

# Research and R

EC 607, Set 01

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Edward Rubin  
Spring 2020

# Prologue

# Schedule

## Today

- Welcome, check in, **admin**, and survey
- Research basics: *Why are we here?* *MHE*: Preface & Ch. 1
- Our class: *What are we doing?*
- R: Part of our *how* in this class: Install and basics.

## Upcoming

- Learn more R.
- Review metrics and building intuition for causality and inference.
- Build momentum.

## Long run

**Goal:** Deepen understandings/intuitions for causality and inference.

# Research

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- **You**

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- **You:** You should be thinking about this question throughout your program/work/life. **Self awareness and mental health are important.**

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For many of people, **this course marks a big shift** in how school works.

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The material and tools are pivotal for **a lot** of what you will do in the future.

### **Take responsibility for your education and career.**

- Commit to spending the necessary time.
- Be proactive and curious.
- Go down rabbit holes.
- Ask questions.
- Learn.



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**A<sub>1/∞</sub>** Causality. 🐱

🐱 Sources for this Q and A: [Dan Hammer](#) and [Max Auffhammer](#).

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**Note:** There are large parts of econometrics that focus on *prediction* rather than *causality* (e.g., forecasting and prediction—see [Jeremy Piger](#)).<sup>†</sup>

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Causality plays a *huge* role in modern applied econometrics (esp. in micro).

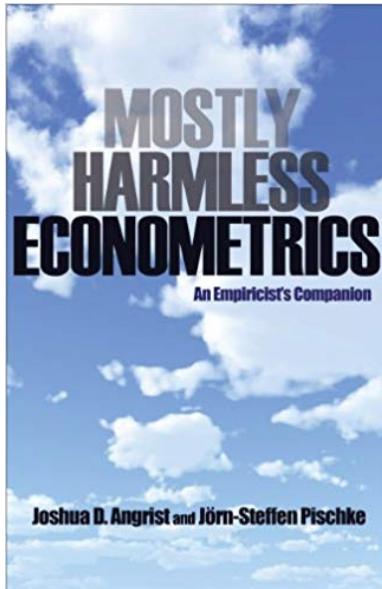
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Toward this end—causality—we will use two books (favoring *MHE*).

