Component 2, Stage 2

Sevastian Sanchez

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```
knitr::opts_chunk$set(
  echo = TRUE, warning = FALSE, message = FALSE,
  tidy = TRUE, tidy.opts = list(width.cutoff = 60)
)
```

1 Set up

```
# set working directory
setwd("~/Documents/GitHub/QMSS_Thesis_Sanchez")

# load libraries/packages
source("packages.R")

# load data
source("Comp2_panel_wrangling.R")

# select relevant variables and arrange data
panel_data1 <- panel_data %>%
    dplyr::select(country_name, country_code, year, sdg_overall,
        spi_comp, di_score, log_gdppc, income_level_recoded) %>%
    dplyr::arrange(country_code, year)

# how many countries
length(unique(panel_data1$country_code))
```

```
## [1] 162
```

1.1 Converting to panel data frame

```
panel_data <- pdata.frame(panel_data1, index = c("country_code",
    "year"))
pdim(panel_data)  # check panel dimensions
```

```
## Balanced Panel: n = 162, T = 8, N = 1296
```

2 2.1) POLS SDG ~ SPI [Stage 2]

```
# Contemporaneous Effect: SDG ~ SPI + DI
ols_sdg_spi <- plm(formula = sdg_overall ~ spi_comp + di_score + log_gdppc
                   + factor(income_level_recoded) + factor(year),
               model = "pooling",
               data = panel_data)
summary(ols_sdg_spi, vcov = vcovHC(ols_sdg_spi, cluster = "group", type = "HC1"))
```

```
## Pooling Model
##
## Note: Coefficient variance-covariance matrix supplied: vcovHC(ols_sdg_spi, cluster = "group", type =
##
## Call:
## plm(formula = sdg_overall ~ spi_comp + di_score + log_gdppc +
##     factor(income_level_recoded) + factor(year), data = panel_data,
##     model = "pooling")
##
## Unbalanced Panel: n = 155, T = 6-8, N = 1234
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -11.96220  -2.86494   0.11405   2.84443  13.98364
##
## Coefficients:
##                                Estimate Std. Error t-value  Pr(>|t|)
## (Intercept)                   27.473206   4.495280  6.1116 1.325e-09 ***
## spi_comp                       0.284667   0.033946  8.3859 < 2.2e-16 ***
## di_score                       0.291655   0.256248  1.1382 0.2552714
## log_gdppc                      1.600463   0.734638  2.1786 0.0295543 *
## factor(income_level_recoded)1  4.718372   1.236004  3.8174 0.0001416 ***
## factor(income_level_recoded)2  8.481679   1.740942  4.8719 1.251e-06 ***
## factor(income_level_recoded)3  7.916414   2.577748  3.0711 0.0021802 **
## factor(year)2017              -0.276635   0.153814 -1.7985 0.0723446 .
## factor(year)2018              -0.831429   0.251746 -3.3027 0.0009855 ***
## factor(year)2019              -0.531674   0.271031 -1.9617 0.0500276 .
## factor(year)2020              -0.710819   0.363210 -1.9570 0.0505695 .
## factor(year)2021              -1.964981   0.495922 -3.9623 7.854e-05 ***
## factor(year)2022              -1.806874   0.480822 -3.7579 0.0001795 ***
## factor(year)2023              -2.226746   0.492036 -4.5256 6.612e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    124070
## Residual Sum of Squares: 24004
## R-Squared:      0.80654
## Adj. R-Squared: 0.80448
## F-statistic: 77.2465 on 13 and 154 DF, p-value: < 2.22e-16
```

```
# Adding Lag1: SPI ~ DI
ols_sdg_spi_L1 <- plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1)
                      + di_score + plm::lag(di_score, 1)
```

```r
                      + log_gdppc
                      #+ factor(income_level_recoded)
                      + factor(year),
               model = "pooling",
               data = panel_data)
summary(ols_sdg_spi_L1, vcov = vcovHC(ols_sdg_spi_L1, cluster = "group", type = "HC1"))
```

```
## Pooling Model
##
## Note: Coefficient variance-covariance matrix supplied: vcovHC(ols_sdg_spi_L1, cluster = "group", typ
##
## Call:
## plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) +
##     di_score + plm::lag(di_score, 1) + log_gdppc + factor(year),
##     data = panel_data, model = "pooling")
##
## Unbalanced Panel: n = 155, T = 5-7, N = 1079
##
## Residuals:
##       Min.    1st Qu.     Median    3rd Qu.       Max.
## -12.088589  -3.084727  -0.060242   3.098490  13.397951
##
## Coefficients:
##                         Estimate Std. Error t-value  Pr(>|t|)
## (Intercept)            19.291677   2.536404  7.6059 6.190e-14 ***
## spi_comp                0.078897   0.066955  1.1784 0.2389142
## plm::lag(spi_comp, 1)   0.211937   0.060640  3.4950 0.0004935 ***
## di_score                0.545687   0.675244  0.8081 0.4191941
## plm::lag(di_score, 1)  -0.374345   0.690778 -0.5419 0.5879885
## log_gdppc               3.279639   0.472111  6.9468 6.489e-12 ***
## factor(year)2018       -0.514305   0.138793 -3.7056 0.0002218 ***
## factor(year)2019       -0.636962   0.237108 -2.6864 0.0073353 **
## factor(year)2020       -0.227394   0.281357 -0.8082 0.4191527
## factor(year)2021       -1.243651   0.446653 -2.7844 0.0054579 **
## factor(year)2022       -2.278122   0.468727 -4.8602 1.348e-06 ***
## factor(year)2023       -2.273578   0.465163 -4.8877 1.177e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    107440
## Residual Sum of Squares: 23790
## R-Squared:      0.77858
## Adj. R-Squared: 0.77629
## F-statistic: 70.2306 on 11 and 154 DF, p-value: < 2.22e-16
```

```r
# Adding Lag2: SPI ~ DI
ols_sdg_spi_L2 <- plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1)
                      + plm::lag(spi_comp, 2) + di_score + plm::lag(di_score, 1)
                      + plm::lag(di_score, 2) + log_gdppc
                      #+ factor(income_level_recoded)
                      + factor(year),
               model = "pooling",
               data = panel_data)
```

```r
summary(ols_sdg_spi_L2, vcov = vcovHC(ols_sdg_spi_L2, cluster = "group", type = "HC1"))
```

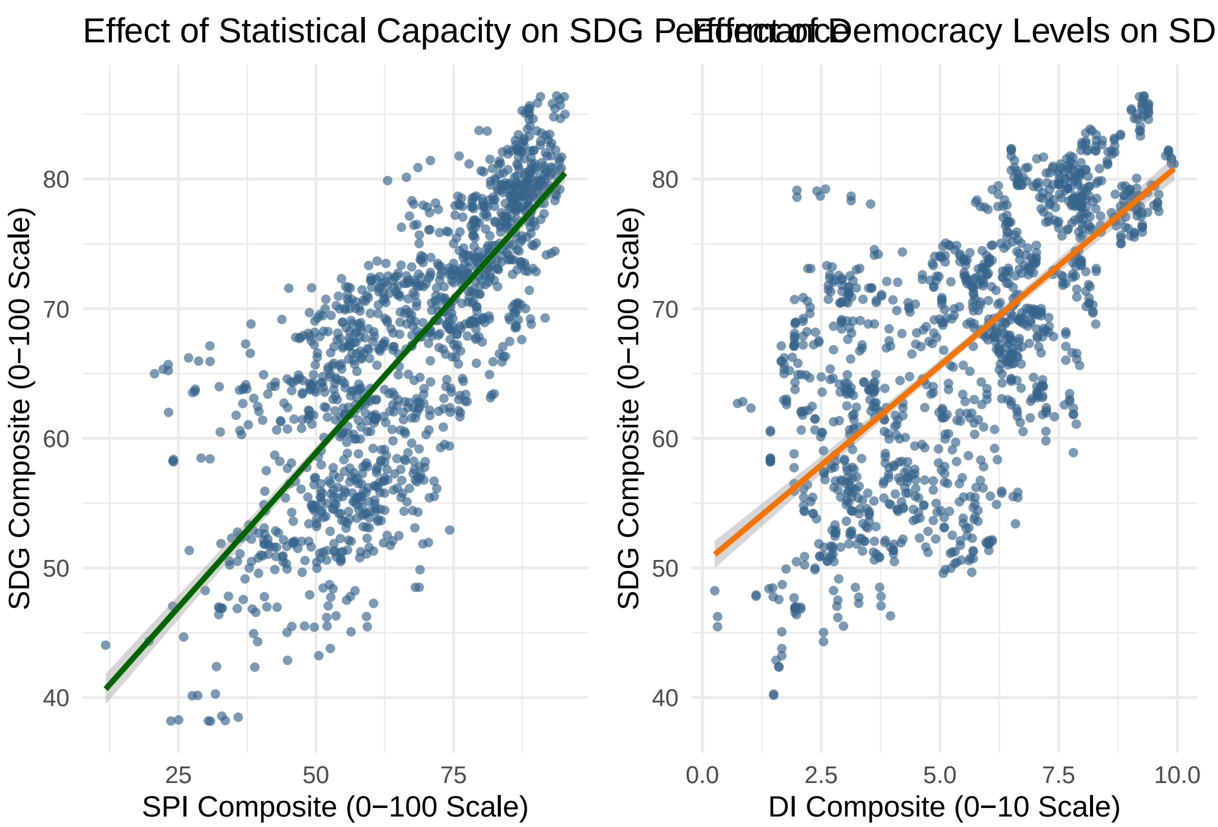
```
## Pooling Model
##
## Note: Coefficient variance-covariance matrix supplied: vcovHC(ols_sdg_spi_L2, cluster = "group", typ
##
## Call:
## plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) +
##     plm::lag(spi_comp, 2) + di_score + plm::lag(di_score, 1) +
##     plm::lag(di_score, 2) + log_gdppc + factor(year), data = panel_data,
##     model = "pooling")
##
## Unbalanced Panel: n = 155, T = 4-6, N = 924
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -11.18756  -3.03893  -0.19835   3.09998  12.60166
##
## Coefficients:
##                        Estimate Std. Error t-value  Pr(>|t|)
## (Intercept)           19.224554   2.553358  7.5291 1.228e-13 ***
## spi_comp               0.117994   0.075368  1.5656 0.1177960
## plm::lag(spi_comp, 1)  0.013656   0.031069  0.4395 0.6603797
## plm::lag(spi_comp, 2)  0.165954   0.060999  2.7206 0.0066406 **
## di_score               0.475898   0.619350  0.7684 0.4424588
## plm::lag(di_score, 1)  0.064283   0.353793  0.1817 0.8558606
## plm::lag(di_score, 2) -0.404698   0.698480 -0.5794 0.5624640
## log_gdppc              3.235028   0.472059  6.8530 1.331e-11 ***
## factor(year)2019      -0.031128   0.190694 -0.1632 0.8703706
## factor(year)2020      -0.057259   0.252872 -0.2264 0.8209142
## factor(year)2021      -0.830884   0.374317 -2.2197 0.0266823 *
## factor(year)2022      -1.257564   0.373981 -3.3626 0.0008042 ***
## factor(year)2023      -2.251831   0.462339 -4.8705 1.312e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    91386
## Residual Sum of Squares: 19961
## R-Squared:      0.78158
## Adj. R-Squared: 0.7787
## F-statistic: 62.5704 on 12 and 154 DF, p-value: < 2.22e-16
```

2.1 POLS Scatterplots

General relationship between SDG and Main Xs: SPI & DI

