The Causal Framework Wars in Economics

Lennart Ackermans

Munich Center for Mathematical Philosophy

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Presentation outline

- "Reflections on the 2021 Nobel Memorial Prize Awarded to David Card, Joshua Angrist, and Guido Imbens" (Ackermans 2023)
- Imbens (2020)
- Imbens' response (via email and 2023 seminar)
- My response to Imbens: economists need causal graphs too

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- The economists' favourite causal framework: Potential Outcomes (Rubin 1974).

Diagnosing the Credibility Crisis

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- The economists' favourite causal framework: Potential Outcomes (Rubin 1974).
- Pearl (2000) has a similar diagnosis, but offers a different framework as solution: the **graphical framework**.

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- **The identification problem:** infinitely many causal mechanisms can generate identical populations.

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- To determine the **correct** model, and to know whether $\mathrm{Cov}(X_i, \varepsilon_i) = 0$, one needs a causal theory that answers at least:
  - What is a causal variable? What is an omitted causal variable? What is a causal effect size?

- Imagine a population in which individuals are assigned a treatment $T_i = 1$ or no treatment $T_i = 0$. The *potential outcomes* if they were treated and not treated are $Y_i(1)$ and $Y_i(0)$. The **individual treatment effect** is
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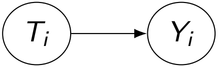
- Such methods (RCT, instrumental variables) rely on the assumption of **unconfoundedness**: T_i is independent of the potential population outcomes $(Y_i(0), Y_i(1))$.

The Graphical Framework

- Causal structure is encoded in **directed acyclic graphs** (DAGs).



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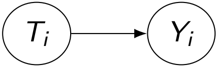

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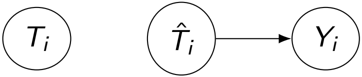

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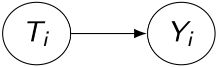

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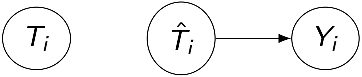

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- Assumptions like unconfoundedness can be assessed based on the graph's structure, assuming it is accurate.

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- My conclusion: use PO when useful but always combine with graphs for verifying assumptions.
- Imbens' reply: (1) economists are familiar enough with assumptions like unconfoundedness that they don't need graphs (Imbens 2020). (2) PO can be used for estimating parameters of equilibrium models, while graphical models can't: see Angrist, Graddy, and Imbens (2000).

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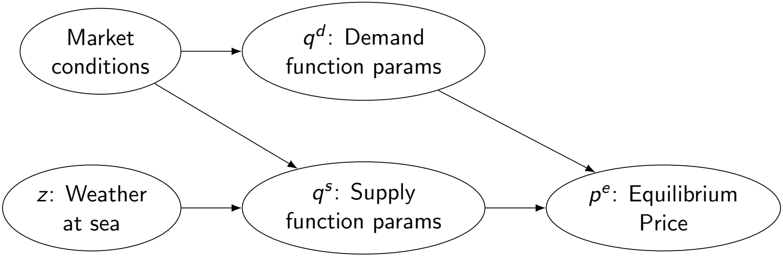

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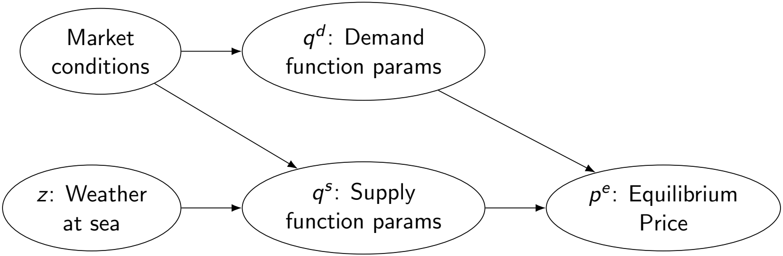

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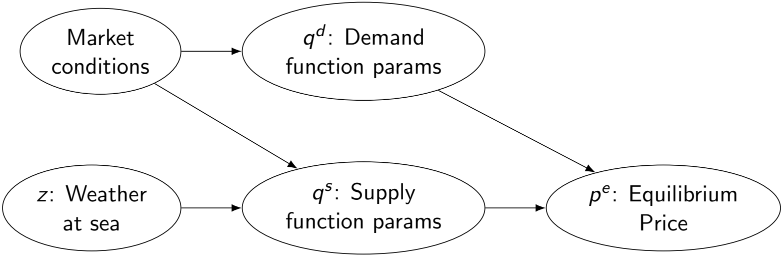

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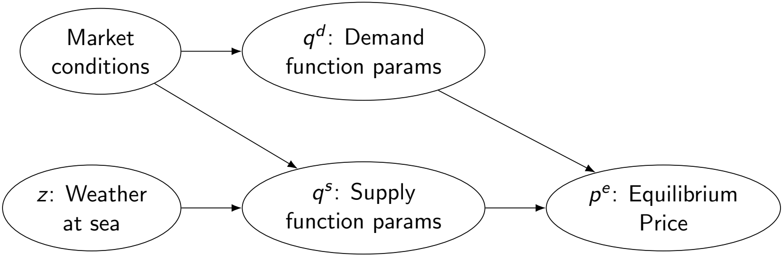

- **Remarkable:** The authors use z as an instrumental variable to get an estimate of the *demand* elasticity!
- This is possible because the study utilises additional theoretical knowledge (shape restrictions)
- A central assumption is **unconfoundedness**: $z \perp\!\!\!\perp (q^d_{z^*,p^*}, q^s_{z^*,p^*})$ for all counterfactual values z^* and p^*.

