Probabilistic and Causal Knowledge in Econometric Models

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Causality and Probability in the Sciences

Motivations

Is causal induction possible in economics (non-experimental setting)?

For causal inference in econometrics one needs:

- *some* background causal knowledge / assumptions
- statistical description of the data (statistical model)

Agreements and disagreements

Distinction between causal and statistical requirements (Hoover 2007)

Questions I want to face:

- Is statistical and causal information separable? Should it be?
- Is statistical knowledge causality-laden?

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- statistical model
- statistical (in-)dependence
- in which sense statistical information is causality laden
- in which sense it is not
- two important pieces of information:
  - functional form
  - level of aggregation

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Statistical models

Statistical models (see Spanos 1999):

- ▷ probability model:
  - density function of random variables
  - space of parameters (in the parametric case)
  - support of the density

  e.g. $\Phi_\theta = \{f(x;\theta), \theta \in \Theta, x \in \mathcal{R}_x\}$
- ▷ sampling model:

  for example: $(X_1, X_2, \ldots, X_n)$ is a random sample.

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Useful statistical information

Statistical information *useful for causal inference*:

- stochastic generating mechanism (GM) (Spanos 1999)

$$Y = E(Y|\mathcal{D}) + u \tag{1}$$

satisfying: $E(u \cdot E(Y|\mathcal{D})) = 0; \quad E(u|\mathcal{D}) = 0; \quad E(u^2|\mathcal{D}) = Var(Y|\mathcal{D}) < \infty$

  - ▷ regression function decomposition
  - ▷ structural equation models (in the Haavelmo's tradition)

- conditional independence (CI) tests
  - ▷ $H_0: \quad X \perp\!\!\!\perp Y|Z \quad \equiv \quad f(x|y,z) = f(x|z)$
  - ▷ graphical causal inference based on conditional independence tests and on inferential rules like Markov and Faithfulness conditions (cfr. Pearl 2000, Spirtes-Glymour-Scheines 2000)

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Caveat: not *any* stochastic GM or any test of CI conveys useful information!

example:

$$Y_{it} = f(X_{it}, Z_{it}) + \epsilon_t \quad (2)$$

Y_{it}: expenditure on some goods g (e.g. food);
X_{it}: income;
Z_{it}: family characteristics

we may be led astray if:

- the conditions for which the data are obtained change at each time point;
- instability;
- if we aggregate heterogenous families.

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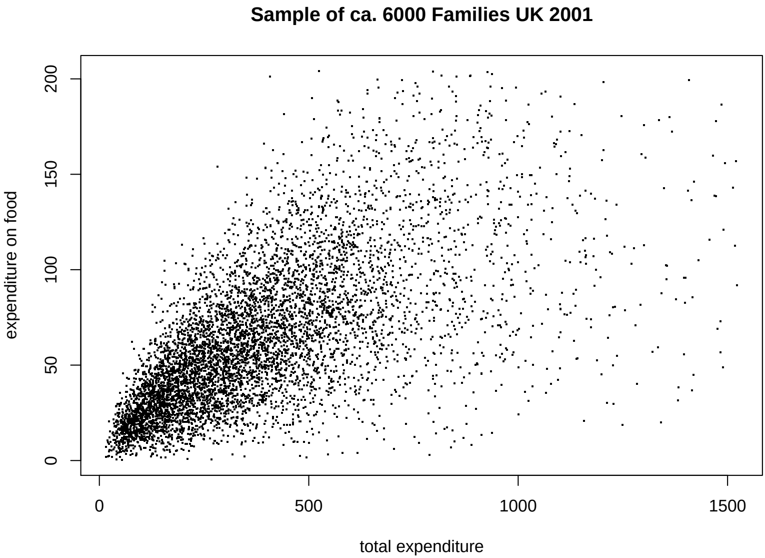
Chance set-ups

A statistical model, to be linked to the world, must represent a chance set-up that gave rise to the observed data (see Cartwright 1999).

Chance set-ups (Hacking 1965):

- device (not necessarily physical) natural / artificial
- generation of trials / observations
- each trial has a result which is a member of class of possible results

phenomena of *chance regularity*


Sample of ca. 6000 Families UK 2001
expenditure on food
0
50
100
150
200
0
500
1000
1500
total expenditure

Chance set-ups

Are there causal presuppositions in thinking about chance set-ups?
in some sense yes:

- cfr. *propensities*

but...

- we do need to have a complete knoweldge of the chance set-up
- chance set-ups with opposite causal relations may be described by the same statistical model

Causal direction

Testing conditional independence does not *in general* require causal presuppositions about:

- presence of cycles, feedbacks
- causal sufficieny (latent variables)

Why? Because statistical tests of independence do not invoke causal notions (properties about directions and sufficiency).

$$X \perp\!\!\!\perp Y|Z \quad \equiv \quad f(x|y,z) = f(x|z)$$

$\equiv$ knowing realizations of Z, information about realization of X conveys useful information about realization of$Y$

Functional form

Functional form of causal dependence

Specification of the functional form of the regression function

Linearity assumptions.
e.g. $Y_t = \beta_0 + \beta_1 x_t + u_t, \quad u_t \sim NIID(0, \sigma^2)$

Correlation coefficient ρ: measure of linear dependence.

Is it possible to test conditional independence without assumptions on the functional form?

Yes: nonparametric tests of conditional independence.

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But: *curse of dimensionality.*

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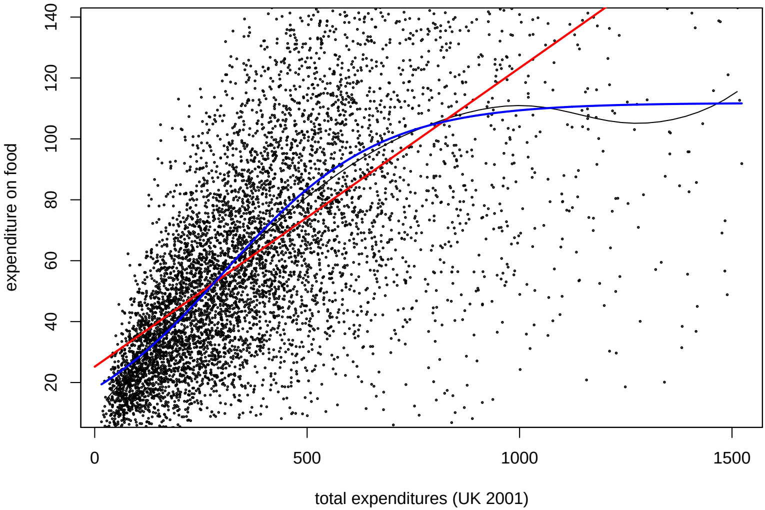
expenditure on food
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total expenditures (UK 2001)

Aggregation

Choice of the variables can be partially theory or *causality-laden*.

Mixing populations:

- Simpson paradox: correlations in a sample vanish in subsamples;

Problem of heterogeneity / aggregation:

- Example: suppose you model the dependence between consumption on a particular commodity (e.g. food) and income. How is this dependence across sub-groups? sub categories of income/commodities?
- a form of dependence at micro level may be different at macro level

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To what extent is the statistical evidence causality laden?

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