```r
# Contemporaneous Relationship: SDG ~ SPI
sdg_spi_s2_scatter <- ggplot(panel_data1, aes(x = spi_comp, y = sdg_overall)) +
    geom_point(color = "steelblue4", size = 1, alpha = 0.65) +
    geom_smooth(method = "lm", se = TRUE, color = "darkgreen",
        size = 1) + labs(title = "Effect of Statistical Capacity on SDG Performance",
    x = "SPI Composite (0-100 Scale)", y = "SDG Composite (0-100 Scale)") +
```

```r
    theme(plot.title = element_text(size = 14)) + theme_minimal()

# Save to specific folder
# ggsave('component_2/figures/stage2/sdg_spi_s2_scatterplot.png',
# sdg_spi_s2_scatter, width = 8, height = 6)

# Contemporaneous Relationship: SDG ~ DI
sdg_di_s2_scatter <- ggplot(panel_data1, aes(x = di_score, y = sdg_overall)) +
    geom_point(color = "steelblue4", size = 1, alpha = 0.65) +
    geom_smooth(method = "lm", se = TRUE, color = "#f27405",
        size = 1) + labs(title = "Effect of Democracy Levels on SDG Performance",
    x = "DI Composite (0-10 Scale)", y = "SDG Composite (0-100 Scale)") +
    theme(plot.title = element_text(size = 14)) + theme_minimal()

# Save to specific folder
# ggsave('component_2/figures/stage2/sdg_di_s2_scatterplot.png',
# sdg_di_s2_scatter, width = 8, height = 6)

# side by side comparison using patchwork
library(patchwork)
sdg_spi_s2_scatter + sdg_di_s2_scatter + plot_layout(ncol = 2)
```




```r
# ggsave('component_2/figures/stage2/s2_scatterplots.png',
# width = 12, height = 8)
```

2.2 Stargazer Table for POLS Models

3 2.2) First Difference [Stage 2]

```
# Contemporaneous Effect: SDG ~ SPI + DI
fd_sdg_spi <- plm(formula = sdg_overall ~ spi_comp + di_score
                  + log_gdppc,
                  #+ factor(income_level_recoded),
               model = "fd",
               data = fd_data)
summary(fd_sdg_spi, vcov = vcovHC(fd_sdg_spi, cluster = "group", type = "HC1"))
```

```
## Oneway (individual) effect First-Difference Model
##
## Note: Coefficient variance-covariance matrix supplied: vcovHC(fd_sdg_spi, cluster = "group", type =
##
## Call:
## plm(formula = sdg_overall ~ spi_comp + di_score + log_gdppc,
##     data = fd_data, model = "fd")
##
## Unbalanced Panel: n = 155, T = 6-8, N = 1234
## Observations used in estimation: 1079
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -1.936438 -0.317256 -0.048017  0.246820  3.136182
##
## Coefficients:
##               Estimate Std. Error t-value  Pr(>|t|)
## (Intercept)  0.3059277  0.0194780 15.7063 < 2.2e-16 ***
## spi_comp     0.0158925  0.0059871  2.6545  0.008061 **
## di_score     0.0364382  0.0837756  0.4350  0.663686
## log_gdppc   -0.2235660  0.2184315 -1.0235  0.306299
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    348.2
## Residual Sum of Squares: 344.9
## R-Squared:      0.009467
## Adj. R-Squared: 0.0067027
## F-statistic: 2.49471 on 3 and 154 DF, p-value: 0.062049
```

```
# Adding Lag1: SPI ~ DI
fd_sdg_spi_L1 <- plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1)
                     + di_score + plm::lag(di_score, 1)
                     + log_gdppc,
                     #+ factor(income_level_recoded),
               model = "fd",
               data = fd_data)
summary(fd_sdg_spi_L1, vcov = vcovHC(fd_sdg_spi_L1, cluster = "group", type = "HC1"))
```

```
## Oneway (individual) effect First-Difference Model
```

```
##
## Note: Coefficient variance-covariance matrix supplied: vcovHC(fd_sdg_spi_L1, cluster = "group", type
##
## Call:
## plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) +
##     di_score + plm::lag(di_score, 1) + log_gdppc, data = fd_data,
##     model = "fd")
##
## Unbalanced Panel: n = 155, T = 5-7, N = 1079
## Observations used in estimation: 924
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -1.932564 -0.310496 -0.047395  0.249050  3.106300
##
## Coefficients:
##                         Estimate Std. Error t-value Pr(>|t|)
## (Intercept)            0.2869939  0.0248546 11.5469  < 2e-16 ***
## spi_comp               0.0111140  0.0064228  1.7304  0.08390 .
## plm::lag(spi_comp, 1)  0.0075453  0.0060299  1.2513  0.21114
## di_score               0.0655585  0.0838080  0.7822  0.43427
## plm::lag(di_score, 1)  0.1369567  0.0735237  1.8628  0.06282 .
## log_gdppc             -0.3168694  0.2451118 -1.2928  0.19642
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    303.64
## Residual Sum of Squares: 300.06
## R-Squared:      0.011763
## Adj. R-Squared: 0.0063802
## F-statistic: 1.60127 on 5 and 154 DF, p-value: 0.16294
```

```r
# Adding Lag2: SPI ~ DI
fd_sdg_spi_L2 <- plm(formula = sdg_overall ~ spi_comp
                     + plm::lag(spi_comp, 1) + plm::lag(spi_comp, 2)
                     + di_score + plm::lag(di_score, 1) + plm::lag(di_score, 2)
                     + log_gdppc,
                     #+ factor(income_level_recoded),
               model = "fd",
               data = fd_data)
summary(fd_sdg_spi_L2, vcov = vcovHC(fd_sdg_spi_L2, cluster = "group", type = "HC1"))
```

```
## Oneway (individual) effect First-Difference Model
##
## Note: Coefficient variance-covariance matrix supplied: vcovHC(fd_sdg_spi_L2, cluster = "group", type
##
## Call:
## plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) +
##     plm::lag(spi_comp, 2) + di_score + plm::lag(di_score, 1) +
##     plm::lag(di_score, 2) + log_gdppc, data = fd_data, model = "fd")
##
## Unbalanced Panel: n = 155, T = 4-6, N = 924
## Observations used in estimation: 769
##
```

```
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -1.85910 -0.30627 -0.03719  0.25491  2.90944
##
## Coefficients:
##                          Estimate Std. Error t-value  Pr(>|t|)
## (Intercept)             0.2363339  0.0283602  8.3333 3.658e-16 ***
## spi_comp                0.0170180  0.0070463  2.4152   0.01596 *
## plm::lag(spi_comp, 1)  0.0063430  0.0057420  1.1047   0.26965
## plm::lag(spi_comp, 2)  0.0132665  0.0059627  2.2249   0.02638 *
## di_score                0.0494996  0.0961530  0.5148   0.60684
## plm::lag(di_score, 1)  0.1845462  0.0756324  2.4400   0.01491 *
## plm::lag(di_score, 2) -0.1754561  0.1254654 -1.3984   0.16239
## log_gdppc              -0.4578589  0.2383173 -1.9212   0.05508 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    229.74
## Residual Sum of Squares: 222.38
## R-Squared:      0.032023
## Adj. R-Squared: 0.023119
## F-statistic: 2.16398 on 7 and 154 DF, p-value: 0.040328
```

```
# CI
coef <- coef(fd_sdg_spi_L2)
se <- sqrt(diag(vcovHC(fd_sdg_spi_L2, cluster = "group", type = "HC1")))  # Get standard errors
crit_value <- qt(0.975, df = nobs(fd_sdg_spi_L2)-length(coef(fd_sdg_spi_L2)))
ci_low <- coef - crit_value * se
ci_high <- coef + crit_value * se
cbind(ci_low, ci_high)
```

```
##                               ci_low     ci_high
## (Intercept)             0.180660429 0.292007434
## spi_comp                0.003185545 0.030850515
## plm::lag(spi_comp, 1) -0.004929001 0.017614983
## plm::lag(spi_comp, 2)  0.001561152 0.024971802
## di_score               -0.139257076 0.238256358
## plm::lag(di_score, 1)  0.036073359 0.333019006
## plm::lag(di_score, 2) -0.421755423 0.070843234
## log_gdppc              -0.925696299 0.009978487
```

