Section 4: Getting data and some additional regression magic

This week, we are going to learn:

- How to download data from two very popular sources in the field of political economy and macroeconomics
- Look at an interesting question related to the effectiveness of international aid.
- Learn about interaction terms and bad controls
- Maybe: Make a quick example about data visualization

In [1]:
```
install.packages(c('WDI','owidR','plotly','showtext','huxtable','jtools'))

library('WDI')
library('owidR')
library('ggplot2')
library('dplyr')
library('plotly')
library('huxtable')
library('tidyr')
library('showtext')
library('jtools')
library('plotly')
print('Installed required packages')

# We set a seed to make sure we get the results if we run the code again, in case we gen
set.seed("1234")
```

```
Installing packages into '/opt/r'
(as 'lib' is unspecified)

also installing the dependency 'RJSONIO'



Attaching package: 'dplyr'


The following objects are masked from 'package:stats':

    filter, lag


The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union



Attaching package: 'plotly'


The following object is masked from 'package:ggplot2':

    last_plot


The following object is masked from 'package:stats':

    filter


The following object is masked from 'package:graphics':

    layout



Attaching package: 'huxtable'


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

    add_rownames


The following object is masked from 'package:ggplot2':

    theme_grey


Loading required package: sysfonts

Loading required package: showtextdb
```

```
[1] "Installed required packages"
```

We first download some data from the World Development Indicators (https://data.worldbank.org/). We can track down the data online and then download it using the official codes provided by the World Bank. We can filter by country and years, have a look at the data, etc.

In [2]:
```
dataset = WDI(indicator=c(oda_per_cap='DT.ODA.ODAT.PC.ZS',
                           perc_below_pov_line='SI.POV.DDAY',
                           gdp_per_cap_ppp='NY.GDP.PCAP.PP.CD',
                           gdp_per_cap='NY.GDP.PCAP.CD',
                         inflation='FP.CPI.TOTL.ZG'),
               country="all",
               start=1960,
               end=2022,
               extra=TRUE)

# Sort by country-year
dataset = dataset[order(dataset$country, dataset$year),]

colnames(dataset)
head(dataset)
print("Done")
```

'iso2c' · 'country' · 'year' · 'status' · 'lastupdated' · 'oda_per_cap' · 'perc_below_pov_line' · 'gdp_per_cap_ppp' · 'gdp_per_cap' · 'inflation' · 'iso3c' · 'region' · 'capital' · 'longitude' · 'latitude' · 'income' · 'lending'

