Time and Event as data

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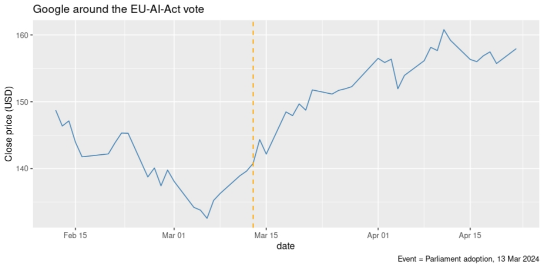
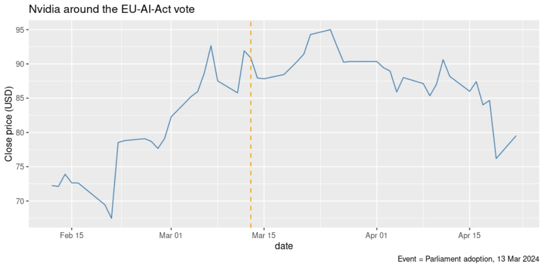
One vote, two reactions: What happened on March 13?

Event: 13 March 2024 — European Parliament adopts the EU Artificial Intelligence Act.

Google (AI deployer)



Nvidia (AI infrastructure)



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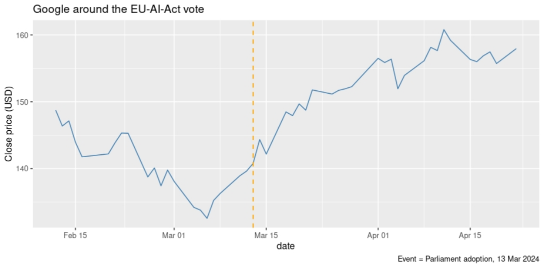

↑ Stock rose — less strict regulation than expected?

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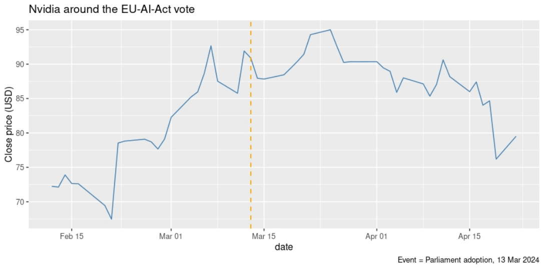


↓ Stock fell — signal of weaker AI demand ahead?

❦ Why do two companies involved in AI move in opposite directions?

Learn to answer questions like this

How can we tell if an event truly changed something?

- Would Nvidia's stock have flattened *even without* the AI Act?
- Was Google's rise part of a positive trend — or is it specific market signal?
- When is a price movement just noise — and when is it meaningful?

Our toolkit:

Handle and align time-stamped data

Use event studies to estimate causal impact

Build and test **counterfactuals**

We start from time. Then move to causality.

Section 1

Motivation

Why study events in time?

Event data is any data that you want to measure about an event

Policy, shocks, news $\rightarrow$ causal impact on markets, firms, outcomes.

Requires **two lenses**: when did it happen and how did series respond.

Today (basic) workflows for time handling & causal inference.

Learning Objectives

1. Parse, manipulate, and align timestamps in R (`lubridate`).
2. Distinguish event, time trend, and outcome.
3. Execute simple and regression-based event studies.
4. Know when to pivot to DiD, staggered adoption, or RDD.
5. Build structural counterfactuals with the gravity model.

What is a time-stamped datum?

- Cross-section: values observed *once* per unit (firm, county, tweet).
- Time record: each observation carries a **timestamp** $\Rightarrow$ ordering, lags, windows.

$$\boxed{\text{datum} = (\text{ID}, t, \text{attributes})}$$

From now on every method we use must respect this ordering.

Granularity of time

- Choose the *coarsest* frequency that still captures the causal effect.
- Finer $\Rightarrow$ more observations, but also noise and dependence.

Date–time objects in R

- Base R distinguishes `Date` (days) and `POSIXct/POSIXlt` (date–times, seconds).
- The **`lubridate`** package (tidyverse) provides a grammar for working with them.
- Always store timestamps with an explicit time zone—preferably UTC.

Creating date and date–time values

```r
library(lubridate)

# A calendar date:
d1 <- ymd("2025-05-26")

# A precise timestamp + time zone support:
t1 <- ymd_hms("2025-05-26 14:30:05", tz = "Europe/Berlin")

class(d1)  # "Date"
class(t1)  # "POSIXct", "POSIXt"
```

Extracting modifying components

```r
# Pull pieces out:
year(t1)                        # 2025
month(t1, label = TRUE)  # May
wday(t1, label = TRUE, week_start = 1)  # Mon

# Overwrite in place:
year(t1) <- 2026
month(t1) <- 12
wday(t1)                        # 6 (= Saturday)
wday(t1, label = TRUE, week_start = 1) # Sat
```

Spans of time: durations, periods, intervals

```r
event <- ymd_hms("2025-02-20 09:30:00", tz = "UTC")

# Add ten *civil* days (period respects DST):
event + days(10)

# Add 10 × 86,400 seconds regardless of DST:
event + ddays(10)  # duration

# How long since the event?
interval(event, now(tzone = "Europe/Berlin")) / days(1)
```

Rounding and aligning timestamps

```r
round_date(t1, "hour")      # 2026-12-26 15:00:00 CET
floor_date(t1, "day")       # 2026-12-26 00:00:00 CET
ceiling_date(t1, "month")   # 2027-01-01 00:00:00 CET
```

Regular vs. irregular sampling

Equally spaced

Irregular / event-driven

- Irregular streams (trades, tweets, sensors) often need **resampling**. Beware of aggregation bias and missing-data artefacts.

