Potential Outcomes and Graphical Models

Comments to Imbens (2020)

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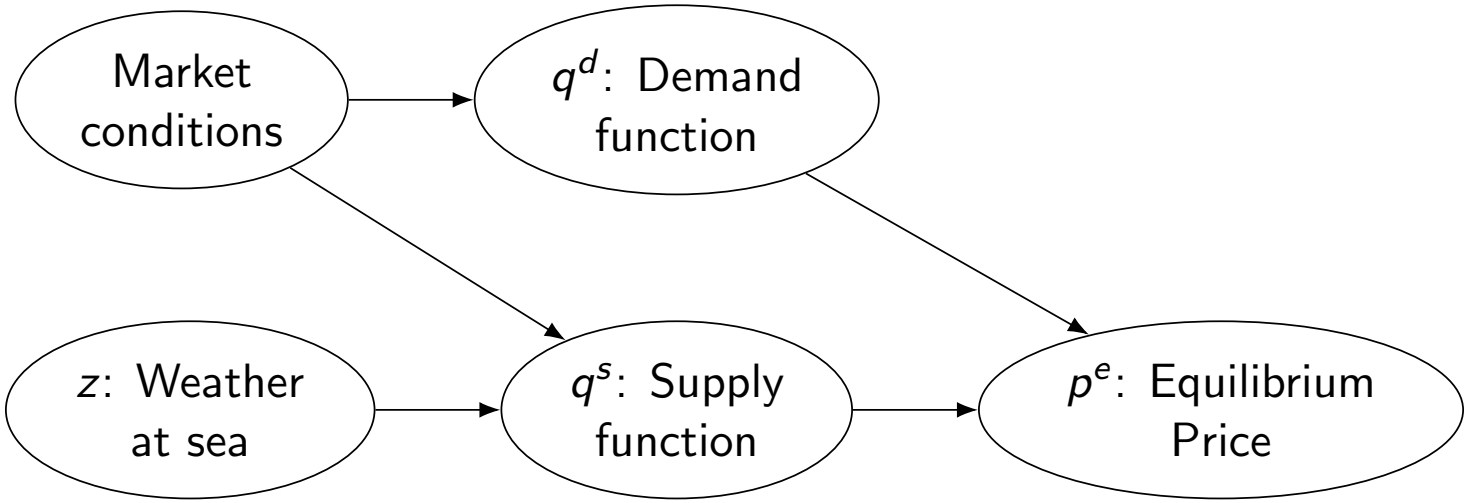
Outline and claims

- **Central claim:** The PO framework and DAG (graphical) framework are complementary.
  - The PO framework is most suitable for developing and executing particular causal methods such as *instrumental variables* – solving *causal* and *statistical* problems in a unified approach.
  - The graphical framework is most suitable for formulating and verifying the strictly *causal* assumptions underlying causal methods
- **Responding to:**
  - That economists don't need graphical models to assess the assumption of unconfoundedness (Imbens 2020, 1163–1166).
  - That PO has a useful distinction between *causal variables* and *non-causal attributes* which the graphical framework lacks (1155–1157).

Example: Angrist, Graddy, and Imbens (2000)



- **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^*.

Fulton Fish Market (NY): assessing unconfoundedness

- **Unconfoundedness**: Take a large hypothetical sample of days with
  - observed weather at sea (z),
  - the counterfactual supply functions given potential values of the weather z^*
  - the counterfactual demand functions given each z^*.

  Observed weather must be independent of the counterfactual supply and demand function for every z^*.
- How do we know this is true? Unconfoundedness refers to unobservable (counterfactual) quantities.

From causes to observations and back: metaphyiscal postulates

- Scientific observations and causal/counterfactual quantities are **fundamentally different things**. To connect the two we need empirical postulates.
  - Reichenbach's common cause principle
  - The Causal Markov Principle
  - Faithfulness

