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.

# 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)) %>%  
 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

# 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)  
  
# 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:

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

# 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

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

# 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

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

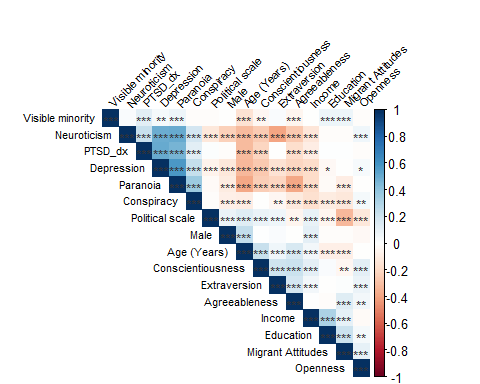
df$W4\_Income\_2019\_categories<-NA  
df$W4\_Income\_2019\_categories[df$W4\_Income\_2019 == 1] <- "£0-15,490 per year"  
df$W4\_Income\_2019\_categories[df$W4\_Income\_2019 == 2] <- "£15,491-£25,340 per year"  
df$W4\_Income\_2019\_categories[df$W4\_Income\_2019 == 3] <- "£25,341-£38,740 per year"  
df$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

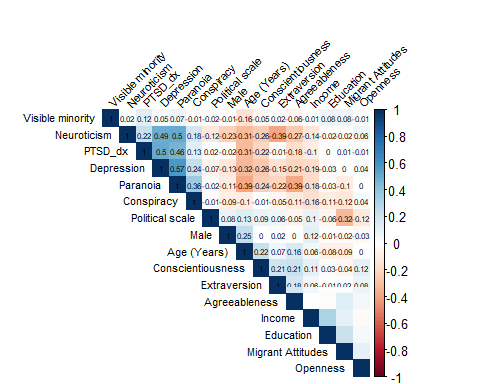
### Descriptive statistics:

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  
  
# 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))



# 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

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)

