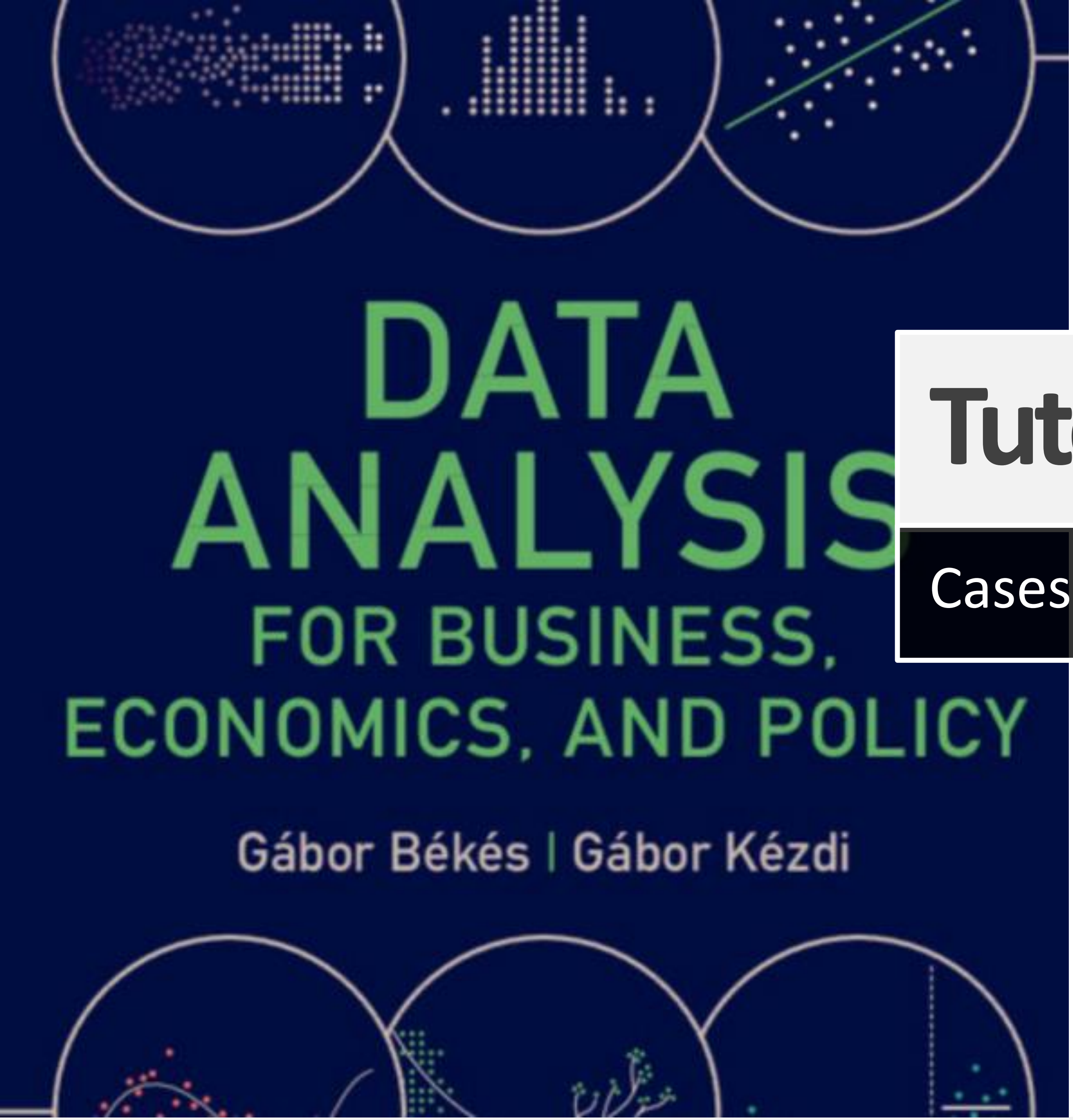


Lecturer: Ferenc Illes

Tutorials

Cases from the book accessible online

In the tutorials we use cases from the book

& we also use real financial data to gain in-depth understanding for applied finance research work, relevant for the industry

Issues/Problems

- If you had any issues with any of the previous data, please ask during the tutorial or post on Moodle in the relevant week discussion forum

- This week finally we explore complex panel data – which are created by pooling several time series of dataset together for several countries.
- Recall the first tutorial, where we talked about the different dimensions of panel data

Tutorial (Week 5)

- Wednesday:
  Measles Immunization data,
  Chapter 23, panel data

  Data

  Code, R

- Friday
  —Haiti Earthquake
  Chapter 24, event, panel

  Data

  Code, R

Panel Regression: Measles Immunization (MI) Case

- In the tutorial class, you will use panel data about measles immunization across 7 countries with a good time coverage from 1998-2017.