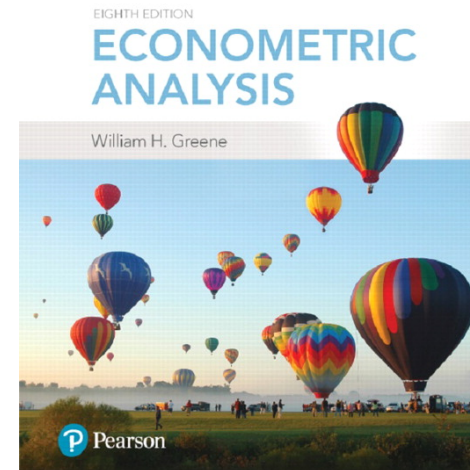
## **Mostly Harmless Econometrics**

*Angrist and Pischke, 2008*



## **Econometric Analysis**

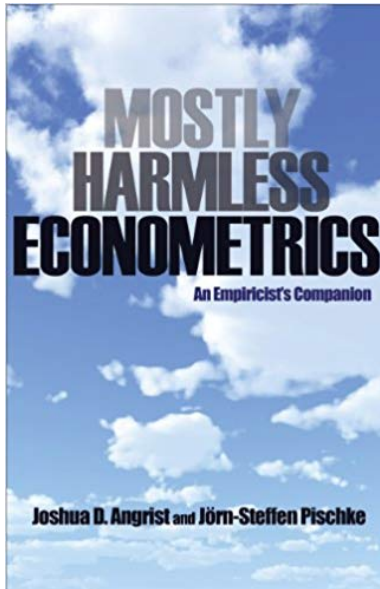
*Greene, 2018*



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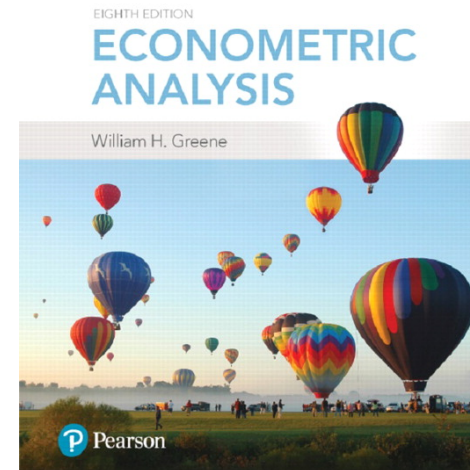
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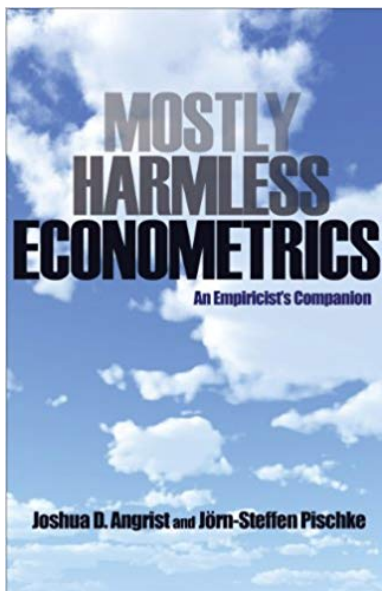
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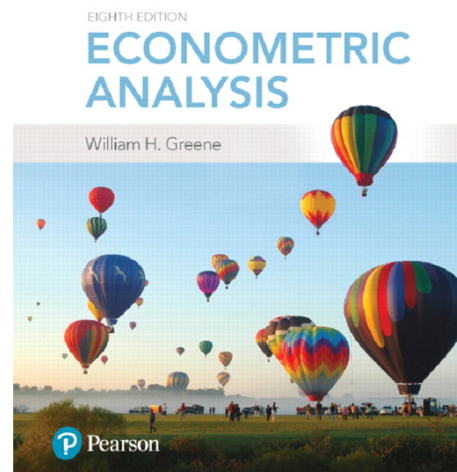


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## Econometric Analysis

Greene, 2018



More of a reference/encyclopedia.  
Classic metrics theory.

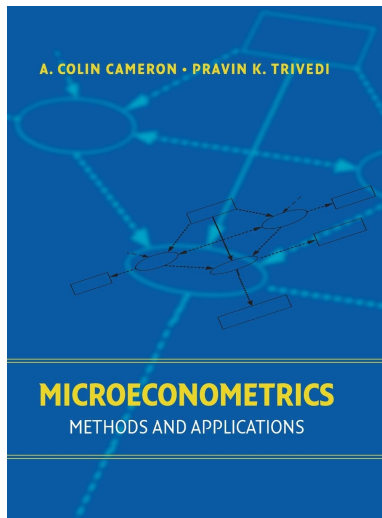
*Greene*



While you're at it, buy one or two more...

## Microeconometrics: Methods and Applications

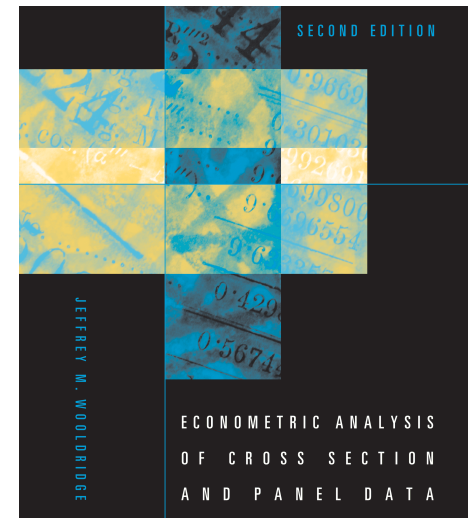
*Cameron and Trivedi, 2005*



We will use more C&T than Greene.

## Econometric Analysis of Cross Section and Panel Data

*Wooldridge, 2010*



This book has some great sections.

