modelo econometrico

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Pre procesamiento de datos

1. Lectura de datos y formato panel

```
df <- read.csv('df_17_21_noclean.csv') %>%
  dplyr::select(year, country, total_earnings, # orden de datos panel
         total_players,
         -iso, -code, #no aplica el modelo
         pbicap,
         gdp_gr,
         CPI, # corrupcion
         internet, elect_acc,
         exp_tech, # tech access
         -age_work,
         life_exp, # edades
         poblacion# people
        ) %>%
  arrange(country, decreasing = FALSE)


head(df, 3)
```

```
##         year country total_earnings total_players   pbicap   gdp_gr CPI
## 1 2017-01-01 Albania        2868.16             2 4531.032 3.898112  38
## 2 2018-01-01 Albania        1346.55             3 5287.661 4.276312  36
## 3 2019-01-01 Albania       37459.64            14 5396.214 2.523541  35
##   internet elect_acc exp_tech life_exp poblacion
## 1 62.40000     99.89 31.52551   79.047   2873457
## 2 65.40000    100.00 30.75579   79.184   2866376
## 3 68.55039    100.00 31.18889   79.282   2854191
```

2. Valores faltantes

- Numero de Valores faltantes por variable

```
sapply(df, function(x) sum(is.na(x)))
```

```
##           year        country total_earnings  total_players         pbicap
##              0              0              0              0             10
##         gdp_gr            CPI       internet      elect_acc       exp_tech
```

```
##              8             6            54            99            38
##       life_exp     poblacion
##             99             0
```

- corriegiendo los NAs

```
# Pbi faltantes
## "Cuba"  "Lebanon"  "Syrian Arab Republic"  "Venezuela"
pbicap_faltantes <- unique(df[is.na(df$pbicap), ]$country)
df <- df[!df$country %in% pbicap_faltantes, ]

# Internet: 2 faltantes -> 2018 cambodia y trinidad y tobago

### Cambodia, hueco en 2018, reemplazdo por el promedio

df[df$country=='Cambodia', 'internet'][2] <-
          (df[df$country=='Cambodia', 'internet'][1] +
             df[df$country=='Cambodia', 'internet'][3])/2

### trinidad y tobago, reemplazdo por el promedio
df[df$country=='Trinidad and Tobago', 'internet'][2] <-
          (df[df$country=='Trinidad and Tobago', 'internet'][1]+
              df[df$country=='Trinidad and Tobago', 'internet'][3])/2

# Acceso a electricidad y life expectanci solo antes del 2022
df <- df %>%
  filter(year < as.Date("2022-01-01"))

# EXportacion tecnologica voy a quitar a los paises que no tiene exportacion por temas politicos
##"Iran, Islamic Republic of" "United Arab Emirates" "Viet Nam"
exp_faltantes <- unique(df[is.na(df$exp_tech), ]$country)
df <- df[!df$country %in% exp_faltantes, ]


# CPI macao no tiene por temas politicos
df <- df[df$country != 'Macao', ]


### Jugadores por poblacion por millon
df$players_ppl <- (df$total_players/df$poblacion)*1000000

###########

# verificamos NAs, ahora no tengo NAS
sapply(df, function(x) sum(is.na(x)))
```

```
##           year        country total_earnings  total_players         pbicap
##              0              0              0              0              0
##         gdp_gr            CPI       internet      elect_acc       exp_tech
##              0              0              0              0              0
##       life_exp      poblacion    players_ppl
##              0              0              0
```

3. Normalizacion con logaritmo

- valores con varianzas muy grandes

```
summary(df)
```

```
##      year              country          total_earnings     total_players
##  Length:455         Length:455         Min.   :      55   Min.   :   1.0
##  Class :character   Class :character   1st Qu.:   48243   1st Qu.:  20.0
##  Mode  :character   Mode  :character   Median :  289199   Median :  83.0
##                                        Mean   : 1948524   Mean   : 275.7
##                                        3rd Qu.: 1358358   3rd Qu.: 269.5
##                                        Max.   :51416470   Max.   :6280.0
##      pbicap           gdp_gr              CPI           internet
##  Min.   :  1243   Min.   :-18.8544   Min.   :18.00   Min.   : 13.78
##  1st Qu.:  4732   1st Qu.: -0.4916   1st Qu.:35.00   1st Qu.: 64.76
##  Median : 12532   Median :  1.9630   Median :44.00   Median : 79.17
##  Mean   : 22561   Mean   :  1.5517   Mean   :50.57   Mean   : 74.82
##  3rd Qu.: 34148   3rd Qu.:  4.4185   3rd Qu.:67.00   3rd Qu.: 88.97
##  Max.   :133712   Max.   : 18.7329   Max.   :89.00   Max.   :100.00
##    elect_acc          exp_tech         life_exp       poblacion
##  Min.   : 80.70   Min.   : 4.167   Min.   :62.34   Min.   :3.434e+05
##  1st Qu.: 99.80   1st Qu.:24.468   1st Qu.:73.02   1st Qu.:5.139e+06
##  Median :100.00   Median :43.495   Median :76.60   Median :1.100e+07
##  Mean   : 98.91   Mean   :42.225   Mean   :76.68   Mean   :6.720e+07
##  3rd Qu.:100.00   3rd Qu.:57.264   3rd Qu.:81.40   3rd Qu.:4.473e+07
##  Max.   :100.00   Max.   :92.665   Max.   :85.50   Max.   :1.412e+09
##   players_ppl
##  Min.   :  0.00604
##  1st Qu.:  1.58751
##  Median :  5.99318
##  Mean   : 12.89707
##  3rd Qu.: 15.43862
##  Max.   :127.57826
```

