Introduction to Handling Data

ECON20222 - Lecture 1

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What is this course unit about?

- Help you implement and interpret the main inference techniques used in Economics
- Focus on:
  - causal inference
  - the main pitfalls of time-series analysis

At the end of this unit . . .

You will be able to:

- Do intermediate data work in R
- Confidently apply regression analysis in R
- Apply more advanced causal inference techniques in R
- Find coding help for any new challenges in R
- Identify inference appropriate for the occasion
- Discuss strengths and weaknesses of particular empirical applications
- Interpret empirical results (with due caution!)

What you need to do

To learn in this unit you need to:

coding, cleaning data, struggling, self-learning, amazement at what you can do

answering real questions, that there is not always a clear answer

Assessment Structure and feedback

Details need to be added

Aim for today

Statistics/Econometrics

- Summary Statistics
- Difference between population and sample
- Hypothesis testing
- Graphical Data Representations
- Simple regression analysis

R Coding

- Introduce you to R and RStudio
- How do I learn R
- Import data into R
- Perform some basic data manipulation
- Perform hypothesis tests
- Estimate a regression

Why Data Matter

Average GDP growth rates (High Income countries - 1946 to 2009):

Debt Category	(0,30]	(30,60]	(60,90]	(90,Inf]
Avg Growth Rate (RR)	4.09%	2.87%	3.40%	-0.02%

Why Data Matter

- Reinhard and Rogoff seem to suggest that there is a level of debt (debt/GDP $> 90\%$) beyond which higher debt levels will significantly reduce growth.
- While they often provided caveats in their arguments, their results were referred to when austerity policies were justified.
  For example George Osborn:
  here on Channel 4: (https://www.channel4.com/news/george-osborne-defends-austerity-plan)
  here in a Conference Speech:
  (https://conservative-speeches.sayit.mysociety.org/speech/601526)

Average GDP growth rates (High Income countries - 1946 to 2009):

Debt Category	(0,30]	(30,60]	(60,90]	(90,Inf]
Avg Growth Rate (RR)	4.09%	2.87%	3.40%	-0.02%
Avg Growth Rate (HAP)	4.17%	3.12%	3.22%	2.17%

Why Data Matter

Some summaries are available here

The New Yorker	The Reinhart and Rogoff Controversy: A Summing U
The Economist	The 90% question
Financial Times	Interviews with Carmen Reinhard [1, 2, 3, 4]

Important issues that arise from this

- Which way is the causality? Debt to Growth or Growth to Debt? Reinhard and Rogoff are suitably careful to not associate any direct causality from the summary statistics.
- But in thepolitical discourse such "subtleties" often go lost
- Would different summary stats have changed the narrative?

The Plan for today

- Replicate the above summary statistics in R
- Why one can get two very different results based on the same data
- Use this example to
  - introduce you to R
  - review some summary satistics
  - review simple regression and its implementation
  - introduce some basic visualisations

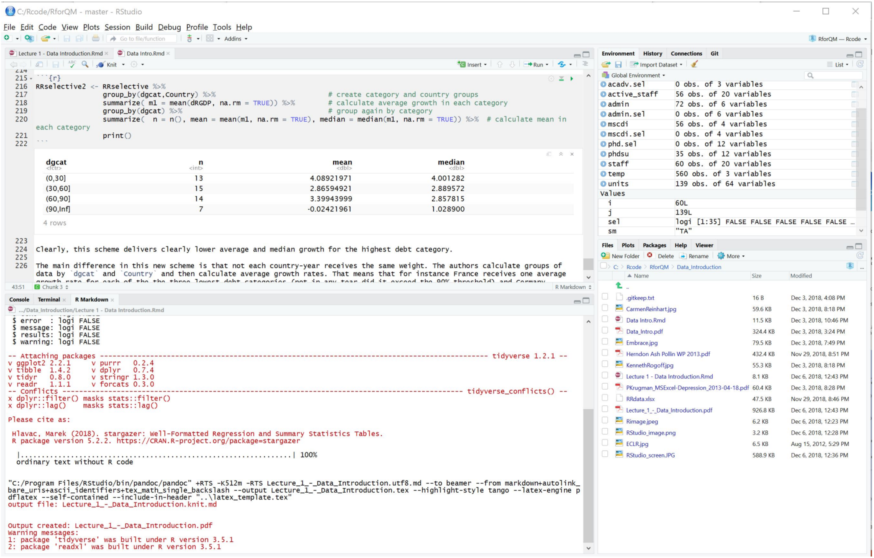
Introduce R/R-Studio

- R is a statistical software package, it is open source and free
- a lot of useful functionality is added by independent researchers via packages (also for free)

- RStudio is a user interface which makes working with R easier. You need to install R before you install RStudio.

