Introduction to Handling Data

ECON20222 - Lecture 1

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What is this course unit about?

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

This Week's Empirical Question

Card, David ; Krueger, Alan B. (1994) Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania, The American Economic Review, 84, 772-793.

Do higher minimum wages decrease employment (as predicted by common-sense and a competitive labour market model)?

The Research Question

"This paper presents new evidence on the effect of minimum wages on establishment-level employment outcomes. We analyze the experiences of 410 fast-food restaurants in New Jersey and Pennsylvania following the increase in New Jersey's minimum wage from \$ 4.25 to \$ 5.05 per hour. Comparisons of employment, wages, and prices at stores in New Jersey and Pennsylvania before and after the rise offer a simple method for evaluating the effects of the minimum wage."

Card, David ; Krueger, Alan B. (1994, p.772)

Why Data Matter

The debate is still alive:

- Overall negative effect on employment, IZA.
  "Research findings are not unanimous, but especially for the US, evidence suggests that minimum wages reduce the jobs available to low-skill workers."
- An overview of the empirical evidence is provided in this report by Arindrajit Dube for the UK Government.
  "Especially for the set of studies that consider broad groups of workers, the overall evidence base suggests an employment impact of close to zero."

At the end of this unit ...

You will be able to:

- Understand and discuss the challenges of making causal inferences
- Perform inference appropriate for the model being estimated
- Interpret empirical results (with due caution!)
- Discuss strengths and weaknesses of particular empirical applications
- 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

What you need to do

To learn in this unit you need to:

Assessment Structure and feedback

- Online test (on the use of R) - 10%
- End-of-Term exam (short answer questions) - 50%
- Group coursework - 40% (see extra info)

Aim for today

Statistics/Econometrics

- Summary Statistics
- Difference between population and sample
- Hypothesis testing
- Graphical Data Representations
- Diff-in-Diff Analysis
- 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

This Week's Plan

- Replicate some of the basic results presented in Card and Krueger (1994)
- Introduce the Difference-in-Difference methodology (Project!!) [Sometimes known as "Diff-in-Diff" or DiD.]
- Use this example to
  - introduce you to R
  - review some summary statistics
  - review simple regression and its implementation
  - introduce some basic visualisations

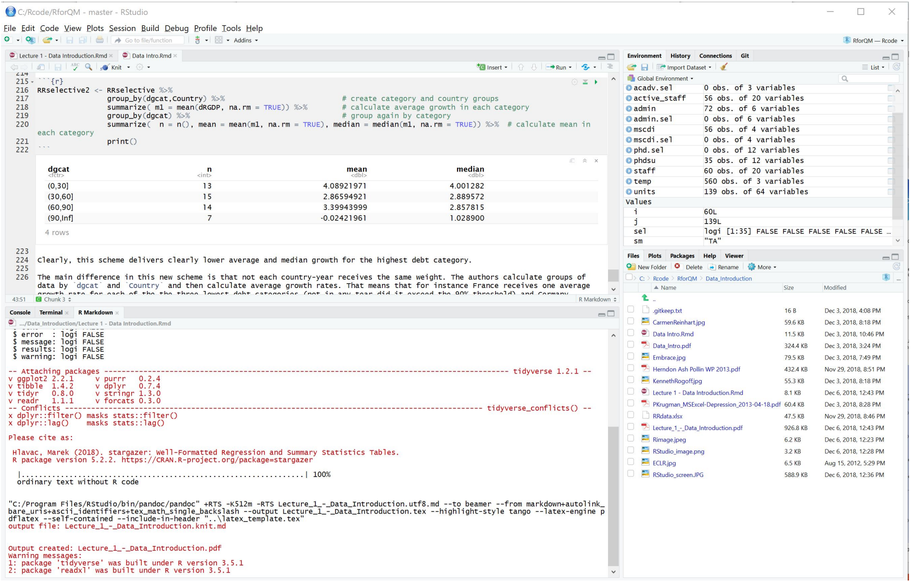
Introduce R/R-Studio

- 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 advice you make it easy for yourself and others to replicate your work.

Prepare your code

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

The first time you need these packages 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

```
CKdata<- read_xlsx("CK_public.xlsx",na = ".")
```

`na = "."` indicates how missing data are coded.