- The regression model aims to establish causality between children survival rate and immunization.
- Data coverage:
  - Immunization rate, Child survival rate
  - Immunization rate: percentage of children of age 12 to 23 months who received vaccination against measles.
  - Child survival rate: 100% minus the percentage of children of age 0 to 5 years who died in the given year. Source: worldbank-immunization dataset.

MI Case: Data preparation

- We want to examine the effect of measles immunization on child survival.
  - With fixed effects (fixed effects for country and time)
  - Use : Source: worldbank-immunization dataset; balanced yearly panel, years 1998–2017 in 172 countries

  - Before we jump into analysis, regression and interpretation, always the first step should be summary statistics..
  - provide pulled summary statistics for all countries, and perhaps look at some countries, separately you are interested in
  - Next you also want to plot trends…

MI Case: Data preparation

```
# load theme and functions
source("ch00-tech-prep/theme_bg.R")
source("ch00-tech-prep/da_helper_functions.R")

use_case_dir <- "ch23-immunization-life/"
data_in <- paste(data_dir,"worldbank-immunization","clean/", sep = "/")
data_out <- use_case_dir
output <- paste0(use_case_dir,"output/")
create_output_if_doesnt_exist(output)
```

MI Case: Data preparation - graph 1

```
#--------------------------------------------------
# Import data

data <- read_csv(paste(data_in, "worldbank-immunization-continents.csv", sep = ""))
# Load from OSF
# data <- read_csv("https://osf.io/58zrj/download")

# ****************************************************
# * info graph on measles vaccination continent aggregates
```

MI Case: Data preparation - graph 2

```
# ****************************************************
# * info graph on measles vaccination continent aggregates
p1 <- ggplot(data, aes(x = year, y = imm_SAS)) +
  geom_line(color = color[1], size = 0.7) +
  geom_line(aes(x = year, y = imm_SSF), color = color[2], size = 0.7) +
  geom_text(data = data[12,], aes(label = "South Asia"), hjust = 1.2, vjust = 1, size=2) +
  geom_text(data = data[16,], aes(y = imm_SSF, label = "Sub-Saharan Africa"), hjust = 0.4, vjust = 1.5, size=2) +
  labs(y = "Immunization rate (percent)", x="Date (year)") +
  scale_y_continuous(expand=c(0,0), breaks = seq(50, 100, by = 10), limits = c(50, 100)) +
  scale_x_continuous(expand=c(0,0), breaks = seq(1998, 2018, by = 5), limits = c(1998, 2018)) +
  theme_bg()
```

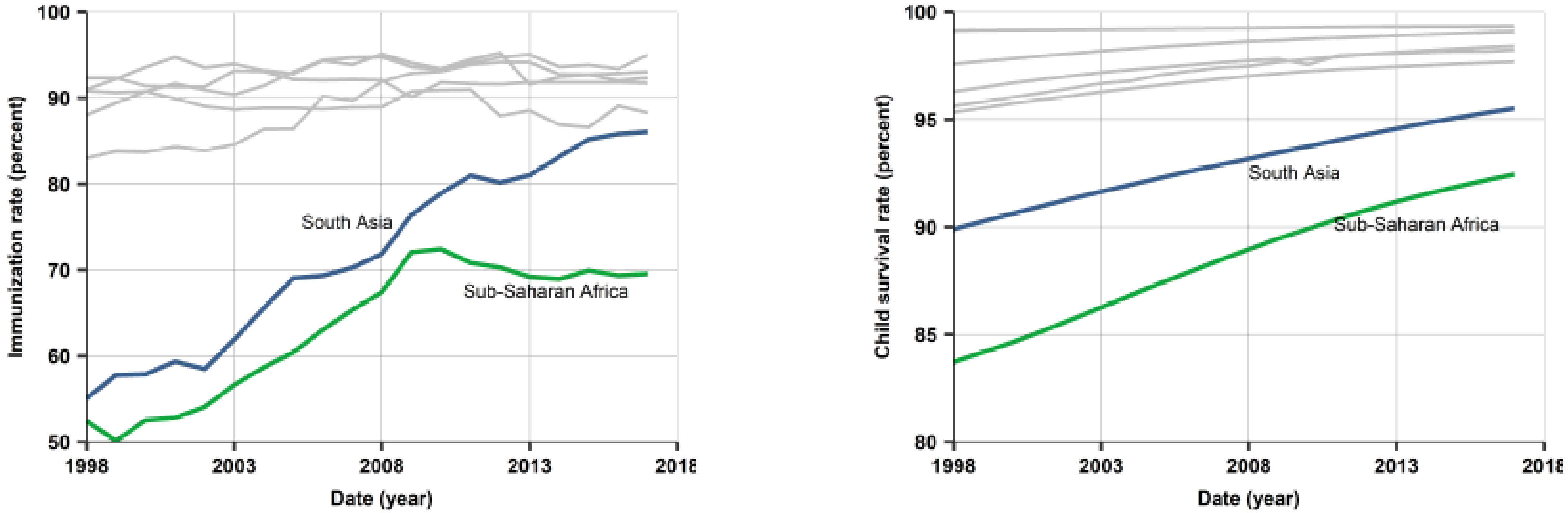
MI Case: Data preparation - graph 3

```
for (name in names(data)[2:6]) {
  p1 <- p1 + geom_line(aes_string(x = "year", y = name), color = "grey", size=0.5)
}
p1
save_fig("ch23-figure-2a-tsimmun", output, size = "small")


data[,9:15] <- data[,9:15] / 10
```