# Causal research

## Motivation

First, we believe that empirical research is most valuable when it uses data to answer specific causal questions, as if in a randomized clinical trial. This view shapes our approach to most research questions. In the absence of a real experiment, we look for well-controlled comparisons and/or natural quasi-experiments. Of course, some quasi-experimental research designs are more convincing than others, but the econometric methods used in these studies are almost always fairly simple.

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1. This ideology inherently compares research to "gold-standard" RCTs.
2. The methods are usually (relatively) straightforward (after training).

# Causal research

## Angrist and Pischke's FAQs<sup>†</sup>

1. What is the **causal relationship of interest**?
2. How would an **ideal experiment** capture this causal effect of interest?
3. What is your **identification strategy**?
4. What is your **mode of inference**?

<sup>†</sup> See *MHE*, chapter 1. <sup>††</sup> Credit for these questions goes to [Reed Walker](#).

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**Note:** Other questions also matter for developing quality research, e.g.,<sup>††</sup>

- Why is your question **important/interesting**?
- Why is the **current literature** lacking or nonexistent?
- How do you propose to **advance the literature**?

<sup>†</sup> See *MHE*, chapter 1. <sup>††</sup> Credit for these questions goes to [Reed Walker](#).

# Causal research

## FAQ<sub>1</sub>: What is the causal relationship of interest?

Descriptive exercises can be **very interesting and important**, but in modern applied econometrics, **causality is king**.

**Why?**

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### **Why?**

- Causal relationships directly **test theories** of how the world works.
- Causal relationships provide us with **counterfactuals**—how the world would have looked with different sets of policies/circumstances.




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 If you can't clearly and succinctly name the causal relationship of interest, then you may not actually have a research project.

# Causal research

FAQ<sub>1</sub>: What is the causal relationship of interest?

*Some classic examples...*

## **Labor and Education**

How does an additional year of schooling affect wages?

## **Political Economy and Development**

How do democratic institutions affect economic development?

## **Environment and Urban**

Do the poor receive substantive benefits from environmental clean ups?

## **Health, Crime, and Law**

Do gun-control laws actually reduce gun violence?

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## FAQ<sub>2</sub>: What is the ideal experiment for this setting?

Describing the *ideal experiment* helps us formulate


- the **exact causal question(s)**
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Angrist and Pischke call questions without ideal experiments *fundamentally unanswerable questions* (FUQs).

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*Examples of potentially answerable questions...*

- **The effect of education on wages:** Randomize scholarships or incentives to remain in school.
- **Democracy and development:** Arbitrarily assign institutional types to countries as they receive independence.
- **Environmental cleanups:** Ask EPA to randomly clean toxic sites.
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*Examples of challenging questions to answer (potentially unanswerable?)...*

- How does gender affect eventual career paths?
- What role does race play in one's wages?

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### **Proposed ideal experiment**

1. Randomize kids to start 1<sup>st</sup> grade at age 6 or 7.
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**Problem** Kids who started later are older in 2<sup>nd</sup> grade. Older kids do better. Do we want the effect of starting later or just being older?

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2. [Control for age](#). Compare test scores when kids are age 8.

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**Problem<sub>2.0</sub>** The two groups will have been in school for different numbers of years (1 vs. 2). More school should mean better scores.

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**Central problem:** Mechanical links between ages and time in school.

$$(\text{Start Age}) = (\text{Current Age}) - (\text{Time in School})$$

No experiment can separate these effects (for school-age children).



# Causal research

## FAQ<sub>3</sub>: What's your identification strategy?

This question 🖐️ describes how you plan to recover/observe *as good as random* assignment of your variable of interest (approximating your ideal experiment) **in real life**.

### **Examples**

- Compulsory school-attendance laws *interacted with* quarter of birth
- Vietnam War draft
- Thresholds for the Clean Air Act violations
- Notches in income-tax policies
- Judge assignments
- Randomly assigned characteristics on résumés

🖐️ You will hear this question asked *a lot*.

# Causal research

## FAQ<sub>3</sub>: What's your identification strategy?

*A brief history*

The term "identification strategy" goes back to Angrist and Krueger (1991).

