The dilemma of causal inference in economics

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“We can either let theory guide us in our attempts to estimate causal relationships from data ... or we don’t let theory guide us.

If we let theory guide us, our knowledge will be “incredible” because our theoretical knowledge is itself not certain. It is often easy to build a number of theoretical models with conflicting conclusions, and quite generally theoreticians do not really trust one another’s assumptions.

If we do not let theory guide us, we have no good reasons to believe that our causal conclusions are true either of the experimental population or of other populations because we have no understanding of the mechanisms that are responsible for a causal relationship to hold in the first place, and it is difficult to see how we could generalize an experimental result to other settings if this understanding does not exist.

Either way, then, causal inference seems to be a cul-de-sac.”

The concept of causality (in economics) is

- important
- multifarious
- problematic
Importance of a causal notion for:

- intervention, policy control
- explanation, understanding
- prediction (helpful, but really necessary?)
Multifariousness

- **Variety of causal notions:**
  - general/singular
    
  
  - retrospective/prospective
    
    Cfr. *Will a cut in labour cost cause a drop in unemployment?*
  
  - explicit/implicit
    
    Cfr. *Does monetary policy matter?*
The problem of causality

It is not straightforward to say what \textit{A causes B} means. What are causes? What is the nature of a causal relation? (\textit{Ontological problem})

But suppose you have a working definition...

It is difficult to uncover causal relations, especially in a non-experimental setting. How can we infer the existence of causal relations from observations? (\textit{Epistemological problem})

But suppose you have inferred a causal relation...

Not clear how you should use it (e.g. for policy intervention). Are causal relations stable? (\textit{Pragmatic problem})
The epistemological problem of causal inference is strictly linked to the problem of induction.

**Problem of induction** (Hume 1739-40): how to support or justify methods that infer, on the basis of experience, claims about things of which we have no experience?

*Cfr. Correlation is not causation*

we have experience of symmetric relations (correlations), but we would like to have claims about asymmetric relations
So what is causation?

- Different accounts in the philosophy of science, linking causation to
  - Regularity and laws
  - Probability
  - Mechanisms (production)
  - Counterfactual
  - Manipulability

- A pluralist approach?
If correlation is not causation, what is it?

- Pearson’s correlation coefficient:

\[
\rho_{XY} = \text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y}
\]

- Correlation is a measure of linear dependence.

- Statistical dependence is not causation. What is statistical dependence?

  Intuitively, two random variables \(X\) and \(Y\) are statistical associated (i.e. dependent) if the realization of \(X\) gives useful information about the likely realization of \(Y\)
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  intuitively, two random variables \(X\) and \(Y\) are statistical associated (i.e. dependent) if the realization of \(X\) gives useful information about the likely realization of \(Y\)
If $X, Y$ are random variables, we say that $X$ is independent of $Y$, and write

$$X \perp \perp Y$$

if

- for discrete variables:
  $$P(X = x, Y = y) = P(X = x)P(Y = y)$$

- for continuous variables:
  $$f_{XY}(x, y) = f_X(x)f_Y(y)$$

We can also write (simplifying the notation):

$$X \perp \perp Y \iff f(x, y) = f(x)f(y)$$

$X$ and $Y$ are statistical dependent if $f(x, y) \neq f(x)f(y)$
If $X, Y, Z$ are random variables, we say that $X$ is conditionally independent of $Y$ given $Z$, and write

\[ X \perp \!\!\!\!\perp Y \mid Z \]  \hspace{1cm} (2)

if

- for discrete variables:

\[ P(X = x, Y = y \mid Z = z) = P(X = x \mid Z = z)P(Y = y \mid Z = z) \]

- for continuous variables:

\[ f_{XY \mid Z}(x, y \mid z) = f_{X \mid Z}(x \mid z)f_{Y \mid Z}(y \mid z) \]

- We can also write (simplifying the notation):

\[ X \perp \!\!\!\!\perp Y \mid Z \iff f(x, y, z)f(z) = f(x, z)f(y, z) \]

\[ \triangleright \quad x \text{ and } y \text{ are statistical dependent conditional on } Z \text{ if } f(x, y, z)f(z) \neq f(x, z)f(y, z) \]
To sum up:

- statistical dependence is a property of the distribution function
- there are different measures of statistical dependence
  - correlation (Pearson correlation coefficient)
  - conditional expectation function $E[Y|X = x]$
  - linear regression coefficient $\beta = \frac{\text{cov}(X,Y)}{\sigma_X^2} = \rho_{XY} \frac{\sigma_Y}{\sigma_X}$
- difference between statistical dependence and causality:
  - s.d. is symmetrical (but measures of s.d. can be asymmetrical)
  - causality is asymmetrical
Statistical dependence and causality

▷ Is s.d. an indicator of causality?