Check some characteristics of the data which are now stored in `CKdata`:

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

```
## tibble [410 x 46] (S3: tbl_df/tbl/data.frame)
##  $ SHEET   : num [1:410] 46 49 506 56 61 62 445 451 455 458 ...
##  $ CHAIN   : num [1:410] 1 2 2 4 4 4 1 1 2 2 ...
##  $ CO_OWNED: num [1:410] 0 0 1 1 1 1 0 0 1 1 ...
##  $ STATE   : num [1:410] 0 0 0 0 0 0 0 0 0 0 ...
##  $ SOUTHJ  : num [1:410] 0 0 0 0 0 0 0 0 0 0 ...
##  $ CENTRALJ: num [1:410] 0 0 0 0 0 0 0 0 0 0 ...
##  $ NORTHJ  : num [1:410] 0 0 0 0 0 0 0 0 0 0 ...
##  $ PA1     : num [1:410] 1 1 1 1 1 1 0 0 0 1 ...
##  $ PA2     : num [1:410] 0 0 0 0 0 0 1 1 1 0 ...
##  $ SHORE   : num [1:410] 0 0 0 0 0 0 0 0 0 0 ...
##  $ NCALLS  : num [1:410] 0 0 0 0 0 2 0 0 0 2
```

The data

To see the entire dataset (like in a spreadsheet):

Either click the little spreadsheet symbol next to the data.frame in the Environment tab, or

```
view(CKdata)  # prints some basic info on variables
```

The data - Unit of observation

A unit of observation is a fast food restaurant.

Say observation 27 in our dataset is a Roy Rogers (`CHAIN = 3`) store in Pennsylvania (`STATE = 0`) with 7 full time employees (`EMPFT`), 19 part-time employees (`EMPPT`) and 4 managers (`NMGRS`) in Feb 1992 and 17.5 in Dec

```
CKdata[27,]  # CKdata[which rows, which columns]
```

```
## # A tibble: 1 x 46
##   SHEET CHAIN CO_OWNED STATE SOUTHJ CENTRALJ NORTHJ   PA1
##   <dbl> <dbl>    <dbl> <dbl>  <dbl>    <dbl>  <dbl> <dbl> <
## 1   515     3        1     0      0        0      0     0
## # ... with 35 more variables: EMPFT <dbl>, EMPPT <dbl>, NMG
## #   WAGE_ST <dbl>, INCTIME <dbl>, FIRSTINC <dbl>, BONUS <db
## #   MEALS <dbl>, OPEN <dbl>, HRSOPEN <dbl>, PSODA <dbl>, PF
## #   PENTREE <dbl>, NREGS <dbl>, NREGS11 <dbl>, TYPE2 <dbl>,
## #   DATE2 <dbl>, NCALLS2 <dbl>, EMPFT2 <dbl>, EMPPT2 <dbl>,
## #   WAGE_ST2 <dbl>, INCTIME2 <dbl>, FIRSTIN2 <dbl>, SPECIAL
```

Addressing particular variables

If you want to call/use the entire spreadsheet/data frame/tibble then you call `CKdata`.

But often you want to call one variable only:

- `CKdata$CHAIN`, calls `CHAIN` only
- `CKdata["CHAIN"]`, calls `CHAIN` only
- `CKdata[2]`, calls `CHAIN` only, as it is the 2nd variable

And sometimes you want to call several, but not all, variables:

- `CKdata[c("STATE","CHAIN")]`

`c("STATE","CHAIN")` creates a list of names. `c` really represents a function, c for concatenation.

Also note: R is case sensitive, `CHAIN` $\neq$ `Chain`

Variable types

These are five 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`
- `factor: a set number of categories`

It is important that you know and understand differences between data types. Each variable has has a particular type and some operations only work for particular datatypes. For instance, we need `num` or `int` for any mathematical operations.

In our data.frame we have only `num` variable types.

We will encounter `logical` variables frequently.

factor variables

We store categorical variables as `factor` variables.