High-frequency data: promises & pitfalls

- **Volume**: millions of rows $\Rightarrow$ storage, speed, and parallel algorithms.
- **Micro-structure noise**: bid-ask bounce, timestamp jitter.
- **Simultaneity**: many units react within milliseconds.
- **Multiple hypothesis risk**: easy to find spurious "events".

Use HF data only when theory *needs* sub-daily resolution, and always report how you filtered and aligned the raw feed.

zoo vs. lubridate: Different Tools for Time

`zoo` (Zeileis, Grothendieck)

- Time-indexed vectors and matrices
- Designed for irregular or financial time series
- Fast rolling stats: `rollmean()`, `rollapply()`
- Plays well with `xts`, `quantmod`
- Base R–style syntax

`lubridate` (part of tidyverse)

- Simplifies parsing and modifying `Date`/`POSIX` objects
- Grammar for extracting: `year()`, `month()`, `wday()`
- Useful for aligning dates, durations, and intervals
- Integrates naturally with `dplyr`, `ggplot2`
- Ideal for **tidy data workflows**

Use `zoo` for time-series math. Use `lubridate` to parse, clean, and wrangle timestamps.

Section 2

Core Event-Study Design

Event Studies

Event study is probably the oldest and simplest causal inference research design

- effect of stock splits on stock prices (Dolley 1933; MacKinlay 1997)
- the information content of earnings announcements (Ball and Brown (1968))

Fama calls event studies a test of how quickly security prices reflect public information announcements (Fama 1991, p. 1576).

($\neq$ Marketing lit: assume market efficiency to measure the value of campaign, ..)

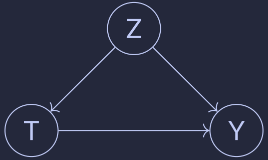
Directed Acyclical Graphs (DAGs): Why Use Them?

- DAGs help us extbfvisualize assumptions about causal structure.
- Each arrow encodes a causal relationship between variables.
- They help identify extcoloryconfounders, extcolorpmediators, and extcolorgcolliders.
- extbfRule: No cycles — a variable cannot cause itself, directly or indirectly.

A DAG is a map of our model assumptions — not data.

Confounding and the Back-Door Criterion

- A **back-door path** is a non-causal path from Treatment to Outcome that could bias our estimates.
- To identify the **causal effect**, we must block all such paths — usually by controlling for confounders.
- A variable satisfies the **back-door criterion** if it blocks all back-door paths and is not a collider.



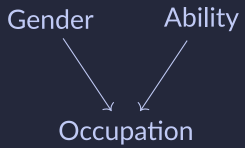
Controlling for Z blocks the confounding path and helps isolate the causal effect.

Collider Bias: Gender and Occupation

Setup: We want to understand the relationship between gender and ability.
In the general population, they are uncorrelated.

But what if we restrict attention to a single occupation?

- Let **occupation** be influenced by both:
    - Gender (e.g., bias in hiring)
    - Ability (e.g., productivity or test scores)
- Conditioning on occupation $\Rightarrow$ opens a collider path
- This induces a spurious negative correlation



Takeaway: Conditioning on a collider (like occupation) can induce bias. Even if gender and ability are independent in the population, they appear negatively correlated in a biased sample.

Source: Cunningham, *Causal Inference: The Mixtape* (2021), §3.5.

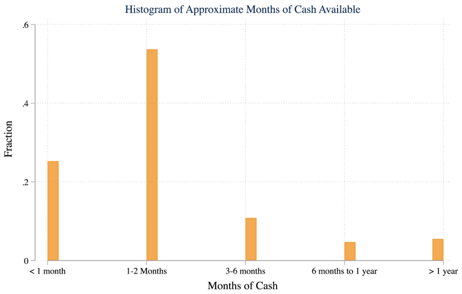
The impact of COVID-19 on small business

- Treatment=Pandemic $\rightarrow$ Outcome=Survival
  - Time series: looking at pre and post pandemics outcome
- Pandemic $\leftarrow$ After Event $\leftarrow$ Time $\rightarrow$ Outcome
  - All the stuff that changes over time independently of the Pandemics

Financial Fragility of Small Business

Survey to SME: “roughly how much cash (e.g. in savings, checking) do you have access to without seeking further loans or money from family or friends to pay for your business?”

Fig. 5.



Months of cash. This figure plots firms' months of cash available as a multiple of January 2020 expenses. We compute this measure by taking the midpoint of categorical responses for the amount of cash on hand and dividing by the midpoint of the categorical response for typical monthly expenses prior to the crisis. The sample size is 4,176.

Bartik et al. (2020), The impact of COVID-19 on small business outcomes

Counterfactual Question

Would those firms that went bankrupt, have gone bankrupt even without the pandemics?