MI Case: Data preparation - graph 4

```
p2 <- ggplot(data, aes(x = year, y = surv_SAS)) +
  geom_line(color = color[1], size = 0.7) +
  geom_line(aes(x = year, y = surv_SSF), color = color[2], size = 0.7) +
  geom_text(data = data[11,], aes(label = "South Asia"), hjust = 0, vjust = 1.5, size=2) +
  geom_text(data = data[15,], aes(y = surv_SSF, label = "Sub-Saharan Africa"), hjust = 0.2, vjust = 1.5, size=2) +
  labs(y = "Child survival rate (percent)", x="Date (year)") +
  scale_y_continuous(expand=c(0,0), breaks = seq(80, 100, by = 5), limits = c(80, 100)) +
  scale_x_continuous(expand=c(0,0), breaks = seq(1998, 2018, by = 5), limits = c(1998, 2018)) +
  theme_bg()
for (name in names(data)[9:13]) {
  p2 <- p2 + geom_line(aes_string(x = "year", y = name), color = "grey", size=0.5)
}
p2
save_fig("ch23-figure-2b-tssurvival", output, size = "small")
```

Ex. Panel Regression - Measles Immunization



Immunization rate Child survival rate
Source: worldbank-immunization dataset. Annual data, 1998–2017, aggregated to seven geographical regions.

MI Case: regression – 1a

```
# **************************************************
# * regressions on countries

data_panel <- read_csv(paste(data_in, "worldbank-immunization-panel.csv", sep = "/"))
# From OSF
#data_panel <- read_csv("https://osf.io/gk5cn/download")

data_panel <- data_panel %>%
  filter(!(is.na(imm) | is.na(gdppc))) %>%
  mutate(c = factor(c)) %>%
  group_by(c) %>%
  mutate(balanced = min(year) == 1998 & max(year) == 2017 & length(unique(year)) == 20) %>%
  ungroup()

data_balanced <- data_panel %>%
  filter(balanced == TRUE)
```

MI Case: regression – 1b

```
data_balanced <- data_balanced %>%
  arrange(c, year) %>%
  group_by(c) %>%
  mutate(
    lnpop=log(pop),
    d_surv = surv- lag(surv),
    d_imm = imm - lag(imm),
    d2_imm = d_imm - lag(d_imm),
    d_lngdppc= lngdppc- lag(lngdppc),
    d_lnpop = lnpop - lag(lnpop),
    avgpop = mean(pop), #for weights in xtreg fe
    year = factor(year)
  ) %>%
  ungroup()
```

MI Case: regression – 1c

```
# ***************************************************
# * FE REGRESSSIONS
# Set the panel.id for all estimation
setFixest_estimation(panel.id = ~c + year)

fe_lm <- feols( surv ~ imm + year | c ,
              data = data_balanced,
              weights = data_balanced$avgpop,
              cluster = "c" )

fe_lm2 <- feols(surv ~ imm + lngdppc + lnpop + year | c ,
              data = data_balanced,
              weights = data_balanced$avgpop,
              cluster = "c" )

etable(fe_lm, fe_lm2  , drop = 'year')
```

MI Case: regression – 1c

```
# ****************************************************
# * FE REGRESSSIONS
# Set the panel.id for all estimation
setFixest_estimation(panel.id = ~c + year)

fe_lm <- feols( surv ~ imm + year | c ,
                data = data_balanced,
                weights = data_balanced$avgpop,
                cluster = "c" )

fe_lm2 <- feols(surv ~ imm + lngdppc + lnpop + year | c ,
                data = data_balanced,
                weights = data_balanced$avgpop,
                cluster = "c" )

etable(fe_lm, fe_lm2  , drop = 'year')
```

Ex. Panel Regression - “effect” of immunization

The effect of measles immunization on child survival. FE regression

Variables	(1) Survival rate	(2) Survival rate
Immunization rate	0.077**	0.038**
	(0.010)	(0.011)
ln GDP per capita		1.593**
		(0.399)
ln population		12.049**
		(1.648)
Year dummies	Yes	Yes
Observations	3,440	3,440
R-squared	0.717	0.848
Number of countries	172	172

Within R-squared presented for FE regressions. Appropriate standard error estimates in parentheses. **p <0.01 and *p <0.05

The slope parameter estimate on immunization is 0.077 without conditioning on any confounders I drops to 0.038 when we condition on GDP per capita and population

When we compare years with the same GDP and population, in years when the immunization rate is higher by 10 percentage points than its average rate within a country, child survival tends to be 0.38 percentage points higher than its average within the country, conditional on aggregate trends in the world.