- aplico normalizacion logaritmica en algunas variables

```
df_standar <- df %>%
  mutate(across(c("total_earnings", "pbicap", "poblacion"), ~log(.)))%>%
  mutate(year = year(df$year))
```

EDA varibales

GRafico a nivel global

```
ggplot(df_standar %>%
        group_by(year) %>%
        summarise(total_earnings = sum(total_earnings)),
       aes(x = year, y = total_earnings)) +
```

```r
  geom_line()+
  # scale_x_continuous(breaks = c(2017, 2018, 2019, 2020, 2021))+
  ggtitle("Total Earnings Global by year")
```

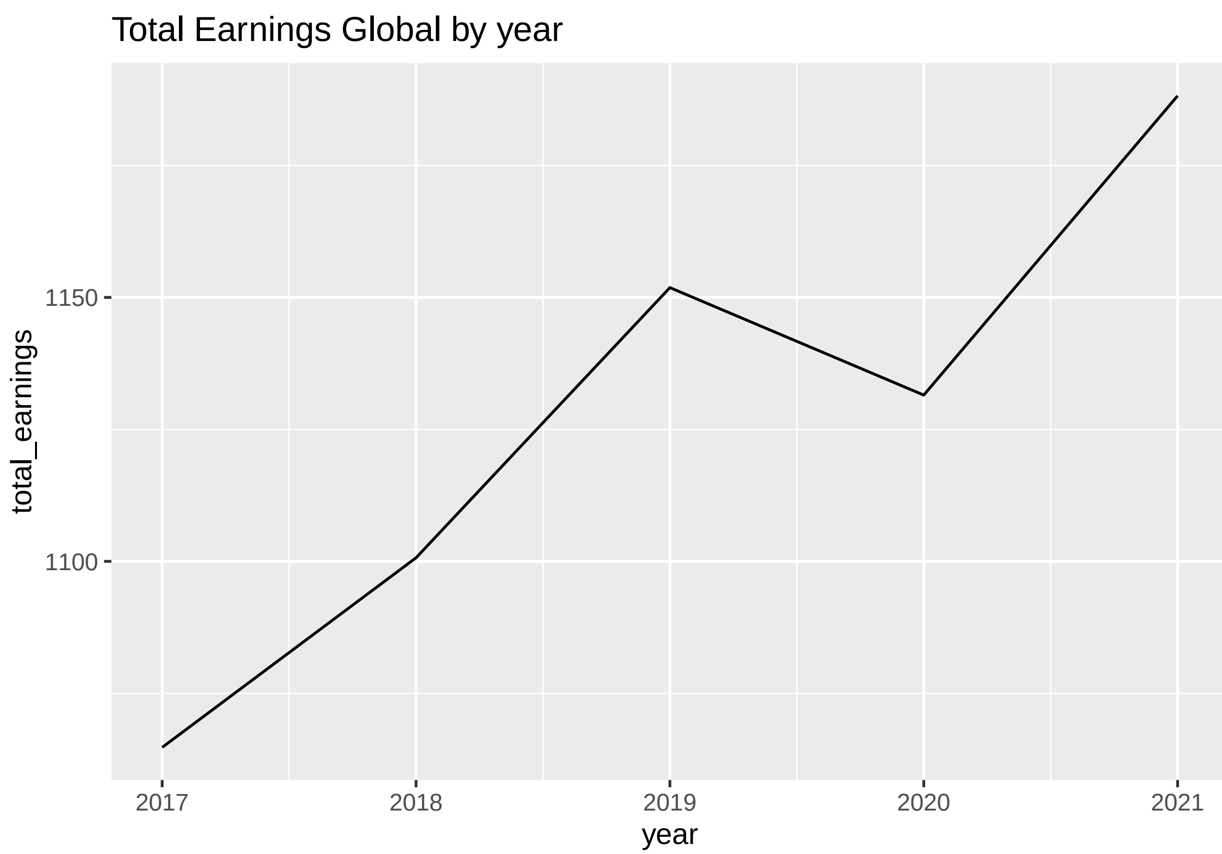


Grafico por variable y pais

```r
# median_earnings <- aggregate(total_earnings ~ country, df_standar, median)
# df_eda <- merge(df_standar, median_earnings, by = "country", suffixes = c("", "_median"))
#
# columnas <- colnames(df_eda)[5:13]
#
# generar_graficos <- function(df, var) {
#   p <- ggplot(df, aes_string(x = var, y = "total_earnings", color = "total_earnings_median")) +
#     geom_point() +
#     facet_wrap(~ year) +
#     scale_color_gradient(low = "red", high = "green") +
#     ggtitle(paste("Relacion de paises y",var,"en el tiempo por Ganancia media"))+
#     theme(legend.position = "none")
#
#   print(p)
# }
#
# lapply(columnas, generar_graficos, df = df_eda)
```

Implementando modelos

0. Preparando los datos

- tenemos datos panel con la siguente forma 90 paises 5 anios y estas cols
- Nuestro panel es balanceado y corto

```
dim(table(df_standar$country,df_standar$year))
```

```
## [1] 91  5
```

```
colnames(df_standar)
```

```
##  [1] "year"           "country"        "total_earnings" "total_players"
##  [5] "pbicap"         "gdp_gr"         "CPI"            "internet"
##  [9] "elect_acc"      "exp_tech"       "life_exp"       "poblacion"
## [13] "players_ppl"
```