1. whatever was going on before would have continued doing its thing if not for the treatment
2. how the actual outcome deviates from that prediction
3. the extent of the deviation is the effect of treatment

Pre-Trend Analysis

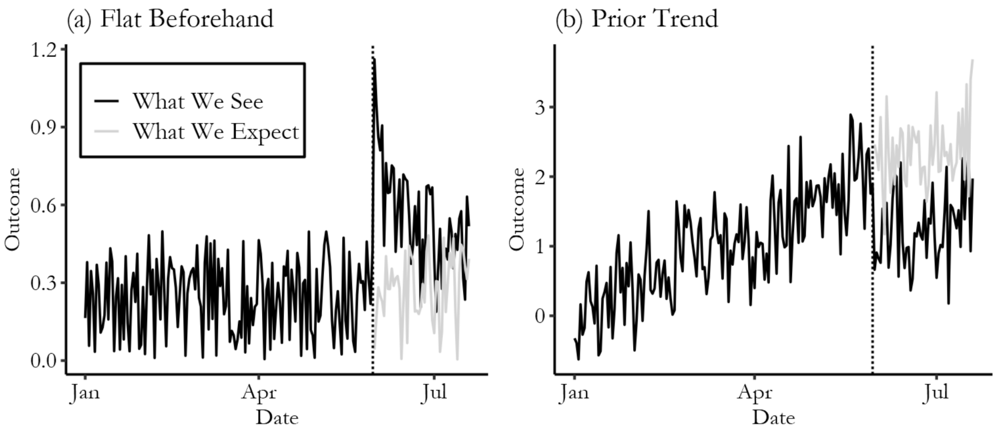


Figure 17.2: Two Examples of Graphs Representing Event Studies

Approaches to Pre-Trends

1. Ignore it! When is this good?
    - panel (a)
    - high-frequency data
2. Predict After-Event Data Using Before-Event Data
    - look at the outcome data you have leading up to the event
    - use the patterns in that data to predict what the outcome would be afterwards

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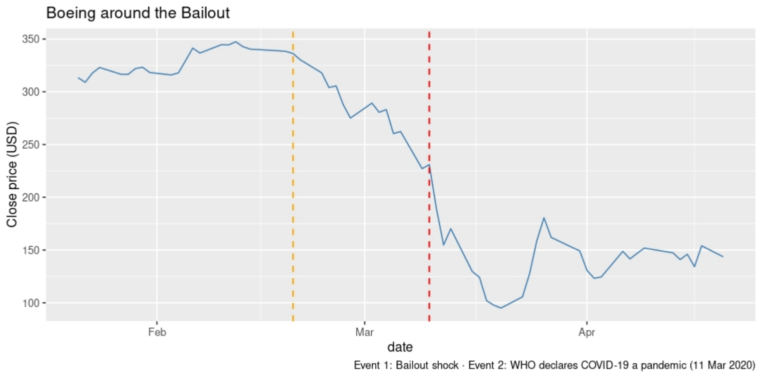
Practical Corner

Boeing stock plunges again after coronavirus bailout quest spooks investors



Would this happen even without bailout? What does the red line tell you?

Check more about bailout here.

Practical Corner

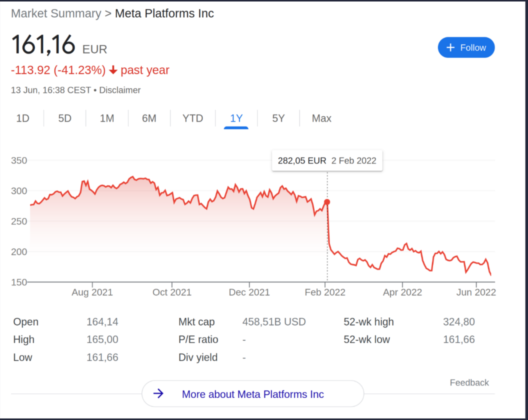
```r
library(tidyverse)
library(lubridate)
library(quantmod)      # pulls Yahoo Finance data

# 1. 30 trading days around the vote
getSymbols("BA", from = "2020-01-01", to = "2020-04-26", src = "yahoo")
ba <- fortify.zoo(BA) |>
  rename(date = Index) |>
  mutate(date = as_date(date))

# 2. Mark the event
event  <- ymd("2020-02-20")          # vote day (non-trading, Wednesday)
window <- ba |> filter(between(date, event - days(30), event + days(60)))
```

Practical Corner

```
ggplot(window, aes(date, BA.Close)) +
  geom_line(colour = "steelblue") +
  geom_vline(xintercept = as.numeric(event), linetype = "dashed",
             colour = "orange", linewidth = .6) +
  geom_vline(xintercept = as.numeric(ymd("2020-03-10")), linetype = "dash
             colour = "red", linewidth = .6) +
  labs(
    title = "Boeing around the Bailout",
    y = "Close price (USD)",
    caption = "Event 1: Bailout shock · Event 2: WHO declares COVID-19 a
  )
```

Event Study Design with Stock Markets

On February 2nd 2022, Meta (FB) release that its global daily active users declined from the previous quarter for the first time, to 1.929 billion from 1.930 billion. More Here



Event Study Design with Stock Markets

1. Event Identification:
   - (e.g., dividends, MA, stock buyback, laws or regulation, privatization vs. nationalization, celebrity endorsements, name changes, or brand extensions etc.).
   - Events must affect either cash flows or on the value of the firm (A. Sorescu, Warren, and Ertekin 2017, 191)
2. pick an estimation period
3. pick an observation period