Sometimes you need to type convert to `factor` variables.

```
str(CKdata[c("STATE","CHAIN")])  # prints some basic info on v
```

```
## tibble [410 x 2] (S3: tbl_df/tbl/data.frame)
##  $ STATE: num [1:410] 0 0 0 0 0 0 0 0 0 0 ...
##  $ CHAIN: num [1:410] 1 2 2 4 4 4 1 1 2 2 ...
```

- `STATE`, 1 if New Jersey (NJ); 0 if Pennsylvania (Pa)
- `CHAIN`, 1 = Burger King; 2 = KFC; 3 = Roy Rogers; 4 = Wendy's

factor variables

```r
CKdata$STATEf <- as.factor(CKdata$STATE)
levels(CKdata$STATEf) <- c("Pennsylvania","New Jersey")

CKdata$CHAINf <- as.factor(CKdata$CHAIN)
levels(CKdata$CHAINf) <- c("Burger King","KFC", "Roy Rogers", "Wendy's")
```

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

```r
str(CKdata[c("STATEf","CHAINf")])  # prints some basic info on variables
```

```
## tibble [410 x 2] (S3: tbl_df/tbl/data.frame)
##  $ STATEf: Factor w/ 2 levels "Pennsylvania",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ CHAINf: Factor w/ 4 levels "Burger King",..: 1 2 2 4 4 4 1 1 2 2 ...
```

`factor` variables

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

```
levels(CKdata$CHAINf)
```

```
## [1] "Burger King" "KFC"         "Roy Rogers"  "Wendy's"
```

Learn more about your data

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

- `WAGE_ST`, starting wage (\$/hr), Wave 1, before min wage increase, Feb 1992
- `EMPFT`, # full-time employees before policy implementation

```
summary(CKdata[c("WAGE_ST","EMPFT")])
```

```
##     WAGE_ST          EMPFT
##  Min.   :4.250   Min.   : 0.000
##  1st Qu.:4.250   1st Qu.: 2.000
##  Median :4.500   Median : 6.000
##  Mean   :4.616   Mean   : 8.203
##  3rd Qu.:4.950   3rd Qu.:12.000
##  Max.   :5.750   Max.   :60.000
##  NA's   :20      NA's   :6
```

Learn more about your data

How many obs in each state and what chains

```
Tab1 <- CKdata %>% group_by(STATEf) %>%
          summarise(n = n()) %>%
          print()
```

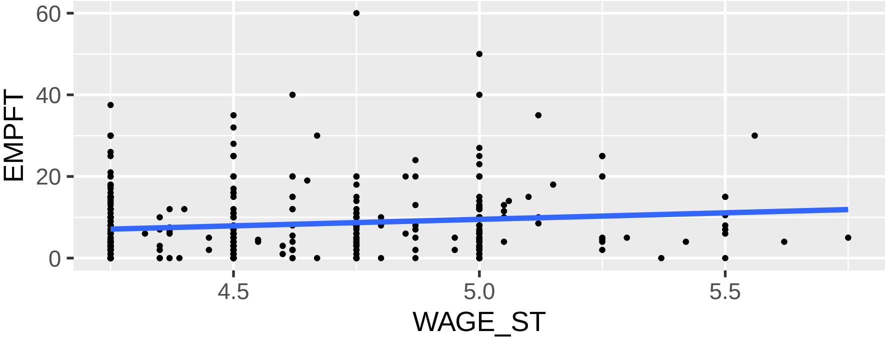
```
## # A tibble: 2 x 2
##   STATEf            n
##   <fct>         <int>
## 1 Pennsylvania     79
## 2 New Jersey      331
```

```
prop.table(table(CKdata$CHAINf,CKdata$STATEf,dnn = c("Chain", "State")),margin = 2)
```

```
##               State
## Chain           Pennsylvania New Jersey
##   Burger King      0.4430380  0.4108761
##   KFC              0.1518987  0.2054381
##   Roy Rogers       0.2151899  0.2477341
##   Wendy's          0.1898734  0.1359517
```

Scatter plot of the data

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



Regression Line

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

$$EMPFT = \alpha + \beta WAGE\_ST + u \quad (\qquad\qquad\qquad \text{Model})$$

- The population model is defined by unknown parameters α and β and the unknown error terms u. We will use sample data to obtain sample estimates of these parameters.
- The error terms u contain the effects of any omitted variables and reflect that any modelled relationship will only be an approximation. The u are

$$EMPFT_{it} = \widehat{\alpha} + \widehat{\beta}\; WAGE\_ST_{it} + \widehat{u}_{it} \quad (\qquad\qquad\qquad \text{Model})$$

Here we have two subscripts as the data have a cross-section ( ) and a time-series dimension ( ).

