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.
• Simple example of a causal structural relationship

\[ Y = X_b\beta_b + X_p\beta_p + U \]  

\( U \): 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 \((\beta_b, \beta_p)\) 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 \( \beta_b \) 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 $(\beta_b, \beta_p)$.
- 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 \( \beta_p \) invariant to certain manipulations in \( X_p \) then OLS is structural for \( \beta_p \) for those manipulations.

• But not necessarily structural for \( \beta_b \).
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:

- Defining counterfactuals.
- Identifying causal models from ideal data (identification problem).
- 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

<table>
<thead>
<tr>
<th>Task</th>
<th>Description</th>
<th>Requirements</th>
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<tbody>
<tr>
<td>1</td>
<td>Defining the Set of Hypotheticals or Counterfactuals</td>
<td>A Well-specified Theory</td>
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<tr>
<td>2</td>
<td>Identifying Causal Parameters from Data</td>
<td>Mathematical Analysis of Point or Set Identification in infinite samples</td>
</tr>
<tr>
<td>3</td>
<td>Estimation</td>
<td>Inference in Actual Samples</td>
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Policy Evaluation Problems and Criteria of Interest
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”
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*
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: \(\{Y_s\}_{s \in S}\).
- \(S\) is the set of indices of potential outcomes: in simple Roy model \(S = \{0, 1\}\).
- The \((Y_0, Y_1)\) depend on \(X = (X_b, X_p)\),
  - e.g., \(E(Y_0 \mid X) = \mu_0(X)\)
  - \(E(Y_1 \mid X) = \mu_1(X)\).
• 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 $Y_1 > Y_0$.

$$D = 1(Y_1 > Y_0).$$

(1)
• **Generalized Roy Model Examples:**

  • $C$ is the cost of going from “0” to “1”

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

  • 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).

• $D = 1(I_D > 0)$. \hspace{1cm} (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 \(E(Y_0 | I)\) and \(E(Y_1 | I)\).
• 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**:

\[
\Pr(I_D > 0) = \Pr(E(Y_1 - Y_0 - C | \mathcal{I}) > 0).
\]

• 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:
\[ Y_0^a = Y_0^b, \quad Y_1^a = Y_1^b, \] 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 \( i \)?
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

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Neyman-Rubin Framework</th>
<th>Structural Framework</th>
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<tbody>
<tr>
<td>Counterfactuals for objective outcomes ($Y_0, Y_1$)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Agent valuations of subjective outcomes ($I_D$)</td>
<td>No (choice-mechanism implicit)</td>
<td>Yes</td>
</tr>
<tr>
<td>Models for the causes of potential outcomes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td><em>Ex ante versus ex post</em> counterfactuals</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Treatment assignment rules that recognize voluntary nature of participation</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Social interactions, general equilibrium effects and contagion</td>
<td>No (assumed away as part of “SU-TUA”’)</td>
<td>Yes (modeled)</td>
</tr>
<tr>
<td>Internal validity (problem P1)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>External validity (problem P2)</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Forecasting effects of new policies (problem P3)</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Distributional treatment effects</td>
<td>No$^a$</td>
<td>Yes (for the general case)</td>
</tr>
<tr>
<td>Analyze relationship between outcomes and choice equations</td>
<td>No (implicit)</td>
<td>Yes (explicit)</td>
</tr>
</tbody>
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$^a$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?
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.