Event Study Design

1. Use the data from the estimation period to estimate a model that can make a prediction of the stock's return in each period:
   1.1 Means-adjusted returns model: average in the estimation period $\hat{R} = \bar{R}$
   1.2 Market-adjusted returns models: Use the market return in each period $\hat{R} = R_M$
   1.3 Risk-adjusted returns model: relation in the estimation period btw returns

$$R = \alpha + \beta R_M + \epsilon$$

$$\hat{R} \quad \text{est.} \quad E[R|R_M]$$

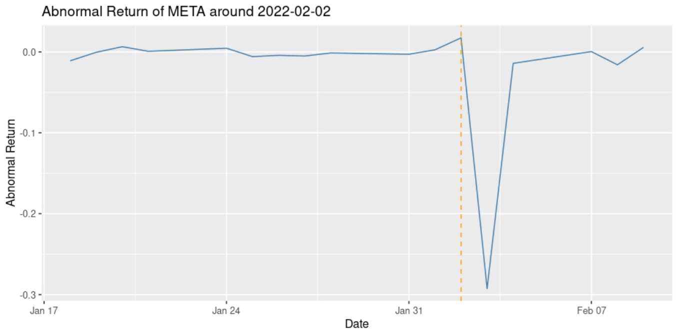
2. Calculate abnormal return $AR = R - \hat{R}$
3. Is AR constant during the observation period?

```r
library(tidyverse); library(lubridate)
sp500 <- read_csv("~/08-event-study/sp_500.csv")
meta <- read_csv("~/08-event-study/META.csv")

event <- ymd("2022-02-02")
# Create estimation data set
sp500 <- sp500 %>%
  mutate(returnSP=(Open-lag(Close))/Open, Date=format(as.Date(Date), "%Y-%m-%d"))
meta <- meta %>%
  mutate(returnM=(Open-lag(Close))/Open, Date=format(as.Date(Date), "%Y-%m-%d"))

est_data <- left_join(sp500, meta, by=c("Date")) %>%
  select(Date, returnM, returnSP) %>% filter(Date < event - days(4) )

# And observation data
obs_data <- est_data %>%
  filter(Date >= event - days(15) & Date <= event + days(7))
```

```r
# Estimate a model predicting stock price with market return
m <- lm(return_meta ~ return_sp_500, data = est_data)
# Get AR
obs_data <- obs_data %>%
  # Using mean of estimation return
  mutate(AR_mean = return_meta - mean(est_data$return_meta),
         # Then comparing to market return
         AR_market = return_meta - return_sp_500,
         # Then using model fit with estimation data
         risk_predict = predict(m, newdata = obs_data),
         AR_risk = return_meta - risk_predict)

# Graph the results
ggplot(obs_data, aes(x = ymd(Date), y = AR_risk, group=1)) +
  geom_line(color="steelblue") +
  geom_vline(aes(xintercept = ymd(event)), linetype = 'dashed', color="yellow") +
  ylab("Abnormal Return") + xlab("Date") +
  scale_colour_Publication() + theme_dark_blue()
```

Meta returns around the announcement of drop in users' accounts

Meta (FB) global daily active users declined from the previous quarter for the first time, to 1.929 billion from 1.930 billion.



Why is the Abnormal Return so Short-lived?

What we observe: META's stock dropped sharply after Feb 2, 2022 — but the abnormal return lasted only 1–2 days.

Why? Efficient Markets Digest News Quickly

- Prices adjust immediately when new public information arrives.
- The drop reflects a **one-time surprise** (decline in active users).
- After the shock, returns revert to **normal levels**.

Key idea: Abnormal return captures the difference from expected return, not the full price level.

- The price may stay low.
- But the "shock" only happens once — when the news hits.

Abnormal return is *short-lived* because markets are fast. No new surprise, no new abnormal return.

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Modelling long-lasting effects

$$Y_t = \beta_0 + \beta_1 t + \beta_2 \text{After}_t + \beta_3 (t \times \text{After}_t) + \varepsilon_t$$

- β_1: pre-event trend.
- β_2: one-time jump.
- β_3: change in slope □ persistent effect.

When to use it? Any intervention that keeps working over time: regulations, infrastructure, training programmes.

Serial correlation is inevitable → report HAC/Newey–West SEs.

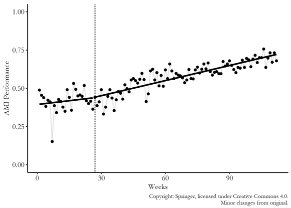
Case study: UK ambulance quality-of-care policy

Policy introduced mid-2010 to improve pre-hospital care for heart attack / stroke.

That's what Taljaard et al. (2014) look at. They run a regression of heart attack performance (AMI, or Acute Myocardial Infarction performance) on $Week - 27$ (subtracting 27 "centers" $Week$ at the event period, which allows the coefficient on $Week - 27$ to represent the jump in the line), $After$ (an indicator variable for being after the 27-week mark of the data where the policy was introduced), and an interaction tern between the two:[11]

$$AMI = \beta_0 + \beta_1(Week - 27) + \beta_2 After + \beta_3(Week - 27) \times After + \varepsilon \quad (17.2)$$

Their results for heart attack can be summarized by Figure 17.5. You can see the two lines that are fit to the points on the left and right sides of the event's starting period. That's the interaction term at work. The line to the left of 27 weeks is $\beta_0 + \beta_1(Week - 27)$, and the line to the right is $(\beta_0 + \beta_2) + (\beta_1 + \beta_3)(Week - 27)$.



- Clear kink → $\beta_3 < 0$: mortality trend fell faster post-policy.
- Taljaard et al. (2014) estimate HAC SEs to confirm significance.

