Paper_MEPOP_1

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The Impact of Political Campaigns on Affection: The Case of the First Chilean Constitutional Process (2022)

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† Este documento es para compartir ideas y tener acceso al código que estamos ocupando.

Environment

Preparing our environment (loading libraries).

```
library(haven)
library(knitr)
library(lattice)
library(tidyverse)
library(here)
library(flextable)
library(devtools)
library(lavaan)
library(ggplot2)
library(plm)
library(naniar)
library(purrr)
library(psych)
library(interactions)
library(semPlot)
```

Cross-Sectional Approach

Importing data and creating variables

```
#Import Data

data_w1 <- read_sav("Data_W1.sav")

# ID
data_w1$id <- data_w1$CodPanelista

# Age
```

```r
data_w1$age_num <- data_w1$age

# Socioeconomic Status
data_w1$ses <- data_w1$RECO_NSE

# Education
data_w1$educ <- data_w1$P60

# Sex (1=women)
data_w1 <- data_w1%>%
  mutate(sex = ifelse(SEX == 2, 1,
                      ifelse(SEX == 1, 0, NA)))

# Ideology
data_w1$ideology <- ifelse(data_w1$P32 == 99, NA, data_w1$P32)

# Online Political Efficacy
data_w1$ope1 <- data_w1$P59_1
data_w1$ope2 <- data_w1$P59_2
data_w1$ope3 <- data_w1$P59_3
data_w1$ope4 <- data_w1$P59_4

# External Political Efficacy (recode)
data_w1$extef1 <- data_w1$P58_1
data_w1$extef2 <- data_w1$P58_2
data_w1$extef3 <- data_w1$P58_3

# To recode efficacies (intef1, intef3, extef1, extef3, extef4)
data_w1 <- data_w1 %>%
  mutate(across(c(extef1, extef2, extef3), ~ 6 - .x))

# Internal Political Efficacy
data_w1$intef1 <- data_w1$P58_4
data_w1$intef2 <- data_w1$P58_5
data_w1$intef3 <- data_w1$P58_6

# Media Exposure
data_w1$tv <- data_w1$P4_1
data_w1$cable <- data_w1$P4_2
data_w1$newspaper <- data_w1$P4_3
data_w1$radio <- data_w1$P4_4
data_w1$tradonline <- data_w1$P4_5
data_w1$online <- data_w1$P4_6
data_w1$podcast <- data_w1$P4_7
data_w1$officialsm <- data_w1$P4_8

# Social Media Exposure
data_w1$fb <- ifelse(data_w1$P5_1 == 99, NA, data_w1$P5_1)
data_w1$insta <- ifelse(data_w1$P5_2 == 99, NA, data_w1$P5_2)
data_w1$twitter <- ifelse(data_w1$P5_3 == 99, NA, data_w1$P5_3)
data_w1$whatsapp <- ifelse(data_w1$P5_4 == 99, NA, data_w1$P5_4)
```

```
data_w1$youtube <- ifelse(data_w1$P5_5 == 99, NA, data_w1$P5_5)
data_w1$tiktok <- ifelse(data_w1$P5_6 == 99, NA, data_w1$P5_6)
data_w1$discord <- ifelse(data_w1$P5_7 == 99, NA, data_w1$P5_7)
data_w1$twitch <- ifelse(data_w1$P5_8 == 99, NA, data_w1$P5_8)

# Franja Exposure
data_w1$franja <- data_w1$P6_1

# Social Media Political Use
data_w1$use1 <- data_w1$P25_5
data_w1$use2 <- data_w1$P25_6
data_w1$use3 <- data_w1$P25_7
data_w1$use4 <- data_w1$P25_8
data_w1$use5 <- data_w1$P25_9
data_w1$use6 <- data_w1$P25_10
data_w1$use7 <- data_w1$P25_11

# Interest
data_w1$polint <- data_w1$P21
data_w1$procint <- data_w1$P22
data_w1$plebint <- data_w1$P23
```