- ECLR is a web-resource we have set up to support you in your R work.

Welcome to RStudio



Write Code Files or the Basic Workflow

- keep an original data file (usually '.xlsx' or '.csv') and do not overwrite this file
- any manipulation we make to the data (data cleaning, statistical analysis etc.) is command based and we collect all these commands in a script file. R will then interpret and execute these commands. It is hence like a recepie which you present to a chef. These script files have extension '.r'
- you can also learn to write Rmarkdown files ('.rmd'). They combine code with normal text and output.
- When you write code you should ensure that you add comments to your code. Comments are bit of text which is ignored by R (everything after an '#') but helps you or someone else to decipher what the code does.

By following the above examples you make it easy for yourself and others to replicate your work. Replication of work is actually at the core of the Reinhard/Rogoff controversy!

Prepare your code

We start by uploading the extra packages we need in our code.

The first time you need these packaes at a computer you may need to install these. Use the following code to do this

```
install.packages(c("readxl","tidyverse","ggplot2","stargazer")
```

This only needs to be done once on a particular computer. However, every time you want to use any of these packages in a code you need to make them available to your code (load them):

```
library(tidyverse)    # for almost all data handling tasks
library(readxl)       # to import Excel data
library(ggplot2)      # to produce nice graphiscs
library(stargazer)    # to produce nice results tables
```

The data

Then we load the data from excel

```
RRData <- read_excel("RRdata.xlsx")
RRData <- as.data.frame(RRData) # forces data.frame structure
```

and check some charecteristics of the data which are now stored in `RRData`:

```
str(RRData)  # prints some basic info on variables
```

```
## 'data.frame':    1171 obs. of  4 variables:
##  $ Year   : num  1946 1947 1948 1949 1950 ...
##  $ Country: chr  "Australia" "Australia" "Australia" "Austr
##  $ debtgdp: num  190 177 149 126 110 ...
##  $ dRGDP  : num  -3.56 2.46 6.44 6.61 6.92 ...
```

Discuss data.frame, number of obs and number of variables, their names and variable types

Variable types

These are the basic data types.

- `character: "a", "swc"`
- `numeric: 2, 15.5`
- `integer: 2L (the L tells R to store this as an integer)`
- `logical: TRUE, FALSE`
- `complex: 1+4i (complex numbers with real and imaginary parts)`

It is important that you know what data types variables have as some operations only work for particular datatypes. For instance we need to `num` or `int` for any mathematical operations. In our data.frame three variables ar e`num` and one is of `chr` type. `logical` variables we will encounter frequently, they are very powerful.

factor variables

It will prove useful to change variables which are categorical variables (here `Country`) to `factor` variables.

```
RRData$Country <- as.factor(RRData$Country)
str(RRData)
```

```
## 'data.frame':    1171 obs. of  4 variables:
##  $ Year    : num  1946 1947 1948 1949 1950 ...
##  $ Country: Factor w/ 20 levels "Australia","Austria",..: 1
##  $ debtgdp: num  190 177 149 126 110 ...
##  $ dRGDP  : num  -3.56 2.46 6.44 6.61 6.92 ...
```

- `RRData$Country` calls variable `Country` in dataframe `RRData`
- `<-` assigns what is on the right `as.factor(RRData$Country)` to the variable on the left `RRData$Country`
- `as.factor(RRData$Country)` calls a function `as.factor` and applies it to `RRData$Country`

`factor` variables

`factor` variables are variables with discrete categories. Which ones they are you can find out with the `levels()` function:

```
levels(RRData$Country)
```

```
##  [1] "Australia"   "Austria"     "Belgium"     "Canada"
##  [6] "Finland"     "France"      "Germany"     "Greece"
## [11] "Italy"       "Japan"       "Netherlands" "New Zealand
## [16] "Portugal"    "Spain"       "Sweden"      "UK"
```

