Introduction to Causal Inference: A Primer

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Why causality matters

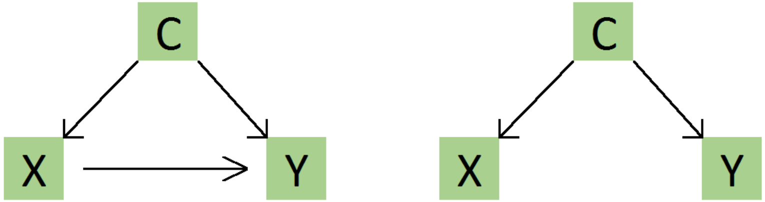
- Social science research is often motivated by simple (and yet important and difficult) **cause-and-effect** questions. To name a few:
  - American politics: Does historical black slavery have a lasting impact on voters' attitudes toward the African American people?
  - Comparative politics: Does the descriptive representation of women and racial minorities in the legislature mitigate people's bias against them?
  - Political economy: Do cash-transfer programs reduce poverty?
  - International relations: Does international peacekeeping reduce conflicts? Does foreign aid work?
- Causality is in particular crucial for "evidence-based" policy-making

Causality is hard to establish

- Presence of confounders or common causes
- True counterfactural cannot be observed
- Causality is complicated and multi-dimensional

Challenge 1: Correlation and common causes (confounders)

- Two variables X (independent or explanatory) and Y (dependent or outcome) can be **correlated** with each other under at least **three** conditions
  - X causes Y
  - X and Y have a common **cause**
  - X and Y have a common **outcome**
- To make sure X causes Y, we have to rule out the influence from all common **causes**, namely the **confounders**, though **statistical controls** in multiple regression
- It is simply impossible and unrealistic to include all possible confounders in multiple regression



Correlation with or without causation. In the directed acyclic graph (DAG), we use **arrows** to denote causality between two variables. Here X, Y, and C refer to **cause**, **outcome**, and **confounders** respectively

- On average, neighborhoods that have more police officers also see more residents killed by gun violence
- Is the police incompetent? Or even worse, are the police officers involved in some covert collusion with the local crime syndicate?

- On average, no statistically significant results exist to show that UN peacekeeping troops reduce the likelihood of communal violence.
- Is sending UN peacekeeping troops a waste of time and money?

Challenge 2: Counterfactural does not exist

- Causal inference is difficult also because of the famous "fundamental problem of causal inference"
  - For any individual, we can never observe what actually happens under **counterfactural** in real life (Holland 1986)
  - Instead of comparing the difference at the **individual** level, we can compare the **average difference** in terms of the outcome of interest between **two (comparable) groups of people**
- The comparison is not straightforward due to the presence of **confounders**
  - Researchers usually attempt to **eliminate the influence of confounders on the cause** by randomly assigning our observations (e.g., survey respondents) into one of the experiment groups
  - **Randomization may not be a perfect solution** (Deaton and Cartwright 2018)

Challenge 3: Causality is more complicated than we thought

- Getting a clear picture of causality is hard
  - Existence: Does X cause Y? If yes, what is the direction?
  - Importance: If yes, X have a non-trivial impact on Y? How do we quantify the size of effect? How do we know an effect is big or small?
  - Mechanism: How and why does X affect Y? **Causal mediation analysis** and (qualitative) **process tracing** are commonly used to unpack a causal mechanism.

- Tradeoff between **internal** and **external** validity: It is also hard to generalize from our findings.

Causal inference in action: Field and “natural” experiments

	Lab/Field Experiment	Natural Experiment
Comparing responses between treatment and control groups?	Yes	Yes
Does the treatment assignment occur at **random**?	Yes	More or less
Does the researcher control the introduction of the intervention (i.e., the treatment)?	Yes	No

Causal inference as a field

- Identification of causal quantities with and without an experiment requires "assumptions" – the combination of assumptions and data needed to render a valid causal conclusion
- Many identification assumptions are best made reasonable by carefully thought-out research designs
- "What is your identification strategy?" – what are the assumptions that allow you to claim you've estimated a causal effect?