Checking the new variables

```
describe(data_w1$age_num)
```

```
   vars    n  mean    sd median trimmed   mad min max range skew kurtosis   se
X1    1 2117 44.26 14.78     42   43.83 16.31  18  84    66 0.27    -0.89 0.32
```

```
table(data_w1$ses)
```

```

  1   2   3   4   5 
293 289 511 740 284 
```

```
table(data_w1$educ)
```

```

  1   2   3   4   5   6   7   8   9  10 
  6  27 105 141 543 182 324 236 414 139 
```

```
table(data_w1$SEX)
```

```

   1    2 
 988 1129 
```

```
table(data_w1$sex)
```

```
  0    1 
988 1129 
```

```
table(data_w1$ideology)
```

```
  0   1   2   3   4   5   6   7   8   9  10 
135  43  95 129 125 571  91 107  80  51 178 
```

```
table(data_w1$ope1)
```

```
  1   2   3   4   5 
590 352 687 268 220 
```

```
table(data_w1$ope2)
```

```
  1   2   3   4   5 
459 335 680 340 303 
```

```
table(data_w1$ope3)
```

```
  1   2   3   4   5 
338 265 689 439 386 
```

```
table(data_w1$ope4)
```

```
  1   2   3   4   5 
719 386 618 210 184 
```

```
table(data_w1$extef1)
```

```
  1   2   3   4   5 
914 384 478 170 171 
```

```
table(data_w1$extef2)
```

```
   1    2    3    4    5 
```

```
1172  334  375  110  126
```

```r
table(data_w1$extef3)
```

```

   1    2    3    4    5 
1003  309  476  154  175 
```

```r
table(data_w1$intef1)
```

```

  1   2   3   4   5 
164 166 732 467 588 
```

```r
table(data_w1$intef2)
```

```

  1   2   3   4   5 
244 242 671 469 491 
```

```r
table(data_w1$intef3)
```

```

  1   2   3   4   5 
133 169 594 485 736 
```

```r
table(data_w1$tv)
```

```

  1   2   3   4   5 
405 298 407 342 665 
```

```r
table(data_w1$cable)
```

```

  1   2   3   4   5 
700 333 398 336 350 
```

```r
table(data_w1$newspaper)
```

```

   1    2    3    4    5 
1069  361  336  192  159 
```

```r
table(data_w1$radio)
```

```
  1   2   3   4   5 
778 335 410 287 307 
```

```
table(data_w1$tradonline)
```

```
  1   2   3   4   5 
757 371 427 314 248 
```

```
table(data_w1$online)
```

```
  1   2   3   4   5 
891 351 361 266 248 
```

```
table(data_w1$podcast)
```

```
   1    2    3    4    5 
1307  288  256  163  103 
```

```
table(data_w1$officialsm)
```

```
  1   2   3   4   5 
615 273 445 337 447 
```

```
table(data_w1$fb)
```

```
  1   2   3   4   5 
494 272 358 300 622 
```

```
table(data_w1$insta)
```

```
  1   2   3   4   5 
539 279 325 287 503 
```

```
table(data_w1$twitter)
```

```
  1   2   3   4   5 
698 185 237 202 309 
```

```
table(data_w1$whatsapp)
```

```
  1   2   3   4   5 
636 276 347 247 583 
```

```
table(data_w1$youtube)
```

```
  1   2   3   4   5 
728 300 317 283 399 
```

```
table(data_w1$tiktok)
```

```
  1   2   3   4   5 
771 181 225 149 277 
```

```
table(data_w1$discord)
```

```
   1    2    3    4    5 
1025   66   80   41   28 
```

```
table(data_w1$twitch)
```

```
  1   2   3   4   5 
999  76  75  36  35 
```

```
table(data_w1$franja)
```

```
  1   2   3   4   5 
661 451 442 255 308 
```

```
table(data_w1$polint)
```

```
  1   2   3   4   5 
533 243 539 430 372 
```

```
table(data_w1$procint)
```

```
  1   2   3   4   5 
```

```
386 186 403 447 695
```

```
table(data_w1$plebint)
```

```
  1   2   3   4   5 
346 171 331 382 887
```

Creating Factors

Reliability Test

```
cronbach_ope <- alpha(na.omit(data_w1[c("ope1", "ope2", "ope3", "ope4")]))
cronbach_ope

cronbach_intef <- alpha(na.omit(data_w1[c("intef1", "intef2", "intef3")]))
cronbach_intef

cronbach_extef <- alpha(na.omit(data_w1[c("extef1", "extef2", "extef3")]))
cronbach_extef

cronbach_media <- alpha(na.omit(data_w1[c("tv", "cable", "newspaper", "radio", "tradonlin
cronbach_media

cronbach_social <- alpha(na.omit(data_w1[c("fb", "insta", "twitter", "whatsapp", "youtube
cronbach_social

cronbach_interest <- alpha(na.omit(data_w1[c("polint", "procint", "plebint")]))
cronbach_interest

cronbach_poluse <- alpha(na.omit(data_w1[c("use1", "use2", "use3", "use4", "use5", "use6"
cronbach_poluse
```

Confirmatory Factor Analysis

```
data_w1_na <- na.omit(data_w1[c("id", "polint", "procint", "plebint", "ope1", "ope2", "op
sum(is.na(data_w1_na))

data_w1_na <- data_w1_na %>%
  mutate(across(where(is.labelled), as.numeric))

cfa.model <- 'ope =~ ope1 + ope2 + ope3 + ope4
              intef =~ intef1 + intef2 + intef3
              extef =~ extef1 + extef2 + extef3
              media =~ tv + cable + newspaper + radio + tradonline + online + podcast + o
              social =~ fb + insta + twitter + whatsapp + youtube + tiktok + discord + tw
              interest =~ polint + procint + plebint
```

```
             poluse =~ use1 + use2 + use3 + use4 + use5 + use6 + use7'


fit_cfa <- cfa(cfa.model, data = data_w1_na)
latent_scores <- predict(fit_cfa)

data_w1_scores <- cbind(data_w1_na, latent_scores)
```

Cross-sectional Analysis

Para estos modelos, debiésemos pensar si incluir o no political interest como control. Yo acá las incluí, pero no estoy seguro. Creo que "teóricamente" sería sensato no incluirla, porque puede esconder parte del efecto (multicolinealidad ¿?)

OLSE for Online Political Efficacy

Media Exposure on OPE

```
ols_ope1 <- lm(ope ~ age_num + ses + educ + sex + interest + media, data = data_w1_scores
summary(ols_ope1)
```

```

Call:
lm(formula = ope ~ age_num + ses + educ + sex + interest + media,
    data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.08246 -0.67363  0.01413  0.58393  2.54230 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.167571   0.222072   0.755 0.450659    
age_num     -0.007486   0.001975  -3.790 0.000159 ***
ses          0.046625   0.029457   1.583 0.113743    
educ         0.008761   0.016388   0.535 0.593047    
sex         -0.109179   0.055913  -1.953 0.051109 .  
interest     0.271343   0.031602   8.586  < 2e-16 ***
media        0.246881   0.052811   4.675  3.3e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9318 on 1127 degrees of freedom
Multiple R-squared:  0.1326,	Adjusted R-squared:  0.1279 
F-statistic:  28.7 on 6 and 1127 DF,  p-value: < 2.2e-16
```

Social Media Exposure on OPE

```
ols_ope2 <- lm(ope ~ age_num + ses + educ + sex + interest + social, data = data_w1_score
summary(ols_ope2)
```

```
Call:
lm(formula = ope ~ age_num + ses + educ + sex + interest + social,
    data = data_w1_scores)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.2066 -0.6774  0.0196  0.5708  2.6678 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.155862   0.218911   0.712 0.476622    
age_num     -0.006537   0.001952  -3.348 0.000841 ***
ses          0.027649   0.029203   0.947 0.343962    
educ         0.014456   0.016167   0.894 0.371409    
sex         -0.122152   0.055164  -2.214 0.027005 *  
interest     0.270681   0.029706   9.112  < 2e-16 ***
social       0.235806   0.031859   7.402 2.63e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9187 on 1127 degrees of freedom
Multiple R-squared:  0.1567,	Adjusted R-squared:  0.1522 
F-statistic: 34.91 on 6 and 1127 DF,  p-value: < 2.2e-16
```

