

# Introduction

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Applied Quantitative Methods II

IC3JM, Spring 2026

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- Focus on **applying** statistical tools in practice
- Less theory, more hands-on work with data
- Goal: go from research question to answer

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- How to choose the right model for your question
- How to interpret and visualize model results
- How to evaluate whether a model is appropriate
- How to work with different types of data (panel, spatial, etc.)
- Best practices in computing and reproducibility

# Course structure

<b>Feb 5</b>	Introduction
<b>Feb 12-19</b>	i2i
<b>Feb 26</b>	i3i
<b>Mar 5</b>	i4i
<b>Mar 12-19</b>	i5i
<b>Mar 26 &amp; Apr 9</b>	i6i
<b>Apr 16</b>	i7i
<b>Apr 23</b>	Project presentations
<b>Apr 30</b>	Advanced topics

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# Evaluation

- Problem sets (20%)
  - Started in class, finished at home
  - Short deadlines
- Proposal presentation and peer review (10% + 10%)
- Final essay (30%)
  - Small research note (max 3,000 words)
  - Original data analysis using R
- Exam (30%)

# The Big Picture

# The research process

**Theory  $\longleftrightarrow$  Data Generating Process  $\longleftrightarrow$  Data**

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- We observe data and try to learn about the underlying process

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- We never observe the DGP directly
- We use statistical models to make inferences about it

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- **Theoretical uncertainty:** Our theories are simplifications
- **Fundamental uncertainty:** Some processes are inherently random
  
- All of these create “noise” in our data
- Statistical models help us deal with this noise



# The logic of statistical inference

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- **Statistical inference:** Given observed data, what can we learn about the process?
- We're doing the reverse: from data back to process

# Review: Key Concepts from AQMSS-I

# The regression model

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$$Y = \beta_0 + \beta_1 X + \varepsilon$$

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- $Y$ : outcome we want to explain
- $X$ : explanatory variable(s)
- $\beta$ : coefficients (what we estimate)
- $\varepsilon$ : error term (what we can't explain)

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- “What is the average  $Y$  for units with a given value of  $X$ ?”
- The slope  $\beta_1$  tells us:
  - How much  $Y$  changes, on average
  - When comparing units that differ by 1 in  $X$



# Descriptive vs. Causal interpretation

- **Descriptive:** How do units with different  $X$  values compare?  
→ “People with more education earn more, on average”
- **Causal:** What happens if we change  $X$  for a given unit?  
→ “If we give someone more education, they will earn more”
- Same coefficient, very different claims!

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- Causal effects are about **counterfactuals**
- “What would have happened if things were different?”
- The problem: we can't observe counterfactuals
- We need strategies to infer them
- This will be a recurring theme throughout the course

# What makes a good analysis?

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- Appropriate data for the question
- Right statistical model for the data
- Correct interpretation of results
- Honest about limitations and uncertainty

# Looking ahead

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- Next session: Applied regression in depth
- How to set up a regression analysis
- How to interpret coefficients correctly
- Common pitfalls and how to avoid them



## For next week

- Read Urdinez & Cruz (2020), chapters 1-5
- Review your notes on OLS from AQMSS-I
- Start Problem Set 1
  
- Check Aula Global for additional materials

Questions?