- definimos las variables para el modelo

```
attach(df_standar)
Y <- cbind(total_earnings)
X <- cbind(pbicap, gdp_gr, internet,
           exp_tech,
           #CPI,
           elect_acc,
           life_exp, poblacion, players_ppl)

df_panel <- pdata.frame(df_standar,
                        index=c('country','year'))

head(df_panel,3)
```

```
##              year country total_earnings total_players   pbicap   gdp_gr CPI
## Albania-2017 2017 Albania       7.961426             2 8.418705 3.898112  38
## Albania-2018 2018 Albania       7.205301             3 8.573131 4.276312  36
## Albania-2019 2019 Albania      10.531019            14 8.593453 2.523541  35
##              internet elect_acc exp_tech life_exp poblacion players_ppl
## Albania-2017 62.40000     99.89 31.52551   79.047  14.87103   0.6960257
## Albania-2018 65.40000    100.00 30.75579   79.184  14.86856   1.0466178
## Albania-2019 68.55039    100.00 31.18889   79.282  14.86430   4.9050677
```

1. Efectos Fijos

```
fijos <- plm(Y ~ X, data=df_panel, index=c('country','year'), model= "within")
summary(fijos)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = Y ~ X, data = df_panel, model = "within", index = c("country",
##     "year"))
##
## Balanced Panel: n = 91, T = 5, N = 455
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -3.120241 -0.368868 -0.030548  0.435261  2.314970
##
## Coefficients:
##                Estimate Std. Error t-value  Pr(>|t|)
## Xpbicap       0.9270400  0.6247540  1.4838 0.1387340
## Xgdp_gr       0.0177229  0.0110039  1.6106 0.1081531
## Xinternet     0.0376996  0.0106105  3.5530 0.0004321 ***
## Xexp_tech     0.0044991  0.0072849  0.6176 0.5372410
## Xelect_acc    0.1333930  0.0479174  2.7838 0.0056592 **
## Xlife_exp    -0.0669311  0.0542884 -1.2329 0.2184336
## Xpoblacion    7.6077135  3.2056717  2.3732 0.0181649 *
## Xplayers_ppl  0.0272544  0.0079486  3.4288 0.0006773 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    359.09
## Residual Sum of Squares: 249.92
## R-Squared:      0.30402
## Adj. R-Squared: 0.11244
## F-statistic: 19.439 on 8 and 356 DF, p-value: < 2.22e-16
```

2. Efectos aleatorios

```r
random <- plm(Y ~ X, data=df_panel, index=c('country','year'), model= "random")
summary(random)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
## plm(formula = Y ~ X, data = df_panel, model = "random", index = c("country",
##     "year"))
##
## Balanced Panel: n = 91, T = 5, N = 455
##
## Effects:
##                  var std.dev share
## idiosyncratic 0.7020  0.8379 0.311
## individual    1.5522  1.2459 0.689
## theta: 0.712
##
## Residuals:
```

```
##     Min.  1st Qu.   Median  3rd Qu.     Max.
## -3.88697 -0.35555  0.04054  0.45321  2.38750
##
## Coefficients:
##                 Estimate  Std. Error z-value  Pr(>|z|)
## (Intercept)  -20.7143244   4.1377360 -5.0062 5.552e-07 ***
## Xpbicap        0.3142342   0.2156708  1.4570  0.145114
## Xgdp_gr        0.0245864   0.0096119  2.5579  0.010530 *
## Xinternet      0.0520006   0.0074358  6.9933 2.686e-12 ***
## Xexp_tech      0.0075196   0.0049359  1.5235  0.127645
## Xelect_acc     0.1090066   0.0365464  2.9827  0.002857 **
## Xlife_exp     -0.0464649   0.0371877 -1.2495  0.211493
## Xpoblacion     1.1033561   0.0945560 11.6688 < 2.2e-16 ***
## Xplayers_ppl   0.0329486   0.0063146  5.2178 1.810e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    563.56
## Residual Sum of Squares: 316.77
## R-Squared:      0.43791
## Adj. R-Squared: 0.42782
## Chisq: 347.463 on 8 DF, p-value: < 2.22e-16
```

3. MCO

```r
mco = plm(Y ~ X, data=df_panel,index=c("state", "year"), model="pooling")
summary(mco)
```

```
## Pooling Model
##
## Call:
## plm(formula = Y ~ X, data = df_panel, model = "pooling", index = c("state",
##     "year"))
##
## Balanced Panel: n = 91, T = 5, N = 455
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -6.383124 -0.638840  0.090762  0.816988  4.330948
##
## Coefficients:
##                 Estimate  Std. Error t-value  Pr(>|t|)
## (Intercept)  -16.5282675   2.8164494 -5.8685 8.588e-09 ***
## Xpbicap        0.1110949   0.1483237  0.7490  0.454250
## Xgdp_gr        0.0472764   0.0149415  3.1641  0.001662 **
## Xinternet      0.0631161   0.0069405  9.0939 < 2.2e-16 ***
## Xexp_tech      0.0076367   0.0036224  2.1082  0.035570 *
## Xelect_acc     0.0607999   0.0276857  2.1961  0.028601 *
## Xlife_exp     -0.0364269   0.0274085 -1.3290  0.184516
## Xpoblacion     1.1474551   0.0519046 22.1070 < 2.2e-16 ***
## Xplayers_ppl   0.0429519   0.0049785  8.6276 < 2.2e-16 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    2823.9
## Residual Sum of Squares: 985.46
## R-Squared:      0.65103
## Adj. R-Squared: 0.64477
## F-statistic: 104.008 on 8 and 446 DF, p-value: < 2.22e-16
```