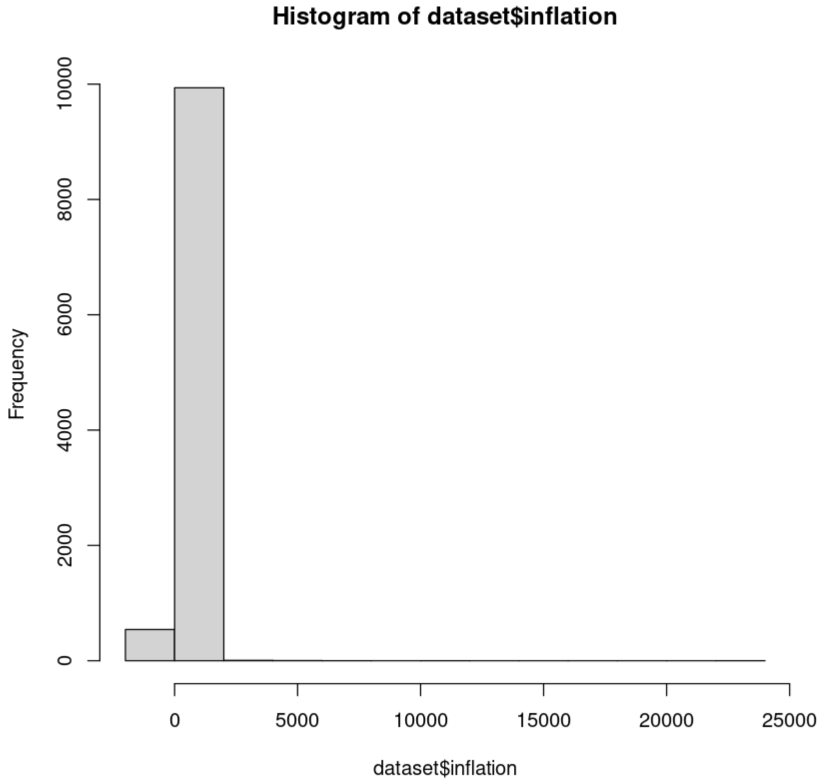
A data.frame: 6 × 17

	iso2c	country	year	status	lastupdated	oda_per_cap	perc_below_pov_line	gdp_per_cap_ppp	gdp_
	<chr>	<chr>	<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	
437	AF	Afghanistan	1960		2022-09-16	1.909532	NA	NA	5
446	AF	Afghanistan	1961		2022-09-16	3.781052	NA	NA	5
447	AF	Afghanistan	1962		2022-09-16	1.810416	NA	NA	5
448	AF	Afghanistan	1963		2022-09-16	3.842526	NA	NA	7
449	AF	Afghanistan	1964		2022-09-16	4.737925	NA	NA	8
450	AF	Afghanistan	1965		2022-09-16	5.416661	NA	NA	10

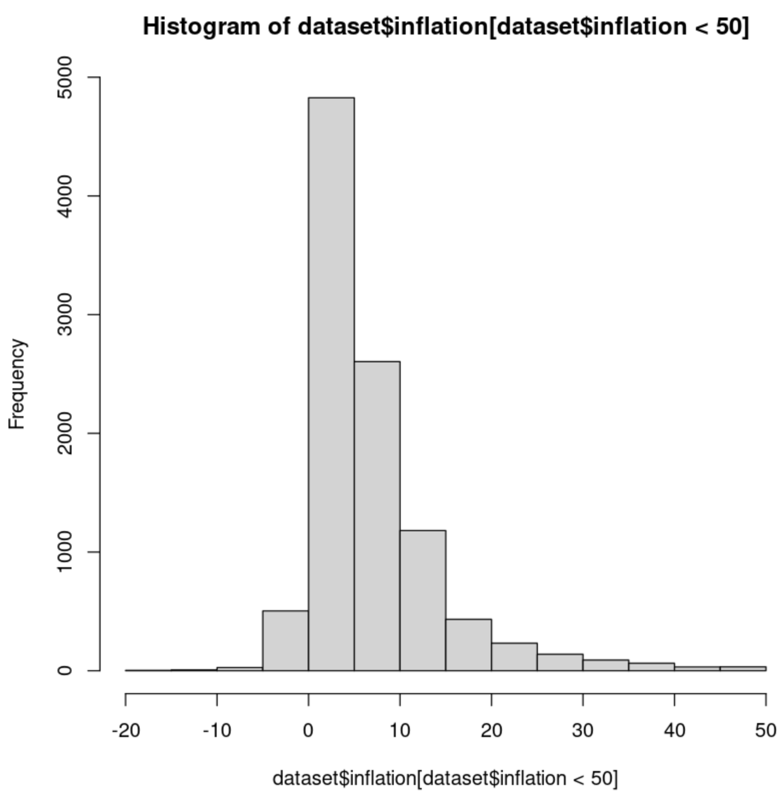
```
[1] "Done"
```

In [3]:
```
# We can, like last week, summarize the data and make histograms to look at its distribu
summary(dataset$gdp_per_cap_ppp)

hist(dataset$inflation)
# This one looks weird because of outliers, let's only look at cases with inflation belo
hist(dataset$inflation[dataset$inflation<50])

summary(dataset$perc_below_pov_line)
```

```
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.     NA's 
   285.3   2947.8   7692.0  14597.4  19250.6 153563.9     9023 
```




```
Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
 0.0     0.5     3.6    13.7    19.7    91.5   14170 
```



Some of the data have missing values in some years. Today, we will solve this pragmatically by just using the previous years' values if an observation is missing. We have to do this *grouped by country*.

In [4]:
```
dataset = dataset %>%
  group_by(iso3c) %>%
      fill(perc_below_pov_line, .direction = "down")

dataset = dataset %>%
```

```
  group_by(iso3c) %>%
  fill(oda_per_cap, .direction = "down")

dataset = dataset %>%
  group_by(iso3c) %>%
  fill(gdp_per_cap_ppp, .direction = "down")
```

We are interested in whether the effect of international aid (ODA - official development assistance) is different in countries with democracies vs. in non-democratic countries. For this we need data on demcracy. We will also get data from schooling for some later analysis. We can get this from https://ourworldindata.org/.

We can first search for terms using the search engine in the package. Next, we can read in the data, rename it, and filter by years (and countries, if we want to).

