1.647
## df$W4_Employment_categoriesStudent
1.385
## df$W4_Income_2019_categories£15,491-£25,340 per year
2.754
## df$W4_Income_2019_categories£25,341-£38,740 per year
4.450
## df$W4_Income_2019_categories£38,741-£57,930 per year
5.181
## df$W4_Income_2019_categories£57,931 or more per year
4.655
## df$W4_Political_scale
-20.276
##
Pr(>|t|)
```

```
## (Intercept)
< 2e-16
## df$W4_Age_year
0.027569
## df$W4_Gender_Binary
0.494315
## df$W4_Visible_minority
0.000282
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical
qualification 0.028752
## df$W4_Education_categoriesUndergraduate degree or Diploma
1.20e-08
## df$W4_Education_categoriesPostgraduate degree
1.17e-09
## df$W4_Education_categoriesOther
0.018490
## df$W4_Employment_categoriesEmployed
0.901860
## df$W4_Employment_categoriesOther Situations
0.099743
## df$W4_Employment_categoriesStudent
0.166189
## df$W4_Income_2019_categories£15,491-£25,340 per year
0.005914
## df$W4_Income_2019_categories£25,341-£38,740 per year
8.86e-06
## df$W4_Income_2019_categories£38,741-£57,930 per year
2.33e-07
## df$W4_Income_2019_categories£57,931 or more per year
3.36e-06
## df$W4_Political_scale
< 2e-16
##
## (Intercept)
***
## df$W4_Age_year
*
## df$W4_Gender_Binary
## df$W4_Visible_minority
***
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical
qualification *
## df$W4_Education_categoriesUndergraduate degree or Diploma
***
## df$W4_Education_categoriesPostgraduate degree
***
## df$W4_Education_categoriesOther
*
## df$W4_Employment_categoriesEmployed
## df$W4_Employment_categoriesOther Situations
```

```
.
## df$W4_Employment_categoriesStudent
## df$W4_Income_2019_categories£15,491-£25,340 per year
**
## df$W4_Income_2019_categories£25,341-£38,740 per year
***
## df$W4_Income_2019_categories£38,741-£57,930 per year
***
## df$W4_Income_2019_categories£57,931 or more per year
***
## df$W4_Political_scale
***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.8 on 3580 degrees of freedom
##   (16 observations deleted due to missingness)
## Multiple R-squared:  0.1598, Adjusted R-squared:  0.1563
## F-statistic: 45.39 on 15 and 3580 DF,  p-value: < 2.2e-16
```

```
m2<-lm(df$W4_TotalMigrantAttitudes ~ df$W4_Extraversion_Total +
df$W4_Agreeable_Total + df$W4_Conscientious_Total + df$W4_Neuroticism_Total +
df$W4_Openness_Total)
summary(m2)
```

```
##
## Call:
## lm(formula = df$W4_TotalMigrantAttitudes ~ df$W4_Extraversion_Total +
##     df$W4_Agreeable_Total + df$W4_Conscientious_Total +
df$W4_Neuroticism_Total +
##     df$W4_Openness_Total)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.9619  -2.4907   0.4149   2.7561   8.9847
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               10.905050   0.573178  19.026  < 2e-16 ***
## df$W4_Extraversion_Total  -0.005929   0.038408  -0.154    0.877
## df$W4_Agreeable_Total      0.362141   0.043730   8.281  < 2e-16 ***
## df$W4_Conscientious_Total -0.208461   0.040939  -5.092 3.72e-07 ***
## df$W4_Neuroticism_Total   -0.017234   0.036163  -0.477    0.634
## df$W4_Openness_Total       0.266926   0.040688   6.560 6.13e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.072 on 3606 degrees of freedom
## Multiple R-squared:  0.03428,    Adjusted R-squared:  0.03294
## F-statistic:  25.6 on 5 and 3606 DF,  p-value: < 2.2e-16
```

```r
m3<-lm(df$W4_TotalMigrantAttitudes ~ df$W4_Dep_Total + df$W4_PTSDdx +
df$W4_Paranoia_Total + df$W4_Conspiracy_Total)
summary(m3)