Test para escoger el mejor modelo

1. Breusch-Pagan

- H0: modelo agrupado (MCO) vs H1: efectos aleatorios
- p<0.05 entonces rechazo la Ho, por ahora el mejor modelo seria aleatorios

```r
plmtest(mco, type=c("bp"))
```

```
##
##  Lagrange Multiplier Test - (Breusch-Pagan)
##
## data:  Y ~ X
## chisq = 400.57, df = 1, p-value < 2.2e-16
## alternative hypothesis: significant effects
```

2. Hausman test

- H0: efectos aleatorios vs H1: efectos fijos
- p<0.05 entonces rechazo Ho y decido que efectos fijos es mejor

```r
phtest(fijos, random)
```

```
##
##  Hausman Test
##
## data:  Y ~ X
## chisq = 26.775, df = 8, p-value = 0.000773
## alternative hypothesis: one model is inconsistent
```

F test

- H0: modelo agrupado (MCO) vs H1: efectos fijos
- p<0.05 entonces rechazo Ho, el mejor modelo seria efectos fijos

```r
pFtest(fijos, mco)
```

```
##
##  F test for individual effects
##
## data:  Y ~ X
## F = 11.642, df1 = 90, df2 = 356, p-value < 2.2e-16
## alternative hypothesis: significant effects
```

Regresiones

Regresieon simple sin efectos fijos

```r
regresion_mco = lm(Y~X)
summary(regresion_mco)
```

```
##
## Call:
## lm(formula = Y ~ X)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.3831 -0.6388  0.0908  0.8170  4.3309
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -16.528268   2.816449  -5.868 8.59e-09 ***
## Xpbicap        0.111095   0.148324   0.749  0.45425
## Xgdp_gr        0.047276   0.014942   3.164  0.00166 **
## Xinternet      0.063116   0.006940   9.094  < 2e-16 ***
## Xexp_tech      0.007637   0.003622   2.108  0.03557 *
## Xelect_acc     0.060800   0.027686   2.196  0.02860 *
## Xlife_exp     -0.036427   0.027409  -1.329  0.18452
## Xpoblacion     1.147455   0.051905  22.107  < 2e-16 ***
## Xplayers_ppl   0.042952   0.004978   8.628  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.486 on 446 degrees of freedom
## Multiple R-squared:  0.651,  Adjusted R-squared:  0.6448
## F-statistic:   104 on 8 and 446 DF,  p-value: < 2.2e-16
```