The regression line in the previous figure is represented by

$$\widehat{EMPFT}_{it} = \widehat{\alpha} + \widehat{\beta} WAGE\_ST_{it} \quad (\qquad\qquad\qquad)$$

Simple Regression Model and OLS

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

How to estimate parameters (get $\widehat{\alpha}$ and $\widehat{\beta}$) using the available sample of data? This is typically done by Ordinary Least Squares (OLS).

Simple Regression Model and OLS

```
mod1 <- lm(EMPFT~WAGE_ST, data= CKdata)
summary(mod1)
```

```
##
## Call:
## lm(formula = EMPFT ~ WAGE_ST, data = CKdata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -11.091  -5.898  -2.100   3.005  51.304
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -6.468      5.807  -1.114   0.2660
## WAGE_ST        3.193      1.255   2.544   0.0114 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.5 on 383 degrees of freedom
##   (25 observations deleted due to missingness)
## Multiple R-squared:  0.01662,    Adjusted R-squared:  0.01405
## F-statistic: 6.472 on 1 and 383 DF,  p-value: 0.01135
```

OLS - calculation and interpretation

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

$$\begin{aligned}
\widehat{\beta} &= \frac{\widehat{Cov}(EMPFT_{it}, WAGE_ST_{it})}{\widehat{Var}(WAGE_ST_{it})} \\
\widehat{\alpha} &= \overline{EMPFT}_{it} - \widehat{\beta} * \overline{WAGE_ST}_{it}
\end{aligned}$$

How to interpret $\widehat{\beta} = 3.193$?

Have we established that higher wages **cause** higher employment?

Regression Analysis - Underneath the hood

Need to recognise that in a sample $\hat{\beta}$ and $\hat{\alpha}$ are really .
For short `EMPFT=E` and `WAGE_ST=W`:

$$
\begin{aligned}
\hat{\beta} &= \frac{\widehat{Cov}(E,W)}{\widehat{Var}(W)} \\
&= \frac{\widehat{Cov}(\alpha + \beta\ W + u, W)}{\widehat{Var}(W)} \\
&= \frac{\widehat{Cov}(\alpha, W) + \beta \widehat{Cov}(W,W) + \widehat{Cov}(u,W)}{\widehat{Var}(W)} \\
&= \beta\ \frac{\widehat{Var}(W)}{\widehat{Var}(W)} + \frac{\widehat{Cov}(u,W)}{\widehat{Var}(W)} = \beta + \frac{\widehat{Cov}(u,W)}{\widehat{Var}(W)}
\end{aligned}
$$

So $\hat{\beta}$ is a function of the random term u and hence is itself a random variable. Once $\widehat{Cov}(E,W)$ and $\widehat{Var}(W)$ are replaced by sample estimates we get value which is draw from a

OLS - estimator properties

What can we learn from this?

- If u_{it} is a random variable, so is
- Any particular value we get is a
- An estimator is unbiased if, on average, the estimates would be equal to the unknown β
- For this to happen we need to assume that $Cov(u, x) = 0$ as then $E(\widehat{\beta}) =$

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 ($WAGE\_ST \rightarrow EMPFT$ and $EMPFT \rightarrow WAGE\_ST$)
- Omitted relevant variables or unobserved heterogeneity
- Measurement error in x_{it}

So how to make causal statements

We can do this if we can argue/believe in the exogeneity assumption. The methodological part of this unit introduces various standard techniques that assume exogeneity:

- First Difference
- Diff-in-Diff, to be used in Project
- Instrumental Variables
- Regression Discontinuity (only if time permits)

All use a generalisation of the simple regression model (above) called the Multiple Regression Model (Week 3 following).