MI Case: regression – Clustered errors

```
# ************************
# ** CLUSTER SE VS BIASED SE

fe_lm3 <- feols(surv ~ imm + lngdppc + lnpop + year | c ,
            data = data_balanced,
            weights = data_balanced$avgpop,
            vcov = 'iid')

etable( fe_lm2 , fe_lm3 , drop = 'year' )


# ************************
```

MI Case: regression – Clustered errors

- Standard errors become larger
- the cluster-robust standard errors car be much larger tha the default becaus **both the regressor interest and the errors are highly correlated within cluster**.

FE regressions with different Simple and Clustered SE estimates.

Variables	(1) Clustered SE	(2) Simple SE
Immunization rate	0.038**	0.038**
	(0.011)	(0.002)
ln GDP per capita	1.593**	1.593**
	(0.399)	(0.071)
ln population	12.049**	12.049**
	(1.648)	(0.227)
Observations	3,440	3,440
R-squared	0.848	0.848
Number of countries	172	172

MI Case: regression – Clustered errors

- If you are still not clear why should you adjust the standard errors for clustering, there is a paper by leading econometrics professors. The title of the paper is very apt:
- When Should You Adjust Standard Errors for Clustering?
- https://economics.mit.edu/sites/default/files/2022-09/cluster-6.pdf

MI Case: regression – first differences.

- Panel Regression in First Differences
- We can also specify xt panel regressions in changes.
- Different approach, alternative to FE model in modeling I panel regression in first differences or FD regression. I
- *FD = changes* -> $\Delta y_{it} = y_{it} - y_{i(t-1)}$.
- FD panel regression with a common intercept across all i.

$$\Delta y_{it}^{E} = \alpha_i + \beta \, \Delta x_{it}$$

Here it is easy to implement, we have balanced data, there are no years missing… still you need to make sure your data is sorted properly, and you calculate first difference within country.

- But here, we have Looks like a pooled a cross-section with first difference.
- a single intercept, α

MI Case: regression – first differences -1a

```
# * FD REGRESSIONS

# * basic FD
fd_lm <- feols(d_surv ~ d_imm ,
          data = data_balanced,
          weights = data_balanced$pop,
          cluster = "c")

# * FD, 5 lags
fd_lm_5 <- feols(d_surv ~ l(d_imm,0:5),
           data = data_balanced,
           weights = data_balanced$pop,
           cluster = "c"
```

MI Case: regression – first differences -1b

```
)

# Showing only the d_imm renamed
dictName = c("l(d_imm,1)"="d_imm lag1",
            "l(d_imm,2)"="d_imm lag2",
            "l(d_imm,3)"="d_imm lag3",
            "l(d_imm,4)"="d_imm lag4",
            "l(d_imm,5)"="d_imm lag5",
            "(Intercept)"="Constant")
etable( fd_lm, fd_lm_5,dict = dictName,
       keep = 'd_imm|Constant', digits = 3)
```

MI Case: regression – first differences -1c

```
# * FD, 5 lags, cumul
fd_lm_5_cumul <- feols( d_surv ~ l( d_imm , 5 )+ l( d2_imm , 0:4) ,
                  data = data_balanced,
                  weights = data_balanced$pop,
                  cluster = "c" )

# * FD, 5 lags, cumul, lead (!different than in book!)
fd_lm_5_cumul_lead <- feols( d_surv ~ l( d_imm , 5 ) + l( d2_imm , -3:4 ) ,
                  data = data_balanced,
                  weights = data_balanced$pop,
                  cluster = "c" )
```

MI Case: regression – first differences -1d

The effect of measles immunization on child survival - FD model estimates

Variables	(1) $\Delta surv$	(2) $\Delta surv$	(3) $\Delta surv$
Δimm cumulative ,	0.052** (0.010)	0.030** (0.009)	0.011** (0.003)
Year dummies	Yes	Yes	Yes
Confounder variables	No	Yes	Yes
Country-specific trends	No	No	Yes
Observations	2,408	2,408	2,408
R-squared	0.088	0.212	0.331

MI Case: regression potential confounders -1a

Lets explore further for potential confounders.