Learn more about your data

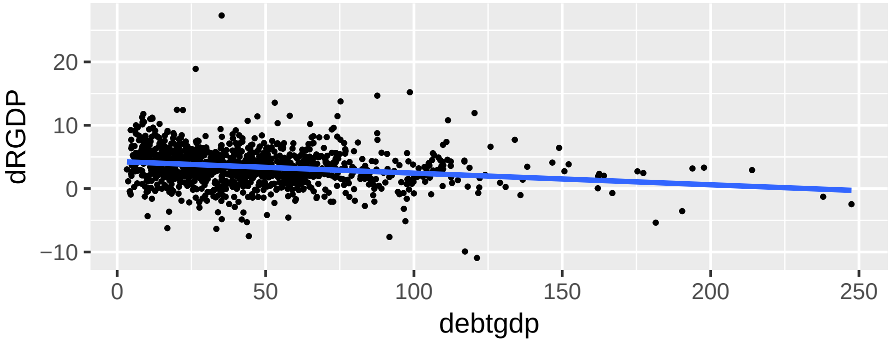
Use the `stargazer` function for some initial summary stats for `num` or `int` variables

```
stargazer(RRData, type = "text")
```

```
##
## =======================================================================
## Statistic   N     Mean    St. Dev.   Min    Pctl(25) Pctl(75)   Max
## -----------------------------------------------------------------------
## Year      1,171 1,979.155  17.944   1,946   1,964    1,995    2,009
## debtgdp   1,171  46.283    32.395   3.279   22.148   61.474  247.482
## dRGDP     1,171   3.430    2.981   -10.942  1.911    5.100   27.329
## -----------------------------------------------------------------------
```

Scatter plot of the data

```r
p1 <- ggplot(RRData,aes(debtgdp,dRGDP)) +
  geom_point(size=0.5) +     # this produces the scatter plot
  geom_smooth(method = "lm", se = FALSE)  # adds the line
p1
```



Point out that each dot represents one country/year's data, e.g. France in 1991. Point out line of best fit

Regression Line

The line in the previous plot is the line of best fit coming for a linear regression

$$rGDP_{it} = \alpha + \beta debtgdp_{it} + u_{it} \text{ (Population Model)}$$

- Here we have two subscripts as the data have a cross-section (`i`) and a time-series dimension (`t`).
- The population model is defined by unknown parameters α and β and the unknown error terms u_{it}. We will use sample data to obtain sample estimates of these parameters.
- The error terms u_{it} contain the effects of any omitted variables and reflect that any modelled relationship will only be an approximation. The u_{it}s are random variables

$$rGDP_{it} = \widehat{\alpha} + \widehat{\beta} debtgdp_{it} + \widehat{u}_{it} \text{ (Sample Model)}$$

The regression line in the previous figure is represented by

$$\widehat{rGDP}_{it} = \widehat{\alpha} + \widehat{\beta} debtgdp_{it} \quad \text{(Regression Line)}$$

Ordinary Least Squares - Simple Regression

Regression analysis is the core technique used in Econometrics. It is based on certain assumptions about the *Population Model* and the error terms u_{it} (more on this in the next few weeks).

How to estimate parameters (get $\widehat{\alpha}$ and $\widehat{\beta}$) using the available sample of data?

Ordinary Least Squares - Simple Regression

```r
mod1 <- lm(dRGDP~debtgdp, data= RRData)
summary(mod1)
```

```
##
## Call:
## lm(formula = dRGDP ~ debtgdp, data = RRData)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.9958  -1.5200  -0.0774   1.5707  23.6960
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.279290   0.148970   28.73  < 2e-16 ***
## debtgdp     -0.018355   0.002637   -6.96 5.67e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.922 on 1169 degrees of freedom
## Multiple R-squared:  0.03979,    Adjusted R-squared:  0.03897
## F-statistic: 48.44 on 1 and 1169 DF,  p-value: 5.666e-12
```

OLS - nice output

```
stargazer(mod1,type="text")
```

```
##
## ===============================================
##                         Dependent variable:
##                     ---------------------------
##                                dRGDP
## -----------------------------------------------
## debtgdp                      -0.018***
##                               (0.003)
##
## Constant                     4.279***
##                               (0.149)
##
## -----------------------------------------------
## Observations                   1,171
## R2                             0.040
## Adjusted R2                    0.039
## Residual Std. Error      2.922 (df = 1169)
## F Statistic          48.439*** (df = 1; 1169)
## ===============================================
```

OLS - calculation and interpretation

How were $\widehat{\beta}$ and $\widehat{\alpha}$ calculated?

$$\begin{aligned}\widehat{\beta} &= \frac{Cov(dRGDP_{it}, debtgdp_{it})}{Var(debtgdp_{it})} \\ \widehat{\alpha} &= \overline{dRGDP}_{it} - \widehat{\beta} * \overline{debtgdp}_{it}\end{aligned}$$

How to interpret $\widehat{\beta} = -0.018$?

