Econometric Causality: Part I on Causality

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Econometric Approach

- Econometric approach to causality
  a. Develops explicit models of outcomes where the *causes of effects* are investigated
  b. The mechanisms governing the choice of treatment are analyzed.
- The relationship between treatment outcomes and treatment choice mechanisms is studied.
- Accounts for the unobservables in outcome and treatment choice equations
- Facilitates understanding of the **causal mechanisms** by which outcomes are produced: both outcome equations and treatment assignment (choice) equations.
- Focuses on **why** interventions work, if they do.
- This approach also facilitates the design of estimators to solve selection and evaluation problems.

- Both objective and subjective evaluations are analyzed
- Subjective valuations: those of the person receiving treatment as well as the persons assigning it.
- Differences between anticipated and realized objective and subjective outcomes.
- Distinction is made between models for potential outcomes and empirical methods for identifying treatment effects.

Treatment Effect Model vs Economic Model

- The treatment effect model focuses on **"effects of causes"** not **"causes of effects"**.
- **The economic approach: examines the "causes of the effects" and the mechanisms that produce outcomes in order to consider and evaluate effective interventions.**

Structural Models: A Definition

- Parameters of a structural system are invariant to *a class* of interventions (Hurwicz, 1962).
- Not necessarily all interventions.
- Has nothing to do with invoking specific functional forms or any particular method of estimation.
- See Haavelmo, 1943, *Econometrica* and Heckman and Pinto, 2015, *Theoretical Econometrics*.

- Simple example of a causal structural relationship

$$Y = X_b\beta_b + X_p\beta_p + U \qquad (*)$$

  U: A variable unobserved *by the analyst* (and possibly agent as well)
  X_b: background variables
  X_p: policy variables (can manipulate by intervention)
  $(*)$ is an "all causes" model:
  (All potential causes of Y are accounted for).
  External manipulations define causal parameters:
  Variations in (X_b, X_p) that hold U fixed
  If the coefficients (β_b, β_p) are invariant to shifts in (X_b, X_p) and variables that cause these shifts, then $(*)$ is structural.

- **Question:** Give examples of economic models where β_b is structural and where it is not, e.g., consider a life cycle model of tax changes on labor supply (Y).

- Also consider models with expectations about future taxes and future labor supply.

- Similar definition in more general models, e.g., $Y = G(X, \theta, U)$
- Structural if G invariant to shifts in X.
- Fixing X vs. conditioning on X.
- Causality is an abstract idea: has nothing specifically to do with any issue of identification or estimation.
- **"Causality is in the mind."**

- Consider a model where X and U are correlated.
- OLS:

$$E^*(Y \mid X_b, X_p) = X_b\beta_b + X_p\beta_p + E^*(U \mid X_b, X_p)$$

- E^* is a linear projection.
- OLS does not necessarily estimate a structural relationship.
- If $E(U \mid X_b, X_p) = 0$, under standard rank conditions on regressors OLS identifies (β_b, β_p).
- But leaves unclear whether or not X_b (and X_p) **can**, in principle, be manipulated.

- If

$$E^*(U \mid X_b, X_p) = E^*(U \mid X_b)$$

  and the coefficient on β_p invariant to certain manipulations in X_p then OLS is structural for β_p **for those manipulations.**
- But not necessarily structural for β_b.

The Structural Versus the Program Evaluation Approach for Evaluating Economic Policies

- Causality at the individual level: based on the notion of controlled variation
- Variation in treatment holding other factors constant.
- Alfred Marshall's (1890) *ceteris paribus* clause: the operational definition of causality in economics for over a century.
- Distinct from other notions of causality sometimes used in economics based on *prediction* (e.g., Granger, 1969, and Sims, 1972).

- Three distinct tasks in causal inference and policy analysis:
  a. Defining counterfactuals.
  b. Identifying causal models from ideal data (identification problem).
  c. Estimating parameters from actual data.
- Table 1 delineates the three distinct problems.

Table 1: Three Distinct Tasks that Arise in the Analysis of Causal Models

Task	Description	Requirements
1	Defining the Set of Hypotheticals or Counterfactuals	A Well-specified Theory
2	Identifying Causal Parameters from Data	Mathematical Analysis of Point or Set Identification in infinite samples
3	Estimation	Inference in Actual Samples

Policy Evaluation Problems and Criteria of Interest

P1

Evaluating the Impacts of Implemented Interventions on Outcomes Including Their Impacts in a particular environment on the Well-Being of the Treated and Society at Large.

- Objective evaluations
- Subjective evaluations
- Ex ante and ex post
- Focuses on impacts on a **particular** population
- Focuses on "Internal Validity"

P2

Forecasting the Impacts (Constructing Counterfactual States) of Interventions Implemented in One Environment in Other Environments, Including Impacts on Well-Being.

- *External validity*: taking a treatment parameter or a set of parameters identified in one environment to another environment.
- Also known as *transportability*

P3

Forecasting the Impacts of Interventions (Constructing Counterfactual States Associated with Interventions) Never Historically Experienced, Including Their Impacts on Well-Being.