```
# Joint significance of DI scores - FD
linearHypothesis(
  fd_sdg_spi_L2,
  c("di_score = 0", "plm::lag(di_score, 1) = 0", "plm::lag(di_score, 2) = 0"),
  vcov. = vcovHC(fd_sdg_spi_L2, cluster = "group", type = "HC1")
)
```

```
##
## Linear hypothesis test:
## di_score = 0
## plm::lag(di_score,0
## plm::lag(di_score, 2) = 0
```

```
##
## Model 1: restricted model
## Model 2: sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp,
##     2) + di_score + plm::lag(di_score, 1) + plm::lag(di_score,
##     2) + log_gdppc
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df  Chisq Pr(>Chisq)
## 1    764
## 2    761  3 5.9731     0.1129
```

```r
# ensure correct names
# names(coef(fd_sdg_spi_L2))

# cumulative effects of DI scores - FD
linearHypothesis(
  fd_sdg_spi_L2,
  c("di_score + plm::lag(di_score, 1) + plm::lag(di_score, 2) = 0"),
  vcov. = vcovHC(fd_sdg_spi_L2, cluster = "group", type = "HC1")
)
```

```
##
## Linear hypothesis test:
## di_score  + plm::lag(di_score,1 plm::lag(di_score, 2) = 0
##
## Model 1: restricted model
## Model 2: sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp,
##     2) + di_score + plm::lag(di_score, 1) + plm::lag(di_score,
##     2) + log_gdppc
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df  Chisq Pr(>Chisq)
## 1    762
## 2    761  1 0.3872     0.5338
```

```r
# Joint significance of SPI scores - FD
linearHypothesis(
  fd_sdg_spi_L2,
  c("spi_comp = 0", "plm::lag(spi_comp, 1) = 0", "plm::lag(spi_comp, 2) = 0"),
  vcov. = vcovHC(fd_sdg_spi_L2, cluster = "group", type = "HC1")
)
```

```
##
## Linear hypothesis test:
## spi_comp = 0
## plm::lag(spi_comp,0
## plm::lag(spi_comp, 2) = 0
##
## Model 1: restricted model
## Model 2: sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp,
##     2) + di_score + plm::lag(di_score, 1) + plm::lag(di_score,
```

```
##     2) + log_gdppc
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df  Chisq Pr(>Chisq)
## 1    764
## 2    761  3 7.2282    0.06497 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# ensure correct names
# names(coef(fd_sdg_spi_L2))

# cumulative effects of SPI scores - FD
linearHypothesis(
  fd_sdg_spi_L2,
  c("spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp, 2) = 0"),
  vcov. = vcovHC(fd_sdg_spi_L2, cluster = "group", type = "HC1")
)
```

```
##
## Linear hypothesis test:
## spi_comp  + plm::lag(spi_comp,1 plm::lag(spi_comp, 2) = 0
##
## Model 1: restricted model
## Model 2: sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp,
##     2) + di_score + plm::lag(di_score, 1) + plm::lag(di_score,
##     2) + log_gdppc
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df  Chisq Pr(>Chisq)
## 1    762
## 2    761  1 6.4111    0.01134 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Result (DI Variables): The *joint significance* tests for FD show no evidence that DI variables are jointly significant in explaining changes in SDG overall scores (Chisq = 5.9731, p = 0.1129), holding SPI terms and all else constant. This suggests that shifts in democracy levels may not have a meaningful immediate impact on SDG performance when considering both current and lagged effects, and accounting for SPI and other controls.

In terms of *cumulative impact*, based on the FD model and panel data, there is no detectable total impact of changes in di_score (at current, lag 1, or lag 2) on SDG performance—over these periods (stat = 0.3872, p = 0.5338).

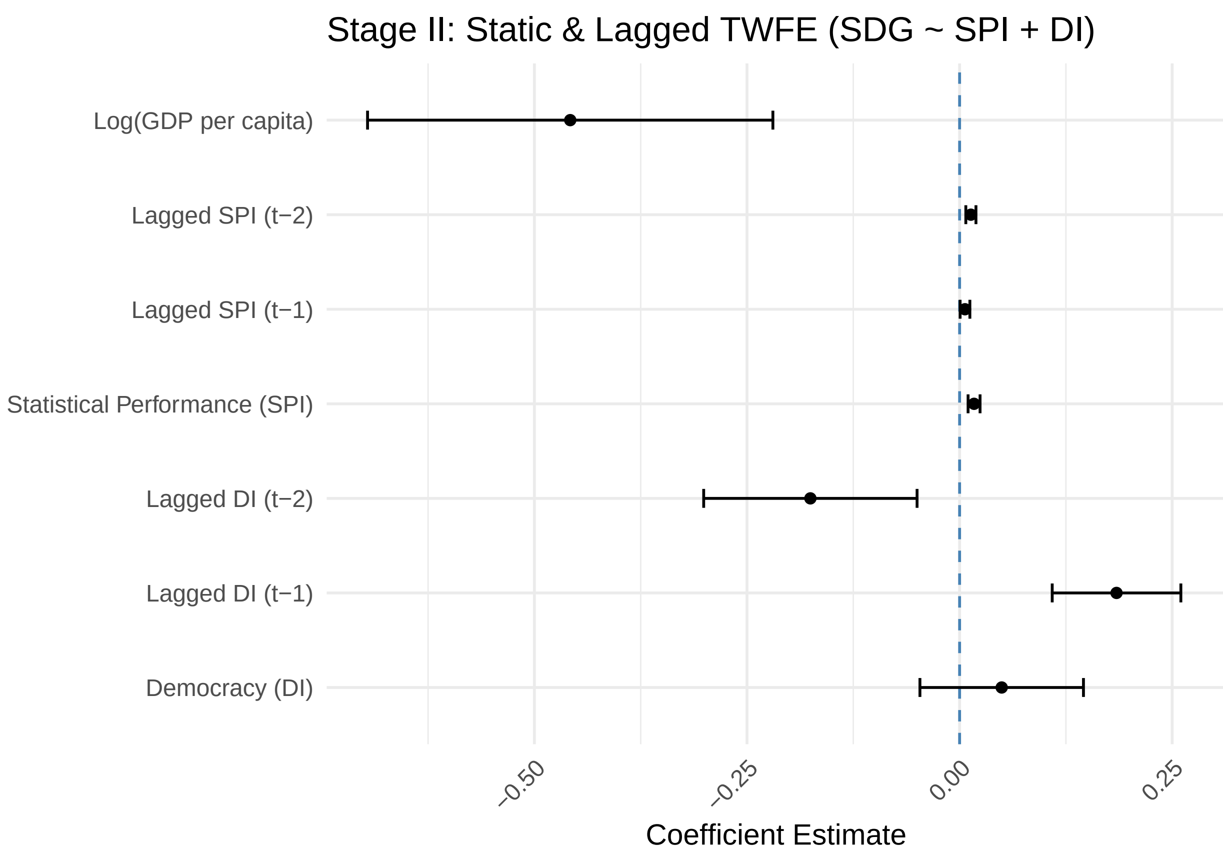
Result (SPI Variables): The *joint significance* tests for FD show marginal evidence that SPI variables are jointly significant in explaining changes in SDG overall scores (Chisq = 7.2282, alpha = 0.1, p = 0.06497), holding DI terms and all else constant. This suggests that shifts in statistical capacity may negligibly have a legitimate immediate impact on SDG performance when considering both current and lagged effects, and accounting for DI and other controls.

In terms of *cumulative impact*, based on the FD model and panel data, there is a detectable total impact of changes in spi_comp (at current, lag 1, or lag 2) on SDG performance—over these periods (stat = 6.4111, p = 0.01134)

3.1 Stargazer Table for FD Models

3.2 First Difference Error Bar Visualization

```
# Extract coefficients and robust standard errors from the
# FD model
coefs_fd <- summary(fd_sdg_spi_L2, vcov = vcovHC(fd_sdg_spi_L2,
    cluster = "group", type = "HC1"))$coefficients
# Create a data frame for visualization
coef_df_fd <- data.frame(term = rownames(coefs_fd), estimate = coefs_fd[,
    "Estimate"], std.error = coefs_fd[, "Std. Error"])
# Create a ggplot error bar chart for the FD model
ebar_fd <- ggplot(coef_df_fd, aes(x = term, y = estimate)) +
    geom_point() + coord_flip() + geom_hline(yintercept = 0,
    linetype = "dashed", color = "steelblue") + geom_errorbar(aes(ymin = estimate -
    std.error, ymax = estimate + std.error), width = 0.2) + labs(title = "Stage II: Static & Lagged TWFE
    x = NULL, y = "Coefficient Estimate") + theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
    scale_x_discrete(labels = c(di_score = "Democracy (DI)",
        `plm::lag(di_score, 1)` = "Lagged DI (t-1)", `plm::lag(di_score, 2)` = "Lagged DI (t-2)",
        spi_comp = "Statistical Performance (SPI)", `plm::lag(spi_comp, 1)` = "Lagged SPI (t-1)",
        `plm::lag(spi_comp, 2)` = "Lagged SPI (t-2)", log_gdppc = "Log(GDP per capita)"),
        limits = c("di_score", "plm::lag(di_score, 1)", "plm::lag(di_score, 2)",
            "spi_comp", "plm::lag(spi_comp, 1)", "plm::lag(spi_comp, 2)",
            "log_gdppc"))

ebar_fd
```




```r
# Save the plot
# ggsave('component_2/figures/stage2/error_bar_fd_sdg_spi_L2.png',
# ebar_fd, width = 10, height = 6)
```