An increase of one unit in `debtgdp` (=1%) is related to a decrease of GDP growth of 0.018 units (=0.018%)

Have we established that higher debt levels **cause** lower GDP growth?

NO

OLS - estimator properties

We need to recognise that paramter estimator is a random variable.

Let's use $y_{it} = \alpha + \beta x_{it} + u_{it}$ for ease of notation:

$$\begin{aligned}
\widehat{\beta} &= \frac{Cov(y_{it}, x_{it})}{Var(x_{it})} \\
&= \frac{Cov(\alpha + \beta x_{it} + u_{it}\ , x_{it})}{Var(x_{it})} \\
&= \frac{Cov(\alpha, x_{it}) + Cov(\beta x_{it}, x_{it}) + Cov(u_{it}, x_{it})}{Var(x_{it})}
\end{aligned}$$

$$\begin{aligned}
\widehat{\beta} &= \frac{Cov(\alpha, x_{it})}{Var(x_{it})} + \beta \frac{Cov(x_{it}, x_{it})}{Var(x_{it})} + \frac{Cov(u_{it}, x_{it})}{Var(x_{it})} \\
&= 0 + \beta \frac{Var(x_{it})}{Var(x_{it})} + \frac{Cov(u_{it}, x_{it})}{Var(x_{it})} \\
&= \beta + \frac{Cov(u_{it}, x_{it})}{Var(x_{it})}
\end{aligned}$$

OLS - estimator properties

What can we learn from this?

- If u_{it} is a random variable, so is $\widehat{\beta}$
- Any particular value we get is a draw from a random distribution
- An estimator is unbiased if, on average, the estimates would be equal to the unknown β
  at this stage the concept of unbiasedness may still be a little hazy and that is fine
- For this to happen we need to assume that $Cov(u_{it}, x_{it}) = 0$ as then $E(\widehat{\beta}) = \beta$
  Why do we need to assume this? Because while we do have values for x_{it} we do not have values for the unobserved error terms u_{it}. Hence we cannot test this. As you will find out this is mainly a thinking exercise and one at the core of much of what we do.

OLS - the exogeneity assumption

For $\widehat{\beta}$ in $y_{it} = \alpha + \beta x_{it} + u_{it}$ to be unbiased (i.e. on average correct) we needed

$$Cov(u_{it}, x_{it}) = 0$$

This is sometimes called the Exogeneity assumption. The error term has to be uncorrelated to the explanatory variable x_{it}

There are a lot of reasons why this assumption may be breached.

- Simultaneity ($debtgdp \rightarrow dRGDP$ and $dRGDP \rightarrow debtgdp$)
  Discuss the fact that we have to assume that causailty here goes in both directions. Hence we cannot attach one one-directional causal interpretation to the estimated coefficient. If you can estimate the model the other way round
- Measurement error in x_{it} (not dealt with here)
- Omitted relevant variables or unobserved heterogeneity

Excursion - Omitted variable bias

Let's imagine I would get all your first year statistics final grades (gr_i) and how often you attended lectures during the semester (att_i). (Note, no time series dimension here. All obs from same year hence no time subscript t.)

$$gr_i = \alpha + \beta \; att_i + u_i$$

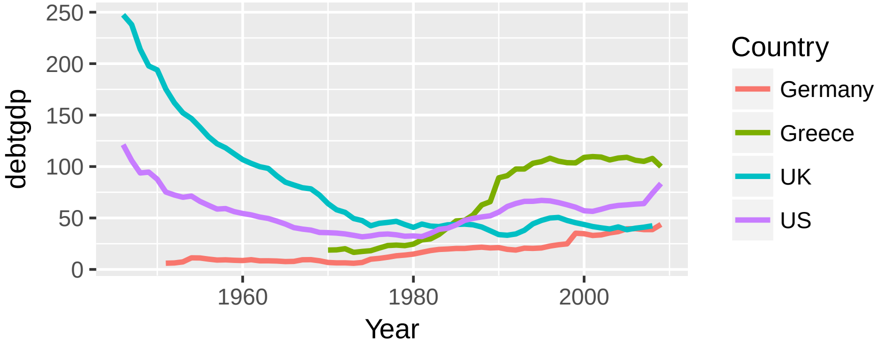
What value would you expect $\widehat{\beta}$ to take?