Franja Exposure on OPE

```
ols_ope3 <- lm(ope ~ age_num + ses + educ + sex + interest + franja, data = data_w1_score
summary(ols_ope3)
```

```
Call:
lm(formula = ope ~ age_num + ses + educ + sex + interest + franja,
    data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.03446 -0.67228  0.04088  0.60559  2.49983 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.113075   0.231997   0.487 0.626071    
age_num     -0.007528   0.001995  -3.774 0.000169 ***
ses          0.051160   0.029724   1.721 0.085499 .  
educ         0.010789   0.016597   0.650 0.515785    
sex         -0.110514   0.056748  -1.947 0.051727 .  
```

```
interest     0.325612   0.030324  10.738  < 2e-16 ***
franja       0.011272   0.020765   0.543 0.587357
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9406 on 1127 degrees of freedom
Multiple R-squared:  0.116, Adjusted R-squared:  0.1113
F-statistic: 24.64 on 6 and 1127 DF,  p-value: < 2.2e-16
```

Social Media Political Use on OPE

```
ols_ope4 <- lm(ope ~ age_num + ses + educ + sex + interest + poluse, data = data_w1_score
summary(ols_ope4)
```

```
Call:
lm(formula = ope ~ age_num + ses + educ + sex + interest + poluse,
    data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max
-2.34027 -0.66994  0.02551  0.58008  2.46143

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.2857804  0.2159867   1.323  0.18606
age_num     -0.0063026  0.0019217  -3.280  0.00107 **
ses          0.0114148  0.0288750   0.395  0.69268
educ        -0.0003239  0.0159404  -0.020  0.98379
sex         -0.1001032  0.0542733  -1.844  0.06538 .
interest     0.1707454  0.0326632   5.227 2.05e-07 ***
poluse       0.3065948  0.0318763   9.618  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9044 on 1127 degrees of freedom
Multiple R-squared:  0.1828,    Adjusted R-squared:  0.1785
F-statistic: 42.02 on 6 and 1127 DF,  p-value: < 2.2e-16
```

OLSE for Internal Efficacy

Media Exposure on IPE

```
ols_intef1 <- lm(intef ~ age_num + ses + educ + sex + interest + media, data = data_w1_sc
summary(ols_intef1)
```

```
Call:
lm(formula = intef ~ age_num + ses + educ + sex + interest +
    media, data = data_w1_scores)
```

```
Residuals:
     Min       1Q   Median       3Q      Max 
-1.94800 -0.33611  0.00455  0.36349  1.46184 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.363010   0.125192  -2.900  0.00381 ** 
age_num      0.006803   0.001114   6.109 1.38e-09 ***
ses          0.003017   0.016606   0.182  0.85586    
educ         0.013575   0.009239   1.469  0.14202    
sex         -0.075822   0.031521  -2.405  0.01631 *  
interest     0.293515   0.017816  16.475  < 2e-16 ***
media        0.095937   0.029772   3.222  0.00131 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5253 on 1127 degrees of freedom
Multiple R-squared:  0.3152,	Adjusted R-squared:  0.3115 
F-statistic: 86.44 on 6 and 1127 DF,  p-value: < 2.2e-16
```

Social Media Exposure on IPE

```r
ols_intef2 <- lm(intef ~ age_num + ses + educ + sex + interest + social, data = data_w1_s
summary(ols_intef2)
```

```
Call:
lm(formula = intef ~ age_num + ses + educ + sex + interest + 
    social, data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.90888 -0.33829  0.00729  0.35953  1.42242 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.371061   0.125720  -2.951  0.00323 ** 
age_num      0.006825   0.001121   6.086 1.58e-09 ***
ses          0.003759   0.016771   0.224  0.82270    
educ         0.014289   0.009284   1.539  0.12408    
sex         -0.075816   0.031680  -2.393  0.01687 *  
interest     0.313414   0.017060  18.371  < 2e-16 ***
social       0.011329   0.018297   0.619  0.53592    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5276 on 1127 degrees of freedom
Multiple R-squared:  0.3091,	Adjusted R-squared:  0.3054 
F-statistic: 84.03 on 6 and 1127 DF,  p-value: < 2.2e-16
```

Franja Exposure on IPE

```
ols_intef3 <- lm(intef ~ age_num + ses + educ + sex + interest + franja, data = data_w1_s
summary(ols_intef3)
```

```
Call:
lm(formula = intef ~ age_num + ses + educ + sex + interest + 
    franja, data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.89064 -0.33505  0.00811  0.35401  1.39402 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.338893   0.130095  -2.605  0.00931 ** 
age_num      0.006747   0.001119   6.031  2.2e-09 ***
ses          0.005225   0.016668   0.313  0.75398    
educ         0.013340   0.009307   1.433  0.15204    
sex         -0.071906   0.031822  -2.260  0.02403 *  
interest     0.320533   0.017004  18.850  < 2e-16 ***
franja      -0.011325   0.011644  -0.973  0.33095    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5275 on 1127 degrees of freedom
Multiple R-squared:  0.3094,	Adjusted R-squared:  0.3057 
F-statistic: 84.16 on 6 and 1127 DF,  p-value: < 2.2e-16
```