Regresieon con efectos fijos

by Country

```r
df_panel$country <- relevel(df_panel$country, ref = "China")
regresion_country = lm(Y ~ X + factor(country), data = df_panel)
summary(regresion_country)
```

```
##
## Call:
## lm(formula = Y ~ X + factor(country), data = df_panel)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.12024 -0.36887 -0.03055  0.43526  2.31497
##
```

```
## Coefficients:
##                                            Estimate Std. Error t value
## (Intercept)                               -1.627e+02  6.791e+01  -2.395
## Xpbicap                                    9.270e-01  6.248e-01   1.484
## Xgdp_gr                                    1.772e-02  1.100e-02   1.611
## Xinternet                                  3.770e-02  1.061e-02   3.553
## Xexp_tech                                  4.499e-03  7.285e-03   0.618
## Xelect_acc                                 1.334e-01  4.792e-02   2.784
## Xlife_exp                                 -6.693e-02  5.429e-02  -1.233
## Xpoblacion                                 7.608e+00  3.206e+00   2.373
## Xplayers_ppl                               2.725e-02  7.949e-03   3.429
## factor(country)Albania                     3.987e+01  1.999e+01   1.995
## factor(country)Algeria                     2.134e+01  1.133e+01   1.883
## factor(country)Argentina                   2.190e+01  1.110e+01   1.972
## factor(country)Armenia                     4.137e+01  2.002e+01   2.066
## factor(country)Australia                   2.572e+01  1.278e+01   2.012
## factor(country)Austria                     3.212e+01  1.613e+01   1.990
## factor(country)Azerbaijan                  3.043e+01  1.599e+01   1.903
## factor(country)Bahrain                     4.344e+01  2.199e+01   1.975
## factor(country)Bangladesh                  1.084e+01  6.957e+00   1.559
## factor(country)Belarus                     3.334e+01  1.617e+01   2.063
## factor(country)Belgium                     3.031e+01  1.535e+01   1.974
## factor(country)Bolivia                     3.126e+01  1.532e+01   2.041
## factor(country)Bosnia and Herzegovina      4.146e+01  1.943e+01   2.133
## factor(country)Brazil                      1.239e+01  6.153e+00   2.014
## factor(country)Bulgaria                    3.692e+01  1.697e+01   2.176
## factor(country)Cambodia                    3.035e+01  1.439e+01   2.108
## factor(country)Canada                      2.325e+01  1.157e+01   2.009
## factor(country)Chile                       2.715e+01  1.383e+01   1.963
## factor(country)Colombia                    2.033e+01  1.075e+01   1.892
## factor(country)Costa Rica                  3.391e+01  1.808e+01   1.876
## factor(country)Croatia                     3.897e+01  1.871e+01   2.082
## factor(country)Czech Republic              3.156e+01  1.560e+01   2.023
## factor(country)Denmark                     3.583e+01  1.745e+01   2.053
## factor(country)Dominican Republic          3.094e+01  1.562e+01   1.981
## factor(country)Ecuador                     2.695e+01  1.411e+01   1.910
## factor(country)Egypt                       1.448e+01  8.418e+00   1.720
## factor(country)Estonia                     4.628e+01  2.229e+01   2.076
## factor(country)Finland                     3.631e+01  1.766e+01   2.056
## factor(country)France                      1.967e+01  9.679e+00   2.032
## factor(country)Georgia                     3.819e+01  1.909e+01   2.001
## factor(country)Germany                     1.753e+01  9.016e+00   1.944
## factor(country)Greece                      3.158e+01  1.556e+01   2.029
## factor(country)Guatemala                   2.765e+01  1.420e+01   1.948
## factor(country)Hong Kong                   3.372e+01  1.672e+01   2.017
## factor(country)Hungary                     3.155e+01  1.592e+01   1.982
## factor(country)Iceland                     5.165e+01  2.635e+01   1.960
## factor(country)India                      -1.419e+00  1.148e+00  -1.237
## factor(country)Indonesia                   1.085e+01  5.337e+00   2.034
## factor(country)Iraq                        2.168e+01  1.123e+01   1.931
## factor(country)Ireland                     3.500e+01  1.802e+01   1.942
## factor(country)Israel                      3.248e+01  1.614e+01   2.012
## factor(country)Italy                       1.957e+01  1.001e+01   1.954
## factor(country)Japan                       1.441e+01  7.740e+00   1.861
```

```
## factor(country)Jordan                          3.470e+01  1.576e+01   2.201
## factor(country)Kazakhstan                      2.829e+01  1.390e+01   2.035
## factor(country)Korea, Republic of              2.205e+01  1.061e+01   2.077
## factor(country)Kuwait                          3.540e+01  1.858e+01   1.905
## factor(country)Kyrgyzstan                      3.670e+01  1.753e+01   2.094
## factor(country)Lao People's Democratic Republic  3.417e+01  1.691e+01   2.021
## factor(country)Latvia                          4.267e+01  2.111e+01   2.022
## factor(country)Lithuania                       4.024e+01  1.984e+01   2.028
## factor(country)Luxembourg                      4.697e+01  2.459e+01   1.911
## factor(country)Malaysia                        2.485e+01  1.213e+01   2.049
## factor(country)Malta                           4.951e+01  2.539e+01   1.950
## factor(country)Mexico                          1.490e+01  7.706e+00   1.933
## factor(country)Moldova, Republic of            4.223e+01  2.012e+01   2.098
## factor(country)Mongolia                        4.156e+01  1.947e+01   2.134
## factor(country)Morocco                         2.207e+01  1.193e+01   1.849
## factor(country)Netherlands                     2.781e+01  1.403e+01   1.982
## factor(country)New Zealand                     3.616e+01  1.800e+01   2.009
## factor(country)Nicaragua                       3.688e+01  1.724e+01   2.140
## factor(country)North Macedonia                 4.372e+01  2.104e+01   2.078
## factor(country)Norway                          3.572e+01  1.772e+01   2.015
## factor(country)Pakistan                        1.350e+01  6.016e+00   2.244
## factor(country)Panama                          3.632e+01  1.845e+01   1.968
## factor(country)Paraguay                        3.115e+01  1.728e+01   1.802
## factor(country)Peru                            2.581e+01  1.202e+01   2.147
## factor(country)Philippines                     1.874e+01  8.236e+00   2.275
## factor(country)Poland                          2.384e+01  1.158e+01   2.058
## factor(country)Portugal                        3.182e+01  1.568e+01   2.030
## factor(country)Romania                         2.738e+01  1.373e+01   1.994
## factor(country)Russian Federation              1.480e+01  7.340e+00   2.017
## factor(country)Saudi Arabia                    2.275e+01  1.180e+01   1.929
## factor(country)Singapore                       3.509e+01  1.757e+01   1.997
## factor(country)Slovakia                        3.625e+01  1.777e+01   2.039
## factor(country)Slovenia                        4.334e+01  2.082e+01   2.081
## factor(country)South Africa                    2.075e+01  1.015e+01   2.045
## factor(country)Spain                           2.125e+01  