positive, more lecture attendance better grade

Can we say that lecture attendances causes higher grades? What do we think is hidden in the error term? Intelligence, Attitude, Aptitude for quants. How are they related to att_i? Presumably some positively, e.g. attitude to studies. But all of tehse variables should really be in the model, right? So some of their effect is going to be capured by att_i and this may bias the estimate $\widehat{\beta}$ up as it now captures, say, the effec of an increase in attendance but also in attitude.

Reinhard/Rogoff Example - debtgdp

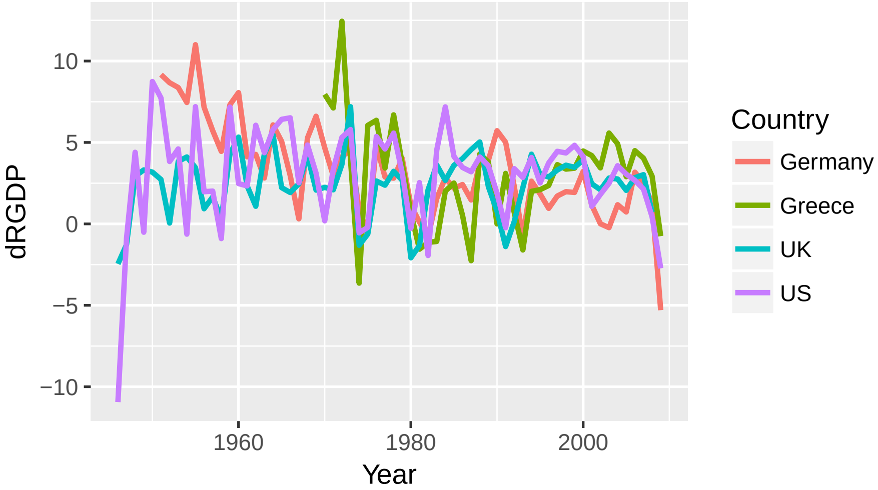
```
tempdata <- RRData %>% filter(Country %in% c("Germany","Greece","UK","US"))
ggplot(tempdata,aes(Year,debtgdp,color=Country)) +
  geom_line(size=1)     # this produces the line plot
```



Point out the piping operator and the filter function and then ggplot and geom_line

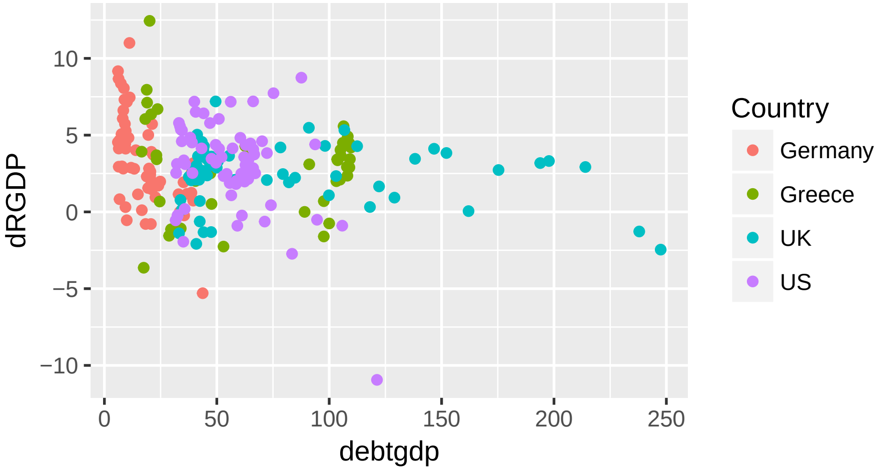
Reinhard/Rogoff Example - dRGDP

```r
tempdata <- RRData %>% filter(Country %in% c("Germany","Greece","UK","US"))
ggplot(tempdata,aes(Year,dRGDP,color=Country)) +
  geom_line(size=1)      # this produces the line plot
```



Reinhard/Rogoff Example - dRGDP v debtgdp

```
tempdata <- RRData %>% filter(Country %in% c("Germany","Greece","UK","US"))
ggplot(tempdata,aes(debtgdp,dRGDP,color=Country)) +
  geom_point()      # this produces the scatter plot
```



Reinhard/Rogoff Example

What have we learned?