Social Media Political Use on IPE

```
ols_intef4 <- lm(intef ~ age_num + ses + educ + sex + interest + poluse, data = data_w1_s
summary(ols_intef4)
```

```
Call:
lm(formula = intef ~ age_num + ses + educ + sex + interest + 
    poluse, data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.98528 -0.32789  0.00003  0.35932  1.41830 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.346221   0.125529  -2.758  0.00591 ** 
age_num      0.007002   0.001117   6.270 5.14e-10 ***
ses         -0.002336   0.016782  -0.139  0.88933    
educ         0.012202   0.009264   1.317  0.18807    
```

```
sex          -0.073798   0.031543  -2.340  0.01948 *  
interest      0.287505   0.018983  15.145  < 2e-16 ***
poluse        0.055401   0.018526   2.990  0.00285 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5256 on 1127 degrees of freedom
Multiple R-squared:  0.3143,	Adjusted R-squared:  0.3106 
F-statistic: 86.09 on 6 and 1127 DF,  p-value: < 2.2e-16
```

OLSE for External Efficacy

Media Exposure on EPE

```
ols_extef1 <- lm(extef ~ age_num + ses + educ + sex + interest + media, data = data_w1_sc
summary(ols_extef1)
```

```
Call:
lm(formula = extef ~ age_num + ses + educ + sex + interest + 
    media, data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.41141 -0.65649 -0.08126  0.49539  2.64045 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.238243   0.188089   1.267   0.2055    
age_num     -0.010794   0.001673  -6.452 1.64e-10 ***
ses          0.045041   0.024949   1.805   0.0713 .  
educ         0.009128   0.013880   0.658   0.5109    
sex          0.062272   0.047357   1.315   0.1888    
interest    -0.044979   0.026766  -1.680   0.0932 .  
media        0.018439   0.044730   0.412   0.6803    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7892 on 1127 degrees of freedom
Multiple R-squared:  0.05861,	Adjusted R-squared:  0.0536 
F-statistic: 11.69 on 6 and 1127 DF,  p-value: 9.626e-13
```

Social Media Exposure on EPE

```
ols_extef2 <- lm(extef ~ age_num + ses + educ + sex + interest + social, data = data_w1_s
summary(ols_extef2)
```

```
Call:
lm(formula = extef ~ age_num + ses + educ + sex + interest + 
```

```
    social, data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.44562 -0.62662 -0.07256  0.50110  2.64300 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.24044    0.18720   1.284  0.19926    
age_num     -0.01042    0.00167  -6.240 6.19e-10 ***
ses          0.03650    0.02497   1.462  0.14409    
educ         0.01087    0.01383   0.786  0.43192    
sex          0.05688    0.04717   1.206  0.22819    
interest    -0.06271    0.02540  -2.469  0.01371 *  
social       0.08806    0.02724   3.232  0.00126 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7856 on 1127 degrees of freedom
Multiple R-squared:  0.06711,	Adjusted R-squared:  0.06215 
F-statistic: 13.51 on 6 and 1127 DF,  p-value: 7.525e-15
```

Franja Exposure on EPE

```r
ols_extef3 <- lm(extef ~ age_num + ses + educ + sex + interest + franja, data = data_w1_s
summary(ols_extef3)
```

```

Call:
lm(formula = extef ~ age_num + ses + educ + sex + interest + 
    franja, data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.46010 -0.65337 -0.06918  0.49670  2.65073 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.170608   0.194509   0.877   0.3806    
age_num     -0.010741   0.001672  -6.422 1.98e-10 ***
ses          0.044755   0.024921   1.796   0.0728 .  
educ         0.010716   0.013915   0.770   0.4414    
sex          0.055948   0.047578   1.176   0.2399    
interest    -0.049246   0.025424  -1.937   0.0530 .  
franja       0.022883   0.017409   1.314   0.1890    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7886 on 1127 degrees of freedom
Multiple R-squared:  0.05991,	Adjusted R-squared:  0.0549 
F-statistic: 11.97 on 6 and 1127 DF,  p-value: 4.612e-13
```

Social Media Political Use on EPE

```
ols_extef4 <- lm(extef ~ age_num + ses + educ + sex + interest + poluse, data = data_w1_s
summary(ols_extef4)
```

```
Call:
lm(formula = extef ~ age_num + ses + educ + sex + interest + 
    poluse, data = data_w1_scores)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.35393 -0.62228 -0.07628  0.48927  2.53237 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.317891   0.185045   1.718   0.0861 .  
age_num     -0.010072   0.001646  -6.118 1.31e-09 ***
ses          0.022173   0.024738   0.896   0.3703    
educ         0.003207   0.013657   0.235   0.8144    
sex          0.066601   0.046498   1.432   0.1523    
interest    -0.132870   0.027984  -4.748 2.32e-06 ***
poluse       0.177769   0.027310   6.509 1.13e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7748 on 1127 degrees of freedom
Multiple R-squared:  0.09258,	Adjusted R-squared:  0.08775 
F-statistic: 19.16 on 6 and 1127 DF,  p-value: < 2.2e-16
```

Longitudinal Approach

Importing data and creating variables

```
#Import Data
data_w3 <- read_sav("Data_W3.sav")

# ID
data_w3$id <- data_w3$CodPanelista

# Age
data_w3$age_num <- data_w3$age

# Socioeconomic Status
data_w3$ses <- data_w3$RECO_NSE

# Sex (1=women)
```

```
data_w3 <- data_w3%>%
  mutate(sex = ifelse(SEX == 2, 1,
                      ifelse(SEX == 1, 0, NA)))

# Ideology
data_w3$ideology <- ifelse(data_w3$P32 == 99, NA, data_w3$P32)

# Social Media Political Use
data_w3$use1 <- data_w3$P25_5
data_w3$use2 <- data_w3$P25_6
data_w3$use3 <- data_w3$P25_7
data_w3$use4 <- data_w3$P25_8
data_w3$use5 <- data_w3$P25_9
data_w3$use6 <- data_w3$P25_10
data_w3$use7 <- data_w3$P25_11

# Online Political Efficacy
data_w3$ope1 <- data_w3$P59_1
data_w3$ope2 <- data_w3$P59_2
data_w3$ope3 <- data_w3$P59_3
data_w3$ope4 <- data_w3$P59_4

# External Political Efficacy (recode)
data_w3$extef1 <- data_w3$P58_1
data_w3$extef2 <- data_w3$P58_2
data_w3$extef3 <- data_w3$P58_3

# To recode efficacies (intef1, intef3, extef1, extef3, extef4)
data_w3 <- data_w3 %>%
  mutate(across(c(extef1, extef2, extef3), ~ 6 - .x))

# Internal Political Efficacy
data_w3$intef1 <- data_w3$P58_4
data_w3$intef2 <- data_w3$P58_5
data_w3$intef3 <- data_w3$P58_6
```