1.088e+01   1.953
## factor(country)Sri Lanka                       2.382e+01  1.334e+01   1.786
## factor(country)Sweden                          3.196e+01  1.569e+01   2.037
## factor(country)Switzerland                     3.156e+01  1.623e+01   1.944
## factor(country)Thailand                        2.057e+01  9.612e+00   2.140
## factor(country)Trinidad and Tobago             4.055e+01  2.183e+01   1.857
## factor(country)Tunisia                         3.047e+01  1.543e+01   1.975
## factor(country)Turkey                          1.816e+01  9.110e+00   1.993
## factor(country)Ukraine                         2.432e+01  1.125e+01   2.162
## factor(country)United Kingdom                  1.905e+01  9.744e+00   1.955
## factor(country)United States                   8.191e+00  4.629e+00   1.769
## factor(country)Uruguay                         3.840e+01  1.927e+01   1.993
## factor(country)Uzbekistan                      2.325e+01  1.220e+01   1.906
##                                               Pr(>|t|)
## (Intercept)                                   0.017124 *
## Xpbicap                                       0.138734
## Xgdp_gr                                       0.108153
## Xinternet                                     0.000432 ***
## Xexp_tech                                     0.537241
## Xelect_acc                                    0.005659 **
```

```
## Xlife_exp                                  0.218434
## Xpoblacion                                 0.018165 *
## Xplayers_ppl                               0.000677 ***
## factor(country)Albania                     0.046831 *
## factor(country)Algeria                     0.060527 .
## factor(country)Argentina                   0.049381 *
## factor(country)Armenia                     0.039533 *
## factor(country)Australia                   0.044951 *
## factor(country)Austria                     0.047306 *
## factor(country)Azerbaijan                  0.057786 .
## factor(country)Bahrain                     0.049003 *
## factor(country)Bangladesh                  0.119989
## factor(country)Belarus                     0.039873 *
## factor(country)Belgium                     0.049124 *
## factor(country)Bolivia                     0.041997 *
## factor(country)Bosnia and Herzegovina      0.033572 *
## factor(country)Brazil                      0.044768 *
## factor(country)Bulgaria                    0.030239 *
## factor(country)Cambodia                    0.035697 *
## factor(country)Canada                      0.045339 *
## factor(country)Chile                       0.050404 .
## factor(country)Colombia                    0.059292 .
## factor(country)Costa Rica                  0.061447 .
## factor(country)Croatia                     0.038024 *
## factor(country)Czech Republic              0.043853 *
## factor(country)Denmark                     0.040775 *
## factor(country)Dominican Republic          0.048312 *
## factor(country)Ecuador                     0.056903 .
## factor(country)Egypt                       0.086233 .
## factor(country)Estonia                     0.038576 *
## factor(country)Finland                     0.040541 *
## factor(country)France                      0.042867 *
## factor(country)Georgia                     0.046150 *
## factor(country)Germany                     0.052639 .
## factor(country)Greece                      0.043228 *
## factor(country)Guatemala                   0.052256 .
## factor(country)Hong Kong                   0.044401 *
## factor(country)Hungary                     0.048279 *
## factor(country)Iceland                     0.050788 .
## factor(country)India                       0.217055
## factor(country)Indonesia                   0.042718 *
## factor(country)Iraq                        0.054328 .
## factor(country)Ireland                     0.052954 .
## factor(country)Israel                      0.044945 *
## factor(country)Italy                       0.051436 .
## factor(country)Japan                       0.063507 .
## factor(country)Jordan                      0.028388 *
## factor(country)Kazakhstan                  0.042565 *
## factor(country)Korea, Republic of          0.038508 *
## factor(country)Kuwait                      0.057613 .
## factor(country)Kyrgyzstan                  0.036999 *
## factor(country)Lao People's Democratic Republic 0.044062 *
## factor(country)Latvia                      0.043939 *
## factor(country)Lithuania                   0.043334 *
```

```
## factor(country)Luxembourg                        0.056862 .
## factor(country)Malaysia                          0.041206 *
## factor(country)Malta                             0.051931 .
## factor(country)Mexico                            0.053968 .
## factor(country)Moldova, Republic of              0.036574 *
## factor(country)Mongolia                          0.033504 *
## factor(country)Morocco                           0.065238 .
## factor(country)Netherlands                       0.048262 *
## factor(country)New Zealand                       0.045268 *
## factor(country)Nicaragua                         0.033046 *
## factor(country)North Macedonia                   0.038418 *
## factor(country)Norway                            0.044604 *
## factor(country)Pakistan                          0.025475 *
## factor(country)Panama                            0.049837 *
## factor(country)Paraguay                          0.072327 .
## factor(country)Peru                              0.032450 *
## factor(country)Philippines                       0.023509 *
## factor(country)Poland                            0.040333 *
## factor(country)Portugal                          0.043129 *
## factor(country)Romania                           0.046967 *
## factor(country)Russian Federation                0.044478 *
## factor(country)Saudi Arabia                      0.054576 .
## factor(country)Singapore                         0.046532 *
## factor(country)Slovakia                          0.042172 *
## factor(country)Slovenia                          0.038123 *
## factor(country)South Africa                      0.041621 *
## factor(country)Spain                             0.051608 .
## factor(country)Sri Lanka                         0.075030 .
## factor(country)Sweden                            0.042437 *
## factor(country)Switzerland                       0.052656 .
## factor(country)Thailand                          0.033057 *
## factor(country)Trinidad and Tobago               0.064073 .
## factor(country)Tunisia                           0.049080 *
## factor(country)Turkey                            0.047035 *
## factor(country)Ukraine                           0.031314 *
## factor(country)United Kingdom                    0.051356 .
## factor(country)United States                     0.077698 .
## factor(country)Uruguay                           0.047033 *
## factor(country)Uzbekistan                        0.057519 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8379 on 356 degrees of freedom
## Multiple R-squared:  0.9115, Adjusted R-squared:  0.8871
## F-statistic: 37.41 on 98 and 356 DF,  p-value: < 2.2e-16
```