In [5]:
```
owid_search("democracy")

democracy <- owid("democracy-polity",
                  rename = "democracy") %>%
  filter(year %in% 1960:2018)


owid_search("schooling")
yos <- owid("mean-years-of-schooling-long-run",
                  rename = "years_of_schooling") %>%
  filter(year %in% 1960:2018)
```

A matrix: 54 × 2 of type chr

titles	chart_id
Child mortality rate vs. liberal democracy	child-mortality-vs-liberal-democracy
Age of democracy	age-of-democracy-bmr
Age of democracy	age-of-democracy-womsuffr-bmr
Age of democracy	age-of-democracy-polity
Age of electoral democracy	age-of-electoral-democracy
Age of electoral democracy	age-of-electoral-democracy-lied
Age of liberal democracy	age-of-liberal-democracy-row
Citizen satisfaction with democracy	citizen-satisfaction-with-democracy
Citizen support for democracy	citizen-support-for-democracy
Deliberative democracy	deliberative-democracy-vdem
Deliberative democracy weighted by population	deliberative-democracy-popw-vdem
Democracy	democracy-polity
Democracy	democracy-eiu
Democracy weighted by population	democracy-popw-polity
Democracy weighted by population	popw-democracy-eiu
Distribution of deliberative democracy	distribution-deliberative-democracy-vdem
Distribution of deliberative democracy weighted by population	distribution-deliberative-democracy-popw-vdem
Distribution of democracy	distribution-democracy-eiu
Distribution of democracy	distribution-democracy-polity
Distribution of democracy weighted by population	distribution-democracy-popw-polity
Distribution of democracy weighted by population	distribution-democracy-popw-eiu
Distribution of egalitarian democracy	distribution-egalitarian-democracy-vdem
Distribution of egalitarian democracy weighted by population	distribution-egalitarian-democracy-popw-vdem
Distribution of electoral democracy	distribution-electoral-democracy-vdem
Distribution of electoral democracy weighted by population	distribution-electoral-democracy-popw-vdem
Distribution of liberal democracy	distribution-liberal-democracy-vdem
Distribution of liberal democracy weighted by population	distribution-liberal-democracy-popw-vdem
Distribution of participatory democracy	distribution-participatory-democracy-vdem
Distribution of participatory democracy weighted by population	distribution-participatory-democracy-popw-vdem
Egalitarian democracy	egalitarian-democracy-vdem
Egalitarian democracy weighted by population	egalitarian-democracy-popw-vdem
Electoral democracy	electoral-democracy
Electoral democracy	electoral-democracy-lied
Electoral democracy	electoral-democracy-row
Electoral democracy weighted by population	electoral-democracy-popw-vdem
Experience with democracy	experience-with-democracy-bmr
Experience with democracy	experience-with-democracy-womsuffr-bmr
Experience with democracy	experience-with-democracy-polity

titles	chart_id
Experience with electoral democracy	experience-with-electoral-democracy
Experience with electoral democracy	experience-with-electoral-democracy-lied
Experience with liberal democracy	experience-with-liberal-democracy-row
GDP per capita vs. liberal democracy	gdp-per-capita-vs-liberal-democracy
Government effectiveness vs. liberal democracy	govt-effectiveness-vs-liberal-democracy
Human rights protection vs. liberal democracy	human-rights-protection-vs-liberal-democracy
Liberal democracy	liberal-democracy
Liberal democracy	liberal-democracy-row
Liberal democracy today vs. past average years of schooling	liberal-democracy-today-vs-past-schooling
Liberal democracy weighted by population	liberal-democracy-popw-vdem
Life expectancy vs. liberal democracy	life-expectancy-vs-liberal-democracy
Participatory democracy	participatory-democracy-vdem
Participatory democracy weighted by population	participatory-democracy-popw-vdem
Taxation vs. liberal democracy	taxation-vs-liberal-democracy
Varieties of democracy	varieties-democracy-vdem
Varieties of democracy weighted by population	varieties-democracy-popw-vdem