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- How do we know this is true? Unconfoundedness refers to unobservable (counterfactual) quantities.

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then each variable in G is statistically independent of its nondescendants conditional on its parents. (Spirtes, Glymour, and Scheines 2000)

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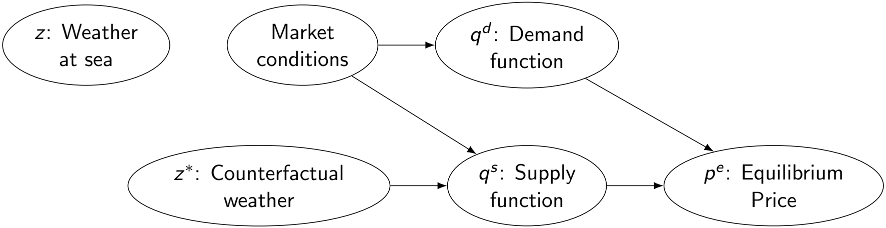

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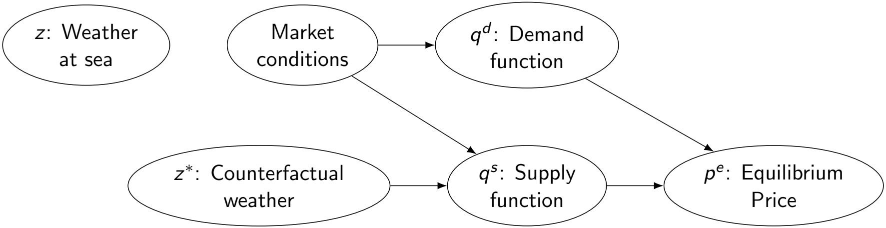

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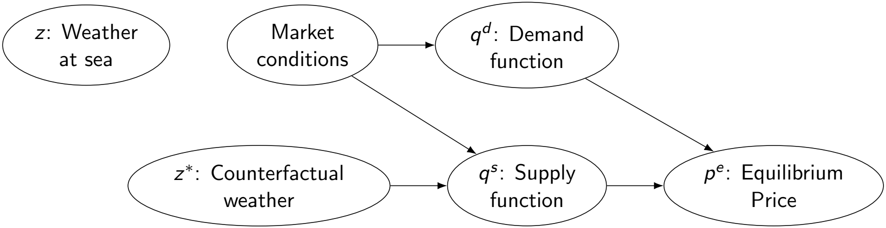

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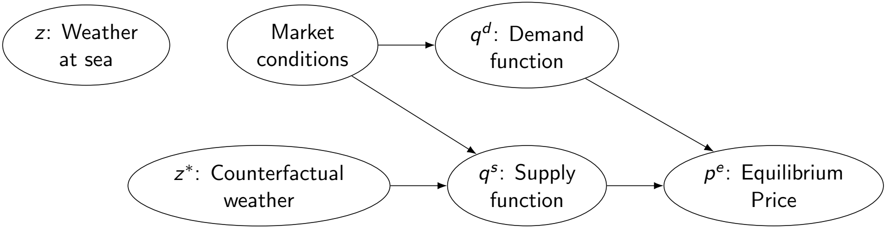

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  - E.g.: "The weather has no common cause with demand, nor causes demand, so they are independent"

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- Combining PO with the graphical framework would solve this

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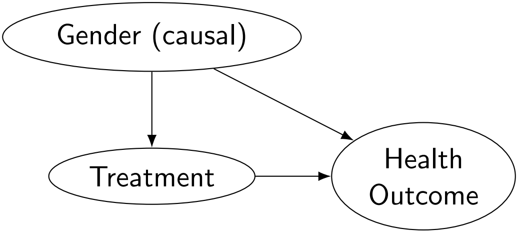
- A **causal variable** has clearly defined manipulations, a **non-causal attribute** does not
- **Markov pitfall:** To apply the Causal Markov Principle, manipulations on all variables need to be defined and non-ambiguous (Spirtes and Scheines 2004)

Example: gender and confounding



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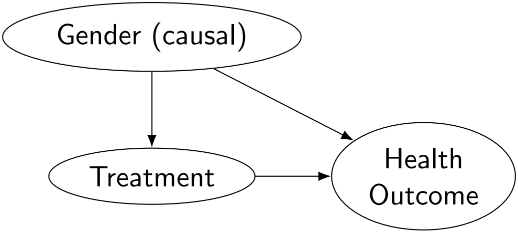