Source: Taljaard, et al., 2014, *Int. J. Epidemiology*

From Simple Event Study to Other Designs

Classic event study = one unit, one date

before | event | after

When do we need more?

- **Many treated dates** (staggered rollout) → use staggered DiD
- **Treated & control groups** → use DiD or synthetic control
- **Treatment assigned by a cutoff** (age, score) → use RDD
- **No clean control — need theory** → use structural models

Goal: always find a credible counterfactual.

One shock, many firms: what changes?

Example. EU GDPR announcement hits every tech stock on the same day.

We now observe two kinds of variation:

1. **Time** — before vs. after the announcement
2. **Cross-section** — some firms more exposed than others

$$Y_{it} \; = \; \beta_i \; + \; \beta_1 t \; + \; \beta_2 \text{After}_t + \beta_3 t \times \text{After}_t + \varepsilon_{it}$$

- β_i soaks up level differences between firms.
- β_3 captures whether the **slope changes** after the shock.

Key question: which variation identifies β_3?

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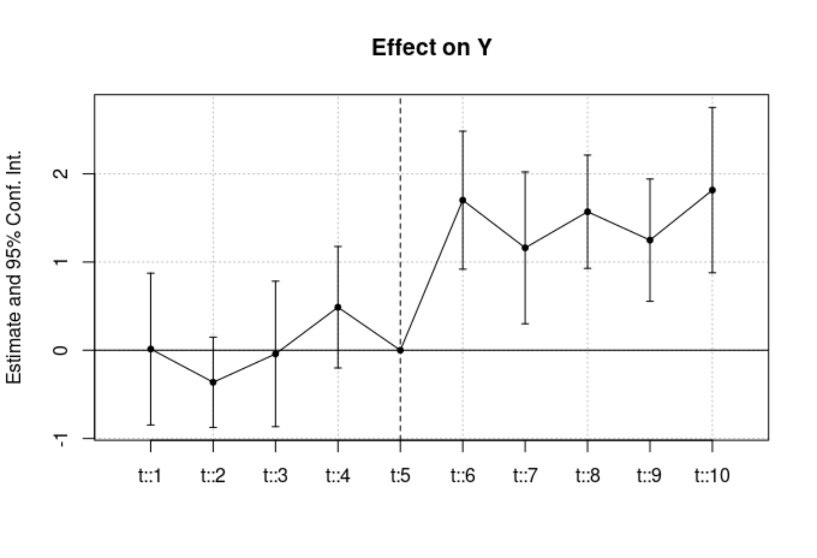
Key question: which variation identifies β_3?

```r
library(tidyverse); library(fixest)
set.seed(10)

# Create data with 10 groups and 10 time periods
df <- crossing(id = 1:10, t = 1:10) %>%
  # Add an event in period 6 with a one-period positive effect
  mutate(Y = rnorm(n()) + 1.5*(t >= 6))

# Use i() in feols to include time dummies,
# specifying that we want to drop t = 5 as the reference
m <- feols(Y ~ i(t, ref = 5), data = df,
           cluster = 'id')

# Plot the results, except for the intercep,# and add a line joining
# them and a space and line for the reference group
coefplot(m, drop = '(Intercept)',
         pt.join = TRUE, ref = c('t:5' = 6), ref.line = TRUE)
```


Effect on Y
Estimate and 95% Conf. Int.
-1
0
1
2
t::1
t::2
t::3
t::4
t:5
t::6
t::7
t::8
t::9
t::10

Difference-in-Differences (DiD)

Idea: Compare the change in outcomes for a treated group to the change for a control group.

- Controls for **unit fixed effects** via before/after difference.
- Controls for **common time shocks** via treated vs. control difference.

Two-period, two-group notation

$$\underbrace{\delta_1}_{\text{Treatment effect}} = \left(\overline{Y}_{2,\text{treat}} - \overline{Y}_{2,\text{control}}\right) - \left(\overline{Y}_{1,\text{treat}} - \overline{Y}_{1,\text{control}}\right)$$

β_0 : baseline in control
β_1 : baseline gap (treat vs. control)
δ_0 : common time shock
δ_1 : causal effect of treatment

*Subscripts: 1 = pre-treatment, 2 = post-treatment

Card & Krueger (1994)

Example: Minimum wage in New Jersey and Pennsylvania

- Card & Krueger (1994) study effect of rise in New Jersey minimum wage on employment in fast food restaurants
- NJ raised minimum wage from $4.25 to $5.05 in 1992
  - PA kept it the same
- Compare employment in fast food stores near the border to control for common trends in employment
  - e.g. business cycle effects
- Need to believe that NJ not growing faster/slower than PA

Employees per store by state and time (Card & Krueger Table 3)

Time / Unit	1991	1992	After-Before
PA	23.33	21.17	-2.16
———	———	———	———
NJ	20.44	21.03	0.59
———	———	———	———
NJ - PA	-2.89	-0.14	2.76

Interpretation

- PA fast food employment shrank, while NJ fast food employment grew slightly
- If we believe nothing different going on in two states aside from minimum wage, this suggests minimum wage raised employment
- Inconsistent with theory that higher minimum wage lowers unemployment

Regression Discontinuity Design

The UK minimum wage at 22 years of age: a regression discontinuity approach

Richard Dickens,

University of Sussex, Brighton, UK

Rebecca Riley

National Institute of Economic and Social Research, London, and Centre for Learning and Life Chances in Knowledge Economies, London, UK

and David Wilkinson

National Institute of Economic and Social Research, London, UK

[Received July 2011. Final revision August 2012]

Summary. A regression discontinuity approach is used to analyse the effect of the legislated increase in the UK national minimum wage that occurs at age 22 years on various labour market outcomes. Using data from the Labour Force Survey we find an increase of 3–4 percentage points in the rate of employment of low skilled individuals. Unemployment declines among men and inactivity among women. We find no such effect before the national minimum wage was introduced and no robust impacts at age 21 or 23 years. Our results are robust to a range of specification tests.