A matrix: 14 × 2 of type chr

titles	chart_id
Child mortality vs. women's average years of schooling	correlation-between-child-mortality-and-mean-years-of-schooling-for-those-aged-15-and-older
Liberal democracy today vs. past average years of schooling	liberal-democracy-today-vs-past-schooling
Average years of schooling vs. GDP per capita	average-years-of-schooling-vs-gdp-per-capita
Average years of schooling vs. expected years of schooling	average-schooling-vs-expected-schooling
Expected years of schooling vs. GDP per capita	expected-years-of-schooling-vs-gdp-per-capita
Gender ratios for average years of schooling	gender-ratios-for-mean-years-of-schooling
Fertility rate vs. average years of schooling	fertility-rate-vs-mean-years-of-schooling
Average years of schooling	mean-years-of-schooling-long-run
Average years of schooling for men	mean-years-of-schooling-male
Average years of schooling for women	mean-years-of-schooling-female
Correlation between Internet usage and average years of schooling	correlation-between-internet-usage-and-mean-years-of-schooling
Expected years of schooling vs. Share in extreme poverty	expected-years-of-schooling-vs-share-in-extreme-poverty
Primary schooling: Adjusted net attendance rate	primary-schooling-adjusted-net-attendance-rate
Productivity vs. share of tertiary schooling	productivity-vs-share-of-tertiary-schooling

The next thing we want to do is to combine these two datasets. We can do this by a process called **merging** the data. We need to have at least one column of data that have the same identifier (for example, survey ID number, country name, year, etc.). We merge with the command `join` and we can do a `right_join` in this case because we want complete observations in the democracy data.

In [6]:
```
democracy$country = democracy$entity
democracy$iso3c = democracy$code

yos$country = yos$entity
yos$iso3c = yos$code


dataset_panel <- dataset %>%
  right_join(democracy)

dataset_panel <- dataset_panel %>%
  left_join(yos)



dataset_panel = dataset_panel[order(dataset_panel$country, dataset_panel$year),]
head(dataset_panel)
```

```
Joining, by = c("country", "year", "iso3c")
Joining, by = c("country", "year", "iso3c", "entity", "code")
```

A gro

iso2c	country	year	status	lastupdated	oda_per_cap	perc_below_pov_line	gdp_per_cap_ppp	gdp_per_c
<chr>	<chr>	<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dl
AF	Afghanistan	1960		2022-09-16	1.909532	NA	NA	59.773
AF	Afghanistan	1961		2022-09-16	3.781052	NA	NA	59.860
AF	Afghanistan	1962		2022-09-16	1.810416	NA	NA	58.458
AF	Afghanistan	1963		2022-09-16	3.842526	NA	NA	78.706
AF	Afghanistan	1964		2022-09-16	4.737925	NA	NA	82.095
AF	Afghanistan	1965		2022-09-16	5.416661	NA	NA	101.108

Next, we have to do some data cleaning and generate some additional variables. I will largely skip over this. (Note: The main problem is that we now have a *panel* (countryXyear)(dataset, which we haven't talked about in class yet. I will convert this into a *cross-sectional* dataset, which only has one observation (year) per unit (country) of analysis. We will talk about the exciting world of panel datasets later in class!)

In [10]:
```
head(dataset_panel)

# Normalize democracy scores: All will lie between 0 and 1
dataset_panel$democracy = (dataset_panel$democracy+10)/20

# Generate cross-sectional data
dataset_cs = dataset_panel %>%
  filter(year==2016)

# Make year averages

data_pov90 = dataset_panel %>%
  filter(year==1990) %>%
  group_by(iso3c) %>%
  dplyr::summarize(pov_1990 = mean(perc_below_pov_line, na.rm=TRUE))
```

```
data_aid9010 = dataset_panel %>%
  filter(year %in% 1990:2010) %>%
  group_by(iso3c) %>%
  dplyr::summarize(aid_9010 = mean(oda_per_cap, na.rm=TRUE))

# Calculate in per year amounts.
data_aid9010$aid_9010 = data_aid9010$aid_9010*20

data_dem9010 = dataset_panel %>%
  filter(year %in% 1990:2010) %>%
  group_by(iso3c) %>%
  dplyr::summarize(dem9010 = mean(democracy, na.rm=TRUE))


data_gdp1990= dataset_panel %>%
  filter(year %in% 1990) %>%
  group_by(iso3c) %>%
  dplyr::summarize(gdp1990 = mean(gdp_per_cap, na.rm=TRUE))


# Merge in year-averages
dataset_cs = dataset_cs %>%
  left_join(data_pov90)

dataset_cs = dataset_cs %>%
  left_join(data_aid9010)

dataset_cs = dataset_cs %>%
  left_join(data_dem9010)

dataset_cs = dataset_cs %>%
  left_join(data_gdp1990)


# Generate happiness variable
dataset_cs$happiness = dataset_cs$gdp_per_cap_ppp + rnorm(nrow(dataset_cs),0,1000)


head(dataset_cs)
```