##
## Call:
## lm(formula = df$W4_TotalMigrantAttitudes ~ df$W4_Dep_Total +
##     df$W4_PTSDdx + df$W4_Paranoia_Total + df$W4_Conspiracy_Total)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.0098  -2.5677   0.3986   2.8901   8.5321
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            15.505625   0.238599  64.986  < 2e-16 ***
## df$W4_Dep_Total         0.042234   0.012599   3.352  0.00081 ***
## df$W4_PTSDdx            0.427971   0.215893   1.982  0.04752 *
## df$W4_Paranoia_Total   -0.095259   0.017451  -5.459 5.12e-08 ***
## df$W4_Conspiracy_Total -0.038663   0.006793  -5.692 1.36e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.093 on 3607 degrees of freedom
## Multiple R-squared:  0.02392,    Adjusted R-squared:  0.02284
## F-statistic:  22.1 on 4 and 3607 DF,  p-value: < 2.2e-16

m4<-lm(df$W4_TotalMigrantAttitudes ~ df$W4_Age_year + df$W4_Gender_Binary +
df$W4_Visible_minority + df$W4_Education_categories +
df$W4_Employment_categories + df$W4_Income_2019_categories +
df$W4_Political_scale + df$W4_Extraversion_Total + df$W4_Agreeable_Total +
df$W4_Conscientious_Total + df$W4_Neuroticism_Total + df$W4_Openness_Total
+df$W4_Dep_Total + df$W4_PTSDdx + df$W4_Paranoia_Total +
df$W4_Conspiracy_Total )
summary(m4)

##
## Call:
## lm(formula = df$W4_TotalMigrantAttitudes ~ df$W4_Age_year +
df$W4_Gender_Binary +
##     df$W4_Visible_minority + df$W4_Education_categories +
df$W4_Employment_categories +
##     df$W4_Income_2019_categories + df$W4_Political_scale +
df$W4_Extraversion_Total +
##     df$W4_Agreeable_Total + df$W4_Conscientious_Total +
df$W4_Neuroticism_Total +
##     df$W4_Openness_Total + df$W4_Dep_Total + df$W4_PTSDdx +
df$W4_Paranoia_Total +
##     df$W4_Conspiracy_Total)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -14.1793  -2.3466   0.3602   2.6465  12.1575 
## 
## Coefficients:
##                                                                                  
Estimate
## (Intercept)                                                                     
15.547636
## df$W4_Age_year                                                                  
-0.018186
## df$W4_Gender_Binary                                                             
0.052794
## df$W4_Visible_minority                                                          
1.120800
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical 
qualification  0.632781
## df$W4_Education_categoriesUndergraduate degree or Diploma                       
1.830007
## df$W4_Education_categoriesPostgraduate degree                                   
2.072075
## df$W4_Education_categoriesOther                                                 
1.285405
## df$W4_Employment_categoriesEmployed                                             
-0.013820
## df$W4_Employment_categoriesOther Situations                                     
0.300456
## df$W4_Employment_categoriesStudent                                              
0.564664
## df$W4_Income_2019_categories£15,491-£25,340 per year                            
0.485691
## df$W4_Income_2019_categories£25,341-£38,740 per year                            
0.889295
## df$W4_Income_2019_categories£38,741-£57,930 per year                            
1.019672
## df$W4_Income_2019_categories£57,931 or more per year                            
0.998153
## df$W4_Political_scale                                                           
-0.669900
## df$W4_Extraversion_Total                                                        
-0.003730
## df$W4_Agreeable_Total                                                           
0.275810
## df$W4_Conscientious_Total                                                       
-0.118692
## df$W4_Neuroticism_Total                                                         
-0.045625
## df$W4_Openness_Total                                                            
0.166621
## df$W4_Dep_Total
```

```
0.026044
## df$W4_PTSDdx
0.374186
## df$W4_Paranoia_Total
-0.061220
## df$W4_Conspiracy_Total
-0.028745
##
Std. Error
## (Intercept)
0.775254
## df$W4_Age_year
0.005765
## df$W4_Gender_Binary
0.133356
## df$W4_Visible_minority
0.305263
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical
qualification   0.318186
## df$W4_Education_categoriesUndergraduate degree or Diploma
0.332763
## df$W4_Education_categoriesPostgraduate degree
0.359963
## df$W4_Education_categoriesOther
0.550909
## df$W4_Employment_categoriesEmployed
0.195204
## df$W4_Employment_categoriesOther Situations
0.243513
## df$W4_Employment_categoriesStudent
0.431206
## df$W4_Income_2019_categories£15,491-£25,340 per year
0.198512
## df$W4_Income_2019_categories£25,341-£38,740 per year
0.200656
## df$W4_Income_2019_categories£38,741-£57,930 per year
0.210744
## df$W4_Income_2019_categories£57,931 or more per year
0.238548
## df$W4_Political_scale
0.035284
## df$W4_Extraversion_Total
0.035867
## df$W4_Agreeable_Total
0.042403
## df$W4_Conscientious_Total
0.039042
## df$W4_Neuroticism_Total
0.039153
## df$W4_Openness_Total
```