However, the comparison of *ideal* and *natural* experiments goes back much farther to Haavelmo (1944)...

# Causal research

A design of experiments... is an essential appendix to any quantitative theory. And **we usually have some such experiment in mind when we construct the theories**, although-unfortunately-most economists do not describe their design of experiments explicitly. If they did, they would see that the experiments they have in mind may be grouped into two different classes, namely, (1) **experiments that we should like to make to see if certain real economic phenomena—when artificially isolated from "other influences"**—would verify certain hypotheses, and (2) **the stream of experiments that Nature is steadily turning out from her own enormous laboratory**, and which we merely watch as passive observers. In both cases the aim of the theory is the same, to become master of the happenings of real life.

*Haavelmo, 1944 (color added)*

# Causal research

## FAQ<sub>4</sub>: What is your mode of inference?

Historically, inference—standard errors, confidence intervals, hypothesis tests, *etc.*—has received much less attention than point estimates. It's becoming more important (more than an afterthought).

- Which **population** does your sample represent?
- How much **noise** (error) exists in your estimator (and estimates)?
- How much **variation** do you actually have in your variable of interest?

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Without careful inference, we don't know the difference between

- 21%  $\pm$  2.3%
- 21%  $\pm$  20.3%

# Our class

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## Mini-syllabus

**Class** Attend/participate. Read assigned readings—especially papers.

**Lab** Practice applying our in-class content in  $\mathbb{R}$  with Colleen/me. Attend.

**Problem sets** 2–5 (3?) problem sets mixing theory and applications in  $\mathbb{R}$ .

**Other grades** Project plus 1–2 take-home exams.

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**Note:** This class/quarter is under development.

- **Challenge:** Less structure.
- **Benefit:** You get more say in what we cover/do. Participate!



R

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What does that mean?

- R was created for the statistical and graphical work required by econometrics.
- R has a vibrant, thriving online community (e.g., [Stack Overflow](#)).
- Plus it's **free** and **open source**.