****
* AGGREG TREND, CONFOUNDERS, CTRY TRENDS
* FD, 5 lags, cumul, aggreg trend

MI Case: regression potential confounders – 1b

```
fd_lm_5_cumul_trend <- feols(d_surv ~ l( d_imm , 5 ) + l(d2_imm , 0 : 4) | year,
                    data = data_balanced,
                    weights = data_balanced$pop,
                    cluster = "c" )

# * FD, 5 lags, cumul, aggreg trend, confounders
fd_lm_5_cumul_trend_c <- feols( d_surv ~ l( d_imm , 5 ) + l(d2_imm , 0 : 4)
                      + l(d_lngdppc , 0:5) + l(d_lnpop,0:5) | year,
                      data = data_balanced,
                      weights = data_balanced$pop,
                      cluster = "c")
```

MI Case: regression potential confounders – 1c

```
# * check: it's not the number of observations
data_balanced_filtered <- data_balanced %>%
  filter(!is.na(d_lngdppc))
fd_lm_5_cumul_trend2 <- feols(d_surv ~ l( d_imm , 5 ) + l(d2_imm , 0 : 4) | year,
                              data = data_balanced_filtered,
                              weights = data_balanced_filtered$pop,
                              cluster = "c")
```

MI Case: regression potential confounders – 1d

```
# * FD, 5 lags, cumul, aggreg trend, cofounders, country linear trend
fd_lm_5_cumul_trend_c_country <- feols(d_surv ~ l( d_imm , 5 ) + l(d2_imm , 0 : 4)
                        + l(d_lngdppc , 0:5) + l(d_lnpop,0:5) | year + c,
                        data = data_balanced,
                        weights = data_balanced$pop,
                        cluster = "c"
)

# etable format for output
etable(fd_lm_5_cumul_trend, fd_lm_5_cumul_trend_c, fd_lm_5_cumul_trend_c_country,
    keep = "d_imm",digits=3,
    extralines = list("Confounders" = c(F,T,T)))
```

MI Case: regression potential confounders – 1e

```
###
# * FD, 5 lags, cumul, aggreg trend, confounders
lags_helper  <- paste(paste0("lag(d2_imm, ", c(0:4), ")"), collapse = " + ")
lags_helper2 <- paste(paste0("lag(d_lngdppc, ", c(0:5), ")"), collapse = " + ")
lags_helper3 <- paste(paste0("lag(d_lnpop, ", c(0:5), ")"), collapse = " + ")
fd_lm_5_cumul_trend_c_formula <- as.formula(paste0("d_surv ~ lag(d_imm, 5) + ",
                                           lags_helper, "+",
                                           lags_helper2, "+",
                                           lags_helper3, "+",
                                           "year"))
fd_lm_5_cumul_trend_c <- lm_robust(fd_lm_5_cumul_trend_c_formula,
                          data = data_balanced,
                          weights = pop,
                          se_type = "stata",
                          clusters = c
)
```

MI Case: regression potential confounders – 1f

```
# run tests
linearHypothesis(fd_lm_5_cumul_trend_c, paste0(lags_helper2," =0"))
linearHypothesis(fd_lm_5_cumul_trend_c, paste0(lags_helper3," =0"))
```

questions

- If you have any last minute question about project, report, please ask

End

NOTE:

Now, you can see messiness of data, most of the time, data cleaning 70-80% of the time.

To get the data in a shape you can and able to work with, takes long time. Do not underestimate that in your work, in your studies.

Panel Data - Even : Haiti Earthquake

- Estimating the effect of the 2010 Haiti earthquake on GDP
- This is a comparative case study
- An event happened in one country
- Case study based on Best and Burke (2019), Use same data sources

Data

Code, R

Panel Data - Even : Haiti Earthquake

- The objective of this analysis to estimate the effect of the 2010 Haiti earthquake on GDP
- A severe earthquake hit Haiti in January 2010
- What was the effect of this earthquake on Haitian GDP in 2010 and subsequent years?
- Total GDP measured in Constant 2010 USD prices
- Need counterfactual (what would have been the GDP in the absence of the earthquake, expecting some trend, growth.

Case Haiti Earthquake: Data

- Let’s go through the code again, and replicate the book analysis

- Make sure you are also able to make figures, and understand the work

Case Haiti Earthquake: Data

```
# load theme and functions
source("ch00-tech-prep/theme_bg.R")
source("ch00-tech-prep/da_helper_functions.R")
use_case_dir <- "ch24-haiti-earthquake-gdp/"
data_in <- paste(data_dir,"haiti-earthquake","clean/", sep = "/")
data_out <- use_case_dir
output <- paste0(use_case_dir,"output/")
create_output_if_doesnt_exist(output)
```

Case Haiti Earthquake: Data

```
# Loading and preparing data -------------------------------------------------
data <- read_dta(paste0(data_in,"haiti-earthquake-mod.dta"))
# donor pool based on threshold calculations below:
# it is those countries with incomethreshold=1, and a balanced panel for all variables
dp_countries <- c("Benin","Burkina Faso","Burundi","Bangladesh","Cambodia","Cameroon",
                  "Kenya","Kyrgyz Republic","Liberia","Madagascar","Mali","Moldova","Mozambique",
                  "Nicaragua","Nepal","Rwanda","Senegal","Sierra Leone","Sudan","Tanzania","Togo","Uganda",
                  "Haiti")
dp_countries <- dp_countries %>%
  .[order(dp_countries)] %>%
  .[.!="Haiti"] %>%
  c("Haiti", .)
```