Keywords: Labour supply; Minimum wages; Policy evaluation; Regression discontinuity; Youth labour market

in France on labour supply. Define a dummy variable that is an indicator for whether someone has passed their 22nd birthday:

$$\text{Dum}_i = \begin{cases} 1 & \text{if } \text{age}_i \geqslant 22, \\ 0 & \text{if } \text{age}_i < 22 \end{cases}$$

where age_i is the individual's age measured in years. We then estimate the following reduced form regression:

$$y_i = f(\text{age}_i, a) + \beta\,\text{Dum}_i + \delta X_i + u_i. \tag{1}$$

- y_i is an employment-related measure for individual i (i.e. a dummy indicating employment status),
- f(age,a) is a flexible polynomial in age with parameters a
- X_i is a set of covariates for individual i

β is the (causal) effect on employment of the increase in the NMW from the youth to the adult rate.

The effect of the threshold on the employment

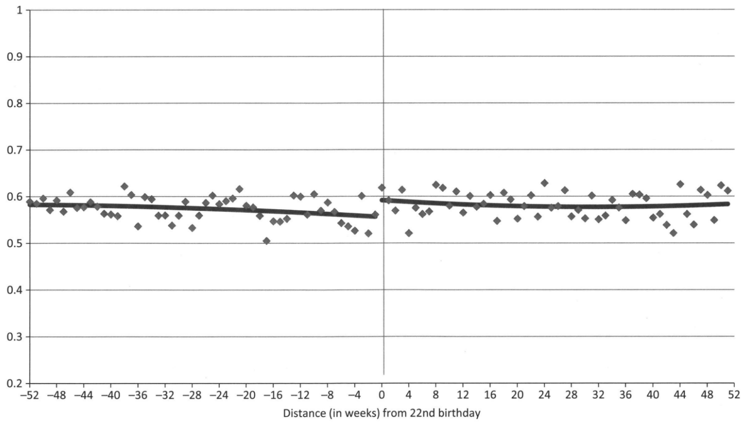


Fig. 2. Employment rate by age in weeks for all low skilled individuals (source, LFS); ♦, actual; ——, predicted

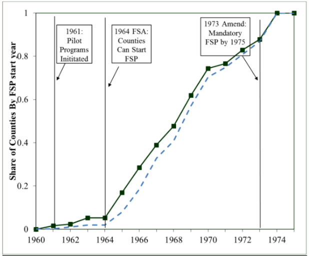
Caption

Multiple affected Groups

Staggered adoption: everyone is treated, but treatment length differs by group
Use: policy is introduced in many different states during many different time periods

Hoynes et al. (2016) use staggered roll-out as their identification strategy to assess the long-run effects of childhood access to the safety net

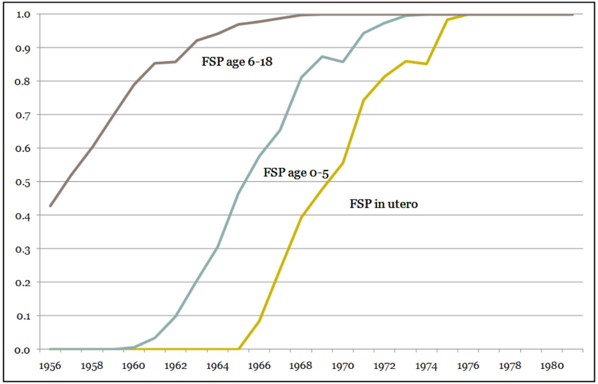
Appendix Figure 1: Weighted Percent of Counties with Food Stamp Program, 1960-1975



Source: Authors' tabulations of food stamp administrative data (U.S. Department of Agriculture, various years). Counties are weighted by their 1960 population. Solid line uses all counties and dashed line uses counties represented in the PSID sample.

Multiple affected Groups

Appendix Figure 2: Food Stamp Exposure in Early Life, Variation by Birth Cohort



Note: Authors' tabulations of food stamp administrative data (U.S. Department of Agriculture, various years) and PSID sample.

Economic models as Counterfactuals

Immagine that you want to evaluate the effect of the effect of the enforcement of a Regional Trade Agreement between countries on their trade flows.

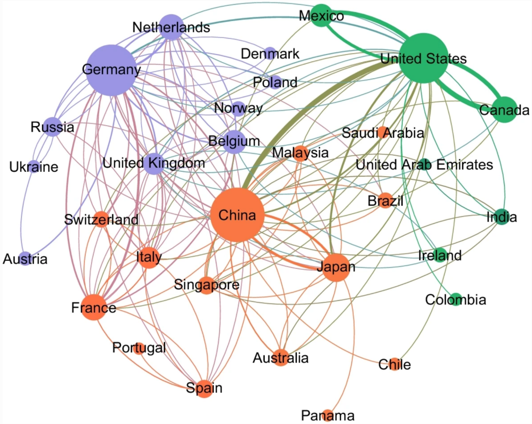
What are Regional Trading Agreements? Regional trading agreements refer to a treaty that is signed by two or more countries to encourage the free movement of goods and services across the borders of its members.