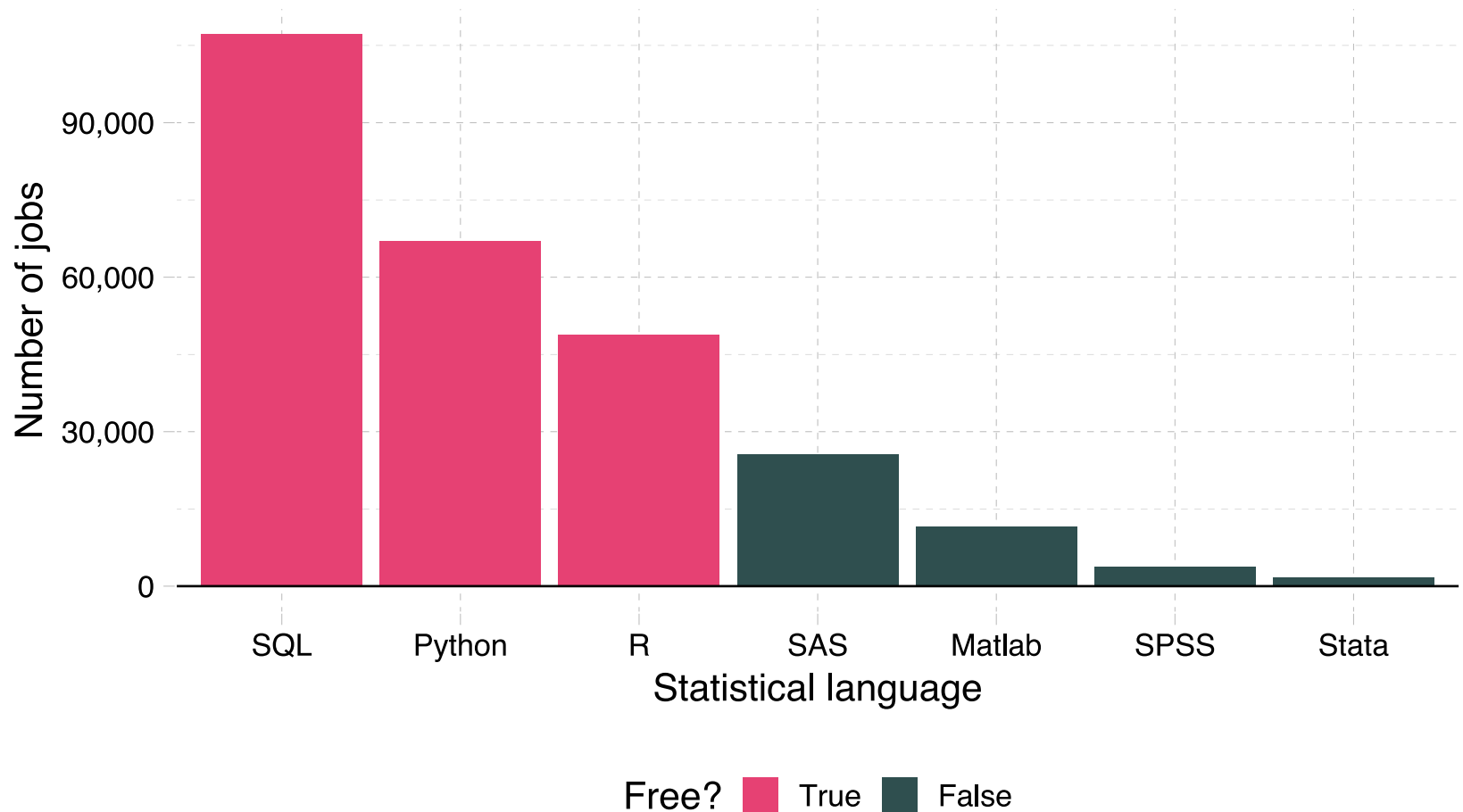
# R basics

## Why are we using R?

1. R is **free** and **open source**—saving both you and the university 💰💰💰.
2. *Related:* Outside of a small group of economists, private- and public-sector **employers favor R** over Stata and most competing softwares.
3. R is very **flexible and powerful**—adaptable to nearly any task, *e.g.*, 'metrics, spatial data analysis, machine learning, web scraping, data cleaning, website building, teaching. [My website](#), the [TWEEDS website](#), and these notes all came out of R.

## Comparing statistical languages

Number of job postings on Indeed.com, 2019/01/06




# R basics

## Why are we using R?

4. *Related*: R imposes **no limitations** on your amount of observations, variables, memory, or processing power. (I'm looking at **you**, Stata.)