A gro

iso2c	country	year	status	lastupdated	oda_per_cap	perc_below_pov_line	gdp_per_cap_ppp	gdp_per_c
<chr>	<chr>	<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dt
AF	Afghanistan	1960		2022-09-16	1.909532	NA	NA	59.773
AF	Afghanistan	1961		2022-09-16	3.781052	NA	NA	59.860
AF	Afghanistan	1962		2022-09-16	1.810416	NA	NA	58.458
AF	Afghanistan	1963		2022-09-16	3.842526	NA	NA	78.706
AF	Afghanistan	1964		2022-09-16	4.737925	NA	NA	82.095
AF	Afghanistan	1965		2022-09-16	5.416661	NA	NA	101.108

```
Joining, by = "iso3c"
Joining, by = "iso3c"
Joining, by = "iso3c"
Joining, by = "iso3c"
```

iso2c	country	year	status	lastupdated	oda_per_cap	perc_below_pov_line	gdp_per_cap_ppp	gdp_per_c
<chr>	<chr>	<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dl
AF	Afghanistan	2016		2022-09-16	115.00937350	NA	1981.118	512.01
NA	Africa	2016	NA	NA	NA	NA	NA	
AL	Albania	2016		2022-09-16	59.46939738	0.1	12078.843	4124.05
DZ	Algeria	2016		2022-09-16	3.56461208	0.5	11624.341	3946.45
AO	Angola	2016		2022-09-16	6.97824841	14.6	7103.226	1728.02
AR	Argentina	2016		2022-09-16	0.06010502	0.7	20307.870	12790.24

Our final datast includes the following variables of interest for our analysis:

- `gdp_per_cap_ppp` : GDP per capita in the year 2011, in PPP and real 2017 USD
- `perc_below_poverty_line` : Share of the population below the poverty line (2.15 USD per day), in 2011.
- `pov_1990` : Share of the population below the poverty line (2.15 USD per day), in 1990
- `aid_9010` : Total development aid received (in USD), per capita, over the years 1990-2010
- `dem_9010` : Average democracy level between 1990 and 2010 (between 0 and 1)
- `happiness` : A fictional happiness score, in 2011

Our hypothesis is that development aid has an effect on the welfare of a country, measured by GDP per capita and the poverty rate. Maybe aid takes many years to have an effect, so we take the sum over 1990 to 2010 and see how this affected our outcomes in 2011. We are also wondering whether democracy was related to welfare, and so we also average the democracy score between 1990 and 2010 to keep everything comparable.

Analysis: Analyzing interaction terms

Last week, I gave a hint that we will talk about interaction terms. Interaction terms can help us to understand questions such as:

- Does having a child have a **different effect** on wages for men and women?
- Do children from different socio-economic backgrounds **respond differently** to free school meals?
- Does development aid **work better** in democratic as opposed to non-democratic countries?

We quickly analyze the math of this model on the blackboard.

Let's run the regression!

In [11]:
```
nointeraction_pov <- lm(perc_below_pov_line ~ pov_1990 +  aid_9010 + dem9010 , data=data

interaction_pov <- lm(perc_below_pov_line ~  pov_1990 +  aid_9010 + dem9010 + I(aid_9010

nointeraction_gdp <- lm(gdp_per_cap_ppp ~ pov_1990 +  aid_9010 + dem9010 , data=dataset_

interaction_gdp <- lm(gdp_per_cap_ppp ~  pov_1990 +  aid_9010 + dem9010 + I(aid_9010*dem
```

```
export_summs(nointeraction_pov, interaction_pov, nointeraction_gdp, interaction_gdp)
```