- dept data are persistant
- growth data as well but less so
- data for different countries have different characteristics

Group the data into debt categories

Let's create the four debt categories: (0,30], (30,60], (60,90], (90,Inf].

```
RRData <- RRData %>% mutate(dgcat = cut(RRData$debtgdp, breaks=c(0,30,60,90,Inf)))

RRData %>% group_by(dgcat) %>%
            summarise_at("dRGDP", funs(mean, median)) %>%
            print()
```

```
## # A tibble: 4 x 3
##   dgcat      mean median
##   <fct>     <dbl>  <dbl>
## 1 (0,30]     4.17   4.15
## 2 (30,60]    3.12   3.11
## 3 (60,90]    3.22   2.9
## 4 (90,Inf]  2.17   2.34
```

Pint out the mutate function in combination with the cut function and the pipe, then the group_by and summarise_at function

These are the statistics we saw before (not the one reported by Reinhard and Rogoff)

Why did Reinhard and Rogoff report different results?

Debt Category	(0,30]	(30,60]	(60,90]	(90,Inf]
Avg Growth Rate (RR)	4.09%	2.87%	3.40%	-0.02%
Avg Growth Rate (HAP)	4.17%	3.12%	3.22%	2.17%

Why did RR get so much lower growth for the highest debt category, (90,Inf]?

Thomas Herndon, Michael Ash and Robert Pollin (2014) replicated the work. They identified the following differences to the above analysis.

1. They excluded early-postwar data for New Zealand, Australia and Canada, arguing that these data are atypical for later periods, essentially they are outliers
2. A spreadsheet error resulted in data for the five countries (Australia, Austria, Belgium, Canada and Denmark) to not be included.
3. Observations are not weighted equally.

Replicate Reinhard and Rogoff's results

```
## Selective treatment of early years
RRselective <- RRData %>%
  filter(!((Year<1950 & Country=="New Zealand") |
           (Year<1951 & Country=="Australia") |
           (Year<1951 & Country=="Canada") ))

## Spreadsheet error omitting five countries
RRselective <- RRselective %>%
  filter(!( Country %in%
            c("Australia","Austria","Belgium","Canada","Denmark") ))

RRselective %>% group_by(dgcat) %>%
            summarise_at("dRGDP", funs(mean, median)) %>%
            print()
```

```
## # A tibble: 4 x 3
##   dgcat     mean median
##   <fct>    <dbl>  <dbl>
## 1 (0,30]    4.24   4.4
## 2 (30,60]   2.98   3.06
## 3 (60,90]   3.16   2.85
## 4 (90,Inf]  1.69   2.33
```

Replicate Reinhard and Rogoff's results

So the first two differences explain some but not all of the differences. Let's implement the different weighting.

```
RRselective2 <- RRselective %>%
    group_by(dgcat,Country) %>%        # create category and country groups
    summarize( m1 = mean(dRGDP, na.rm = TRUE)) %>%  # calculate cat average
    group_by(dgcat) %>%                # group again by category
    summarize(  n = n(), mean = mean(m1, na.rm = TRUE),
            median = median(m1, na.rm = TRUE)) %>%
    print()
```

```
## # A tibble: 4 x 4
##   dgcat         n    mean median
##   <fct>     <int>   <dbl>  <dbl>
## 1 (0,30]       13  4.09     4.00
## 2 (30,60]      15  2.87     2.89
## 3 (60,90]      14  3.40     2.86
## 4 (90,Inf]      7 -0.0242   1.03
```

Don't worry too much about the full details of this weighting scheme.

The combination of the three changes make a massive difference

Why data (and their treatment) matter

The combination of these changes made a significant difference to the summary statistics.

Remember, the data were very persistent.

Reinhard and Rogoff
For each country all years which fall into one of the four categories are averaged and then treated as one observation

Herndon, Ash and Pollin
Each country/year observationis treated as one independent observation.

Perhaps it is right to not treat each observation as a new piece of information. But the RR weighting scheme seems to discard a lot of information.

These results made a significant difference in the political discourse.

Outlook

Over the next weeks you will learn

- to perform more advanced statistical analysis in R, such as:
  - Hypothesis testing
  - Multivariate regression analysis
  - specification testing
- to devise methods to draw causal inference
- to understand the main pitfalls of time-series modelling and forecasting