- This entails structural models with new (never previously experienced) ingredients
- **P3** is a problem that policy analysts solve daily.
- Structural econometrics addresses this question.
- The program evaluation approach does not except through “demonstration programs” (i.e., that explicitly implement the policies).

A Prototypical Economic Model for Causal Analysis, Policy Evaluation and Forecasting the Effects of New Policies

- **Roy Model (1951):** Agents face two potential outcomes (Y_0, Y_1) characterized by distribution $F_{Y_0,Y_1}(y_0, y_1)$
    - where "0" refers to a no treatment state and "1" refers to the treated state and
    - (y_0, y_1) are particular values of random variables (Y_0, Y_1).
- More generally, set of potential outcomes: $\{Y_s\}_{s \in \mathcal{S}}$.
- $\mathcal{S}$ is the set of indices of potential outcomes: in simple Roy model $\mathcal{S} = \{0, 1\}$.
- The (Y_0, Y_1) depend on $X = (X_b, X_p)$,

  e.g., $$\begin{aligned} E(Y_0 \mid X) &= \mu_0(X) \\ E(Y_1 \mid X) &= \mu_1(X). \end{aligned}$$

- Analysts observe either Y_0 or Y_1, but not both, for any person.
- In the program evaluation literature, this is called the **evaluation problem**.

- The **selection problem**.
- Values of Y_0 or Y_1 that are observed are not necessarily a random sample of the potential Y_0 or Y_1 distributions.
- In the original Roy model, an agent selects into sector 1 if $Y_1 > Y_0$.

$$D = \mathbf{1}(Y_1 > Y_0). \tag{1}$$

- **Generalized Roy Model Examples:**
- C is the cost of going from "0" to "1"

$$D = \mathbf{1}(Y_1 - Y_0 - C > 0). \tag{2}$$

- The observed outcome, Y:

$$Y = DY_1 + (1 - D)Y_0. \tag{3}$$

  Switching regression model: Quandt (1958, 1972)
- C can depend on cost shifters (e.g. Z)

$$E(C \mid Z) = \mu_C(Z)$$

- Z play role of instruments (policy parameters) if Z does not affect (Y_0, Y_1) i.e., $(Z \perp\!\!\!\perp (Y_0, Y_1)$.
- "$\perp\!\!\!\perp$" denotes independence

- Let $\mathcal{I}$ denote information set **of the agent**.
- In advance of participation, the agent may be uncertain about all components of (Y_0, Y_1, C).
- Expected benefit: $I_D = E(Y_1 - Y_0 - C \mid \mathcal{I})$ (subjective evaluation).
- $$D = \mathbf{1}(I_D > 0). \tag{4}$$

- The decision maker selecting "treatment" may be different than the person who has the possible outcomes (Y_0, Y_1).

- The *ex post* objective outcomes are (Y_0, Y_1).
- The *ex ante* outcomes are $E(Y_0 \mid \mathcal{I})$ and $E(Y_1 \mid \mathcal{I})$.
- The *ex ante* subjective evaluation is I_D.
- The *ex post* subjective evaluation is $Y_1 - Y_0 - C$.
- **Question:** Can agents *ex ante* evaluate the *ex post* evaluation?
- Agents may regret their choices because realizations may differ from anticipations.

Treatment Effects Versus Policy Effects

- $Y_1 - Y_0$: (*ex post*) individual level treatment effect.
- Marshallian *ceteris paribus* causal effect.
- Because of the evaluation problem, it is generally impossible to identify individual level treatment effects (Task 2).
- Even if it were possible, $Y_1 - Y_0$ is not the *ex ante* subjective evaluation I_D
- Or the *ex post* assessment $Y_1 - Y_0 - C$.

- Economic policies can operate through changing (Y_0, Y_1) or through changing C.
- Changes in $Y_0, Y_1,$ and C can be brought about by changing both the X and the Z.
- The structural approach considers policies affecting both returns and costs.

Population Parameters of Interest:

- Conventional parameters include the Average Treatment Effect ($\text{ATE} = E(Y_1 - Y_0)$).
- The effect of Treatment on The Treated TT or TOT ($\text{TT} = E(Y_1 - Y_0 \mid D = 1)$).
- The effect of Treatment on the Untreated TUT ($\text{TUT} = E(Y_1 - Y_0 \mid D = 0)$).

- In positive political economy, the fraction of the population that *ex ante* perceives a benefit from treatment is of interest and is called the **voting criterion**:

$$\Pr(I_D > 0) = \Pr(E(Y_1 - Y_0 - C \mid \mathcal{I}) > 0).$$

- In measuring support for a policy in place, the percentage of the population that *ex post* perceives a benefit is also of interest: $\Pr(Y_1 - Y_0 - C > 0)$.
- **Question:** How can agents identify what might have been for states they have not experienced? Consider alternative approaches.