```
0.037762
## df$W4_Dep_Total
0.012300
## df$W4_PTSDdx
0.204571
## df$W4_Paranoia_Total
0.017970
## df$W4_Conspiracy_Total
0.006301
##
t value
## (Intercept)
20.055
## df$W4_Age_year
-3.155
## df$W4_Gender_Binary
0.396
## df$W4_Visible_minority
3.672
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical
qualification   1.989
## df$W4_Education_categoriesUndergraduate degree or Diploma
5.499
## df$W4_Education_categoriesPostgraduate degree
5.756
## df$W4_Education_categoriesOther
2.333
## df$W4_Employment_categoriesEmployed
-0.071
## df$W4_Employment_categoriesOther Situations
1.234
## df$W4_Employment_categoriesStudent
1.309
## df$W4_Income_2019_categories£15,491-£25,340 per year
2.447
## df$W4_Income_2019_categories£25,341-£38,740 per year
4.432
## df$W4_Income_2019_categories£38,741-£57,930 per year
4.838
## df$W4_Income_2019_categories£57,931 or more per year
4.184
## df$W4_Political_scale
-18.986
## df$W4_Extraversion_Total
-0.104
## df$W4_Agreeable_Total
6.504
## df$W4_Conscientious_Total
-3.040
## df$W4_Neuroticism_Total
```

```
-1.165
## df$W4_Openness_Total
4.412
## df$W4_Dep_Total
2.117
## df$W4_PTSDdx
1.829
## df$W4_Paranoia_Total
-3.407
## df$W4_Conspiracy_Total
-4.562
##
Pr(>|t|)
## (Intercept)
< 2e-16
## df$W4_Age_year
0.001620
## df$W4_Gender_Binary
0.692213
## df$W4_Visible_minority
0.000245
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical
qualification 0.046809
## df$W4_Education_categoriesUndergraduate degree or Diploma
4.08e-08
## df$W4_Education_categoriesPostgraduate degree
9.32e-09
## df$W4_Education_categoriesOther
0.019690
## df$W4_Employment_categoriesEmployed
0.943563
## df$W4_Employment_categoriesOther Situations
0.217344
## df$W4_Employment_categoriesStudent
0.190449
## df$W4_Income_2019_categories£15,491-£25,340 per year
0.014467
## df$W4_Income_2019_categories£25,341-£38,740 per year
9.62e-06
## df$W4_Income_2019_categories£38,741-£57,930 per year
1.36e-06
## df$W4_Income_2019_categories£57,931 or more per year
2.93e-05
## df$W4_Political_scale
< 2e-16
## df$W4_Extraversion_Total
0.917180
## df$W4_Agreeable_Total
8.88e-11
## df$W4_Conscientious_Total
```

```
0.002382
## df$W4_Neuroticism_Total
0.243978
## df$W4_Openness_Total
1.05e-05
## df$W4_Dep_Total
0.034290
## df$W4_PTSDdx
0.067465
## df$W4_Paranoia_Total
0.000665
## df$W4_Conspiracy_Total
5.24e-06
##
## (Intercept)
***
## df$W4_Age_year
**
## df$W4_Gender_Binary
## df$W4_Visible_minority
***
## df$W4_Education_categoriesO-Level/GCSE or A-Level or Technical
qualification *
## df$W4_Education_categoriesUndergraduate degree or Diploma
***
## df$W4_Education_categoriesPostgraduate degree
***
## df$W4_Education_categoriesOther
*
## df$W4_Employment_categoriesEmployed
## df$W4_Employment_categoriesOther Situations
## df$W4_Employment_categoriesStudent
## df$W4_Income_2019_categories£15,491-£25,340 per year
*
## df$W4_Income_2019_categories£25,341-£38,740 per year
***
## df$W4_Income_2019_categories£38,741-£57,930 per year
***
## df$W4_Income_2019_categories£57,931 or more per year
***
## df$W4_Political_scale
***
## df$W4_Extraversion_Total
## df$W4_Agreeable_Total
***
## df$W4_Conscientious_Total
**
## df$W4_Neuroticism_Total
## df$W4_Openness_Total
***
```