4 2.3) Fixed Effects [Stage 2]

```r
# Contemporaneous Effect: SDG ~ SPI + DI
fe_sdg_spi <- plm(formula = sdg_overall ~ spi_comp + di_score
                  + log_gdppc
                  #+ factor(income_level_recoded)
                  + factor(year),
                  data = panel_data,
                  model = "within" #FE
)
summary(fe_sdg_spi, vcov = vcovHC(fe_sdg_spi, cluster = "group", type = "HC1")) # Robust SEs
```

```
## Oneway (individual) effect Within Model
##
## Note: Coefficient variance-covariance matrix supplied: vcovHC(fe_sdg_spi, cluster = "group", type =
##
## Call:
## plm(formula = sdg_overall ~ spi_comp + di_score + log_gdppc +
##     factor(year), data = panel_data, model = "within")
```

```
##
## Unbalanced Panel: n = 155, T = 6-8, N = 1234
##
## Residuals:
##       Min.    1st Qu.     Median    3rd Qu.       Max.
## -2.8383110 -0.3014919 -0.0055603  0.3235414  3.4415657
##
## Coefficients:
##                   Estimate Std. Error t-value  Pr(>|t|)
## spi_comp          0.043690   0.014911  2.9300  0.003462 **
## di_score          0.096001   0.089973  1.0670  0.286215
## log_gdppc         0.412324   0.332591  1.2397  0.215346
## factor(year)2017 0.333735   0.054558  6.1170 1.335e-09 ***
## factor(year)2018 0.554422   0.093703  5.9168 4.415e-09 ***
## factor(year)2019 0.943784   0.099870  9.4502 < 2.2e-16 ***
## factor(year)2020 1.270535   0.108616 11.6975 < 2.2e-16 ***
## factor(year)2021 1.241928   0.167769  7.4026 2.700e-13 ***
## factor(year)2022 1.438483   0.171331  8.3959 < 2.2e-16 ***
## factor(year)2023 1.611548   0.188216  8.5622 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    1162.9
## Residual Sum of Squares: 447.51
## R-Squared:      0.61517
## Adj. R-Squared: 0.55614
## F-statistic: 57.0598 on 10 and 154 DF, p-value: < 2.22e-16
```

```
# Adding Lag1: SPI ~ DI
fe_sdg_spi_L1 <- plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1)
                     + di_score + plm::lag(di_score, 1)
                     + log_gdppc
                     #+ factor(income_level_recoded)
                     + factor(year),
               model = "within",
               data = panel_data)
summary(fe_sdg_spi_L1, vcov = vcovHC(fe_sdg_spi_L1, cluster = "group", type = "HC1"))
```

```
## Oneway (individual) effect Within Model
##
## Note: Coefficient variance-covariance matrix supplied: vcovHC(fe_sdg_spi_L1, cluster = "group", type
##
## Call:
## plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) +
##     di_score + plm::lag(di_score, 1) + log_gdppc + factor(year),
##     data = panel_data, model = "within")
##
## Unbalanced Panel: n = 155, T = 5-7, N = 1079
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -2.658102 -0.266671 -0.014237  0.259776  3.149806
##
## Coefficients:
```

```
##                          Estimate Std. Error t-value  Pr(>|t|)
## spi_comp                0.0242798  0.0113188  2.1451 0.0322088 *
## plm::lag(spi_comp, 1)   0.0221931  0.0098094  2.2624 0.0239044 *
## di_score                0.2089459  0.0876375  2.3842 0.0173194 *
## plm::lag(di_score, 1) -0.0345650  0.1078151 -0.3206 0.7485902
## log_gdppc               0.3781954  0.3864323  0.9787 0.3279950
## factor(year)2018        0.2213588  0.0656081  3.3740 0.0007722 ***
## factor(year)2019        0.5649481  0.0797209  7.0866 2.748e-12 ***
## factor(year)2020        0.9354472  0.0896732 10.4317 < 2.2e-16 ***
## factor(year)2021        0.9611212  0.1371212  7.0093 4.654e-12 ***
## factor(year)2022        1.0380810  0.1651579  6.2854 5.060e-10 ***
## factor(year)2023        1.2559573  0.1724737  7.2820 7.098e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    740.6
## Residual Sum of Squares: 317.02
## R-Squared:      0.57195
## Adj. R-Squared: 0.49459
## F-statistic: 41.4617 on 11 and 154 DF, p-value: < 2.22e-16
```

```r
# Adding Lag2: SPI ~ DI
fe_sdg_spi_L2 <- plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1)
                     + plm::lag(spi_comp, 2) + di_score + plm::lag(di_score, 1)
                     + plm::lag(di_score, 2) + log_gdppc
                     #+ factor(income_level_recoded)
                     + factor(year),
               model = "within",
               data = panel_data)
summary(fe_sdg_spi_L2, vcov = vcovHC(fe_sdg_spi_L2, cluster = "group", type = "HC1"))
```

```
## Oneway (individual) effect Within Model
##
## Note: Coefficient variance-covariance matrix supplied: vcovHC(fe_sdg_spi_L2, cluster = "group", type
##
## Call:
## plm(formula = sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) +
##     plm::lag(spi_comp, 2) + di_score + plm::lag(di_score, 1) +
##     plm::lag(di_score, 2) + log_gdppc + factor(year), data = panel_data,
##     model = "within")
##
## Unbalanced Panel: n = 155, T = 4-6, N = 924
##
## Residuals:
##       Min.    1st Qu.     Median    3rd Qu.       Max.
## -2.4066416 -0.2350016 -0.0064308  0.2388494  2.8673678
##
## Coefficients:
##                          Estimate Std. Error t-value  Pr(>|t|)
## spi_comp                0.0343922  0.0120002  2.8660  0.004273 **
## plm::lag(spi_comp, 1)   0.0042770  0.0077243  0.5537  0.579945
## plm::lag(spi_comp, 2)   0.0155108  0.0088438  1.7539  0.079858 .
## di_score                0.1262507  0.0799246  1.5796  0.114611
## plm::lag(di_score, 1)   0.1752362  0.0968028  1.8102  0.070655 .
```

```
## plm::lag(di_score, 2) -0.2359582  0.1278788 -1.8452  0.065403 .
## log_gdppc              -0.0010185  0.3868273 -0.0026  0.997900
## factor(year)2019        0.3409033  0.0450779  7.5625 1.147e-13 ***
## factor(year)2020        0.6307859  0.0778682  8.1007 2.186e-15 ***
## factor(year)2021        0.6912256  0.1080382  6.3980 2.757e-10 ***
## factor(year)2022        0.8508653  0.1324075  6.4261 2.314e-10 ***
## factor(year)2023        0.9597129  0.1660486  5.7797 1.094e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    440.52
## Residual Sum of Squares: 201.98
## R-Squared:      0.54148
## Adj. R-Squared: 0.44093
## F-statistic: 34.4067 on 12 and 154 DF, p-value: < 2.22e-16
```

```
# CI for all variables (L2 model)
coef <- coef(fe_sdg_spi_L2)
se <- sqrt(diag(vcovHC(fe_sdg_spi_L2, cluster = "group", type = "HC1")))  # Get standard errors
crit_value <- qt(0.975, df = nobs(fe_sdg_spi_L2)-length(coef(fe_sdg_spi_L2)))
ci_low <- coef - crit_value * se
ci_high <- coef + crit_value * se
cbind(ci_low, ci_high)
```

```
##                              ci_low    ci_high
## spi_comp                0.010840994 0.05794343
## plm::lag(spi_comp, 1) -0.010882519 0.01943649
## plm::lag(spi_comp, 2) -0.001845724 0.03286727
## di_score               -0.030606839 0.28310821
## plm::lag(di_score, 1) -0.014745917 0.36521825
## plm::lag(di_score, 2) -0.486929028 0.01501270
## log_gdppc              -0.760193662 0.75815665
## factor(year)2019        0.252434829 0.42937187
## factor(year)2020        0.477964189 0.78360758
## factor(year)2021        0.479193148 0.90325806
## factor(year)2022        0.591006479 1.11072403
## factor(year)2023        0.633831167 1.28559473
```

```
# Joint significance FE - DI scores
linearHypothesis(
  fe_sdg_spi_L2,
  c("di_score = 0", "plm::lag(di_score, 1) = 0", "plm::lag(di_score, 2) = 0"),
  vcov. = vcovHC(fe_sdg_spi_L2, cluster = "group", type = "HC1")
)
```

```
##
## Linear hypothesis test:
## di_score = 0
## plm::lag(di_score,0
## plm::lag(di_score, 2) = 0
##
## Model 1: restricted model
## Model 2: sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp,
```

```
##     2) + di_score + plm::lag(di_score, 1) + plm::lag(di_score,
##     2) + log_gdppc + factor(year)
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df  Chisq Pr(>Chisq)
## 1    760
## 2    757  3 10.873    0.01244 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# ensure correct names
# names(coef(fe_sdg_spi_L2))

# cumulative effects of DI scores - FE
linearHypothesis(
  fe_sdg_spi_L2,
  c("di_score + plm::lag(di_score, 1) + plm::lag(di_score, 2) = 0"),
  vcov. = vcovHC(fe_sdg_spi_L2, cluster = "group", type = "HC1")
)
```

```
##
## Linear hypothesis test:
## di_score  + plm::lag(di_score,1 plm::lag(di_score, 2) = 0
##
## Model 1: restricted model
## Model 2: sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp,
##     2) + di_score + plm::lag(di_score, 1) + plm::lag(di_score,
##     2) + log_gdppc + factor(year)
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df  Chisq Pr(>Chisq)
## 1    758
## 2    757  1 0.4482     0.5032
```

```r
# Joint significance FE - DI scores
linearHypothesis(
  fe_sdg_spi_L2,
  c("spi_comp = 0", "plm::lag(spi_comp, 1) = 0", "plm::lag(spi_comp, 2) = 0"),
  vcov. = vcovHC(fe_sdg_spi_L2, cluster = "group", type = "HC1")
)
```

```
##
## Linear hypothesis test:
## spi_comp = 0
## plm::lag(spi_comp,0
## plm::lag(spi_comp, 2) = 0
##
## Model 1: restricted model
## Model 2: sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp,
##     2) + di_score + plm::lag(di_score, 1) + plm::lag(di_score,
##     2) + log_gdppc + factor(year)
```

```
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df  Chisq Pr(>Chisq)
## 1    760
## 2    757  3 10.214    0.01683 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# cumulative effects of SPI scores - FE
linearHypothesis(
  fe_sdg_spi_L2,
  c("spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp, 2) = 0"),
  vcov. = vcovHC(fe_sdg_spi_L2, cluster = "group", type = "HC1")
)
```

```
##
## Linear hypothesis test:
## spi_comp  + plm::lag(spi_comp,1 plm::lag(spi_comp, 2) = 0
##
## Model 1: restricted model
## Model 2: sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp,
##     2) + di_score + plm::lag(di_score, 1) + plm::lag(di_score,
##     2) + log_gdppc + factor(year)
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df  Chisq Pr(>Chisq)
## 1    758
## 2    757  1 9.3778   0.002196 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# ensure correct names
# names(coef(fe_sdg_spi_L2))
```

Result (DI Variables): The *joint significance* tests for FE show evidence that DI variables are jointly significant in explaining changes in SDG overall scores (Chisq = 10.873, p = 0.01244), holding SPI terms and all else constant. This suggests that shifts in democracy levels have a meaningful incremental impact on SDG performance when considering both current and lagged effects, and accounting for SPI and other controls.