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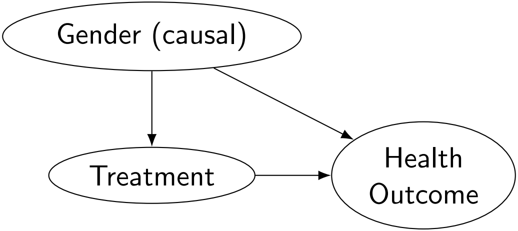

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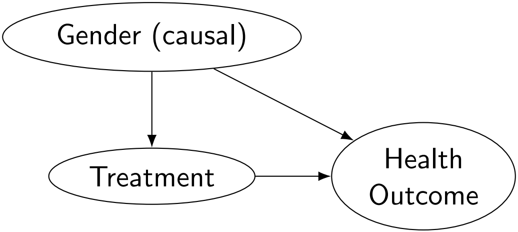

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- This might be overlooked in PO studies in which *Gender* is an attribute

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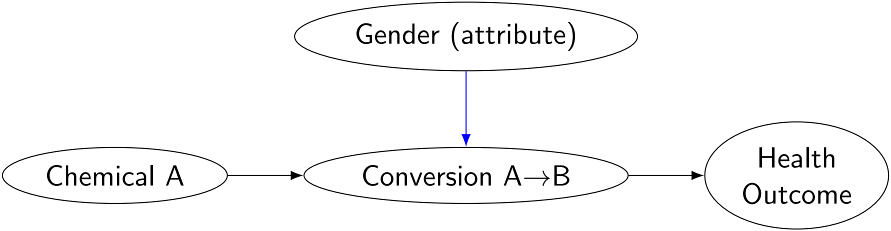

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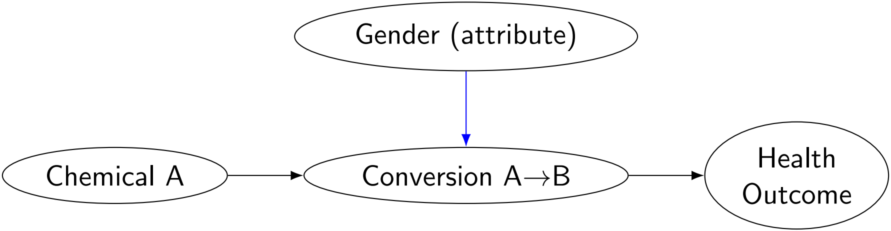

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  $$\mathrm{E}(\text{Outcome}|\text{A}) - \mathrm{E}(\text{Outcome}|\text{no A})$$

  is the average causal effect of *chemical A* on *Outcome*.

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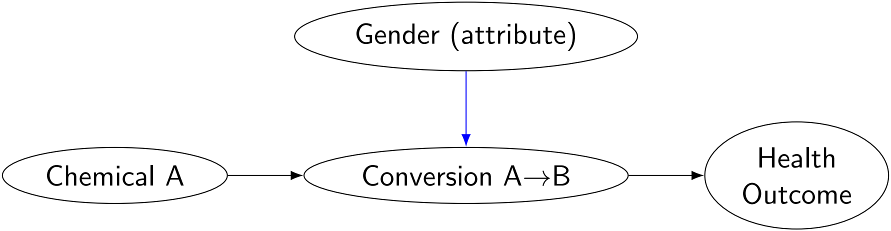

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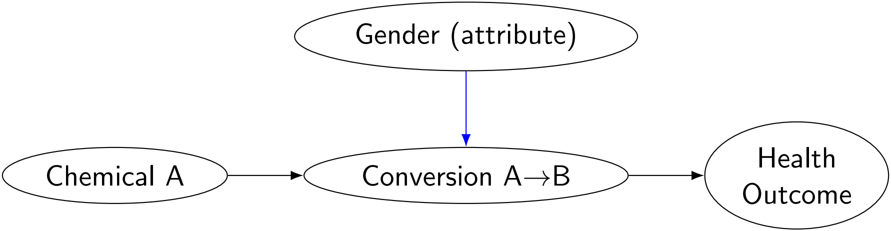
  $$\mathrm{E}(\text{Outcome}|\text{A}) - \mathrm{E}(\text{Outcome}|\text{no A})$$
  is the average causal effect of *chemical A* on *Outcome*.
- There might still be non-causal bias: The average causal effect is uninformative if the sign of the causal effect is different for men and women

Example: gender and treatment effect heterogeneity



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- There might still be non-causal bias: The average causal effect is uninformative if the sign of the causal effect is different for men and women
- The graphical framework stops at causality; PO is concerned with additional problems.

- Summarising,

The graphical approach and non-causal attributes

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  1. Causal methods work only if all variables are causal
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    1. Causal methods work only if all variables are causal
    2. *Non-causal* biases may require conditioning on non-causal attributes
- The graphical framework focuses only on (1); the PO framework on (1) and (2) combined
- Use of PO exclusively runs the risk of mistakenly conditioning on non-causal attributes to solve causal problems.

Conclusion

- Econometrics has improved greatly due to better causal methodology and use of the PO framework.
- To better assess assumptions of causal methods, economists should incorporate causal graphs.
- Imbens' arguments against graphical models fail.

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