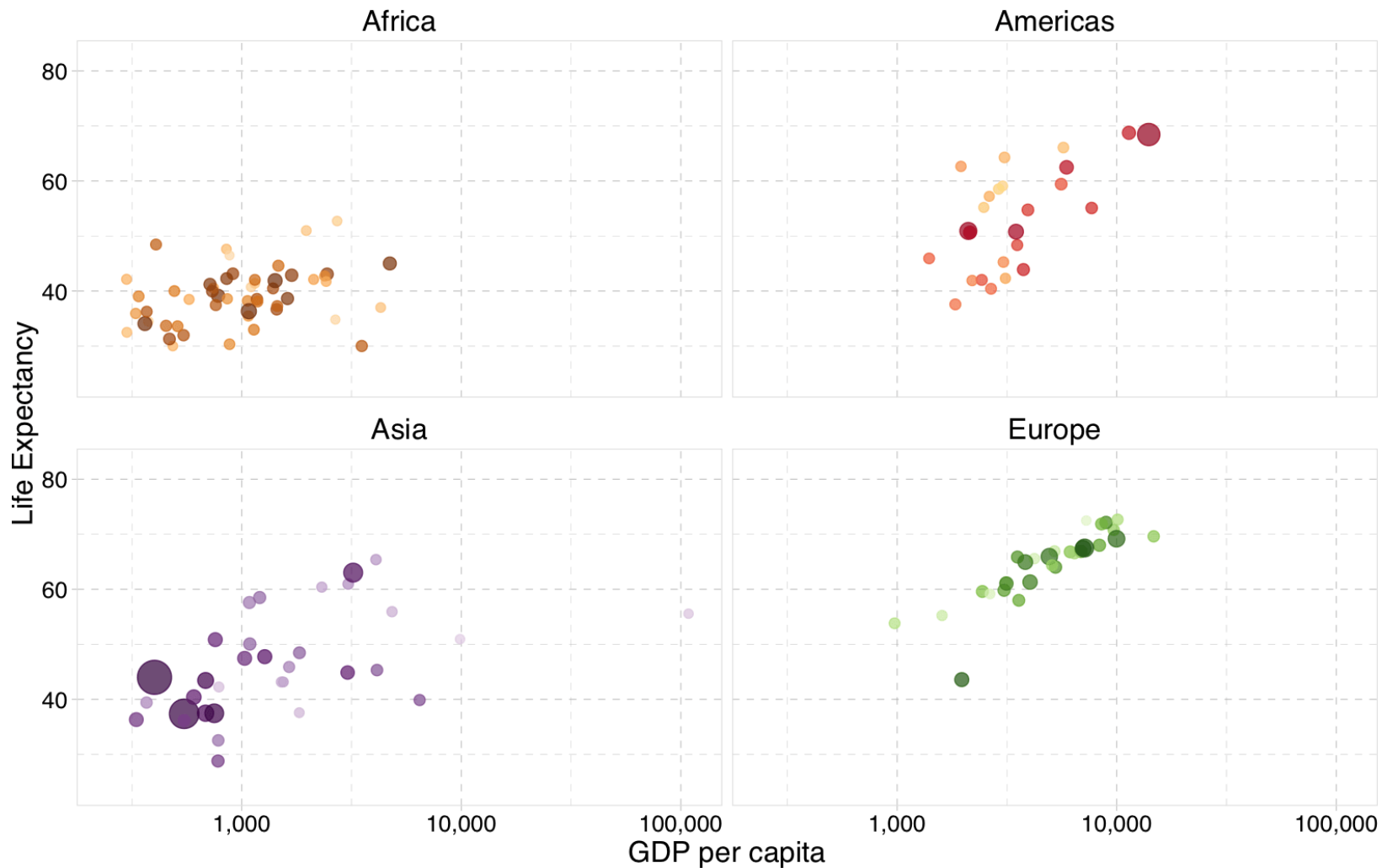
5. If you put in the work,<sup>■</sup> you (and your students!) will come away with a **valuable and marketable** tool.

6. I  R

 : Learning R definitely requires time and effort.

# R basics

Year: 1952



# R basics

## The install

Installing R is fairly straightforward, but it occasionally involves challenges for older computers.

**Step 1:** Download ([r-project.org](https://www.r-project.org)) and install R for your operating system.

**Step 2:** Download ([rstudio.com](https://www.rstudio.com)) and install RStudio Desktop for your operating system.

DataCamp has a nice tutorial on installing R and RStudio for Windows, Mac, and Linux operating systems.<sup>†</sup>

<sup>†</sup> I applied for free access to DataCamp for our class. I'll let you know when I hear back.



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5. R will try to **help** you.

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5. R will try to **help** you.

```
?dplyr
```

# R basics

## Fundamentals

Let's get started. There are a few principals to keep in mind with R:

1. Everything is an **object**.

```
foo
```

2. Every object has a **name** and **value**.

```
foo ← 2
```

3. You use **functions** on these objects.

```
mean(foo)
```

4. Functions come in **libraries (packages)**

```
library(dplyr)
```

5. R will try to **help** you.

```
?dplyr
```

6. R has its **quirks**.

# R basics

## Fundamentals

Let's get started. There are a few principals to keep in mind with R:

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foo
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foo ← 2
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3. You use **functions** on these objects.

```
mean(foo)
```

4. Functions come in **libraries (packages)**

```
library(dplyr)
```

5. R will try to **help** you.

```
?dplyr
```

6. R has its **quirks**.

```
NA; error; warning
```

## Fundamentals of functions

Functions operate on objects, but they need some guidance—arguments.