Diff-in-Diff - The Problem

Do higher minimum wages decrease employment (as predicted by a simplistic labour market model)?

The Research Question

"This paper presents new evidence on the effect of minimum wages on establishment-level employment outcomes. We analyze the experiences of 410 fast-food restaurants in New Jersey and Pennsylvania following the increase in New Jersey's minimum wage from \$ 4.25 to \$ 5.05 per hour. Comparisons of employment, wages, and prices at stores in New Jersey and Pennsylvania before and after the rise offer a simple method for evaluating the effects of the minimum wage."

Card, David ; Krueger, Alan B. (1994, p.772)

Wage distribution - Pre

Look at the distribution of starting wages before the change in minimum wage in New Jersey (`WAGE_ST`).

At this stage it is not so important to understand the commands for these plots.

The easiest way to plot a histogram is

`hist(CKdata$WAGE_ST[CKdata$STATEf == "Pennsylvania"])`

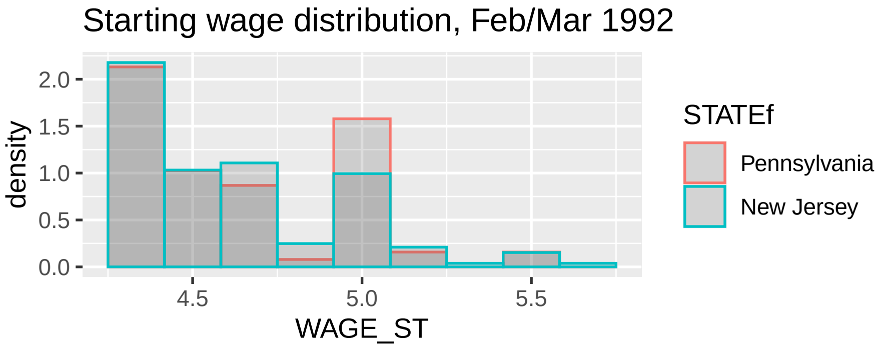
where, in square brackets, we select that we only want data fram Pennsylvania.

```
hist(CKdata$WAGE_ST[CKdata$STATEf == "Pennsylvania"])
hist(CKdata$WAGE_ST[CKdata$STATEf == "New Jersey"])
```

Wage distribution - Pre

Or here an alternative visualisation.

```
ggplot(CKdata,aes(WAGE_ST, colour = STATEf), colour = STATEf) +
    geom_histogram(position="identity",
                   aes(y = ..density..),
                   bins = 10,
                   alpha = 0.2) +
    ggtitle(paste("Starting wage distribution, Feb/Mar 1992"))
```



Wage distribution - Pre

Both plots show that the starting wage distribution is fairly similar in both states, with peaks at the minimum wage of \$4.25 and \$5.00.

Policy Evaluation

First we can evaluate whether the legislation has been implemented.

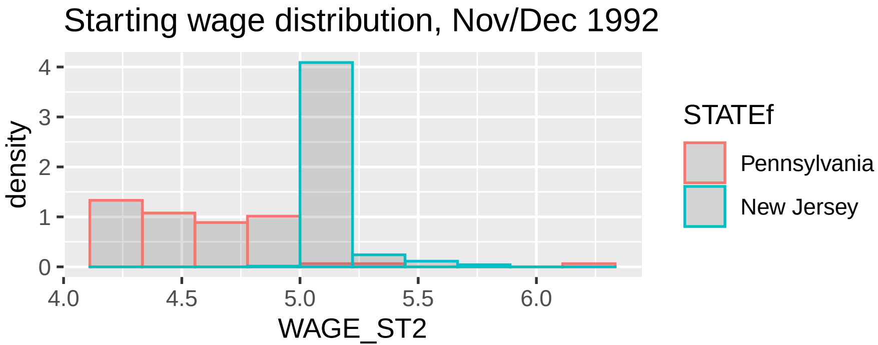
```
Tab1 <- CKdata %>% group_by(STATEf) %>%
          summarise(wage_FEB = mean(WAGE_ST,na.rm = TRUE),
                    wage_DEC = mean(WAGE_ST2,na.rm = TRUE)) %>%
          print()
```

```
## # A tibble: 2 x 3
##   STATEf       wage_FEB wage_DEC
##   <fct>           <dbl>    <dbl>
## 1 Pennsylvania     4.63     4.62
## 2 New Jersey       4.61     5.08
```

Average wage in New Jersey has increased.