Checking the new variables

```
describe(data_w3$age_num)
```

```
   vars   n mean    sd median trimmed   mad min max range skew kurtosis   se
X1    1 902 45.4 14.42     44      45 16.31  18  84    66 0.23    -0.87 0.48
```

```
table(data_w3$ses)
```

```

  1   2   3   4   5 
148 132 244 281  97 
```

```
table(data_w3$SEX)
```

```

  1   2 
438 464 
```

```
table(data_w3$sex)
```

```

  0   1 
438 464 
```

```
table(data_w3$P32)
```

```

  0   1   2   3   4   5   6   7   8   9  10  99 
 53  19  49  36  51 276  51  36  50  18  64 199 
```

```
table(data_w3$ideology)
```

```

  0   1   2   3   4   5   6   7   8   9  10 
 53  19  49  36  51 276  51  36  50  18  64 
```

```
table(data_w3$ope1)
```

```

  1   2   3   4   5 
227 118 325 105 127 
```

```
table(data_w3$ope2)
```

```

  1   2   3   4   5 
178 108 321 147 148 
```

```
table(data_w3$ope3)
```

```

  1   2   3   4   5 
132 100 321 184 165 
```

```
table(data_w3$ope4)
```

```

  1   2   3   4   5 
```

```
308 145 271 102  76
```

```r
table(data_w3$extef1)
```

```
  1   2   3   4   5 
465 176 169  37  55 
```

```r
table(data_w3$extef2)
```

```
  1   2   3   4   5 
568 133 136  31  34 
```

```r
table(data_w3$extef3)
```

```
  1   2   3   4   5 
453 145 182  55  67 
```

```r
table(data_w3$intef1)
```

```
  1   2   3   4   5 
 59  65 327 194 257 
```

```r
table(data_w3$intef2)
```

```
  1   2   3   4   5 
 83 104 307 176 232 
```

```r
table(data_w3$intef3)
```

```
  1   2   3   4   5 
 40  46 279 198 339 
```

Creating Long Dataset

```r
# Subset the necessary variables
data_w1_selec <- data_w1 %>% select(id, ope1, ope2, ope3, ope4, intef1, intef2, intef3, e

data_w3_selec <- data_w3 %>% select(id, ope1, ope2, ope3, ope4, intef1, intef2, intef3, e

# Find common ids in both datasets
common_ids <- intersect(data_w1_selec$id, data_w3_selec$id)
```

```
# Filter both data frames to include only those ids
data_w1_selec <- data_w1_selec %>% filter(id %in% common_ids)
data_w3_selec <- data_w3_selec %>% filter(id %in% common_ids)

# Add a wave identifier
data_w1_selec$wave <- 1
data_w3_selec$wave <- 2

# Combine the datasets into a long format
data_long <- rbind(data_w1_selec, data_w3_selec)

# Check the first few rows of the combined dataset
head(data_long)

# Check the distribution of data across waves
table(data_long$wave)
```

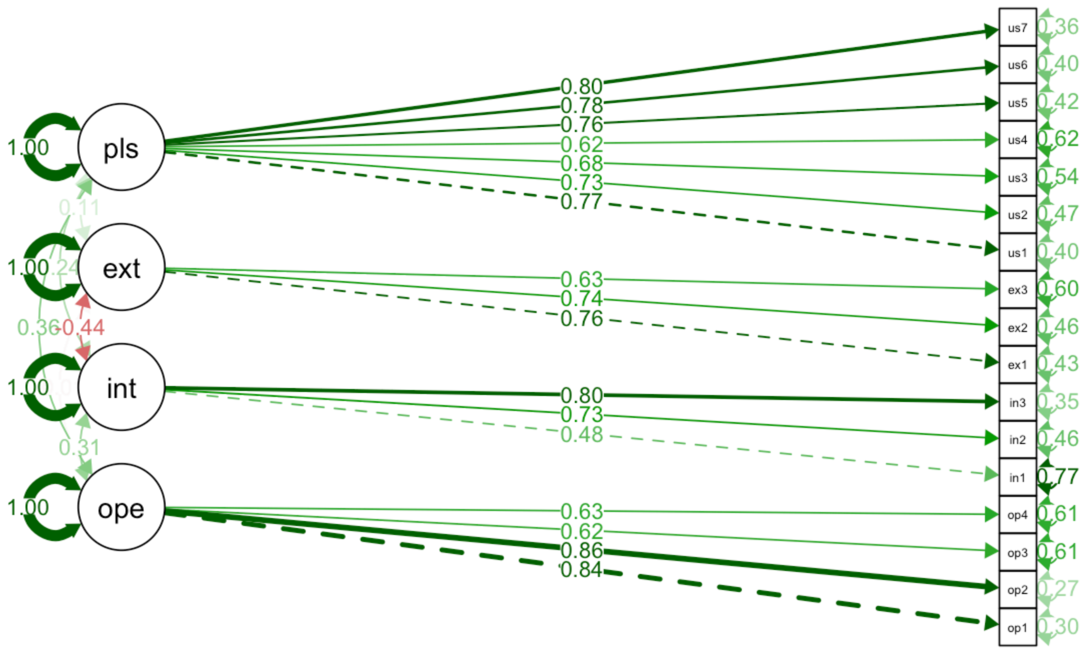
Reliability Test for Long Dataset

```
cronbach_ope_long <- alpha(na.omit(data_long[c("ope1", "ope2", "ope3", "ope4")]))
cronbach_ope_long

cronbach_intef_long <- alpha(na.omit(data_long[c("intef1", "intef2", "intef3")]))
cronbach_intef_long

cronbach_extef_long <- alpha(na.omit(data_long[c("extef1", "extef2", "extef3")]))
cronbach_extef_long

cronbach_poluse_long <- alpha(na.omit(data_long[c("use1", "use2", "use3", "use4", "use5",
cronbach_poluse_long
```