A huxtable: 14 × 5

	names	Model 1	Model 2	Model 3	Model 4
	<chr>	<chr>	<chr>	<chr>	<chr>
		Model 1	Model 2	Model 3	Model 4
1	(Intercept)	-61.2374795071691	-128.785951684016	-100473.050623957	743.840399071715
2		(131.151998543101)	(184.46296744571)	(50308.6071500479)	(65918.4780877931)
3	pov_1990	0.465746047021812 ***	0.478817136761546 ***	-170.119670411957 **	-189.705828663991 ***
4		(0.125929692234316)	(0.129811946126957)	(48.3053821940856)	(46.388746992385)
5	aid_9010	0.00143573381067744	0.0889241284377262	1.78207531734834	-129.313462736596 *
6		(0.00237476791877688)	(0.165961798407396)	(0.910937443770791)	(59.3070214754539)
7	dem9010	111.590525363933	236.236210579241	217161.635844753 *	30388.3702126576
8		(243.232174121096)	(341.274800056792)	(93301.451979696)	(121955.727704969)
9	I(aid_9010 * dem9010)		-0.162697591926318		243.791515944305 *
10			(0.308598125471292)		(110.278605258806)
1.1	N	35	35	35	35
2.1	R2	0.310724982601861	0.317052621256712	0.485566742578144	0.557630737582579
.1	*** p < 0.001; ** p < 0.01; * p < 0.05.	*** p < 0.001; ** p < 0.01; * p < 0.05.	*** p < 0.001; ** p < 0.01; * p < 0.05.	*** p < 0.001; ** p < 0.01; * p < 0.05.	*** p < 0.001; ** p < 0.01; * p < 0.05.

Bad controls

When we talked about omitted variables, we always talked about how forgetting an important variable can have bad consequences for your analysis. But there is also the opposite problem: Bad controls! The bad controls problem arises when we control for a variable in a regression that is actually an outcome (a variable on the left-hand side).

For example:

- A treatment gives people money at time t, and we want to study how it changes their consumption at time t+1. We control for their wage at time t+1.
- We want to study whether winning the lottery at time t makes you happier at time t+1. We control for whether you bought a Ferrari at time t+1.

Let's make an example. We know that happiness is strongly related to income (at least, to some extent: https://ourworldindata.org/happiness-and-life-satisfaction). Aid in the past will affect income today and happiness today. Therefore, controlling for happiness today introduces a bad control problem!

In [14]:
```
basic_regression <- lm( gdp_per_cap_ppp ~  gdp1990 , data=dataset_cs)

bad_controls <- lm( gdp_per_cap_ppp ~  gdp1990  + happiness, data=dataset_cs)

export_summs(basic_regression, bad_controls)
```

A huxtable: 10 × 3

	names	Model 1	Model 2
	<chr>	<chr>	<chr>
		Model 1	Model 2
1	(Intercept)	7978.42432394203 ***	-47.7777015498555
2		(1239.0877614923)	(138.307999063505)
3	gdp1990	2.04469323680988 ***	0.00333770097061518
4		(0.11501970977029)	(0.021294596424702)
5	happiness		0.999164381516758 ***
6			(0.00893164138740528)
1.1	N	117	117
2.1	R2	0.733189781839178	0.997591438771217
.1	*** p < 0.001; ** p < 0.01; * p < 0.05.	*** p < 0.001; ** p < 0.01; * p < 0.05.	*** p < 0.001; ** p < 0.01; * p < 0.05.

We can interpret bad controls through the OVB formula we learnt last time:

$$\rho_s = \rho + \gamma \cdot \delta$$

where ρ is the "long" coefficient, γ is the coefficient of the omitted variable in the long regression, δ is the coefficient in the auxiliary regression (regress omitted variable on included variable), and ρ_s is the "short" regression coefficient.

Remember? It told you that this formula **ALWAYS** holds - no matter what variable I include.

Extreme case: Include GDP$\times$10 on the RHS - what will happen?

Do you need an OVB revision?

In [15]:

```
# Revise OVB
a = lm(log(gdp_per_cap_ppp) ~  democracy  , data=dataset_cs)
b = lm(log(gdp_per_cap_ppp) ~ years_of_schooling +  democracy  , data=dataset_cs)
c = lm(years_of_schooling  ~ democracy  , data=dataset_cs)
export_summs(a,b,c)
```