Policy Evaluation - Wage distribution

```
ggplot(CKdata,aes(WAGE_ST2, colour = STATEf), colour = STATEf) +
    geom_histogram(position="identity",
                   aes(y = ..density..),
                   bins = 10,
                   alpha = 0.2) +
    ggtitle(paste("Starting wage distribution, Nov/Dec 1992"))
```



Policy Evaluation - Employment outcomes

Let's measure employment before and after the policy change.

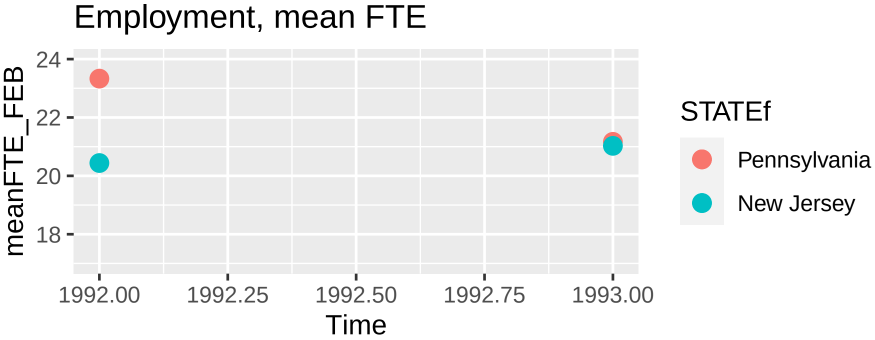
Calculate two new variables FTE and FTE2 (full time employment equivalent before and after policy change)

```
CKdata$FTE <- CKdata$EMPFT + CKdata$NMGRS + 0.5*CKdata$EMPPT
CKdata <- CKdata %>%  mutate(FTE2 = EMPFT2 + NMGRS2 + 0.5*EMPPT2)
```

```
TabDiD <- CKdata %>% group_by(STATEf) %>%
          summarise(meanFTE_FEB = mean(FTE,na.rm = TRUE),
                    meanFTE_DEC = mean(FTE2,na.rm = TRUE)) %>%
          print()
```

```
## # A tibble: 2 x 3
##   STATEf       meanFTE_FEB meanFTE_DEC
##   <fct>              <dbl>       <dbl>
## 1 Pennsylvania        23.3        21.2
## 2 New Jersey          20.4        21.0
```

Policy Evaluation - Diff-in-Diff estimator



Policy Evaluation - Diff-in-Diff estimator

```
print(TabDiD)
```

```
## # A tibble: 2 x 3
##   STATEf       meanFTE_FEB meanFTE_DEC
##   <fct>              <dbl>       <dbl>
## 1 Pennsylvania        23.3        21.2
## 2 New Jersey          20.4        21.0
```

Numerically the DiD estimator is calculated as follows:

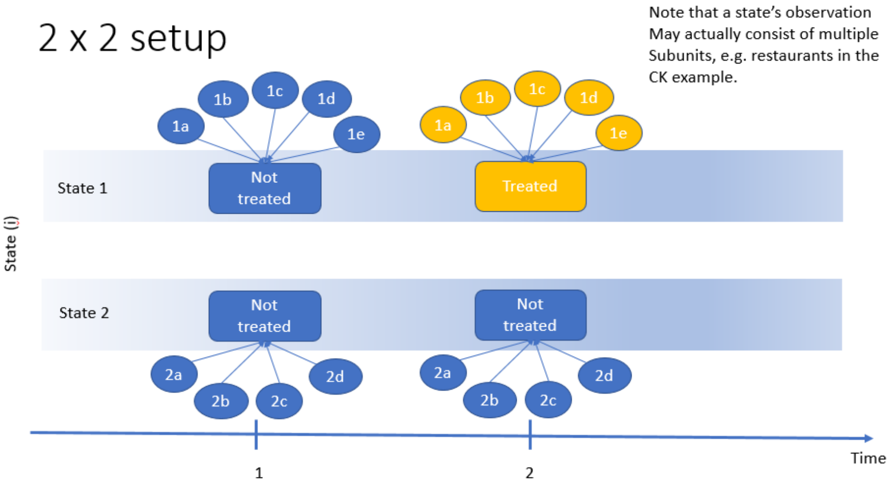
$(21 - 20.4) - (21.2 - 23.3) = 2.7$

Later: This can be calculated using a regression approach (has some additional advantages)