Causal inference as a field

- Identification of causal quantities with and without an experiment requires "assumptions" – the combination of assumptions and data needed to render a valid causal conclusion
- Many identification assumptions are best made reasonable by carefully thought-out research designs
- "What is your identification strategy?" – what are the assumptions that allow you to claim you've estimated a causal effect?
- **Identification strategies are not the same as estimation strategies**
  - If an effect is not identified, no estimation method will recover it
  - Estimation methods (e.g., t-test, regression, matching, weighting, 2SLS, 3SLS, SEM, GMM, GEE, dynamic panel, etc.) are secondary to the identification assumptions

Experiment vs. observational studies

- Randomized experiment: well-defined treatment, clear distinction between covariates and outcomes, control of assignment mechanism
- Good observational study: Well-defined treatment, clear distinction between covariates and outcomes, (nearly) precise knowledge of assignment mechanism
- Poor observational study: Hard to say when treatment began or what the treatment really is; distinction between covariates and outcomes is blurred; no precise knowledge of assignment mechanism

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The bottom line: Causal inference requires that treated and control units in the study population are comparable such that the only difference is the treatment status

ID strategies for observational studies: An informal overview

- Selection on observables (SOO)
- Instrumental variables (IV)
- Regression discontinuity design (RDD)
- Difference-in-difference (DID)
- ... and many more (e.g., fixed effect regressions and synthetic control)

Example: White et al (APSR 2015)

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What Do I Need to Vote? Bureaucratic Discretion and Discrimination by Local Election Officials

ARIEL R. WHITE *Harvard University*
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Do street-level bureaucrats discriminate in the services they provide to constituents? We use a field experiment to measure differential information provision about voting by local election administrators in the United States. We contact over 7,000 election officials in 48 states who are responsible for providing information to voters and implementing voter ID laws. We find that officials provide different information to potential voters of different putative ethnicities. Emails sent from Latino aliases are significantly less likely to receive any response from local election officials than non-Latino white aliases and receive responses of lower quality. This raises concerns about the effect of voter ID laws on access to the franchise and about bias in the provision of services by local bureaucrats more generally.

- Do local election officials in the US respond to voters of different ethnicities differently?
- 7,000 email requests were sent to local election offices; each request has a fictional voter from a uniquely "randomized" ethnicity (Latino v non-Latino)
- Emails sent from Latino aliases were less likely to receive a response or more likely to receive a response of lower quality

Example: Cheng and Urpelainen (SCID 2019)

Studies in Comparative International Development (2019) 54:501–527
https://doi.org/10.1007/s12116-019-09290-5

Criminal Politicians and Socioeconomic Development: Evidence from Rural India

Chao-Yo Cheng[1] · Johannes Urpelainen[2]

- Does the election of criminal politicians undermine socioeconomic development in rural India?
- Analysis draws on fine-grained village-level (on local public goods and socioeconomic development) and constituency-level data (on candidate characteristics)
- Identification considers the victory of criminal politicians in close election "as-if" random
- Criminal politicians may undermine household-level poverty alleviation while having no statistically discernible impact on infrastructure construction (e.g., paved roads)

How causal “revolution” changes social research

- Qualitative and multi-method researchers in demand
- Design-based "identification" precedes model-based inference
- Statistical learning: The rise of "causal" learning

How causal “revolution” changes social research

- Qualitative and multi-method researchers in demand
  - Qualitative information is important for research design and the search for proper setting for natural experiments (Dunning 2015)
  - It is possible to use qualitative methods/information to strengthen causal estimation (Glynn and Ichino 2015) and the study of mechanisms (Walder 2012)

- Design-based "identification" precedes model-based inference

- Statistical learning: The rise of "causal" learning (DAG recovering, heterogeneous treatment effects and covariate/control selection)

How causal “revolution” changes social research

- Qualitative and multi-method researchers in demand

- Design-based "identification" precedes model-based inference
  - The conventional approach is to include "all" possible predictors in multiple regression (i.e., the notorious "kitchen-sink" approach).
  - Design-based causal "identification" urges us to think hard about the distinction between the "cause" and pre-treatment/control variables.