```
## df$W4_Dep_Total
*
## df$W4_PTSDdx
.
## df$W4_Paranoia_Total
***
## df$W4_Conspiracy_Total
***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.728 on 3571 degrees of freedom
##   (16 observations deleted due to missingness)
## Multiple R-squared:  0.1935, Adjusted R-squared:  0.1881
## F-statistic:  35.7 on 24 and 3571 DF,  p-value: < 2.2e-16

# Export the models

stargazer(m1,m2,m3,m4)

##
## % Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy
Institute. E-mail: marek.hlavac at gmail.com
## % Date and time: Mon, Apr 22, 2024 - 17:46:45
## \begin{table}[!htbp] \centering
##   \caption{}
##   \label{}
## \begin{tabular}{@{\extracolsep{5pt}}lcccc}
## \\[-1.8ex]\hline
## \hline \\[-1.8ex]
##  & \multicolumn{4}{c}{\textit{Dependent variable:}} \\
## \cline{2-5}
## \\[-1.8ex] & \multicolumn{4}{c}{W4\_TotalMigrantAttitudes} \\
## \\[-1.8ex] & (1) & (2) & (3) & (4)\\
## \hline \\[-1.8ex]
##  W4\_Age\_year & $-$0.012$^{**}$ &  &  & $-$0.018$^{***}$ \\
##   & (0.006) &  &  & (0.006) \\
##   & & & & \\
##  W4\_Gender\_Binary & 0.091 &  &  & 0.053 \\
##   & (0.133) &  &  & (0.133) \\
##   & & & & \\
##  W4\_Visible\_minority & 1.125$^{***}$ &  &  & 1.121$^{***}$ \\
##   & (0.310) &  &  & (0.305) \\
##   & & & & \\
##  W4\_Education\_categoriesO-Level/GCSE or A-Level or Technical
qualification & 0.709$^{**}$ &  &  & 0.633$^{**}$ \\
##   & (0.324) &  &  & (0.318) \\
##   & & & & \\
##  W4\_Education\_categoriesUndergraduate degree or Diploma & 1.933$^{***}$
&  &  & 1.830$^{***}$ \\
```