DiD

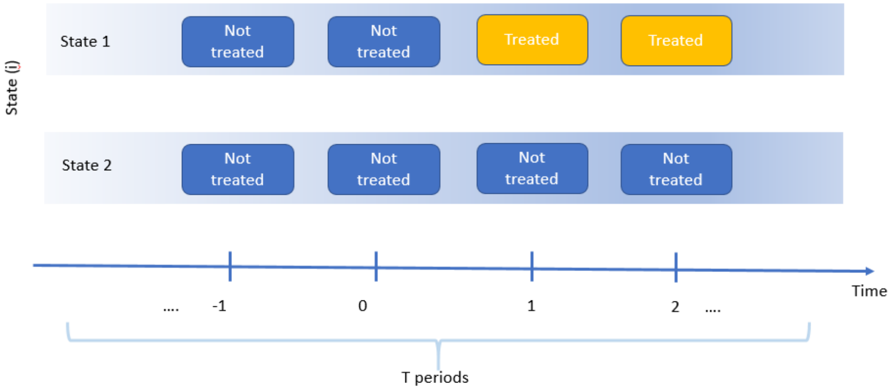
2 x 2 setup
Note: States don't have to be states, but could be Firms, countries, industries, etc.
State (i)
State 1
Not treated
Treated
State 2
Not treated
Not treated
1
2
Time (t)

DiD

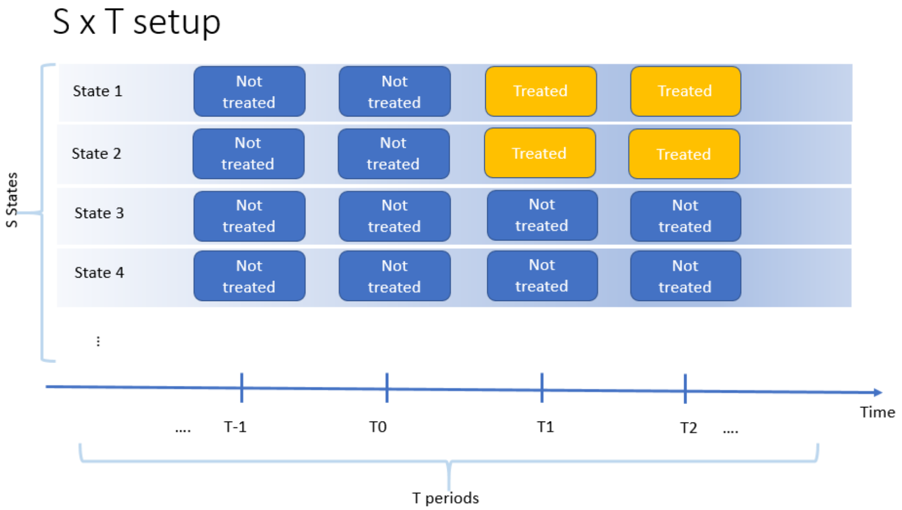

2 x 2 setup
Note that a state's observation
May actually consist of multiple
Subunits, e.g. restaurants in the
CK example.
1a
1b
1c
1d
1e
State 1
Not treated
Treated
State (i)
State 2
Not treated
Not treated
2a
2b
2c
2d
1
2
Time