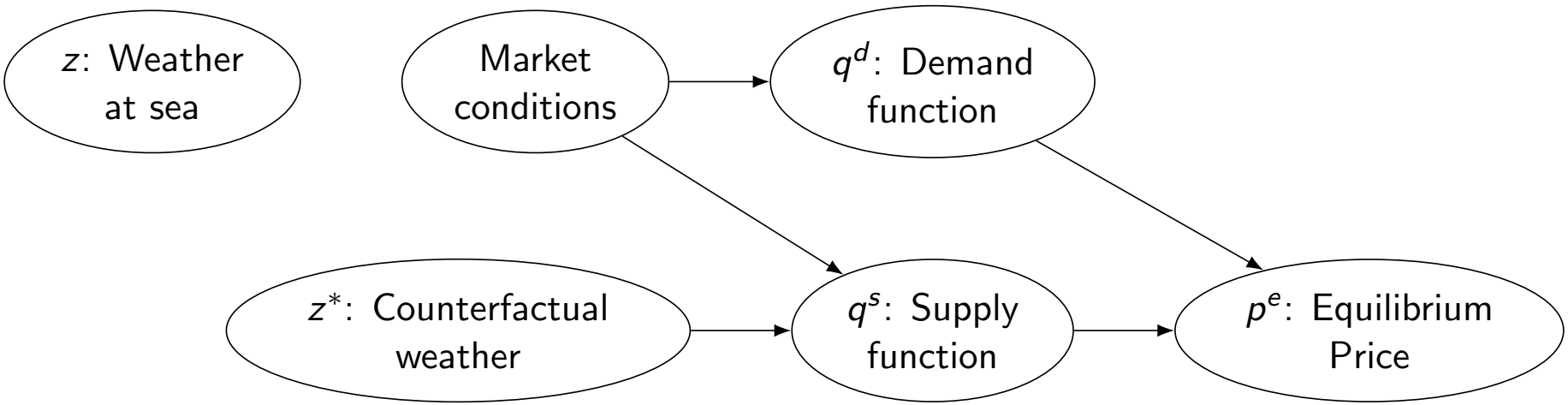
The Causal Markov Principle

The Causal Markov Principle:
Let G be a DAG describing some population. If

- G accurately describes the causal structure at work,
- Every common cause of two variables in G is either (a) itself in G or (b) has the same value for all units in the population,
- G is not otherwise deficient (see later),

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

Fulton Fish Market (NY): unconfoundedness



- **Unconfoundedness:** z is indendent of counterfactual supply and demand functions q^s and q^d given z^*.
- **Causal Markov Principle**: "variables in G are independent of their nondescendants conditional on their parents"
- Causal Markov Principle $\longrightarrow$ Unconfoundedness

Causal Inference in practice

- Steps of causal inference:
  1. Gain knowledge about causal structure
     - *Faithfulness*
     - Experimentation
     - Theory
  2. Assess causal assumptions needed for a method
     - *Causal Markov Principle* or similar
     - Knowledge from (1)
  3. Create and execute a method to estimate a causal effect size
- The PO framework is very versatile with respect to (3). But has less to say about (1) and (2).
- Economists still do steps 1 and 2, but in a more informal and implicit way.
  - E.g.: "The weather has no common cause with demand, nor causes demand, so they are independent"