Creating Latent Variables for Long Dataset

```
data_long <- data_long %>%
  mutate(across(where(is.labelled), as.numeric))

cfa.model_long <- 'ope =~ ope1 + ope2 + ope3 + ope4
                intef =~ intef1 + intef2 + intef3
                extef =~ extef1 + extef2 + extef3
                poluse =~ use1 + use2 + use3 + use4 + use5 + use6 + use7'

fit_cfa_long <- cfa(cfa.model_long, data = data_long)
latent_scores_long <- predict(fit_cfa_long)

data_long_scores <- cbind(data_long, latent_scores_long)

# Plot the CFA model
```

```
semPaths(fit_cfa_long, "std", layout = "tree", rotation = 2,
         whatLabels = "std", edge.label.cex = 0.8,
         sizeMan = 3, sizeLat = 7, title = TRUE)
```



Converting to Panel Dataset

```
# Convert your data to a panel data frame
pdata <- pdata.frame(data_long_scores, index = c("id", "wave"))
```

Panel Regression for OPE

Primero, estimamos dos modelos, uno con efectos fijos (FE) y otros con random effects (RA). Luego de estimar el test de Hausman (p-value > 0,05), decidimos reportar el modelo con random effects:

```
# Fit a random effects model
model_re_ope <- plm(ope ~ poluse + ideology + ses + sex + age_num, data = pdata, model =

# Fit a FE model
model_fe_ope <- plm(ope ~ poluse + ideology + ses + sex + age_num, data = pdata, model =

# Perform the Hausman test
hausman_test_ope <- phtest(model_fe_ope, model_re_ope)
```

```
# Print the results of the Hausman test
print(hausman_test_ope)
```

```
	Hausman Test

data:  ope ~ poluse + ideology + ses + sex + age_num
chisq = 2.9046, df = 4, p-value = 0.5739
alternative hypothesis: one model is inconsistent
```

```
# Summary of the random effects model
summary(model_re_ope)
```

```
Oneway (individual) effect Random Effect Model 
   (Swamy-Arora's transformation)

Call:
plm(formula = ope ~ poluse + ideology + ses + sex + age_num, 
    data = pdata, model = "random")

Unbalanced Panel: n = 771, T = 1-2, N = 1403

Effects:
                 var std.dev share
idiosyncratic 0.5286  0.7270 0.608
individual    0.3401  0.5832 0.392
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.2199  0.3387  0.3387  0.3270  0.3387  0.3387 

Residuals:
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max. 
-1.90094 -0.52418  0.02308  0.00054  0.46377  2.18764 

Coefficients:
              Estimate Std. Error z-value Pr(>|z|)    
(Intercept)  0.1400564  0.1504043  0.9312  0.35175    
poluse       0.3942251  0.0267159 14.7562  < 2e-16 ***
ideology     0.0152520  0.0106178  1.4365  0.15087    
ses         -0.0102614  0.0234937 -0.4368  0.66227    
sex          0.0415483  0.0583131  0.7125  0.47615    
age_num     -0.0039471  0.0020856 -1.8925  0.05842 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    856.36
Residual Sum of Squares: 736.75
R-Squared:      0.13967
```

```
Adj. R-Squared: 0.13659
Chisq: 227.325 on 5 DF, p-value: < 2.22e-16
```

Panel Regression for IPE

Primero, estimamos dos modelos, uno con efectos fijos (FE) y otros con random effects (RA). Luego de estimar el test de Hausman (p-value < 0,05), decidimos reportar el modelo con efectos fijos:

```
# Fit a random effects model
model_re_intef <- plm(intef ~ poluse + ideology + ses + sex + age_num, data = pdata, mode

# Fit a fixed effects model
model_fe_intef <- plm(intef ~ poluse + ideology + ses + sex + age_num, data = pdata, mode

# Perform the Hausman test
hausman_test_intef <- phtest(model_fe_intef, model_re_intef)

# Print the results of the Hausman test
print(hausman_test_intef)
```

```
	Hausman Test

data:  intef ~ poluse + ideology + ses + sex + age_num
chisq = 17.792, df = 4, p-value = 0.001355
alternative hypothesis: one model is inconsistent
```

```
# Summary of the random effects model
summary(model_fe_intef)
```

```
Oneway (individual) effect Within Model

Call:
plm(formula = intef ~ poluse + ideology + ses + sex + age_num,
    data = pdata, model = "within")

Unbalanced Panel: n = 771, T = 1-2, N = 1403

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.03647 -0.10495  0.00000  0.10495  1.03647

Coefficients:
           Estimate Std. Error t-value Pr(>|t|)
poluse   0.03420092 0.02366427  1.4453   0.1489
ideology 0.00092247 0.01222762  0.0754   0.9399
ses      0.01853026 0.03654759  0.5070   0.6123
age_num  0.02178730 0.04529339  0.4810   0.6307
```

```
Total Sum of Squares:    70.951
Residual Sum of Squares: 70.664
R-Squared:      0.0040503
Adj. R-Squared: -1.2234
F-statistic: 0.638481 on 4 and 628 DF, p-value: 0.63521
```