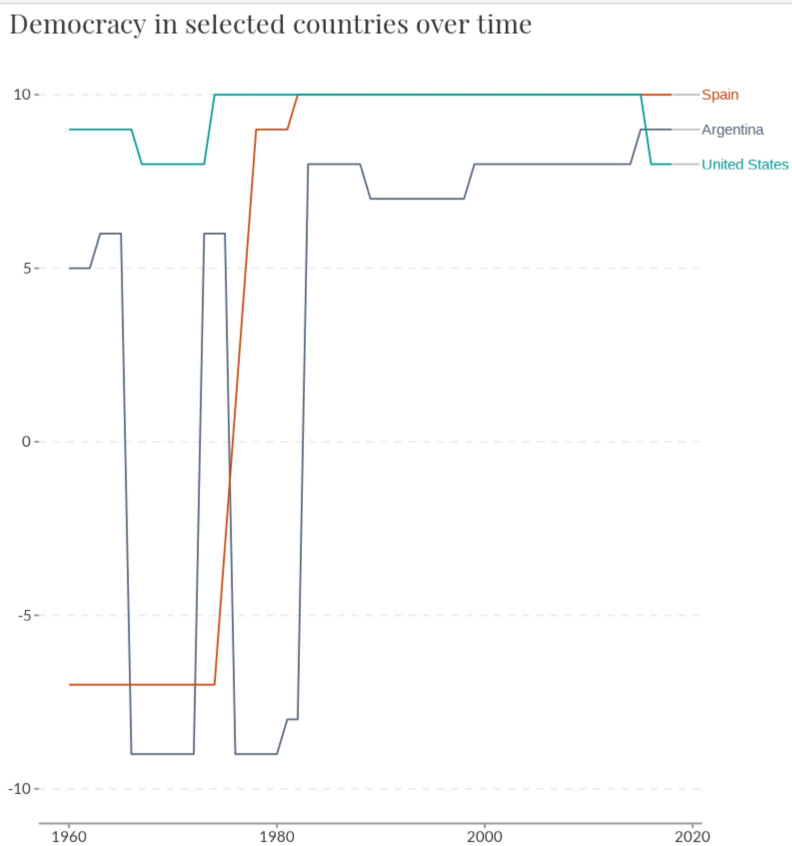
A huxtable: 10 × 4

	names	Model 1	Model 2	Model 3
	<chr>	<chr>	<chr>	<chr>
		Model 1	Model 2	Model 3
1	(Intercept)	1.09009171786149	8.96440800542877 ***	-25.4438428120717 **
2		(3.5845626524535)	(1.94872769203634)	(8.62215636672121)
3	democracy	15.2527368966298 *	-4.28199504589645	63.1104742397465 ***
4		(6.67806650043998)	(3.69542563257363)	(16.0966995706918)
5	years_of_schooling		0.313394531780118 ***	
6			(0.0166755807608285)	
1.1	N	145	144	162
2.1	R2	0.035196299293719	0.725080867999958	0.0876534587488713
.1	*** p < 0.001; ** p < 0.01; * p < 0.05.	*** p < 0.001; ** p < 0.01; * p < 0.05.	*** p < 0.001; ** p < 0.01; * p < 0.05.	*** p < 0.001; ** p < 0.01; * p < 0.05.

Data visualizations

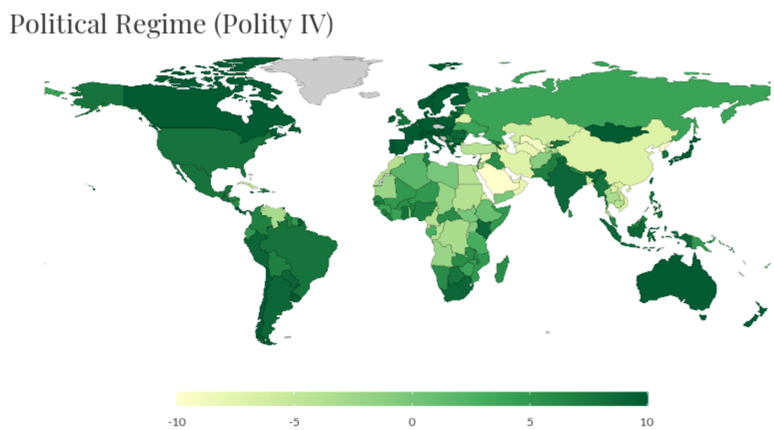
An important skill - this is just a quick example and we'll do more in the next weeks!

In [16]:
```
a = c("Argentina","Spain", "United States")
owid_plot(democracy, filter = a, summarise=FALSE) +
  labs(title = paste0("Democracy in selected countries over time")) +
  scale_y_continuous(limits = c(-10, 10))
```



In [17]:
```
# Make a map

democracy2 <- owid("democracy-polity",
                   rename = "democracy") %>%
```

```
  filter(year==2018)

owid_map(democracy2, palette = "YlGn") +
  labs(title = "Political Regime (Polity IV)")
```




```
In [ ]:
```