In terms of *cumulative impact*, based on the FE model and panel data, there is no detectable total impact of changes in di_score (at current, lag 1, or lag 2) on SDG performance—over these periods (stat = 0.4482, p = 0.5032).

Interestingly, this suggest that the effect is not consistent over time, with short term impacts lasting up to 2 years, but not accumulating over time.

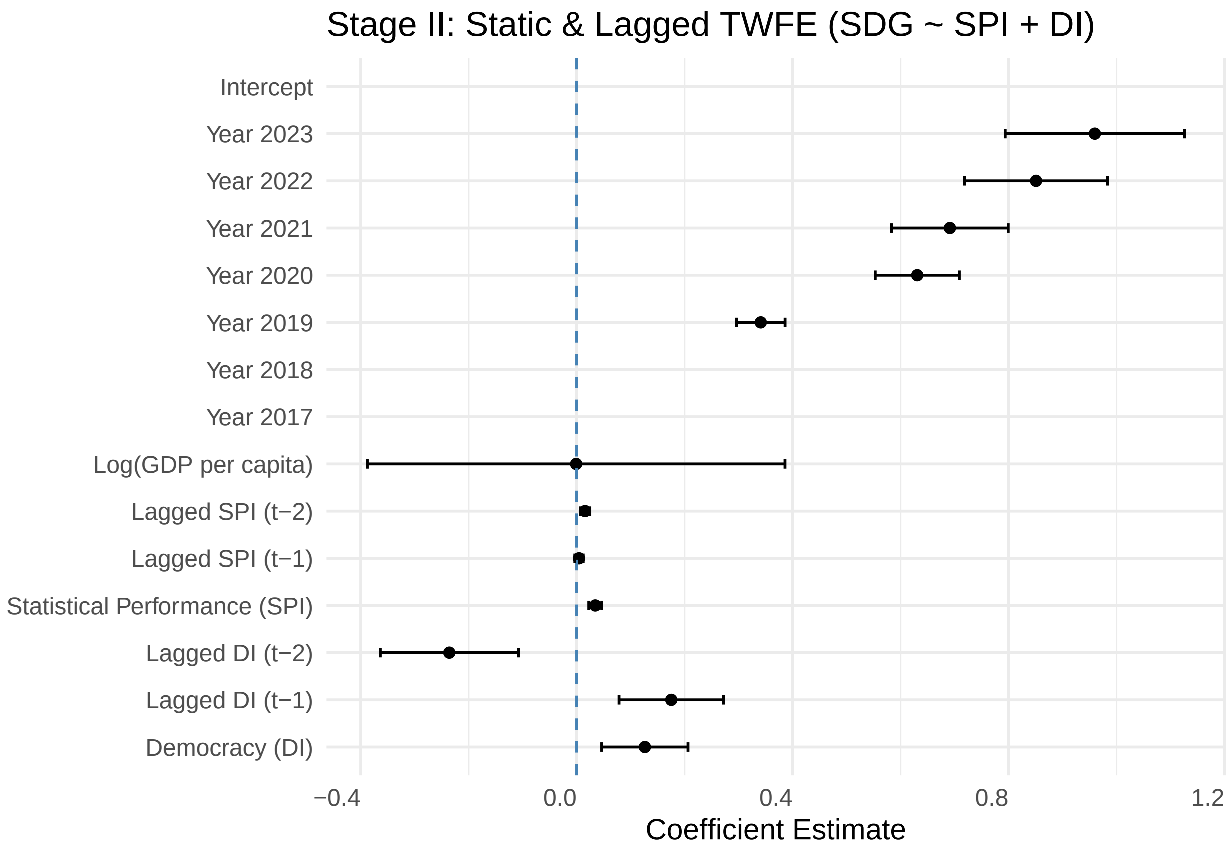
Result (SPI Variables): The *joint significance* tests for FE show evidence that SPI variables are jointly significant in explaining changes in SDG overall scores (Chisq = 10.214, p = 0.01683), holding DI terms and all else constant. This suggests that shifts in statistical capacity have a legitimate incremental impact on SDG performance when considering both current and lagged effects, and accounting for DI and other controls.

In terms of *cumulative impact*, based on the FE model and panel data, there is relatively stong evidence of detectable total impact of changes in spi_comp (at current, lag 1, or lag 2) on SDG performance—over these periods (stat = 9.3778, p = 0.002196 **)

5 Stargazer Table for FE Models

5.1 Fixed Effects Error Bar Visualization

```
# Extract coefficients and robust standard errors from the
# FE model
coefs <- summary(fe_sdg_spi_L2, vcov = vcovHC(fe_sdg_spi_L2,
    cluster = "group", type = "HC1"))$coefficients
# Create a data frame for visualization
coef_df <- data.frame(term = rownames(coefs), estimate = coefs[,
    "Estimate"], std.error = coefs[, "Std. Error"])
# Create a ggplot error bar chart
ebar_fe <- ggplot(coef_df, aes(x = term, y = estimate)) + geom_point() +
    coord_flip() + geom_hline(yintercept = 0, linetype = "dashed",
    color = "steelblue") + geom_errorbar(aes(ymin = estimate -
    std.error, ymax = estimate + std.error), width = 0.2) + labs(title = "Stage II: Static & Lagged TWFE
    x = NULL, y = "Coefficient Estimate") + theme_minimal() +
    theme(axis.text.x = element_text(hjust = 1)) + scale_x_discrete(labels = c(di_score = "Democracy (DI
    `plm::lag(di_score, 1)` = "Lagged DI (t-1)", `plm::lag(di_score, 2)` = "Lagged DI (t-2)",
    spi_comp = "Statistical Performance (SPI)", `plm::lag(spi_comp, 1)` = "Lagged SPI (t-1)",
    `plm::lag(spi_comp, 2)` = "Lagged SPI (t-2)", log_gdppc = "Log(GDP per capita)",
    `factor(year)2017` = "Year 2017", `factor(year)2018` = "Year 2018",
    `factor(year)2019` = "Year 2019", `factor(year)2020` = "Year 2020",
    `factor(year)2021` = "Year 2021", `factor(year)2022` = "Year 2022",
    `factor(year)2023` = "Year 2023", Intercept = "Intercept"),
    limits = c("di_score", "plm::lag(di_score, 1)", "plm::lag(di_score, 2)",
        "spi_comp", "plm::lag(spi_comp, 1)", "plm::lag(spi_comp, 2)",
        "log_gdppc", "factor(year)2017", "factor(year)2018",
        "factor(year)2019", "factor(year)2020", "factor(year)2021",
        "factor(year)2022", "factor(year)2023", "Intercept"))

ebar_fe
```




```
# Save the plot
# ggsave('component_2/figures/stage2/error_bar_fe_sdg_spi_L2.png',
# ebar_fe, width = 10, height = 6)
```

5.2 make a stargazer table of all Lag2 models for POLS, FD and FE

5.3 Check for Autocorrelation

```
# APPLY Wooldridge Test for AR(1) Errors in FE Panel
# Models: pwartest()
# https://search.r-project.org/CRAN/refmans/plm/html/pwartest.html
# This is MUCH BETTER for panel data with small T AND
# unbalanced panels!!!
pbgtest(fe_sdg_spi_L2)  # Panel
```

```
##
##  Breusch-Godfrey/Wooldridge test for serial correlation in panel models
##
## data:  sdg_overall ~ spi_comp + plm::lag(spi_comp, 1) + plm::lag(spi_comp,  ...
## chisq = 92.796, df = 4, p-value < 2.2e-16
## alternative hypothesis: serial correlation in idiosyncratic errors
```

```r
pwartest(fe_sdg_spi_L2)  # FE [significant]
```

```
##
##  Wooldridge's test for serial correlation in FE panels
##
## data:  fe_sdg_spi_L2
## F = 73.832, df1 = 1, df2 = 767, p-value < 2.2e-16
## alternative hypothesis: serial correlation
```

```r
pwfdtest(fd_sdg_spi_L2)  # FD [not significant]
```

```
##
##  Wooldridge's first-difference test for serial correlation in panels
##
## data:  fd_sdg_spi_L2
## F = 7.933, df1 = 1, df2 = 612, p-value = 0.005011
## alternative hypothesis: serial correlation in differenced errors
```

Significant p-value indicates the presence of autocorrelation in the residuals of the fixed effects model. This suggests that the errors are correlated over time, which violates one of the key assumptions of linear regression models.

5.4 Check for Heteroskedasticity

```r
# Apply Breusch-Pagan test for heteroskedasticity
bptest(fe_sdg_spi_L2, studentize = TRUE)  # Heteroskedasticity [significant]
```

```
##
##  studentized Breusch-Pagan test
##
## data:  fe_sdg_spi_L2
## BP = 160.33, df = 12, p-value < 2.2e-16
```

```r
bptest(fd_sdg_spi_L2, studentize = TRUE)  # Heteroskedasticity [significant]
```

```
##
##  studentized Breusch-Pagan test
##
## data:  fd_sdg_spi_L2
## BP = 148.67, df = 7, p-value < 2.2e-16
```

The Breusch-Pagan test indicates the presence of heteroskedasticity in the residuals of the fixed effects model. This suggests that the variance of the errors is not constant across observations, which violates another key assumption of linear regression models.