Economic models as Counterfactuals

Immagine that you want to evaluate the effect of the effect of the enforcement of a Regional Trade Agreement between countries on their trade flows.

What are the drivers of trade?

From: Analysis of the global trade network using exponential random graph models



The trades network is depicted using a sample of all trades in 2011. Node sizes and edge thicknesses are proportional to degree and edge weight, respectively. The countries in the same community calculated using the Louvain algorithm are depicted using the same color

Box 1 Analogy between the Newtonian theory of gravitation and the gravity trade model

To see the remarkable resemblance between the trade gravity equation and the corresponding equation from physics, two terms, T_{ij}^{θ} and $\tilde{G}$ have to be defined in equation (1-8) as reported in the right-hand side of the table below.

Newton's Law of Universal Gravitation	*Gravity Trade Model*
$F_{ij} = G\frac{M_i M_j}{D_{ij}^2}$	$X_{ij} = \tilde{G}\frac{Y_i E_j}{T_{ij}^{\theta}}$
where:	where:
– F_{ij}: gravitational force between objects i and j	– X_{ij}: exports from countries i and j
– G: gravitational constant	– $\tilde{G}$: inverse of world production $\tilde{G} \equiv 1/Y$
– M_i: object i's mass	– Y_i: country i's domestic production
– M_j: object j's mass	– E_j: country j's aggregate expenditure
– D_{ij}: distance between objects i and j	– T_{ij}^{θ}: total trade costs between countries i and j $T_{ij}^{\theta} \equiv \left(t_{ij}/\left(\Pi_i P_j\right)\right)^{\sigma-1}$

Based on the metaphor of Newton's Law of Universal Gravitation, the gravity model of trade predicts that international trade (gravitational force) between two countries (objects) is directly proportional to the product of their sizes (masses) and inversely proportional to the trade frictions (the square of distance) between them.

Counterfactuals in Trade

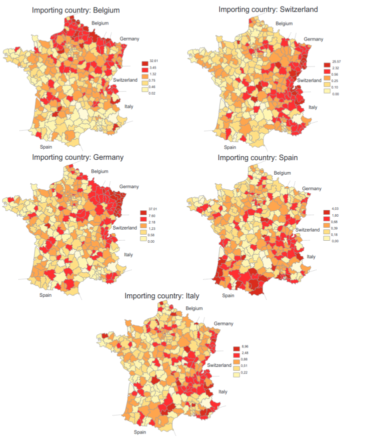
Trade flows$_{ij}$ $=$ Size$_i$ $\times$ Size$_j$ $\times$ Frictions to trade$_{ij}$

- Size=$\frac{Y_i E_j}{Y}$
- Frictions:

1. Bilateral trade cost between partners i and j, $t_i j$, is typically approximated in the literature by various geographic and trade policy variables, such as bilateral distance, tariffs etc.
2. The structural term Pj , coined by Anderson and van Wincoop (2003) as inward multilateral resistance represents importer j's ease of market access.
3. The structural term Πi , defined as outward multilateral resistances by Anderson and van Wincoop (2003), measures exporter i's ease of market access

Intensive Margin of Trade: Export Value

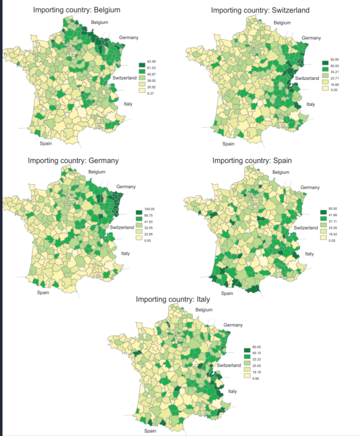
Figure 1: Mean value of individual-firm exports (single-region firms, 1992)



Head and Mayer (2014)

Extensive Margin of Trade: Number of non-zero trade flows

Figure 2: Percentage of firms which export (single-region firms, 1992)



Head and Mayer (2014)

Reduced Form Estimation

Two Commonly-Used Reduced-Form Estimators

1. OLS Estimation:

$$lnX_{ij} = \underbrace{\beta_d lnDist_{ij} + Controls_{ij} + M_i + X_j}_{\beta Z_{ij}} + \epsilon_{ij}. \tag{1}$$

   - moment condition: $\sum_{ij} Z_{ij} \dot{(} lnX_i j - ln\hat{X}_{ij}) = 0$

2. PPML Estimation:

$$Xij = exp\underbrace{(\beta_d lnDist + ij + Controls_{ij} + M_i + X_j)}_{\beta Z_{ij}} + \epsilon_{ij} \tag{2}$$

   - moment condition: $\sum_{ij} Z_{ij} \dot{(} X_i j - \hat{X}_{ij}) = 0$

PPML vs OLS

Advantages of the PPML estimator:

1. It can naturally account for zeros
2. The estimated fixed effects, $\hat{M}_i$ and $\hat{X}_i$, are consistent with equilibrium conditions (Fally, 2015).
3. Provides consistent estimates in the presence of heteroskedasticity.

Disadvantage of the PPML estimator: it is prone to small sample bias.