```
##   & (0.338) &  &  & (0.333) \\
##   & & & & \\
##  W4\_Education\_categoriesPostgraduate degree & 2.233$^{***}$ &  &  &
2.072$^{***}$ \\
##   & (0.366) &  &  & (0.360) \\
##   & & & & \\
##  W4\_Education\_categoriesOther & 1.323$^{**}$ &  &  & 1.285$^{**}$ \\
##   & (0.561) &  &  & (0.551) \\
##   & & & & \\
##  W4\_Employment\_categoriesEmployed & 0.024 &  &  & $-$0.014 \\
##   & (0.196) &  &  & (0.195) \\
##   & & & & \\
##  W4\_Employment\_categoriesOther Situations & 0.405$^{*}$ &  &  & 0.300 \\
##   & (0.246) &  &  & (0.244) \\
##   & & & & \\
##  W4\_Employment\_categoriesStudent & 0.606 &  &  & 0.565 \\
##   & (0.437) &  &  & (0.431) \\
##   & & & & \\
##  W4\_Income\_2019\_categories£15,491-£25,340 per year & 0.555$^{***}$ &  &
& 0.486$^{**}$ \\
##   & (0.202) &  &  & (0.199) \\
##   & & & & \\
##  W4\_Income\_2019\_categories£25,341-£38,740 per year & 0.905$^{***}$ &  &
& 0.889$^{***}$ \\
##   & (0.203) &  &  & (0.201) \\
##   & & & & \\
##  W4\_Income\_2019\_categories£38,741-£57,930 per year & 1.103$^{***}$ &  &
& 1.020$^{***}$ \\
##   & (0.213) &  &  & (0.211) \\
##   & & & & \\
##  W4\_Income\_2019\_categories£57,931 or more per year & 1.114$^{***}$ &  &
& 0.998$^{***}$ \\