Case Haiti Earthquake: Data

```
data <- data %>%
  mutate(dp = as.numeric(country %in% dp_countries)) %>%
  filter(dp==1) %>%
  mutate(country = factor(country, levels = dp_countries, ordered = TRUE)) %>%
  arrange(country) %>%
  mutate(country = as.character(country)) %>%
  mutate(ccode = as.numeric(factor(countrycode, levels = unique(countrycode), ordered = TRUE)))
```

Case Haiti Earthquake: Again, check trend

```
# lets focus first on Haiti time data and plot again. It is important to have a  feel for data.
tsdata<-data %>%
  filter(ccode==1)
g1<- ggplot(data=tsdata, aes(x = year, y = gdptb_us)) +
  geom_line(color = color[1], size = 0.7) +
  geom_vline(xintercept = 2010, color = color[3], size = 0.7, linetype="dashed") +
  labs(y = "Total GDP (bn US dollars)", x = "Date (year)") +
  scale_y_continuous(breaks = seq(6, 9.5, 0.5), limits = c(6, 9.5)) +  scale_x_continuous(breaks = seq(2004, 2014, 2), limits = c(2004, 2015)) +
  geom_segment(aes(x = 2009, y = 7.7, xend = 2010, yend = 7.7), arrow = arrow(length = unit(0.05, "cm")))+
  annotate("text", x = 2008, y = 7.7, label = "Earthquake", size=2)+
  theme_bg()
g1
save_fig("ch24-figure-1-haiti-gdp", output, "small")
```

Case Haiti Earthquake: Again, check trend - 2

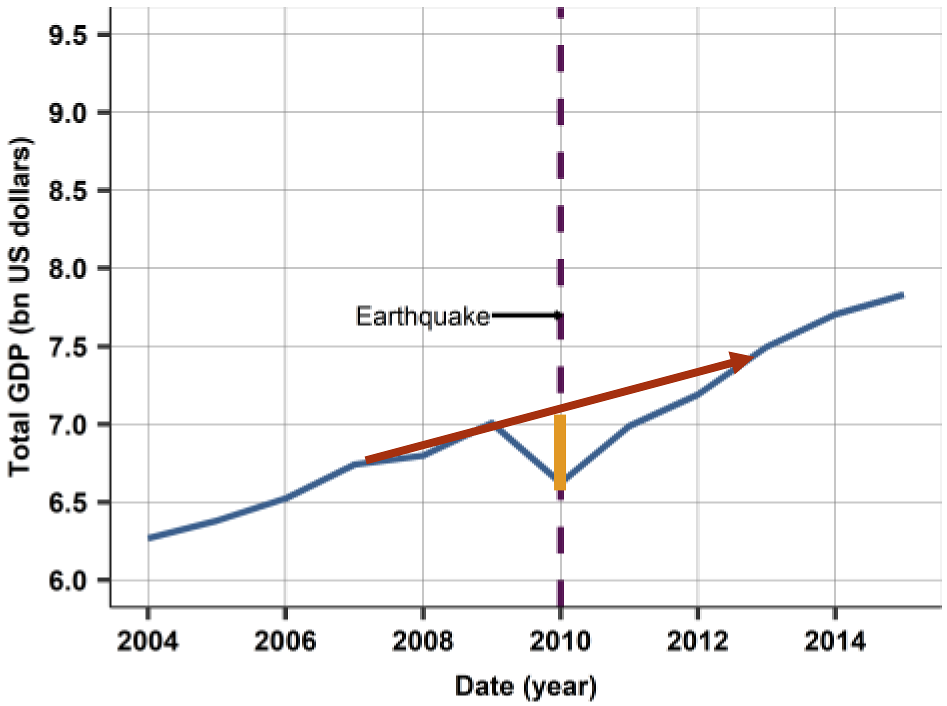
```
# figure with total GDP in Haiti and synthetid control
# line _Y_treated _Y_synth _time, lw(vthick vthick) lc(blue mint) ///
g2 <- ggplot(data=data_helper, aes(x = year, y = Ytreated)) +
  geom_line(color = color[1], size = 1) +
  geom_line(aes(y = Ysynthetic), color = color[2], size = 0.7) +
  geom_vline(xintercept = 2010, color = color[3], size = 0.7, linetype="dashed") +
  labs(y = "Total GDP (bn US dollars)", x = "Date (year)") +
  geom_segment(aes(x = 2009, y = 7.7, xend = 2010, yend = 7.7), arrow = arrow(length = unit(0.05, "cm")))+
  annotate("text", x = 2008, y = 7.7, label = "Earthquake", size=2)+
  scale_y_continuous(breaks = seq(6, 9.5, 0.5), limits = c(6, 9.5)) +
  scale_x_continuous(breaks = seq(2004, 2014, 2), limits = c(2004, 2015)) +
  theme_bg()
g2
save_fig("ch24-figure-2a-haiti-gdp-synth", output, "small")
```

