

Introduction and Overview

EC 421, Set 1

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Prologue

Why?

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One simple answer: Learn about the world using data.

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2. Why do economists (or other people) study or use econometrics?

One simple answer: Learn about the world using data.

- *Learn about the world* = Raise, answer, and challenge questions, theories, assumptions.
- *data* = Plural of datum.

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Example

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where

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We expect that sales ↑ with advertising and ↓ with price and competition.

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We can *test* these hypotheses **using regression**.

More importantly: Regression estimates the *size* of these effects

- *How much* does an additional dollar of *advertising* increase *sales*?
- *How much* does a one-dollar increase in *price* decrease *sales*?
- *How much* does an additional *competitor* reduce *sales*?

These (causal) questions are central to efficient decision-making and are the bread and butter of econometrics.

Why?

Example, cont.

Regression model:

$$\text{Sales}_i = \beta_0 + \beta_1 \text{Ad}_i + \beta_2 \text{Price}_i + \beta_3 \text{Comp}_i + \varepsilon_i$$

With this basic regression model, we can test/estimate/quantify the (linear) relationship between sales and advertising, price, and competition.

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(Review) Questions

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(Review) Questions

- Q: How do we interpret β_1 ?

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- Q: How do we interpret β_1 ?
- A: An additional dollar of advertising corresponds with a β_1 -unit change in sales (holding price and competition fixed).

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- Q: Are the β_k terms population parameters or sample statistics?

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- A: Greek letters denote **population parameters**. Their estimates get hats, e.g., $\hat{\beta}_k$. Population parameters represent the **average** behavior across the population.

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- Q: Can we interpret the estimates for β_2 as causal?

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(Review) Questions

- Q: Can we interpret the estimates for β_2 as causal?
- A: Not without making more assumptions and/or knowing more about the data-generating process.

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(Review) Questions

- Q: What is ε_i ?
- A: An individual's random deviation/disturbance from the population parameters.

Population parameters are averages; individuals are rarely average.

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- A:
 - The relationship between the sales and the **explanatory variables** is linear in parameters, and ε enters additively.
 - The **explanatory variables** are **exogenous**, i.e., $E[\varepsilon|X] = 0$.
 - You've also typically assumed something along the lines of:
 $E[\varepsilon_i] = 0$, $E[\varepsilon_i^2] = \sigma^2$, $E[\varepsilon_i \varepsilon_j] = 0$ for $i \neq j$.
 - And (maybe) ε_i is distributed normally.

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However, the results you learned required assumptions.

Real life often violates these assumptions.

EC421 asks "What happens when we violate these assumptions?"

- Can we find a fix? (Especially: How/when is β causal?)
- What happens if we don't (or can't) apply a fix?

OLS still does some amazing things—but you need to know when to be **cautious, confident, or dubious.**

Not everything is causal

But what *is*?

Suppose you estimate our sales model for your boss.

$$\text{Sales}_i = \hat{\beta}_0 + \hat{\beta}_1 \text{Ad}_i + \hat{\beta}_2 \text{Price}_i + \hat{\beta}_3 \text{Comp}_i + e_i$$

Can you trust that $\hat{\beta}_2$ gives you the actual effect of **price** on **sales**?

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1. *Where* does the *variation in price* come from?
 - Is it *random* (*exogenous*)?
 - *Why* are some products (or times) *more* expensive than others?
2. *Whom* do the data represent? Are they *relevant* to your setting?
3. How *confident* are you in your answer?

Econometrics

Applied econometrics, data science, analytics require:

1. Intuition for the **theory** behind statistics/econometrics
(assumptions, results, strengths, weaknesses).
2. Practical knowledge of how to **apply theoretical methods** to data.
3. Efficient methods for **working with data**
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- 1: As before.
- 2–3: R

Econometrics

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- most interesting questions are **causal**;
- **selection into treatment** dominates correlation (esp. cross-sectional);
- **measurement error** can too;
- causality comes from **design**—not from models/assumptions;
- ask about the **counterfactual**;
- **non-stationary** time series will lead you to bad conclusions;

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- quantifying **uncertainty** is just as important as the effect estimate;
- consider **which population** your data represent;
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- don't mistake **mean reversion** for treatment effects/heterogeneity;
- many **maps** are just *population*;
- **graphs** should clearly communicate a *message*... beautifully.

Next: R basics + (More) Metrics review(s)