DiD

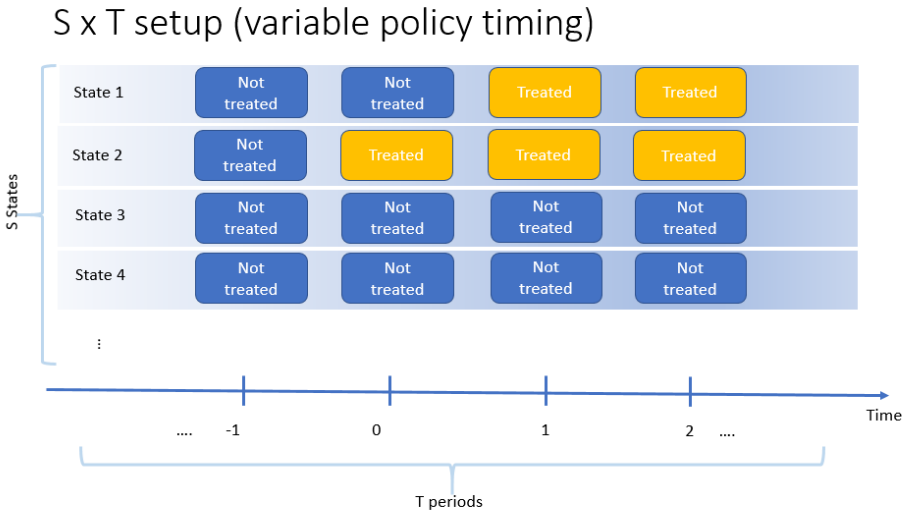
2 x T setup



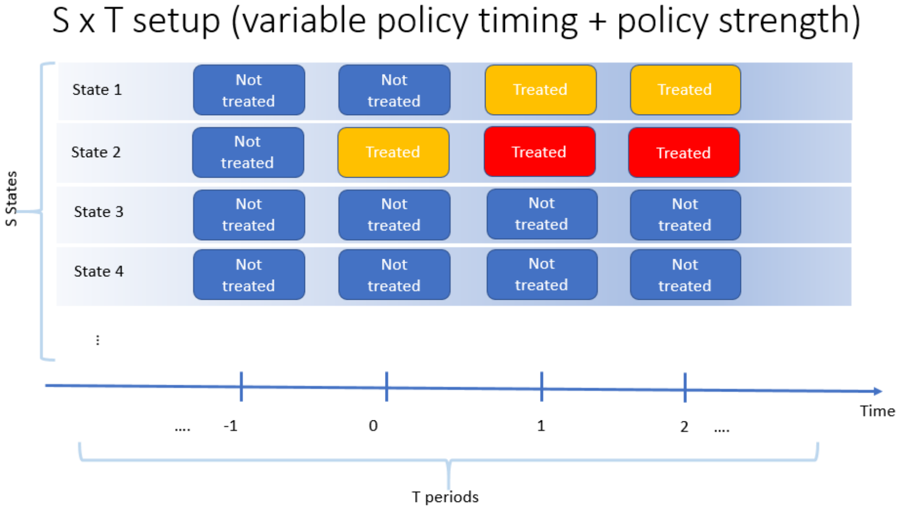
DiD


S x T setup
S States
State 1
Not treated
Not treated
Treated
Treated
State 2
Not treated
Not treated
Treated
Treated
State 3
Not treated
Not treated
Not treated
Not treated
State 4
Not treated
Not treated
Not treated
Not treated
⋮
....
T-1
T0
T1
T2
....
Time
T periods

DiD


S x T setup (variable policy timing)
S States
State 1
Not treated
Not treated
Treated
Treated
State 2
Not treated
Treated
Treated
Treated
State 3
Not treated
Not treated
Not treated
Not treated
State 4
Not treated
Not treated
Not treated
Not treated
⋮
Time
.... -1
0
1
2 ....
T periods

DiD


S x T setup (variable policy timing + policy strength)
S States
State 1
Not treated
Not treated
Treated
Treated
State 2
Not treated
Treated
Treated
Treated
State 3
Not treated
Not treated
Not treated
Not treated
State 4
Not treated
Not treated
Not treated
Not treated
⋮
.... -1
0
1
2 ....
Time
T periods

DiD and Regression

To take care of the subtleties these different schemes come with you will have to estimate the policy effect using a regression model instead of merely calculating averages.

Different schemes will require different setups.

This will be covered in detail in Week 7.

But here is a glimpse at one of the regression models you will come across then

$$y_{st} = \eta + \alpha d_s + \lambda p_t + \tau d_s p_t + u_{st}$$

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