Econometric Policy Analysis

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Econometric Approach to Causality

- 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, 2022, *Annual Reviews of Economics*.

- Go back to our 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 or thought experiment)
$(*)$ 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.

- Similar definition in more general models, e.g., $Y = G(X, \theta, U)$
- Structural if G invariant to shifts in X.
- By invariance we mean: map $G : (X, \theta, U) \rightarrow Y$ is not changed by changes in X, θ, U.
- Values of Y obviously are changed.
- 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**, as a thought experiment, 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 those for X_b.
- But not necessarily structural for β_b.

The Economic 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 by thought experiments.
  b. Identifying causal models from ideal data (identification problem).
  c. Estimating parameters from actual data.
- Table 1 delineates 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 within which to conduct thought experiments
2	Identifying Causal Parameters from Data	Mathematical Analysis of Point or Set Identification in infinite samples
3	Estimation and Testing	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

Understanding the Mechanisms Producing Treatment Effects

P3

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*

P4

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 (aka economic policy analysis) addresses this question.
- The program evaluation approach does not except through "demonstration programs" (i.e., that explicitly implement the policies).
- **Experiments are not essential to definition of causality.**
- **Thought experiments are**

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*: $\{Y_s\}_{s \in \mathcal{S}}$.
- Some selection mechanism determines with Y^1 and Y^0, we observe:
- $\mathcal{S}$ 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., $$\begin{aligned} E(Y_0 \mid X) &= \mu_0(X) \\ E(Y_1 \mid X) &= \mu_1(X). \end{aligned}$$
- A major issue is which X affect $E(Y_0|X)$ and $E(Y_1|X)$ and with what strength.

- Analysts often 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"

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

- C is a random variable.
- 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
- When C is a constant: **Extended Roy model**

- 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 econometric approach considers policies affecting both returns and costs.

Common Population Parameters:

- 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?

- 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? For what policy questions is it useful?

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**, e.g., (I_D)
- Casts the entire enterprise into a hypothesis testing framework
- That is a poor general framework for learning from data

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 (the X)	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.
- **Causality is about thought experiments, not actual experiments**

- 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 side.

Marschak's Maxim and the Relationship Between the Structural Literature and the Statistical Treatment Effect Literature

- The absence of explicit economic models is a prominent feature of the statistical treatment effect literature.
- Scientifically well-posed models make explicit the assumptions used by analysts regarding preferences, technology, the information available to agents, the constraints under which they operate and the rules of interaction among agents in market and social settings and the sources of variability among persons.
- These explicit features make these models, like all scientific models, useful vehicles:
  a. for interpreting empirical evidence using theory;
  b. for collating and synthesizing evidence using theory;
  c. for measuring the welfare effects of policies;
  d. for forecasting the welfare and direct effects of previously implemented policies in new environments and the effects of new policies.

- These features are absent from the modern treatment effect literature.
- At the same time, this literature makes fewer statistical assumptions in terms of exogeneity, functional form, exclusion and distributional assumptions than the standard structural estimation literature in econometrics.
- These are the attractive features of this approach.

- Marschak (1953) noted that for many specific questions of policy analysis, it is unnecessary to identify full structural models where by structural I mean parameters invariant to classes of policy modifications.
- Marschak's Maxim.
- All that is required is combinations of subsets of the structural parameters, corresponding to the parameters required to forecast particular policy modifications, which are much easier to identify (i.e., require fewer and weaker assumptions).

- The modern statistical treatment effect literature as implicitly implementing Marschak's Maxim where the policies analyzed are the treatments and the goal of policy analysis is restricted to evaluating policies in place (Problem1; P-1) and not in forecasting the effects of new policies or the effects of old policies on new environments.

- 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.

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- 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.
- If $E(U \mid X_b, X_p) = 0$, under standard rank conditions on regressors OLS identifies (β_b, β_p).

- 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.**
- Can identify β_p if $E^*(U|X_b)$ not collinear with X_b.
- Notice, you do not identify β_p.

Are structural causal models necessarily parametric?

- Considerable progress has been made in relaxing the parametric structure assumed in the early structural models in econometrics (see Matzkin, 2007).
- As the treatment effect literature is extended to address the more general set of policy forecasting problems entertained in the structural literature, the distinction between the two literatures vanishes.
- Heckman and Vytlacil (2007a, 2005) and Heckman (2007) are attempt to bridge this gulf.

Are Parametric Models Necessarily Bad?

- What is wrong with Newton's law?
-

$$F = ma$$
$$F = G\left(\frac{m_1 m_2}{r^2}\right)$$

- Most of the models of economics you have learned are parametric
- Cobb Douglas: workhorse of macro $Y = AK^{\alpha}L^{\beta}$