- suppose one augments s.d. with some temporal order (e.g. $X$ and $Y$ are correlated and $X$ happens before $Y$). Is this sufficient for causality?
  
  of course no (drop in the mercury in a barometer does not cause a storm)

- possibility of latent variables (confounders)

▷ principle of the common cause (cfr. Reichenbach 1956):

if $X$ and $Y$ are statistical dependent either (i) $X$ causes $Y$, (ii) $Y$ causes $X$, (iii) or there is a common cause $Z$ causing $X$ and $Y$. 
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The reasons of correlation

- If we accept the principle of the common cause, then the reason of an observed correlation (s.d.) is the presence of a causal structure

  correlation is generated by causation

- Counterexample of spurious regression: e.g. measured correlation between bread prices in Britain and sea level in Venice (Sober 1987)

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Note: measured correlation and regression coefficients are

\[
\hat{\rho}_{XY} = \frac{\sum_{k=1}^{n} (X_k - \bar{X})(Y_k - \bar{Y})}{\sqrt{\sum_{k=1}^{n} (X_k - \bar{X})^2 \sum_{k=1}^{n} (Y_k - \bar{Y})^2}}
\]

\[
\hat{r}_{YX} = \frac{\sum_{k=1}^{n} (X_k - \bar{X})(Y_k - \bar{Y})}{\sum_{k=1}^{n} (X_k - \bar{X})^2}
\]

▷ Are \(\hat{\rho}_{XY}\) and \(\hat{r}_{YX}\) adequate measures of the s.d. between \(X_k\) and \(Y_k\)?

it depends, for sure not in the case of the bread price/water level example

▷ Thus there are measured statistical dependencies that are **meaningful**, other are **irrelevant**

terms to be distinguished from the use in the literature of the terms **spurious correlation** and **spurious regression**
Correlation and causality

- Correlation is not causality but meaningful statistical dependencies are generated by a causal structure.

- Unobserved chance set up, i.e. data generating mechanism.

- Importance of the concept of statistical model

  A statistical model is a specification (i.e. reduction) of the joint distribution of the observable random variables, say \( f(X_1, X_2, \ldots, X_n; \phi) \)

  According to Spanos (1986, 1999) specification is done by imposing probabilistic assumptions from three basic categories: Distribution, Dependence, and Heterogeneity.

- If a statistical model is adequately specified, then it describes, from a statistical point of view the data generating process.
Causality is *not reducible* to probability but it renders relationships of statistical dependencies *meaningful*.

Key role played by the chance set up / data generating mechanism.

A chance set up incorporates causal relationships, most of them remain *uncertain*.

*Difference making* notion.

Another important account of causality: production / mechanism (cfr. Hall 2004).

where does knowledge of economic mechanisms come from?

role of economic theory

institutional knowledge.
The practical problem of induction

D. Hume (1739-40): philosophical problem of induction

J.S. Mill (1843, 1844) formulated a *practical* problem of induction

- causal *tendencies* in economics are usually accompanied by *disturbing factors*: they hold only *ceteris paribus*

- impossibility of applying the "method of difference", i.e. running controlled experiments

- economic phenomena are too complex

- deductivist approach: emphasis on theory
Ideal experiments in economics

- The impossibility of running controlled experiments is not seen as insurmountable

- Haavelmo 1944
  - nature can run experiments for us
  - variety of independent sources of variation
  - conformity to well-defined distributions
  - similarity to randomized controlled trial
What is causation?

Experiments as benchmark?

In *Mostly Harmless Econometrics* (2009) J.D. Angrist and J.S. Pischke claim that the exploitation of natural experiments (random assignment of treatment independent of potential outcome) has induced a “credibility revolution” in empirical economics.

Much of the research we do ... attempts to exploit ... readily available sources of variation. We hope to find natural or quasi-experiments that mimic a randomized trial by changing the variable of interest while other factors are kept balanced. Can we always find a convincing natural experiment? Of course not. Nevertheless, we take the position that a notional randomized trial is our benchmark (Angrist and Pischke 2009: 21).
Similarity of causal inference

- There is only a gradual variation among these methods:
  - controlled experiment
  - randomized controlled trial
  - instrumental variable
  - structural equation models
  - graphical models

- These methods share some key conditions required to infer causation
  - use of control variables

- And they all share the intrinsic difficulty of causal inference as well.
  - local vs. external validity
  - all these methods tend to be black boxes: lack of the understanding of the underlying mechanism
Some remarks to (provisionally) conclude

I suggest these claims are **wrong**:

- Only experimental studies [RCT] can support causal conclusions
- They are purely data-driven model for causal inference
- Correlations [more in general stat. dependencies] are useless for causal inference
- Empirical investigation is always about causal inference
The eternal dilemma of causal inference between inductivist and deductivists:

- *Methodenstreit* (C. Menger vs. G. Schmoller), end XIX cent.
- Cowles Commission approach vs. Granger causality VAR (Cooley vs. C. Sims), 1980s.
- “Mostly Harmless Econometrics” debate (J.D. Angrist. J.S. Pischke, G. Imbens vs. J. Heckman, A. Deaton), 2009-??