Case Haiti Earthquake: Again, check trend - 3

```
# figure with differenence in log total GDP
g3 <- ggplot(data=data_helper, aes(x = year, y = log(Ytreated) - log(Ysynthetic))) +
  geom_line(color = color[1], size = 1) +
  geom_vline(xintercept = 2010, color = color[3], size = 0.7, linetype="dashed") +
  geom_hline(yintercept = 0, color = color[5], size = 0.7) +
  labs(y = "Effect estimate, ln(bn US dollars)", x = "Date (year)") +
  geom_segment(aes(x = 2009, y = -0.17, xend = 2010, yend = -0.17), arrow = arrow(length = unit(0.05, "cm")))+
  annotate("text", x = 2008, y = -0.17, label = "Earthquake", size=2)+
  scale_y_continuous(breaks = seq(-0.2, 0.05, 0.05), limits = c(-0.2, 0.05)) +
  scale_x_continuous(breaks = seq(2004, 2014, 2), limits = c(2004, 2015)) +
  theme_bg()
g3
save_fig("ch24-figure-2b-haiti-lndiffgdp-synth", output, "small")
```

Case Haiti Earthquake: Again, check trend

Total GDP in Haiti



Data does not lie

Clearly some effect is there… and we cannot just say that GDP is less than what it was in 2009, we would need to compare the drop in GDP to what could have been in 2010

We are interested in yellow line

The synthetic control for Haiti, “ matching”

- The synthetic control for Haiti , Recall the Matching example from Week 4
- Donor pool
  - Countries with less than USD 4000 GDP per capita (2009 PPP USD)
  - Appropriate data available in 2004 through 2015
  - 21 countries altogether (plus Haiti)
  - Variables
    - Land size and pre-intervention (2004-9) average values of population, GDP per capita, imports, exports, consumption, gross capital formation, inflation I Total GDP in 2005, 2007, 2009
    - The synthetic control subject : 5 countries with nonzero weight : Burundi 23%, Cameroon 21%, Moldova 9%, Togo 47%, Liberia 0.2%

Case Haiti Earthquake: Adjustments with controls

```
# Haiti and synthetic control
depvar <- "gdptb_us"
unitvar <- "ccode"
unit_values <- unique(pull(data, get(unitvar)))
timevar <- "year"
predictorvars <- c("cons", "exp", "imp", "gcf", "land", "pop", "inf", "gdppc_w")
special_predictorvars <- list(list("gdptb_us",seq(2005,2009,2),c("mean")))
trunit <- 1
trperiod <- c(2004:2009)
xperiod <- c(2004:2009)
timeplot <-  c(2004:2015)
unitnames <- "country"
```

Case Haiti Earthquake: Adjustments with controls

```
dataprep.out <-
  dataprep(
    foo = as.data.frame(data)
    ,predictors= predictorvars
    ,predictors.op = c("mean")
    ,dependent     = depvar
    ,unit.variable = unitvar
    ,time.variable = timevar
    ,special.predictors = special_predictorvars
    ,treatment.identifier  = trunit
    ,controls.identifier   = unit_values[unit_values != trunit]
    ,time.predictors.prior = xperiod
    ,time.optimize.ssr     = trperiod
    ,unit.names.variable   = unitnames
    ,time.plot          = timeplot
  )
```

Case Haiti Earthquake: Adjustments with controls

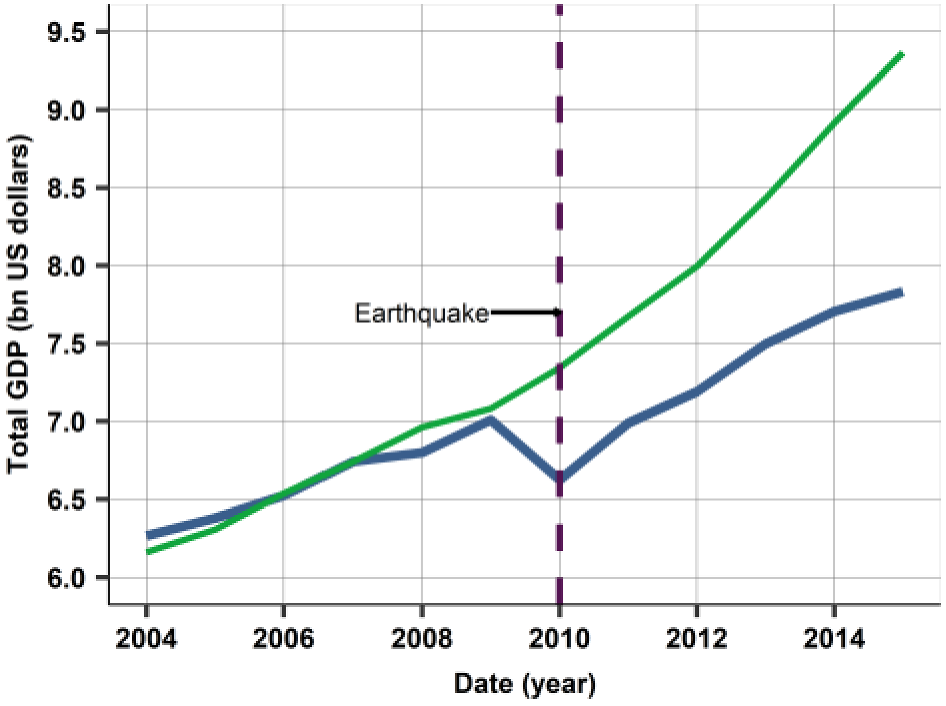
```
 figure with total GDP in Haiti and synthetid control

tsdata<-data %>%
  filter(ccode==1)


g2 <- ggplot(data=tsdata, aes(x = year, y = gdptb_us)) +
  geom_line(color = color[1], size = 1) +
  geom_line(aes(y = syn_haiti), color = color[5], size = 1) +
  geom_vline(xintercept = 2010, color = color[2], size = 0.7) +
  labs(y = "Total GDP (billion US dollar)", x = "Date (year)") +
  scale_x_continuous(breaks = seq(2004, 2014, 2), limits = c(2004, 2015)) +
  theme_bg()
g2
save_fig("haiti-gdp-synth", "small")
```