Analizando significancias

```
p_values <- summary(regresion_country)$coefficients[,4]
coeficiente <- summary(regresion_country)$coefficients[,1]

no_significativo <- names(p_values)[which(p_values > 0.05)]
```

```r
significativo_positivos <- names(p_values)[which(p_values < 0.05 & coeficiente>0)]

significativo_negativos <- names(p_values)[which(p_values < 0.05 & coeficiente<0)]
```

```r
significativo_negativos
```

```
## [1] "(Intercept)"
```

By year

- El año en sí mismo no parece tener un efecto significativo en Y después de ajustar por X

```r
regresion_years = lm(Y~X+factor(year))
summary(regresion_years)
```

```
##
## Call:
## lm(formula = Y ~ X + factor(year))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.7102 -0.6705  0.1154  0.8141  4.5668
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -16.469432   2.864067  -5.750 1.66e-08 ***
## Xpbicap           0.145660   0.150191   0.970  0.33266
## Xgdp_gr           0.070852   0.023774   2.980  0.00304 **
## Xinternet         0.063258   0.007602   8.321 1.10e-15 ***
## Xexp_tech         0.007933   0.003838   2.067  0.03929 *
## Xelect_acc        0.060776   0.027711   2.193  0.02881 *
## Xlife_exp        -0.043360   0.028259  -1.534  0.12565
## Xpoblacion        1.143389   0.051993  21.991  < 2e-16 ***
## Xplayers_ppl      0.041776   0.005006   8.346 9.12e-16 ***
## factor(year)2018  0.154273   0.221100   0.698  0.48570
## factor(year)2019  0.401698   0.225908   1.778  0.07607 .
## factor(year)2020  0.375691   0.300567   1.250  0.21198
## factor(year)2021 -0.073873   0.261205  -0.283  0.77745
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.485 on 442 degrees of freedom
## Multiple R-squared:  0.6549, Adjusted R-squared:  0.6455
## F-statistic:  69.9 on 12 and 442 DF,  p-value: < 2.2e-16
```

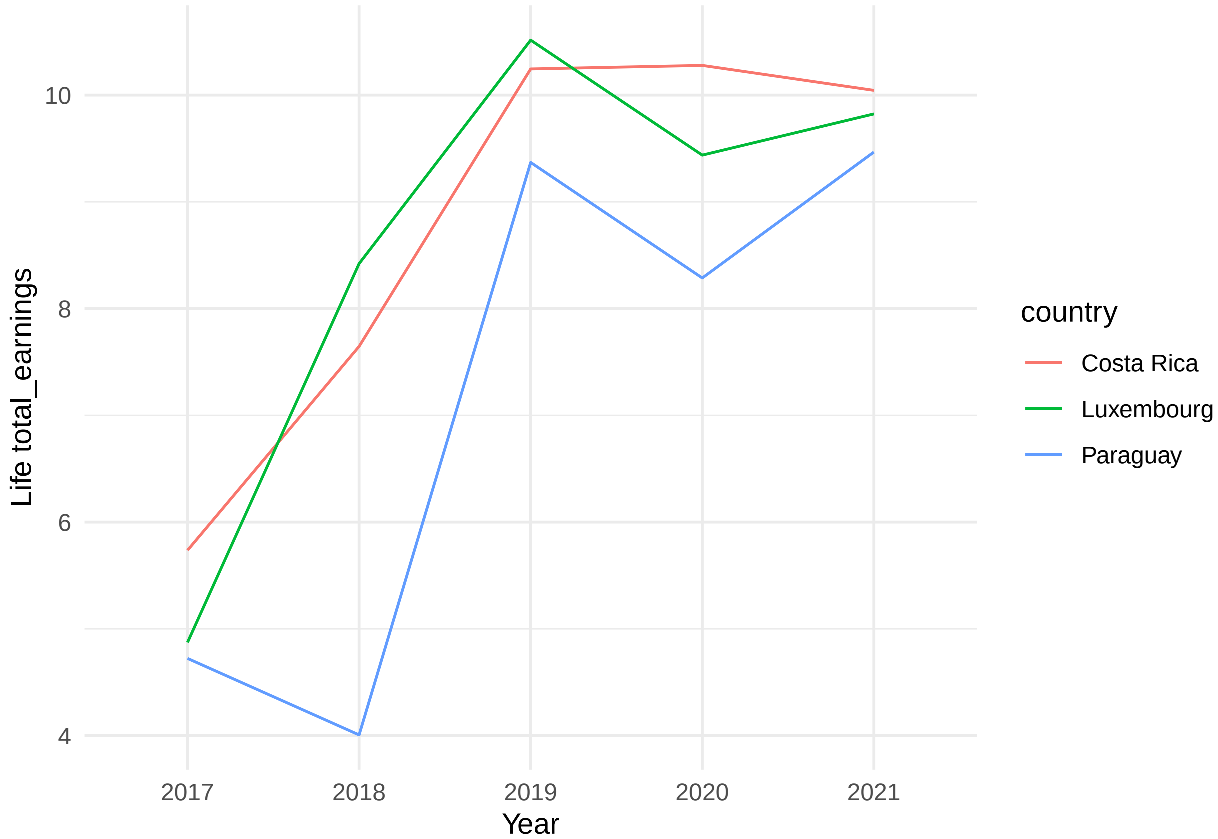
```r
 df_panel %>%
  group_by(country) %>%
  top_n(3, total_earnings) %>%
  arrange(desc(total_earnings))
```

```
## # A tibble: 273 x 13
## # Groups:   country [91]
##    year  country        total_earnings total_players pbicap gdp_gr   CPI internet
##    <fct> <fct>                   <dbl>         <int>  <dbl>  <dbl> <dbl>    <dbl>
##  1 2021  China                    17.8          2013   9.44   8.35    45     73.1
##  2 2019  United States            17.7          6280  11.1    1.83    69     89.4
##  3 2021  United States            17.3          5129  11.2    5.78    67     91.8
##  4 2018  United States            17.2          4413  11.0    2.40    71     88.5
##  5 2019  China                    17.0          1454   9.22   5.58    41     64.1
##  6 2020  China                    17.0          1596   9.25   2.00    42     70.1
##  7 2021  Russian Fede~            17.0          1112   9.44   5.53    29     88.2
##  8 2019  Korea, Repub~            16.7          1226  10.4    1.89    59     96.2
##  9 2018  Korea, Repub~            16.5          1283  10.4    2.46    57     96.0
## 10 2021  Korea, Repub~            16.4          1127  10.5    4.49    62     97.6
## # i 263 more rows
## # i 5 more variables: elect_acc <dbl>, exp_tech <dbl>, life_exp <dbl>,
## #   poblacion <dbl>, players_ppl <dbl>
```