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**Example:** `ex_fun(arg1, arg2, arg3)`

## Fundamentals of functions

Functions operate on objects, but they need some guidance—arguments.

**Example:** `ex_fun(arg1, arg2, arg3)`

- Our function is named `ex_fun`.
- This function takes three arguments: `arg1`, `arg2`, `arg3`.
- You can tell R which values to assign to which arguments:  
`ex_fun(arg1 = 13, arg2 = 25, arg3 = 7)` (probably best practice)
- ... or R will assign the values using the arguments' defined order:  
`ex_fun(13, 25, 7)` (shorter/lazier but has the same result)
- You must assign a name to a function's outputted object (to keep it).



# R basics

## Example function: `matrix`

We will need to create matrices in this class.

Enter: R's `matrix()` function!

```
# 3x2 matrix filled w/ zeros
matrix(
  data = 0, nrow = 3, ncol = 2
)
```

```
#>      [,1] [,2]
#> [1,]    0    0
#> [2,]    0    0
#> [3,]    0    0
```

```
# 3x2 matrix filled w/ zeros
matrix(
  data = 0, nrow = 3, ncol = 2
)
```

```
#>      [,1] [,2]
#> [1,]    0    0
#> [2,]    0    0
#> [3,]    0    0
```

```
# 3x2 matrix filled w/ 1 to 6
matrix(
  data = 1:6, nrow = 3, ncol = 2
)
```

```
#>      [,1] [,2]
#> [1,]    1    4
#> [2,]    2    5
#> [3,]    3    6
```

```
# 3x2 matrix filled w/ 1:6 by row  
matrix(  
  data = 1:6, nrow = 3, ncol = 2,  
  byrow = T  
)
```

```
#>      [,1] [,2]  
#> [1,]    1    2  
#> [2,]    3    4  
#> [3,]    5    6
```

```
# 3x2 matrix filled w/ 1:6 by row
matrix(
  data = 1:6, nrow = 3, ncol = 2,
  byrow = T
)
```

```
#>      [,1] [,2]
#> [1,]    1    2
#> [2,]    3    4
#> [3,]    5    6
```

```
# 3x2 matrix filled w/ 1:3
matrix(
  data = 1:3,
  nrow = 3, ncol = 2
)
```

```
#>      [,1] [,2]
#> [1,]    1    1
#> [2,]    2    2
#> [3,]    3    3
```

```
# 3x2 matrix filled w/ 1:6 by row
matrix(
  data = 1:6, nrow = 3, ncol = 2,
  byrow = T
)
```

```
#>      [,1] [,2]
#> [1,]    1    2
#> [2,]    3    4
#> [3,]    5    6
```

```
# 3x2 matrix filled w/ 1:3
matrix(
  data = 1:3,
  nrow = 3, ncol = 2
)
```

```
#>      [,1] [,2]
#> [1,]    1    1
#> [2,]    2    2
#> [3,]    3    3
```

```
# 3x2 matrix filled w/ 1:3
# Assigned to memory
our_matrix ← matrix(
  data = 1:3,
  nrow = 3, ncol = 2
)
```

## Help and functions

**Q** How do we know which arguments a function requires/accepts?

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**A** ?



## Help and functions

**Q** How do we know which arguments a function requires/accepts?

**A** `?` Meaning you can type `?matrix` into your R console to find the help file associated with the functions/objects named `matrix`.

## Help and functions

**Q** How do we know which arguments a function requires/accepts?

**A** `?` Meaning you can type `?matrix` into your R console to find the help file associated with the functions/objects named `matrix`.

**Double bonus:** Use `??matrix` to perform a fuzzy search for the term `matrix` in all of the help files.

# R basics

## Example function: `matrix`

**Q** How do we know which arguments a function requires/accepts?

**A<sub>2</sub>** `RStudio` will also try to help you.

- Type a name (e.g., `matrix`) into the console; `RStudio` will show you some info about the function.
- After you type the name and parentheses (e.g., `matrix()`), press `tab`, and `RStudio` will show you a list of arguments for the function.

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