##   & (0.239) &  &  & (0.239) \\
##   & & & & \\
##  W4\_Political\_scale & $-$0.716$^{***}$ &  &  & $-$0.670$^{***}$ \\
##   & (0.035) &  &  & (0.035) \\
##   & & & & \\
##  W4\_Extraversion\_Total &  & $-$0.006 &  & $-$0.004 \\
##   &  & (0.038) &  & (0.036) \\
##   & & & & \\
##  W4\_Agreeable\_Total &  & 0.362$^{***}$ &  & 0.276$^{***}$ \\
##   &  & (0.044) &  & (0.042) \\
##   & & & & \\
##  W4\_Conscientious\_Total &  & $-$0.208$^{***}$ &  & $-$0.119$^{***}$ \\
##   &  & (0.041) &  & (0.039) \\
##   & & & & \\
##  W4\_Neuroticism\_Total &  & $-$0.017 &  & $-$0.046 \\
##   &  & (0.036) &  & (0.039) \\
##   & & & & \\
##  W4\_Openness\_Total &  & 0.267$^{***}$ &  & 0.167$^{***}$ \\
```

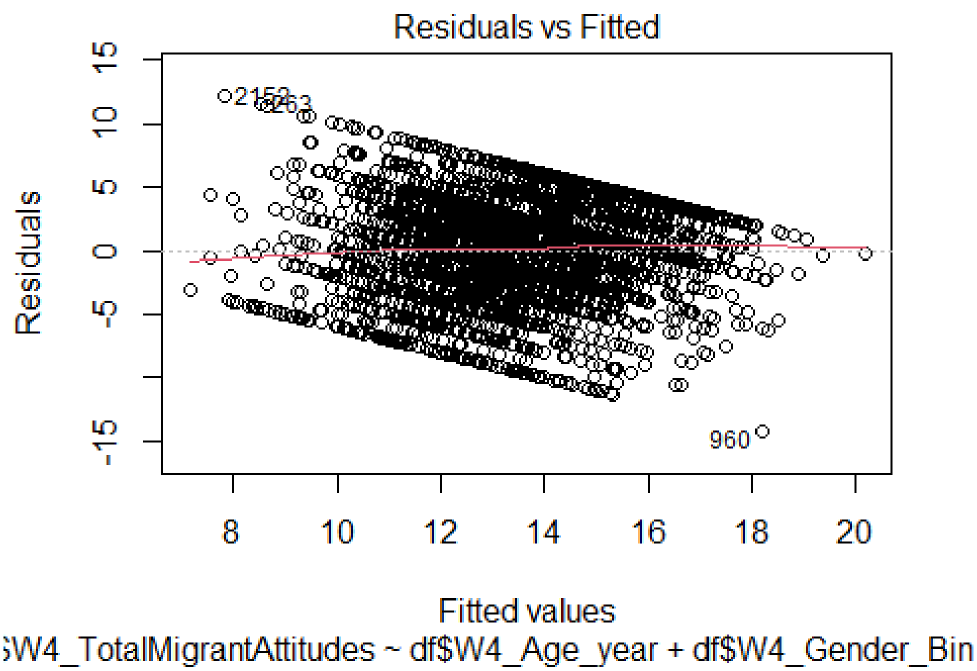
```
##   &  & (0.041) &  & (0.038) \\
##   & & & & \\
##  W4\_Dep\_Total &  &  & 0.042$^{***}$ & 0.026$^{**}$ \\
##   &  &  & (0.013) & (0.012) \\
##   & & & & \\
##  W4\_PTSDdx &  &  & 0.428$^{**}$ & 0.374$^{*}$ \\
##   &  &  & (0.216) & (0.205) \\
##   & & & & \\
##  W4\_Paranoia\_Total &  &  & $-$0.095$^{***}$ & $-$0.061$^{***}$ \\
##   &  &  & (0.017) & (0.018) \\
##   & & & & \\
##  W4\_Conspiracy\_Total &  &  & $-$0.039$^{***}$ & $-$0.029$^{***}$ \\
##   &  &  & (0.007) & (0.006) \\
##   & & & & \\
##  Constant & 15.681$^{***}$ & 10.905$^{***}$ & 15.506$^{***}$ &
15.548$^{***}$ \\