Both violations are corrected by using robust standard errors clustered at the country level, which accounts for autocorrelation and heteroskedasticity.

5.5 Residual Diagnostics

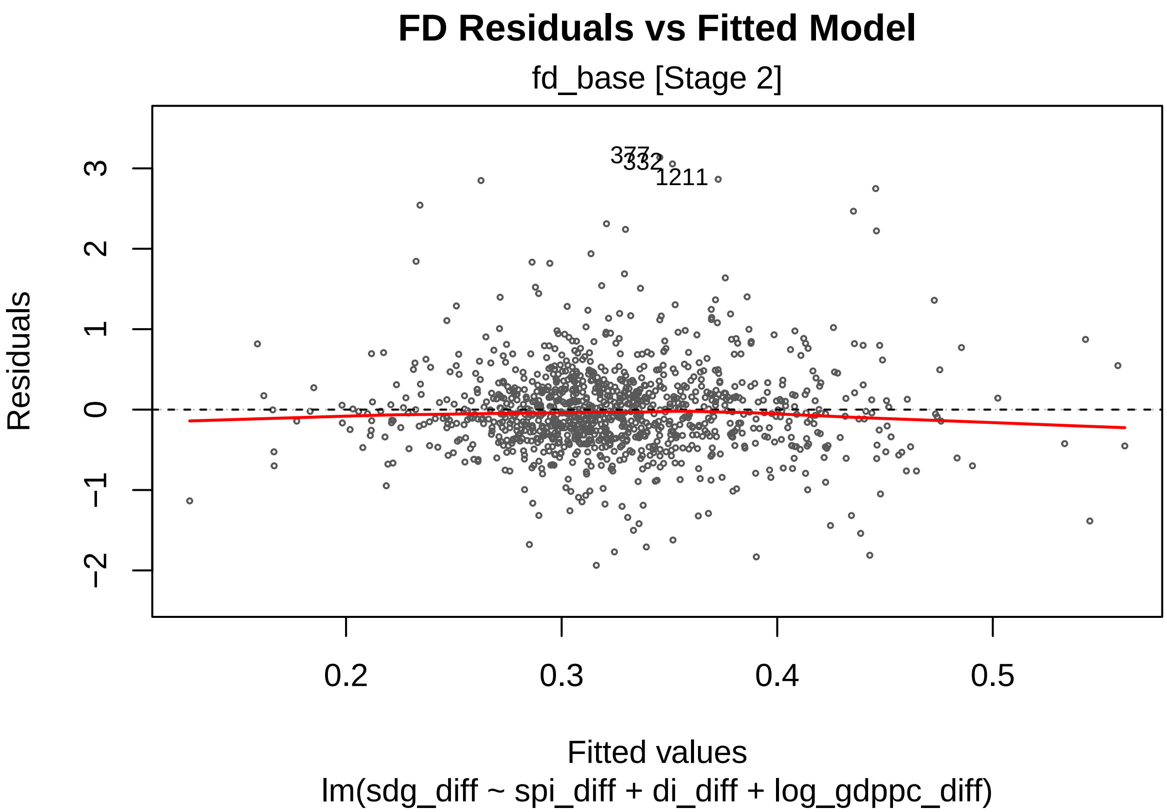
5.5.1 POLS Residuals for base/outcome model: SDG ~ SPI + DI + Controls [STAGE 2]

```r
# Extract the data actually used in the base model
ols_base_lm <- lm(sdg_overall ~ spi_comp + di_score + log_gdppc +
    factor(year), data = panel_data)  # regular linear model
model_data2 <- model.frame(ols_base_lm)

# saving all stage-two plots
png("component_2/figures/stage2/all_s2_residual_plots.png", width = 8.5,
    height = 6.5, units = "in", res = 300)
par(mfrow = c(3, 4))

# Residuals vs Fitted Values plot for ols_base_lm
plot(ols_base_lm, which = 1, main = "Residuals vs Fitted Model",
    caption = "ols_base [Stage 2]", pch = 1, cex = 0.35, col = "#595959")
abline(h = 0, col = "black", lty = 2, lwd = 1)
fitted_vals <- fitted(ols_base_lm)
lines(lowess(fitted_vals, resid(ols_base_lm)), col = "red", lwd = 1.5)

# Residuals vs spi_comp plots
plot(model_data2$spi_comp, resid(ols_base_lm), xlab = "spi_comp",
    ylab = "", yaxt = "n", main = "Residuals vs spi_comp", pch = 1,
    cex = 0.35, col = "darkblue")
abline(h = 0, col = "black", lty = 2, lwd = 1)
lines(lowess(model_data2$spi_comp, resid(ols_base_lm)), col = "red",
    lwd = 1.5)

# Residuals vs di_score plot
plot(model_data2$di_score, resid(ols_base_lm), xlab = "di_score",
    ylab = "", yaxt = "n", main = "Residuals vs di_score", pch = 1,
    cex = 0.35, col = "darkred")
abline(h = 0, col = "black", lty = 2, lwd = 1)
lines(lowess(model_data2$di_score, resid(ols_base_lm)), col = "red",
    lwd = 1.5)

# Residuals vs log_gdppc plot
plot(model_data2$log_gdppc, resid(ols_base_lm), xlab = "log_gdppc",
    ylab = "", yaxt = "n", main = "Residuals vs log_gdppc", pch = 1,
    cex = 0.35, col = "darkgreen")
abline(h = 0, col = "black", lty = 2, lwd = 1)
lines(lowess(model_data2$log_gdppc, resid(ols_base_lm)), col = "red",
    lwd = 1.5)

# dev.off() # to save par(mfrow = c(1, 1))
```

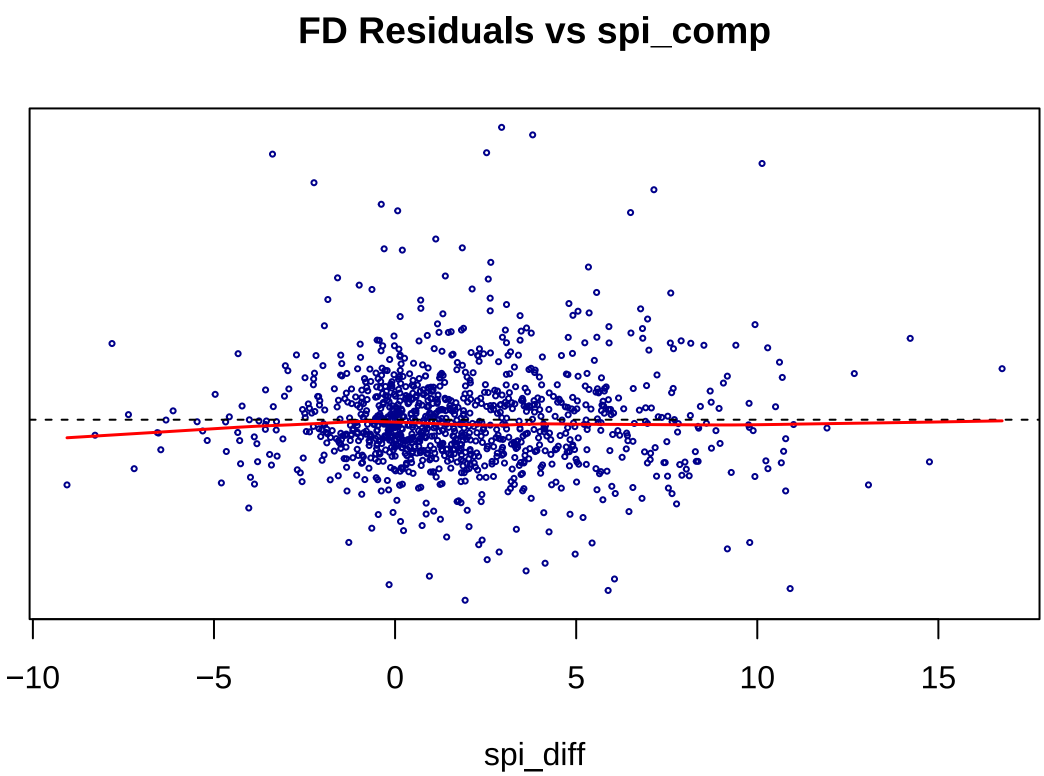
The residuals vs fitted values plot shows a clear pattern, indicating non-linearity in the relationship between the predictors and the SDG performance. The residuals are not randomly distributed around zero, suggesting that the linear model does not adequately capture the underlying relationship.