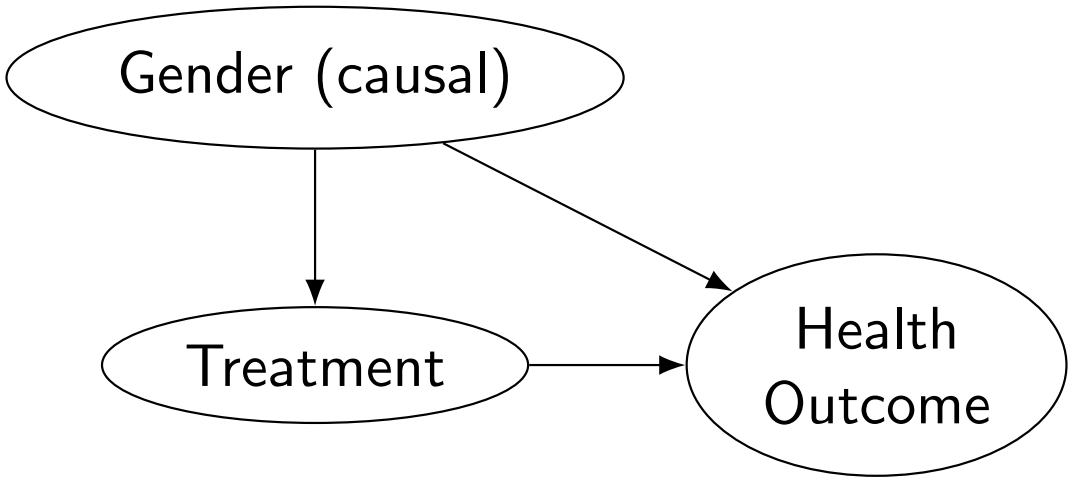
Problem with PO framework in practice

- Economists still do steps 1 and 2, but in a more informal and implicit way.
- This is problematic:
  1. Informal reasoning is bound to go wrong
  2. There are various pitfalls of the *Causal Markov Principle* and similar postulates
  3. Economists miss out on a large literature about empirical postulates and their application
- Combining PO with the DAG approach would solve this

Causal variables versus non-causal attributes

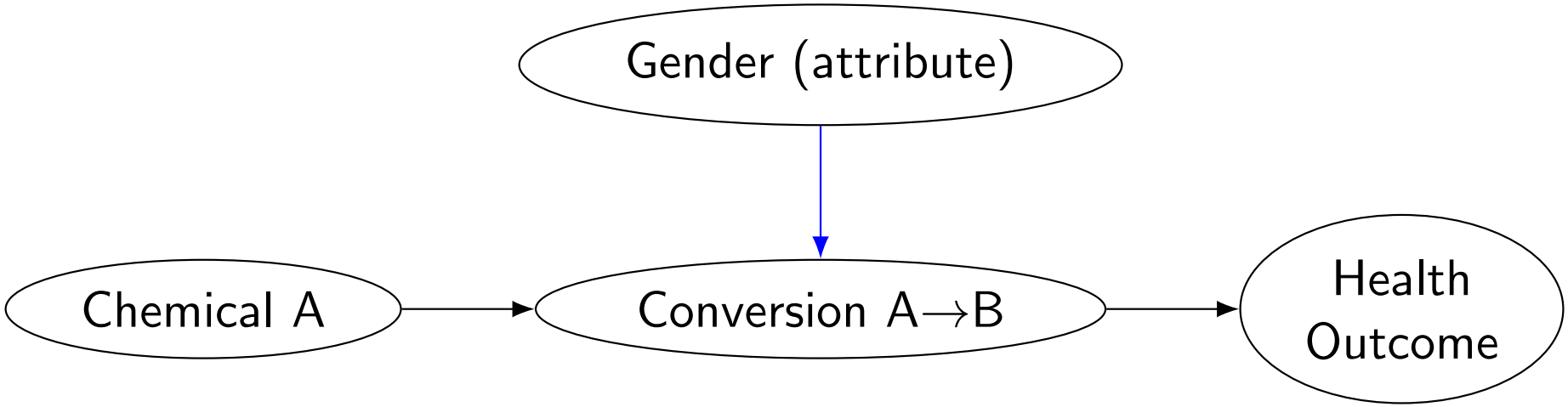
- **Imbens**: PO has a useful distinction between *causal variables* and *non-causal attributes* which the graphical framework lacks
- A **causal variable** has clearly defined manipulations, a **non-causal attribute** does not
- **Markov pitfall:** To apply the Causal Markov Principle, manipulations on all variables need to be defined and non-ambiguous (Spirtes and Scheines 2004)

Example: gender and confounding



- One should condition on *Gender* to adjust for confounding
- **Causal Markov**: we know this works *only* if *Gender* is a causal variable!
- This might be overlooked in PO studies in which *Gender* is an attribute

Example: gender and treatment effect heterogeneity



- Since there is no confounding,
  $$\mathrm{E}(\text{Outcome}|\text{A}) - \mathrm{E}(\text{Outcome}|\text{no A})$$
  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
- The DAG approach stops at causality; PO is concerned with additional problems.

The graphical approach and non-causal attributes

- Summarising,
  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 runs the risk of mistakenly conditioning on non-causal attributes to solve causal problems.

Summary

- The PO framework is good for creating practical methods that solve causal and statistical problems in a unified way
- The graphical framework is good for verifying the assumptions for causal methods and solving causal problems in isolation
- While the PO framework has clear benefits, it is risky to rely on informal reasoning for assessing causal assumptions

Bibliography

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