##   & (0.451) & (0.573) & (0.239) & (0.775) \\
##   & & & & \\
## \hline \\[-1.8ex]
## Observations & 3,596 & 3,612 & 3,612 & 3,596 \\
## R$^{2}$ & 0.160 & 0.034 & 0.024 & 0.194 \\
## Adjusted R$^{2}$ & 0.156 & 0.033 & 0.023 & 0.188 \\
## Residual Std. Error & 3.800 (df = 3580) & 4.072 (df = 3606) & 4.093 (df =
3607) & 3.728 (df = 3571) \\
## F Statistic & 45.386$^{***}$ (df = 15; 3580) & 25.602$^{***}$ (df = 5;
3606) & 22.100$^{***}$ (df = 4; 3607) & 35.702$^{***}$ (df = 24; 3571) \\
## \hline
## \hline \\[-1.8ex]
## \textit{Note:}  & \multicolumn{4}{r}{$^{*}$p$<$0.1; $^{**}$p$<$0.05;
$^{***}$p$<$0.01} \\
## \end{tabular}
## \end{table}
```

Calculate VIF:

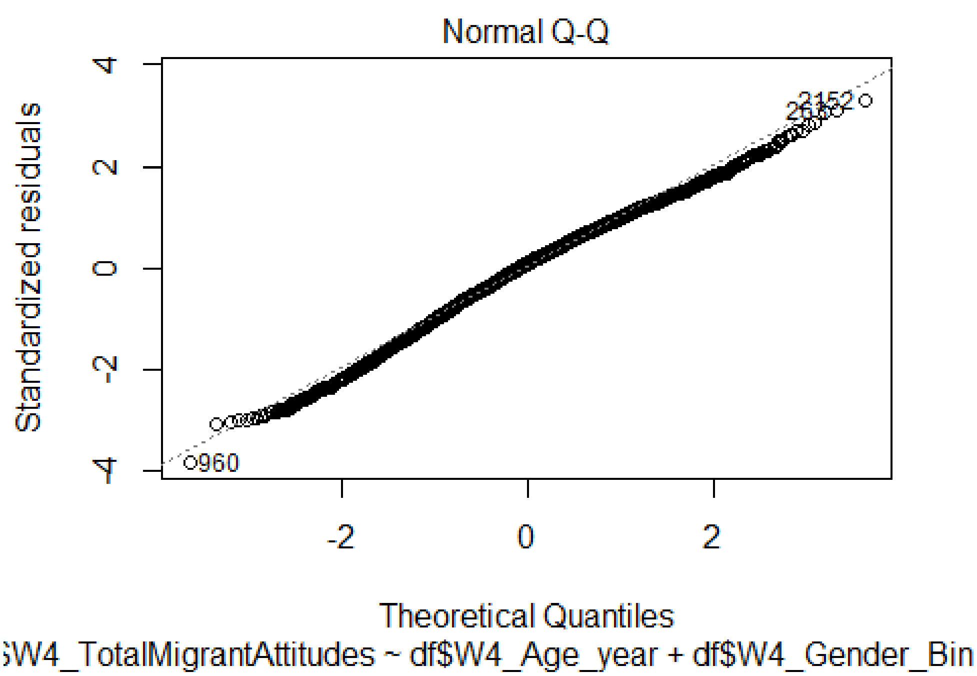
```
# Calculate VIF
vif_values <- vif(m4)
write.csv(vif_values, "vif_values.csv")
```

Assumption plots:

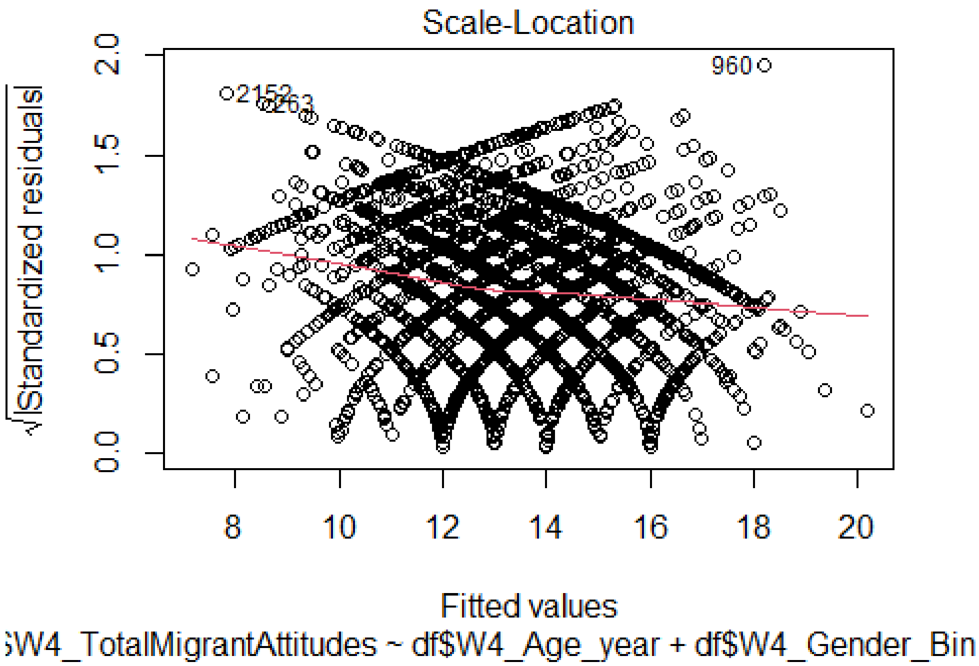
```
plot(m4)
```

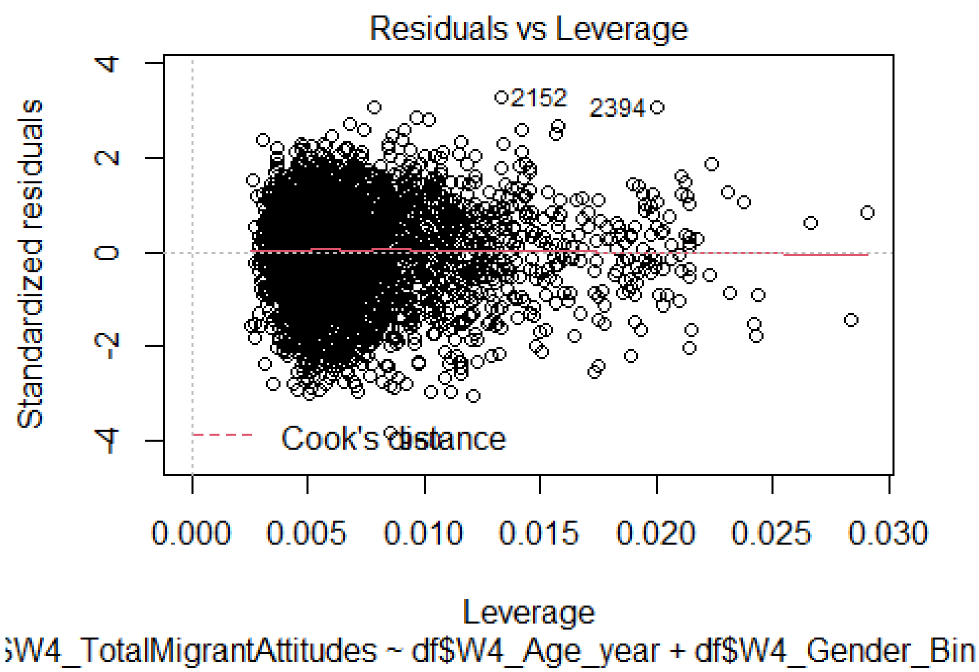


Residuals vs Fitted
Residuals
Fitted values
$W4_TotalMigrantAttitudes ~ df$W4_Age_year + df$W4_Gender_Bin
2152
263
960



Normal Q-Q
Standardized residuals
Theoretical Quantiles
$W4_TotalMigrantAttitudes ~ df$W4_Age_year + df$W4_Gender_Bin
2152
263
960


Scale-Location
√|Standardized residuals|
Fitted values
$W4_TotalMigrantAttitudes ~ df$W4_Age_year + df$W4_Gender_Bin
960
2152


Residuals vs Leverage
Standardized residuals
Leverage
$W4_TotalMigrantAttitudes ~ df$W4_Age_year + df$W4_Gender_Bin
2152
2394
Cook's distance