Case Haiti Earthquake: Adjustments with controls

```
# figure with differenence in log total GDP
tsdata<-data %>%
  filter(ccode==1)
g3 <- ggplot(data=tsdata, aes(x = year, y = log(gdptb_us) - log(syn_haiti))) +
  geom_line(color = color[1], size = 2) +
  geom_vline(xintercept = 2010, color = color[2], size = 1.5) +
  geom_hline(yintercept = 0, color = "red", size = 1) +
  labs(y = "Effect estimate, ln(total GDP)", x = "Date (year)") +
  scale_x_continuous(breaks = seq(2004, 2014, 2), limits = c(2004, 2015)) +
  theme_bg()
g3
save_fig("haiti-lndiffgdp-synth", "small")
```

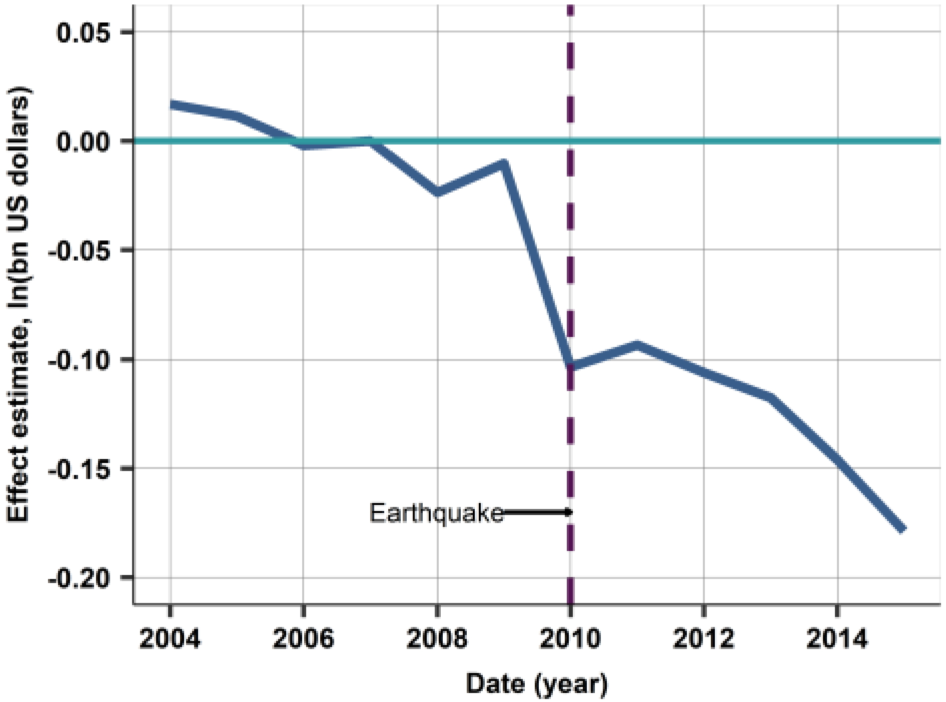
Case Haiti Earthquake: Adjustments with controls

Total GDP in Haiti and in the synthetic control country



Case Haiti Earthquake: Adjustments with controls

Log difference of total GDP in Haiti and the synthetic control country



Total GDP dropped by 10%,
And remained lower level, because it was growing potentially at a lower rate than it would have been growing, see the previous slide.

Compare the steepness of the line on slide 46 with slide 42

Case Haiti Earthquake - explore

Please think further

How would you formulate a panel regression, how could you nail down the earthquake effect?

Potentially collect data from multiple countries on earthquake?

That could be ideal.

(review carefully lecture notes on how to design event studies)