5.5.2 First Differences Residuals for base/outcome model: SDG ~ SPI + DI + Controls [STAGE 2]

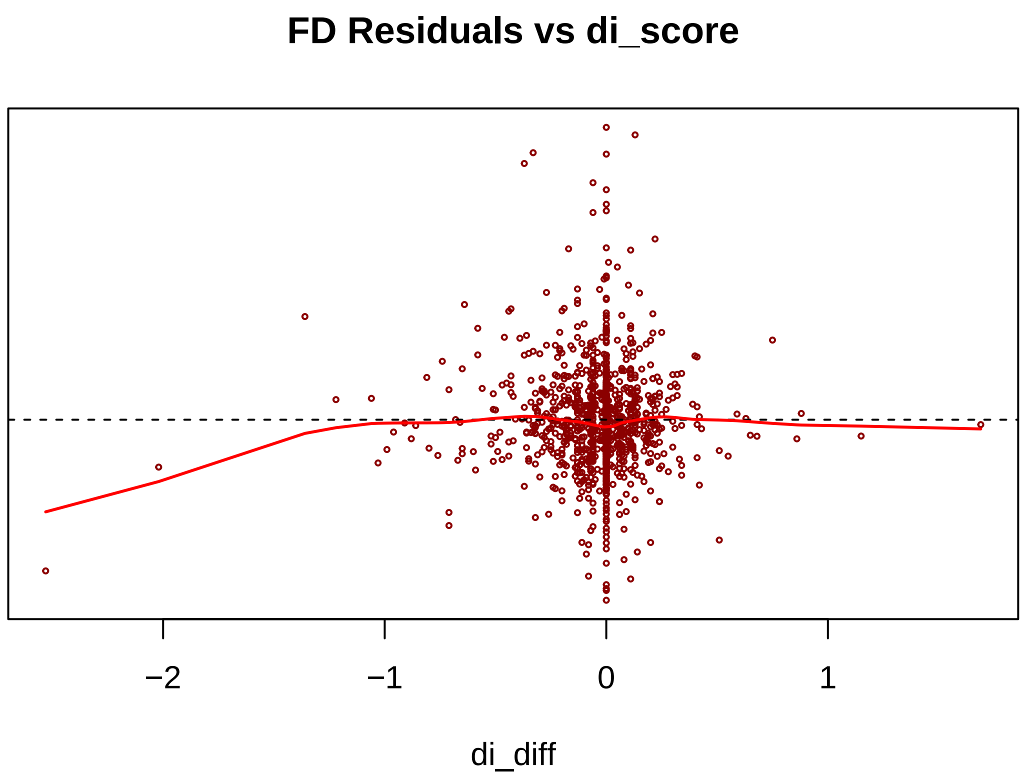
```r
# Extract the data actually used in the base model
fd_base_lm <- lm(sdg_diff ~ spi_diff + di_diff + log_gdppc_diff,
    data = fd_data)
model_data_fd2 <- model.frame(fd_base_lm)

# Residuals vs Fitted Values plot for fd_base_lm
plot(fd_base_lm, which = 1, main = "FD Residuals vs Fitted Model",
    caption = "fd_base [Stage 2]", pch = 1, cex = 0.35, col = "#595959")
abline(h = 0, col = "black", lty = 2, lwd = 1)
fitted_vals_fd2 <- fitted(fd_base_lm)
lines(lowess(fitted_vals_fd2, resid(fd_base_lm)), col = "red",
    lwd = 1.5)
```



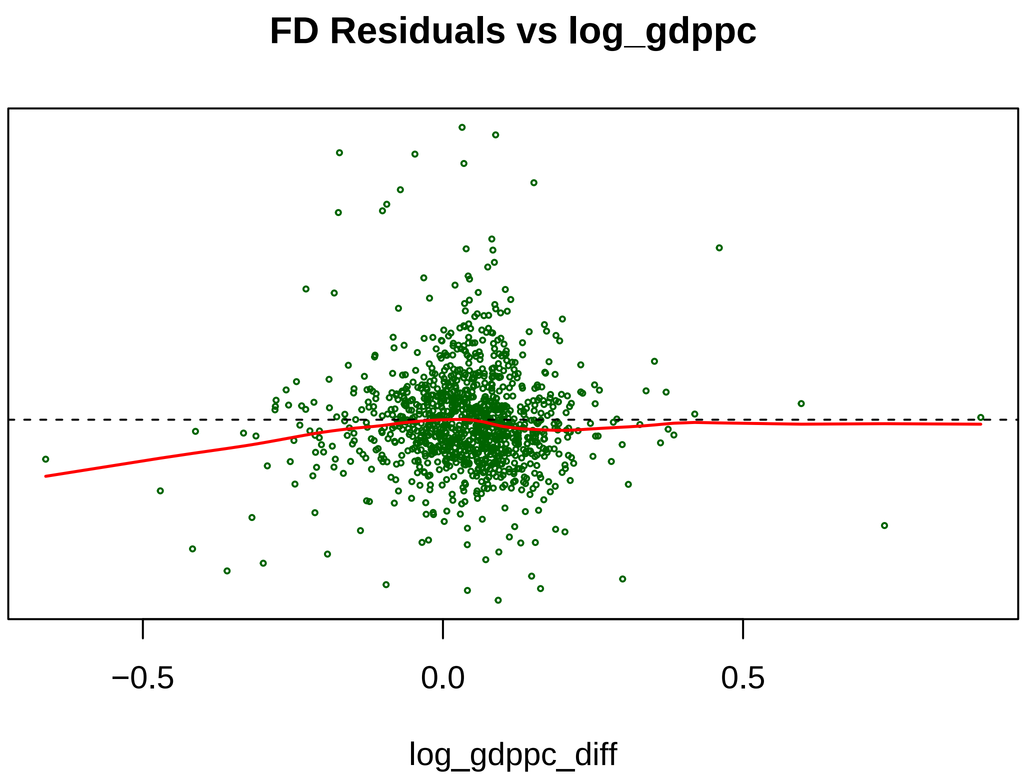

```r
# Residuals vs spi_comp plots
plot(model_data_fd2$spi_diff, resid(fd_base_lm), xlab = "spi_diff",
    ylab = "", yaxt = "n", main = "FD Residuals vs spi_comp",
    pch = 1, cex = 0.35, col = "darkblue")
abline(h = 0, col = "black", lty = 2, lwd = 1)
lines(lowess(model_data_fd2$spi_diff, resid(fd_base_lm)), col = "red",
    lwd = 1.5)
```




```r
# Residuals vs di_score plot
plot(model_data_fd2$di_diff, resid(fd_base_lm), xlab = "di_diff",
    ylab = "", yaxt = "n", main = "FD Residuals vs di_score",
    pch = 1, cex = 0.35, col = "darkred")
abline(h = 0, col = "black", lty = 2, lwd = 1)
lines(lowess(model_data_fd2$di_diff, resid(fd_base_lm)), col = "red",
    lwd = 1.5)
```



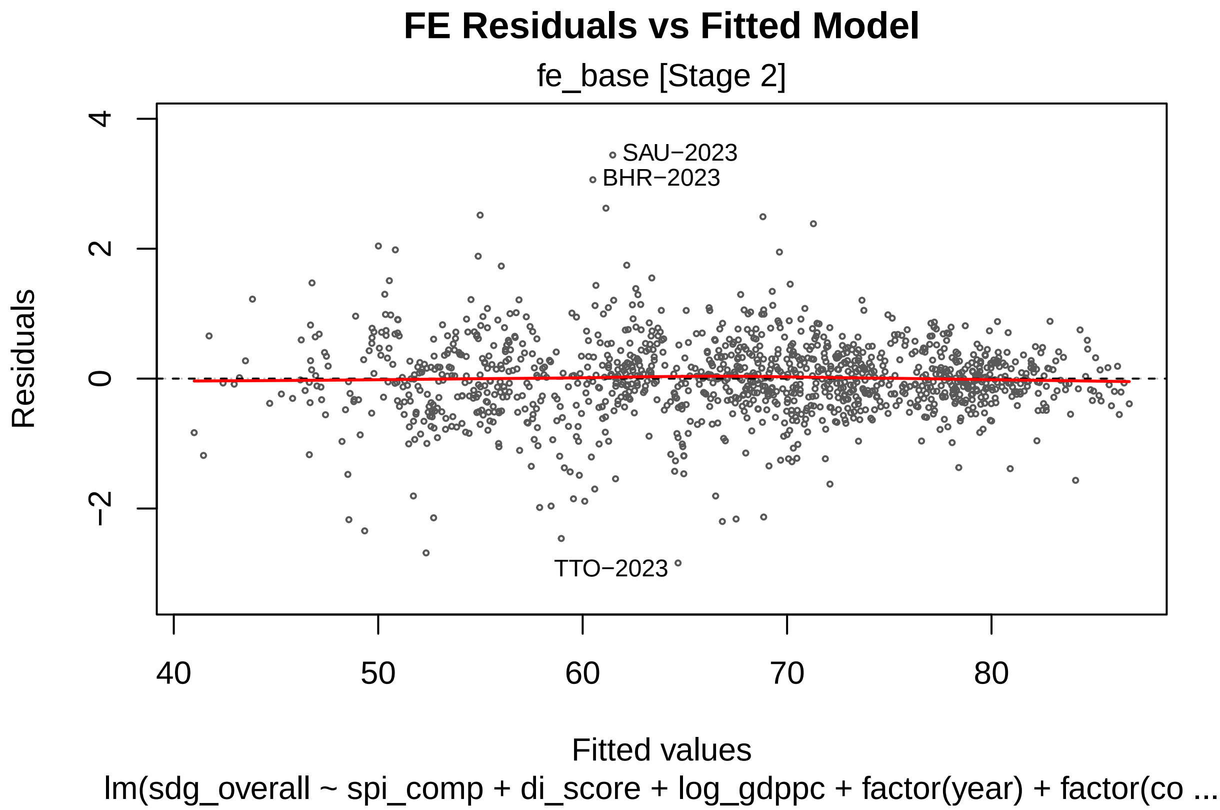

```r
# Residuals vs log_gdppc_diff plot
plot(model_data_fd2$log_gdppc_diff, resid(fd_base_lm), xlab = "log_gdppc_diff",
    ylab = "", yaxt = "n", main = "FD Residuals vs log_gdppc",
    pch = 1, cex = 0.35, col = "darkgreen")
abline(h = 0, col = "black", lty = 2, lwd = 1)
lines(lowess(model_data_fd2$log_gdppc_diff, resid(fd_base_lm)),
    col = "red", lwd = 1.5)
```