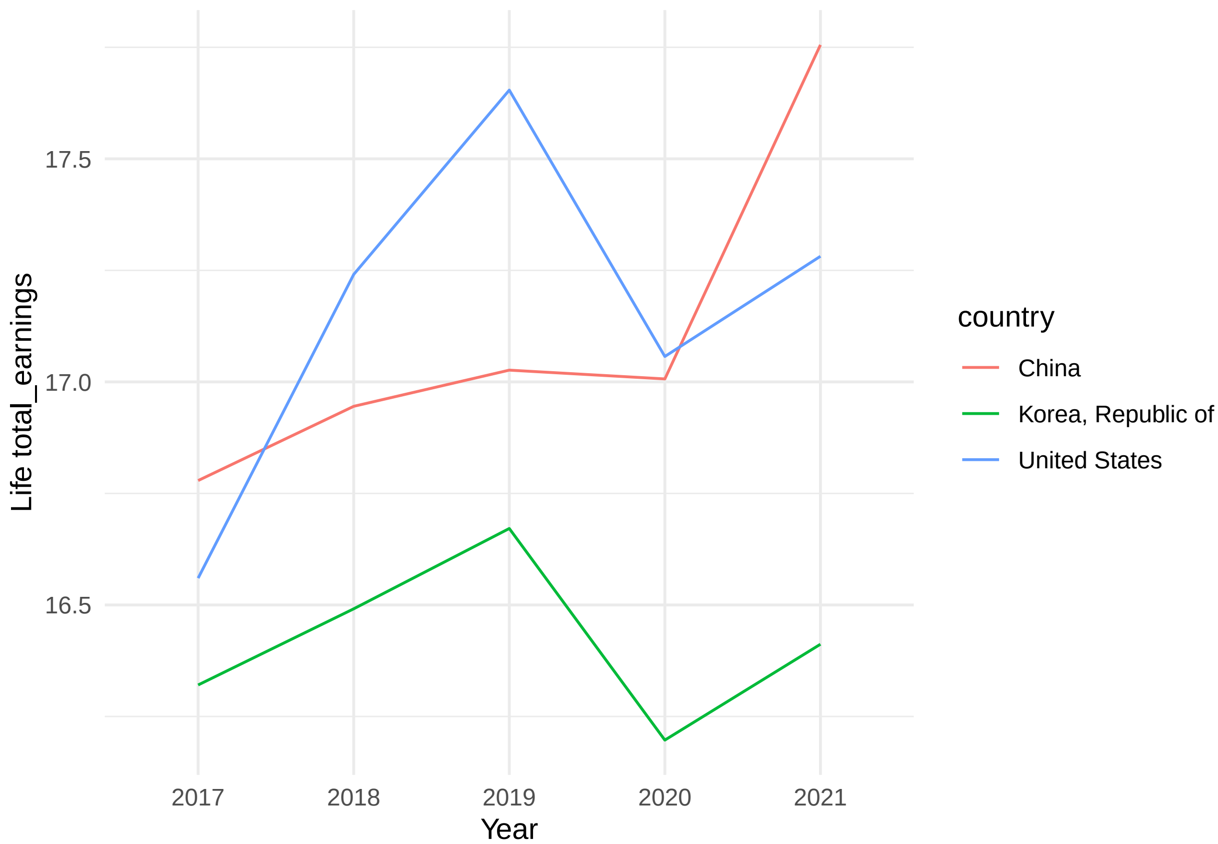
```r
df_panel %>%
  group_by(country) %>%
  mutate(year = as.integer(year)) %>%
  summarise(CAGR = ifelse((last(year) - first(year)) != 0,
                         (last(total_earnings) / first(total_earnings))^(1/(last(year)-first(year))) -
  arrange(desc(CAGR))
```

```
## # A tibble: 91 x 2
##    country                           CAGR
##    <fct>                            <dbl>
##  1 Luxembourg                      0.192
##  2 Paraguay                        0.190
##  3 Costa Rica                      0.150
##  4 Bangladesh                      0.141
##  5 Bolivia                         0.125
##  6 Azerbaijan                      0.113
##  7 Uzbekistan                      0.103
##  8 Egypt                           0.0978
##  9 Lao People's Democratic Republic 0.0945
## 10 Georgia                         0.0777
## # i 81 more rows
```

```r
# Supongamos que tu dataframe se llama df_eda y tienes las variables year, lifeExp, country y continent
# Ajusta tu gráfico
ggplot(df_panel %>%
  group_by(year) %>%
  filter(country %in% c('Luxembourg', 'Paraguay', 'Costa Rica')), aes(x = year, y = total_earnings, grou
  geom_line() +
  labs(x = "Year", y = "Life total_earnings") +
  theme_minimal() +
  theme()
```




```
ggplot(df_panel %>%
  group_by(year) %>%
  filter(country %in% c('China', 'United States', 'Korea, Republic of')), aes(x = year, y = total_earni
  geom_line() +
  labs(x = "Year", y = "Life total_earnings") +
  theme_minimal() +
  theme()
```



17.5
17.0
16.5
Life total_earnings
2017
2018
2019
2020
2021
Year
country
China
Korea, Republic of
United States