Estimating the effects of being part of an RTA

$$X_{ij,t} = \exp\left[\pi_{i,t} + \chi_{j,t} + \beta_{DIST} \ln DIST_{ij} + \beta_{RTA} RTA_{ij,t} + \beta_{TARIFF} \tilde{\tau}_{ij,t}\right] \times \varepsilon_{ij,t} \qquad (1\text{-}15)$$

The variable ln $DIST_{ij}$ denotes the logarithm of bilateral distance between countries i and j. The covariate $RTA_{ij,t}$ represents an indicator variable taking the value of one if there is a RTA between countries i and j at time t, and zero otherwise. For expositional purposes, both variables ln $DIST_{ij}$ and $RTA_{ij,t}$ will be used, respectively, as representative continuous variable and dummy variable in gravity regressions. Finally, $\tilde{\tau}_{ij,t} = \ln(1 + tariff_{ij,t})$ accounts for bilateral tariffs, where $tariff_{ij,t}$ is the ad-valorem tariff that country j imposes on imports from country i at time t. Importantly, as emphasized earlier, the coefficient on bilateral tariffs, $\tilde{\tau}_{ij,t}$, can be interpreted in the context of the structural gravity model as the trade elasticity of substitution, namely $\beta_{TARIFF} = -\sigma$. Overall, the interpretation of the coefficient on tariffs in gravity regressions depends on the trade flow data used to estimate the model, which here are assumed to be expressed at *cost, insurance and freight (c.i.f) prices*, but not tariffs. See Appendix B of this chapter for further details.

Caption: Yoto V. Yotov et al.

Meta Analysis of gravity estimates

Table 3.4 Estimates of Typical Gravity Variables

	All Gravity				Structural Gravity			
Estimates:	**Median**	**Mean**	**s.d.**	**#**	**Median**	**Mean**	**s.d.**	**#**
Origin GDP	.97	.98	.42	700	.86	.74	.45	31
Destination GDP	.85	.84	.28	671	.67	.58	.41	29
Distance	−.89	−.93	.4	1835	−1.14	−1.1	.41	328
Contiguity	.49	.53	.57	1066	.52	.66	.65	266
Common language	.49	.54	.44	680	.33	.39	.29	205
Colonial link	.91	.92	.61	147	.84	.75	.49	60
RTA/FTA	.47	.59	.5	257	.28	.36	.42	108
EU	.23	.14	.56	329	.19	.16	.5	26
NAFTA	.39	.43	.67	94	.53	.76	.64	17
Common currency	.87	.79	.48	104	.98	.86	.39	37
Home	1.93	1.96	1.28	279	1.55	1.9	1.68	71

Notes: The number of estimates is 2508, obtained from 159 papers. Structural gravity refers here to some use of country fixed effects or ratio-type method.

Source: Head and Mayer (2014, Handbook Chapter)

The effect of RTAs

Table 3 Estimating the Effects of Regional Trade Agreements

	(1) *OLS*	(2) *PPML*	(3) *INTRA*	(4) *ENDG*	(5) *LEAD*	(6) *PHSNG*	(7) *GLBZN*
Log distance	−1.216	−0.822	−0.800				
	(0.039)**	(0.031)**	(0.030)**				
Contiguity	0.223	0.416	0.393				
	(0.203)	(0.083)**	(0.079)**				
Common language	0.661	0.250	0.244				
	(0.082)**	(0.077)**	(0.077)**				
Colony	0.670	−0.205	−0.182				
	(0.149)**	(0.114)+	(0.113)				
RTA	−0.004	0.191	0.409	0.557	0.520	0.291	0.116
	(0.054)	(0.066)**	(0.069)**	(0.102)**	(0.086)**	(0.089)**	(0.087)
RTA($t+4$)					0.077		
					(0.092)		
RTA($t-4$)						0.414	0.288
						(0.067)**	(0.062)**
RTA($t-8$)						0.169	0.069
						(0.043)**	(0.048)
RTA($t-12$)						0.119	0.002
						(0.030)**	(0.029)
International border 1986							−0.706
							(0.048)**
International border 1990							−0.480
							(0.043)**
International border 1994							−0.367
							(0.033)**
International border 1998							−0.158
							(0.023)**
International border 2002							−0.141
							(0.017)**
Observations	25689	28152	28566	28482	28482	28482	28482
Total RTA effect						0.992	0.475
						(0.094)**	(0.109)**
Intra-national trade	No	No	Yes	Yes	Yes	Yes	Yes

Source: Authors' calculations

Notes: All estimates are obtained with data for the years 1986, 1990, 1994, 1998, 2002, and 2006, and use exporter-time and importer-time fixed effects. The estimates of the fixed effects are omitted for brevity. Columns (1) and (2) use data on *international* trade flows only. Column (1) applies the OLS estimator and column (2) uses the PPML estimator. Column (3) adds *intra-national* trade observations and uses country-specific dummies for internal trade. Column (4) adds pair fixed effects. The estimates of the pair fixed effects are omitted for brevity. Column (5) introduces RTA lead. Column (6) allows for phasing-in effects of RTAs. Finally, column (7) accounts for the effects of globalization. Standard errors are clustered by country pair and are reported in parentheses. The *p*-values read as follows: $^{+}\ p < 0.10$; $^{*}\ p < 0.05$; and $^{**}\ p > 0.01$.

Other studies using the Gravity framework as counterfactual

- Effect of trade liberalizations (NAFTA, Mexico-US Canada) trade agreements, etc.
- Eu integration
- Migration flows

Sources

- About event data design, Nick Huntington-Klein, here
- About Gravity estimation, here