# FLS 6441 - Methods III: Explanation and Causation

## Week 11 - Comparative Case Studies & Process Tracing

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May 2020

Comparative Case Studies	Mixed Methods	Process Tracing
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## Classification of Research Designs

		Independence of Treatment Assignment	Researcher Con- trols Treatment Assignment?
Controlled	Field Experiments	√	√
Experiments	Survey and Lab Experiments	√	√
	Natural Experiments	√	
Natural	Instrumental Variables	√	
experiments	Discontinuities	√	
	Difference-in-Differences		
Observational	Controlling for Confounding		
Studies	Matching		
	Comparative Cases and Process Tracing		

## Section 1

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- Exactly the same causal inference logic as Large-N
- ► The Fundamental Problem of Causal Inference
  - We need counterfactuals to estimate treatment effects:
    Comparative Cases

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Why can't we achieve causal inference from single case studies?

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- If we have only one 'treated' observation, we cannot know what would have happened in the absence of treatment
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- Common error: "research that tries to explain the outbreak of war with studies only of wars" (KKV)

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  - Matching: More useful

## Matching is the 'Comparative Method'

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- Our Large-N dataset reduced after matching might look reasonably similar to comparative case studies

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  - 4. Slow economic growth

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#### Does Development cause Democracy?

	Variable	Case A	Case B
Outcome	Democracy	?	?
Treatment	Development	Low	High
Controls	Religion	Christian	Christian
	Continent	Europe	Europe
	Inequality	0.45	0.65
	Economic growth	1.2%	2%
	National dish	Pasta	Corn
	Length of Railways	400km	120km

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  - Statistical Inference: Non-random case-selection, so generalization is harder

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  - Our goal is not to explain why outcome Y happened in one case, but why it happens generally

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- And it helps us avoid researcher bias
- ► But:
  - Randomization does not guarantee balance on confounders in small samples
  - Randomized sampling is not the same as randomized treatment
- More reliable to pick equal numbers of treated and control units, ensuring balance on key confounders - purposive sampling

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- Can we really ignore the outcome variable??
  - ► **DO NOT** select cases by the value of the outcome (Geddes)

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- But: If we select cases explicitly for a range of values of the outcome, that's better

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- If we want to compare men's and women's running speeds,
  DO NOT pick Usain Bolt and Florence Griffith-Joyner
- Pick units with 'median' values or a range of values on the confounding and outcome variables
- At the same time as balancing confounders hard!

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  - Extreme cases: Highest and lowest values of treatment, eg. Lieberman

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#### Methods for alternative objectives:
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  - Influential cases: How sensitive is our relationship to mismeasurement of a key case?

# Section 2

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  - 2. Comparative cases to identify explanation, then **tested for generalizability** in Large-N sample (Lieberman)
  - Large-N analysis to show causal effect within-case, then generalized using comparative case studies (Ziblatt and Slater)

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Strategies for increasing the number of observations:
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- Causal Process Observations:
  - Evidence must support or undermine a specific theory
  - What observable implications are there of theory A? How do they differ from the implications of theory B?
  - Is the evidence consistent with theory A? Or inconsistent with theory B?

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- 4. Compare the data to each theory
- 5. Can we eliminate all other theories except our treatment?
  - Sherlock Holmes' Method of Elimination

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- But we don't have any counterfactual to compare against
- The outcome could instead have been caused by a confounder



- One way to support our theory is to test the mechanisms along the causal path of treatment:
  - Evidence of M NOT occurring is proof Treatment did not have a causal effect
  - Evidence of M occurring is consistent with Treatment having a causal effect



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- This is a 'hoop' test



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  - Evidence of M occurring is consistent with Treatment having a causal effect
- If there are no other possible confounders consistent with this mechanism, this is a 'Smoking Gun' test



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We can also test mechanisms on the causal path of confounders:

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- We can also test mechanisms on the causal path of confounders:
  - Evidence of Mechanism X NOT occurring can rule out this confounder, but there might still be others
  - Evidence of Mechanism X occurring is consistent with Treatment having no effect, but not proof
- This is a 'straw in the wind' test



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- Unusually, a mechanism might explicitly separate two theories:
  - M = 0 if treatment is active
  - M = 1 if the confounder is active
- This is a 'Doubly-Decisive' test



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- We only have knowledge about South Korea: It got much richer between 1960 and 1987 when it became a democracy
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- Theory: Higher incomes raise the demand for democracy, and diversify power away from the state
- If this were true we should see:
  - Opinion polls show increased support for democracy
  - Street protests, especially among the new middle-class
  - Private sector and civil society lobbying for democracy

- Alternative Theory: Or was it American pressure?
- South Korean elites faced costs to continuing dictatorship, and choose to democratize
- If this were true we should see:
  - Discussions (public or private) between US and Korean elites
  - Korean vulnerability to US pressure
  - Elites choosing the time and form of democratization

Comparative Case Studies	Mixed Methods	Process Tracing
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► What does the evidence show?

Mixed Methods

#### **Process Tracing**

What does the evidence show?



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  - And we assume the only way confounding works is through the mechanism we specify
- So everything depends on how confident we are in our theory/assumptions about mechanisms

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- Will the same causal effect occur in other contexts?