Panel Regression for EPE

Primero, estimamos dos modelos, uno con efectos fijos (FE) y otros con random effects (RA). Luego de estimar el test de Hausman (p-value > 0,05), decidimos reportar el modelo con random effects:

```
# Fit a random effects model
model_re_extef <- plm(extef ~ poluse + ideology + ses + sex + age_num, data = pdata, mode

# Fit a fixed effects model
model_fe_extef <- plm(extef ~ poluse + ideology + ses + sex + age_num, data = pdata, mode

# Perform the Hausman test
hausman_test_extef <- phtest(model_fe_extef, model_re_extef)

# Print the results of the Hausman test
print(hausman_test_extef)
```

```

	Hausman Test

data:  extef ~ poluse + ideology + ses + sex + age_num
chisq = 1.1179, df = 4, p-value = 0.8914
alternative hypothesis: one model is inconsistent
```

```
# Summary of the random effects model
summary(model_re_extef)
```

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = extef ~ poluse + ideology + ses + sex + age_num,
    data = pdata, model = "random")

Unbalanced Panel: n = 771, T = 1-2, N = 1403

Effects:
                 var std.dev share
idiosyncratic 0.3226  0.5680 0.539
individual    0.2757  0.5251 0.461
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.2657  0.3925  0.3925  0.3799  0.3925  0.3925 
```

```
Residuals:
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max. 
-1.23285 -0.43847 -0.12064 -0.00252  0.36063  2.30798 

Coefficients:
              Estimate Std. Error z-value  Pr(>|z|)    
(Intercept)  0.4189241  0.1271025  3.2960 0.0009809 ***
poluse       0.1102612  0.0221566  4.9764 6.476e-07 ***
ideology    -0.0155444  0.0089000 -1.7466 0.0807124 .  
ses         -0.0079190  0.0197904 -0.4001 0.6890530    
sex          0.0798354  0.0495226  1.6121 0.1069404    
age_num     -0.0077897  0.0017703 -4.4002 1.081e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    471.34
Residual Sum of Squares: 451.68
R-Squared:      0.041723
Adj. R-Squared: 0.038293
Chisq: 60.7255 on 5 DF, p-value: 8.6054e-12
```

What's next

Esta es mi primera vez analizando datos panel, entonces me quedé con dudas sobre la parte panel regression.

1. Incluí variables sociodemográficas como control, pero son variables constantes en ambas olas… Creo que no está del todo correcto incluirlas, quizás es mejor estimar panel regression con FE.

2. Hay que ver cómo reportar el R-squared within, between y overall. Parece ser clave para interpretar los resultados del panel regression, pero no es algo que el código reporte por defecto.

Appendix Analyses With a Balanced Panel

En este apéndice testeamos los modelos pero, antes, balanceamos el panel En los modelos reportados antes, la muestra seguía desbalanceada, probablemente por casos que tenían NAs en algunas de las variables y algunas de las olas. Los resultados utilizando el panel balaneado son iguales.

```
# Subset and check for complete cases in each wave
data_w1_complete <- data_w1 %>%
  select(id, ope1, ope2, ope3, ope4, intef1, intef2, intef3, extef1, extef2, extef3, use1
  filter(complete.cases(.))

data_w3_complete <- data_w3 %>%
  select(id, ope1, ope2, ope3, ope4, intef1, intef2, intef3, extef1, extef2, extef3, use1
  filter(complete.cases(.))
```

```
# Find common ids that are complete in both datasets
common_ids_complete <- intersect(data_w1_complete$id, data_w3_complete$id)

# Filter both data frames to include only those complete ids
data_w1_selec <- data_w1_complete %>% filter(id %in% common_ids_complete)
data_w3_selec <- data_w3_complete %>% filter(id %in% common_ids_complete)

# Add a wave identifier
data_w1_selec$wave <- 1
data_w3_selec$wave <- 2

# Combine the datasets into a long format
data_long_complete <- rbind(data_w1_selec, data_w3_selec)

# Check the first few rows of the combined dataset
head(data_long_complete)
```

```
# A tibble: 6 × 23
  id       ope1    ope2    ope3    ope4    intef1  intef2  intef3  extef1 extef2
  <chr>    <dbl+l> <dbl+l> <dbl+l> <dbl+l> <dbl+l> <dbl+l> <dbl+l>  <dbl>  <dbl>
1 010a9d3… 1 [1 M… 1 [1 M… 1 [1 M… 1 [1 M… 5 [5 M… 3 [3]   2 [2]        1      1
2 0191331… 4 [4]   4 [4]   5 [5 M… 1 [1 M… 4 [4]   4 [4]   5 [5 M…      1      1
3 023294d… 2 [2]   1 [1 M… 3 [3]   2 [2]   5 [5 M… 1 [1 M… 2 [2]        1      1
4 030ff44… 2 [2]   3 [3]   3 [3]   5 [5 M… 4 [4]   5 [5 M… 4 [4]        2      1
5 038d5d9… 3 [3]   3 [3]   4 [4]   3 [3]   4 [4]   3 [3]   4 [4]        2      3
6 03c9053… 1 [1 M… 1 [1 M… 1 [1 M… 1 [1 M… 3 [3]   3 [3]   3 [3]        3      5
# ℹ 13 more variables: extef3 <dbl>, use1 <dbl+lbl>, use2 <dbl+lbl>,
#   use3 <dbl+lbl>, use4 <dbl+lbl>, use5 <dbl+lbl>, use6 <dbl+lbl>,
#   use7 <dbl+lbl>, sex <dbl>, ses <dbl+lbl>, age_num <dbl>, ideology <dbl>,
#   wave <dbl>
```

```
# Check the distribution of data across waves
table(data_long_complete$wave)
```

```

  1   2 
632 632 
```

```
data_long_complete <- data_long_complete %>%
  mutate(across(where(is.labelled), as.numeric))

cfa.model_long_complete <- 'ope =~ ope1 + ope2 + ope3 + ope4
                intef =~ intef1 + intef2 + intef3
                extef =~ extef1 + extef2 + extef3
                poluse =~ use1 + use2 + use3 + use4 + use5 + use6 + use7'

fit_cfa_long_complete <- cfa(cfa.model_long_complete, data = data_long_complete)
latent_scores_long_complete <- predict(fit_cfa_long_complete)
```