Returns at the Margin

- Determining marginal returns to a policy is a central goal of economic analysis.
- The margin is specified by people who are indifferent between "1" and "0" in the binary treatment model, i.e., those for whom $I_D = 0$.
- The mean effect of treatment for those at the margin of indifference is

$$E(Y_1 - Y_0 \mid I_D = 0).$$

- **Policy Relevant Treatment Effect** (Heckman and Vytlacil, 2001) extends the Average Treatment Effect by accounting for voluntary participation in programs.
- Designed to address problems **P2** and **P3**.
- "b": baseline policy ("before") and "a" represent a policy being evaluated ("after").
- Y^a: outcome under policy a; Y^b is the outcome under the baseline.
- (Y_0^a, Y_1^a, C^a) and (Y_0^b, Y_1^b, C^b) are outcomes under the two policy regimes.

- Policy invariance facilitates the job of answering problems **P2** and **P3**.
- If some parameters are invariant to policy changes, they can be safely transported to different policy environments.
- Structural econometricians search for policy invariant "deep parameters" that can be used to forecast policy changes.
- **Question:** What are the precise requirements for solving P3 for the PRTE?

- One commonly invoked form of policy invariance: policies that keep the potential outcomes unchanged for each person: $Y_0^a = Y_0^b$, $Y_1^a = Y_1^b$, but affect costs ($C^a \neq C^b$).
- Such invariance rules out social effects including peer effects and general equilibrium effects affecting possible outcomes.
- Invariance implicitly used in the recent IV literature ("SUTVA")
- **Question:** In the context of a policy of tuition reduction, under what conditions is $Y_0^a = Y_0^b$; $Y_1^a = Y_1^b$ where Y_i^j denotes the present value of life cycle earnings under policy j in state i?

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- Let D^a and D^b be the choices taken under each policy regime.
- Invoke invariance of potential outcomes.
- The observed outcomes under each policy regime:
- $Y^a = Y_0 D^a + Y_1(1 - D^a)$.
- $Y^b = Y_0 D^b + (1 - D^b)$.

- The **Policy Relevant Treatment Effect** (PRTE) is

$$\text{PRTE} = E(Y^a - Y^b).$$

- Benthamite comparison of aggregate outcomes under policies "*a*" and "*b*".
- PRTE extends ATE by recognizing that policies affect incentives to participate (C) but do not force people to participate.
- Only if C is very large under b and very small under a, so there is universal nonparticipation under b and universal participation under a, would ATE and PRTE be the same parameter. (This is large support: "identification at infinity")
- **Question:** What is the relationship between PRTE and ITT (Intention To Treat)? Is PRTE a causal parameter?

The Econometric Approach Versus the "Rubin" Model Treatment Effect Approach

- Econometric approach examines the **causes of effects**
- How Y_1 and Y_0 vary as X varies
- How treatment (D) gets determined through variations in Z, X.
- This is the goal of science
- The treatment effect approach ("Rubin model") looks at *effects of causes*
- Does not examine choice **mechanisms**
- Framework is ill-suited to the study of effective economic policy

Table 2: Comparison of the Aspects of Evaluating Social Policies that are Covered by the Neyman-Rubin Approach and the Structural Approach

	Neyman-Rubin Framework	Structural Framework
Counterfactuals for objective outcomes (Y_0, Y_1)	Yes	Yes
Agent valuations of subjective outcomes (I_D)	No (choice-mechanism implicit)	Yes
Models for the causes of potential outcomes	No	Yes
Ex ante versus *ex post* counterfactuals	No	Yes
Treatment assignment rules that recognize voluntary nature of participation	No	Yes
Social interactions, general equilibrium effects and contagion	No (assumed away as part of "SUTUA")	Yes (modeled)
Internal validity (problem **P1**)	Yes	Yes
External validity (problem **P2**)	No	Yes
Forecasting effects of new policies (problem **P3**)	No	Yes
Distributional treatment effects	No[a]	Yes (for the general case)
Analyze relationship between outcomes and choice equations	No (implicit)	Yes (explicit)

[a] An exception is the special case of common ranks of individuals across counterfactual states: "rank invariance." See the discussion in Abbring and Heckman (2007).

- **Question:** Is LATE a causal parameter? How does it address P1-P3?

Methods of Estimation (Task 2)

- Rubin-Neyman model elevates randomization to be the "gold standard."
- Holland (1986): there can be no causal effect of gender on earnings because analysts cannot randomly assign gender.
- This statement confuses the act of defining a causal effect (a purely mental act performed within a model) with empirical difficulties in estimating it.
- It confuses the tasks of formulating a theory and the concept of causality within a model with the practical problems of testing it and estimating the parameters of it.

- Unaided, data from randomized trials cannot identify the voting criterion ($\Pr(Y_1 - Y_0) > 0$) i.e., percentage of people who benefit.
- Do not identify the joint distribution of $Y_0 Y_1$ under general conditions.
- Matching assumes that the marginal recipient of treatment gets the same return as the average.
- Unaided IV or "LATE" identifies people at an unspecified margin – doesn't tell us which people are induced to switch.
- **Question:** Verify each claim in this box.