- Statistical learning: The rise of "causal" learning

How causal “revolution” changes social research

- Qualitative and multi-method researchers in demand
- Design-based "identification" precedes model-based inference
- Statistical learning: The rise of "causal" learning
  - (Supervised) machine learning techniques may help with variable selection in multiple regression
  - Statistical learning may also help with the analysis of "heterogeneous" causal effects

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https://www.bbk.ac.uk/courses/postgraduate/social-research-and-law-and-legal-studies

What we offer at Birkbeck

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  - Generalized/non-linear multiple regression
  - Multilevel/hierarchical modeling
  - Basic tools for (observational) causal inference
- Experiments in social science (Dr Barry Maydom)
  - Lab and lab-in-the-field experiments
  - Survey experiments
  - Natural experiments

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Studying admin litigation in China

- The release of **China Judgements Online** (`https://wenshu.court.gov.cn/`) made a crucial breakthrough in the empirical legal studies in China (Ma, Yu and He 2016; Liebman et al 2020).
  - In 2020, through a special partnership, we acquired all publicly available court records of administrative cases after 2014 and extract a variety of crucial information about each case.
  - Our RAs scrutinized a random sample of the processed records – for the variables included in the study, the percentage of correct annotations ranges between 90% and 99%, with a mean of 97.9%.
  - In our analysis, we focus on the records between 2014 and 2019 published by the LPCs at the intermediate (city) and primary (county or district) levels.

Empirical study I: Railway transport court

- **Background**
  - In 2014, the Supreme People's Court (SPC) announced the decision to allow the **railway transport courts** (RTCs) to accept and hear administrative cases
  - In contrast to the local people's courts (LPCs), the RTCs are under the direct administration of the provincial high courts
- **Key variables**
  - Explanatory: Whether the case was ruled by an RTC (=1)
  - Outcome: Whether the citizen(s) won the case (=1)
- **Research design**: Hierarchical modeling in which we include case- and city-level covariates
  - Case-level: Plaintiff was natural person, had lawyer, was a group; defendant had lawyer, from upper admin levels, was a group; case types
  - City-level: GDP per capita, population, real estate (fixed asset) investment

Table 1: Intermediate and Primary RTCs with Administrative Tribunals, 2015–2019

	Railway Transport Courts (RTCs)
Intermediate Courts	Beijing (北京); Guangzhou (廣州); Kunming (昆明); Lanzhou (蘭州); Nanchang (南昌); Nanning (南寧); Shanghai (上海); Wuhan (武漢); Xi’an (西安); Zhengzhou (鄭州)
Primary Courts	Ankang (安康); Baicheng (白城); Guangzhou (廣州); Hangzhou (杭州); Hengyang (衡陽); Huaihua (懷化); Jilin (吉林); Jinan (濟南); Kaiyuan (開遠); Kunming (昆明); Lanzhou (蘭州); Liuzhou (柳州); Luoyang (洛陽); Nanchang (南昌); Nanning (南寧); Nanjing (南京); Qingdao (青島); Shanghai (上海); Tianjin (天津); Tonghua (通化); Wuhan (武漢); Xian (西安); Xining (西寧); Xuzhou (徐州); Yanbian (延邊); Yinchuan (銀川); Changchun (長春); Changsha (長沙); Zhengzhou (鄭州)

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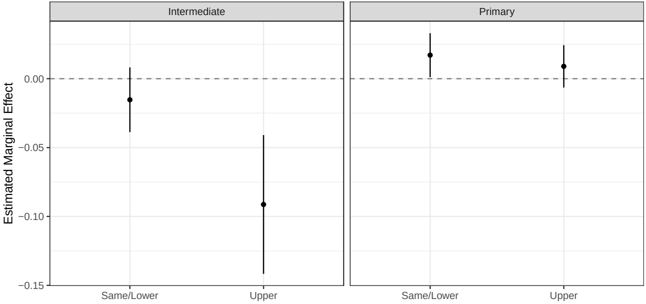

- At the primary level, RTCs are more likely to side with the citizens when the cases are filed against county-level government agencies
- The pro-citizen effect of RTCs disappears when we focus on cases with higher political stakes
- Provincial government agencies are less likely to be defeated in both intermediate and primary RTCs