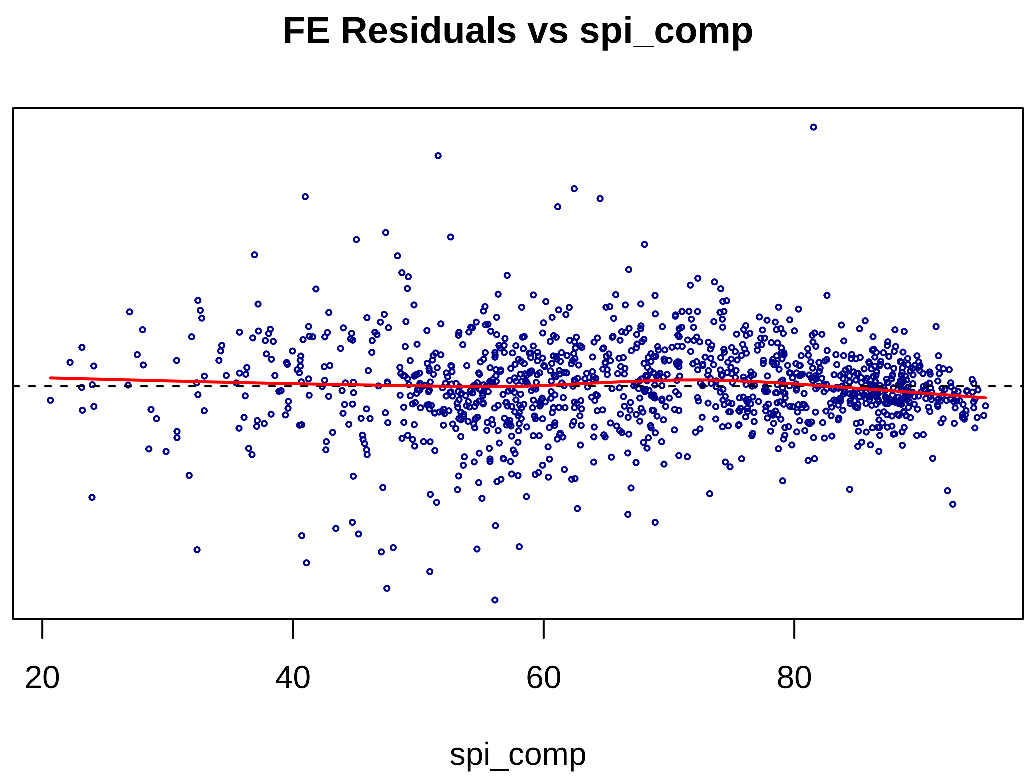

```
# dev.off() # to save par(mfrow = c(1, 1))
```

5.5.3 FE Residuals for base/outcome model: SDG ~ SPI + DI + Controls [STAGE 2]

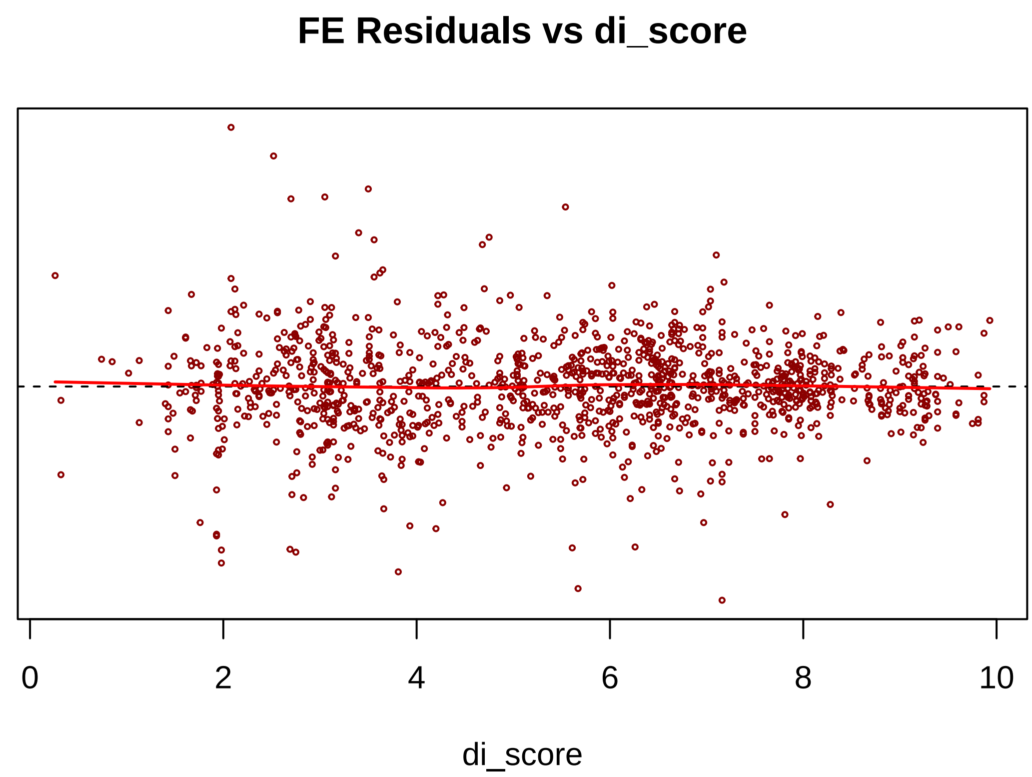
```
# Extract the data actually used in the base model
fe_base_lm <- lm(sdg_overall ~ spi_comp + di_score + log_gdppc +
    factor(year) + factor(country_code), data = panel_data)
model_data_fe2 <- model.frame(fe_base_lm)

# Residuals vs Fitted Values plot for fe_base_lm
plot(fe_base_lm, which = 1, main = "FE Residuals vs Fitted Model",
    caption = "fe_base [Stage 2]", pch = 1, cex = 0.35, col = "#595959")
abline(h = 0, col = "black", lty = 2, lwd = 1)
fitted_vals_fe2 <- fitted(fe_base_lm)
lines(lowess(fitted_vals_fe2, resid(fe_base_lm)), col = "red",
    lwd = 1.5)
```



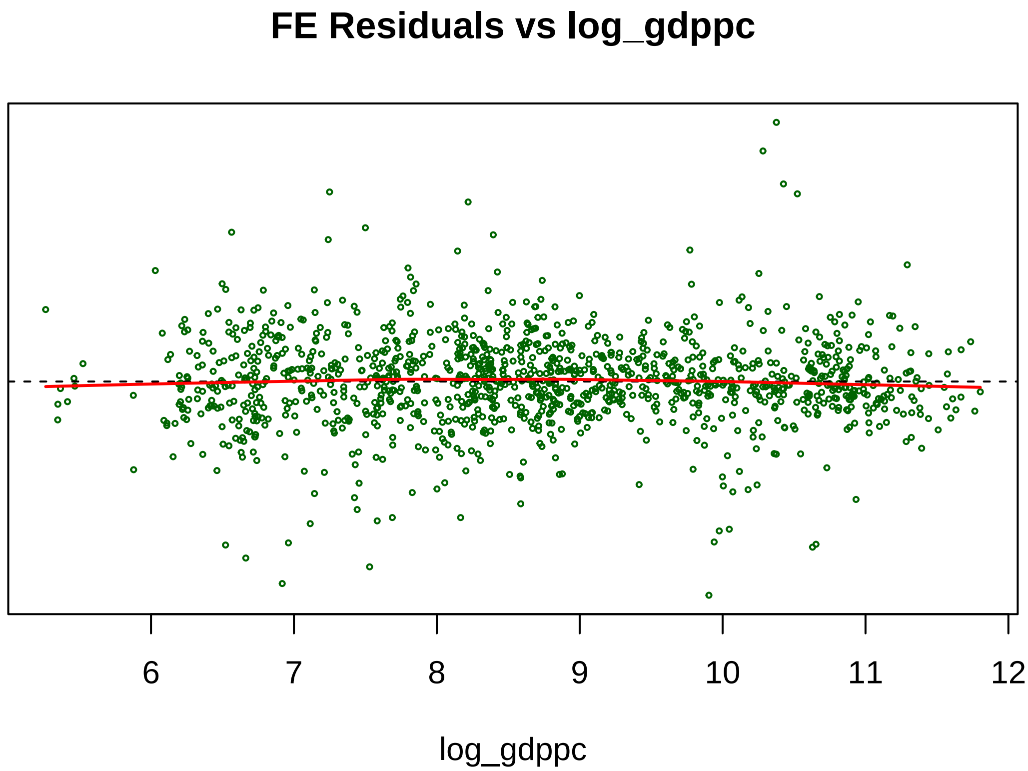

```r
# Residuals vs spi_comp plots
plot(model_data_fe2$spi_comp, resid(fe_base_lm), xlab = "spi_comp",
    ylab = "", yaxt = "n", main = "FE Residuals vs spi_comp",
    pch = 1, cex = 0.35, col = "darkblue")
abline(h = 0, col = "black", lty = 2, lwd = 1)
lines(lowess(model_data_fe2$spi_comp, resid(fe_base_lm)), col = "red",
    lwd = 1.5)
```




```r
# Residuals vs di_score plot
plot(model_data_fe2$di_score, resid(fe_base_lm), xlab = "di_score",
    ylab = "", yaxt = "n", main = "FE Residuals vs di_score",
    pch = 1, cex = 0.35, col = "darkred")
abline(h = 0, col = "black", lty = 2, lwd = 1)
lines(lowess(model_data_fe2$di_score, resid(fe_base_lm)), col = "red",
    lwd = 1.5)
```




```r
# Residuals vs log_gdppc plot
plot(model_data_fe2$log_gdppc, resid(fe_base_lm), xlab = "log_gdppc",
    ylab = "", yaxt = "n", main = "FE Residuals vs log_gdppc",
    pch = 1, cex = 0.35, col = "darkgreen")
abline(h = 0, col = "black", lty = 2, lwd = 1)
lines(lowess(model_data_fe2$log_gdppc, resid(fe_base_lm)), col = "red",
    lwd = 1.5)
```




```r
dev.off()  # to save
```

```
## quartz_off_screen
##                 3
```

```r
par(mfrow = c(1, 1))
```

- No unsusual curvatures or patterns.
- Homoscedasticity seems reasonable.
- No obvious outliers.
- Residuals appear roughly normally distributed.
- Overall, the residual diagnostics suggest that the linear regression assumptions are reasonably met for both models.