```
data_long_complete_scores <- cbind(data_long_complete, latent_scores_long_complete)

# Convert your data to a panel data frame
pdata_complete <- pdata.frame(data_long_complete_scores, index = c("id", "wave"))
```

Panel Regressions OPE

```
# Fit a random effects model
model_re_ope_bal <- plm(ope ~ poluse + ideology + ses + sex + age_num, data = pdata_compl

# Fit a FE model
model_fe_ope_bal <- plm(ope ~ poluse + ideology + ses + sex + age_num, data = pdata_compl

# Perform the Hausman test
hausman_test_ope_bal <- phtest(model_fe_ope_bal, model_re_ope_bal)

# Print the results of the Hausman test
print(hausman_test_ope_bal)
```

```
    Hausman Test

data:  ope ~ poluse + ideology + ses + sex + age_num
chisq = 2.6035, df = 4, p-value = 0.6262
alternative hypothesis: one model is inconsistent
```

```
# Summary of the random effects model
summary(model_re_ope_bal)
```

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = ope ~ poluse + ideology + ses + sex + age_num,
    data = pdata_complete, model = "random")

Balanced Panel: n = 632, T = 2, N = 1264

Effects:
                 var std.dev share
idiosyncratic 0.5147  0.7174 0.608
individual    0.3321  0.5763 0.392
theta: 0.3393

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.886505 -0.514816  0.027464  0.468951  2.148464

Coefficients:
```

```
              Estimate Std. Error z-value Pr(>|z|)
(Intercept)  0.1424367  0.1589574  0.8961  0.37022
poluse       0.3974195  0.0283958 13.9957  < 2e-16 ***
ideology     0.0149748  0.0108462  1.3807  0.16739
ses         -0.0113996  0.0251782 -0.4528  0.65073
sex          0.0575954  0.0621716  0.9264  0.35424
age_num     -0.0045821  0.0022110 -2.0724  0.03822 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    753.66
Residual Sum of Squares: 646.79
R-Squared:      0.1418
Adj. R-Squared: 0.13839
Chisq: 207.853 on 5 DF, p-value: < 2.22e-16
```

Panel Regressions IPE

```
# Fit a random effects model
model_re_intef_bal <- plm(intef ~ poluse + ideology + ses + sex + age_num, data = pdata_c

# Fit a fixed effects model
model_fe_intef_bal <- plm(intef ~ poluse + ideology + ses + sex + age_num, data = pdata_c

# Perform the Hausman test
hausman_test_intef_bal <- phtest(model_fe_intef_bal, model_re_intef_bal)

# Print the results of the Hausman test
print(hausman_test_intef_bal)
```

```

    Hausman Test

data:  intef ~ poluse + ideology + ses + sex + age_num
chisq = 14.977, df = 4, p-value = 0.00475
alternative hypothesis: one model is inconsistent
```

```
# Summary of the random effects model
summary(model_fe_intef_bal)
```

```
Oneway (individual) effect Within Model

Call:
plm(formula = intef ~ poluse + ideology + ses + sex + age_num,
    data = pdata_complete, model = "within")

Balanced Panel: n = 632, T = 2, N = 1264

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
```

```
-9.3478e-01 -1.1405e-01 -5.5511e-17  1.1405e-01  9.3478e-01

Coefficients:
           Estimate Std. Error t-value Pr(>|t|)
poluse   0.02603575 0.02226596  1.1693   0.2427
ideology 0.00095487 0.01130251  0.0845   0.9327
ses      0.01747224 0.03378143  0.5172   0.6052
age_num  0.01849735 0.04186544  0.4418   0.6588

Total Sum of Squares:    60.546
Residual Sum of Squares: 60.372
R-Squared:      0.002878
Adj. R-Squared: -1.0054
F-statistic: 0.453155 on 4 and 628 DF, p-value: 0.77012
```

```r
# Fit a random effects model
model_re_extef_bal <- plm(extef ~ poluse + ideology + ses + sex + age_num, data = pdata_c

# Fit a fixed effects model
model_fe_extef_bal <- plm(extef ~ poluse + ideology + ses + sex + age_num, data = pdata_c

# Perform the Hausman test
hausman_test_extef_bal <- phtest(model_fe_extef_bal, model_re_extef_bal)

# Print the results of the Hausman test
print(hausman_test_extef_bal)
```

```
    Hausman Test

data:  extef ~ poluse + ideology + ses + sex + age_num
chisq = 0.7499, df = 4, p-value = 0.945
alternative hypothesis: one model is inconsistent
```

```r
# Summary of the random effects model
summary(model_re_extef_bal)
```

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = extef ~ poluse + ideology + ses + sex + age_num,
    data = pdata_complete, model = "random")

Balanced Panel: n = 632, T = 2, N = 1264

Effects:
                 var std.dev share
idiosyncratic 0.3282  0.5729  0.55
```

```
individual    0.2690  0.5187  0.45
theta: 0.3845

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.18351 -0.43023 -0.12477  0.34248  2.33106

Coefficients:
              Estimate Std. Error z-value  Pr(>|z|)
(Intercept)  0.3686503  0.1354970  2.7207  0.006514 **
poluse       0.1381676  0.0237726  5.8121 6.171e-09 ***
ideology    -0.0143471  0.0091673 -1.5650  0.117576
ses         -0.0171061  0.0213970 -0.7995  0.424023
sex          0.0995493  0.0532494  1.8695  0.061555 .
age_num     -0.0063578  0.0018923 -3.3598  0.000780 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    431.91
Residual Sum of Squares: 411.86
R-Squared:      0.046423
Adj. R-Squared: 0.042633
Chisq: 61.2435 on 5 DF, p-value: 6.7243e-12
```