Econometric Causality

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- The relationship between treatment outcomes and treatment choice mechanisms is studied.
- A careful accounting of the unobservables in outcome and treatment choice equations facilitates the design of estimators to solve selection and evaluation problems.
- It also facilitates understanding of the **causal mechanisms** by which outcomes are produced: both outcome equations and treatment assignment (choice) equations.

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- Differences between anticipated and realized objective and subjective outcomes are analyzed.
- Models for simultaneous treatment effects are developed. (Joint causation)
- A careful distinction is made between models for potential outcomes and empirical methods for identifying treatment effects.

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- **The econometric approach examines the "causes of the effects" and the mechanisms that produce outcomes in order to consider and evaluate effective interventions that promote personality.**

- An example of a structural relationship (Haavelmo, 1944, *Econometrica*)

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

U: A variable unobserved *by the analyst*
X_b: background variables
X_p: policy variables (can manipulate by interventions)
$*$ is an "all causes" model
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), then $(*)$ is structural.

- Notice that OLS is

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

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- OLS is not estimating a structural relationship.
- If $E(U \mid X_b, X_p) = 0$, OLS gives a structural estimator for (β_b, β_p).

- If
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and the coefficient in the original model is invariant to manipulations in X_p then OLS is structural for β_p.

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and the coefficient in the original model is invariant to manipulations in X_p then OLS is structural for β_p.
- But not necessarily for β_b.

The Structural Versus the Program Evaluation Approach to Evaluating Economic Policies

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- Based on the notion of controlled variation — variation in treatment holding other factors constant.
- This is Alfred Marshall's (1890) *ceteris paribus* clause which has been the operational definition of causality in economics for over a century.
- It is distinct from other notions of causality sometimes used in economics that are based on prediction (e.g., Granger, 1969, and Sims, 1972).

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- Table 1 delineates the two distinct problems.

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

Task	Description	Requirements
1	Defining the Set of Hypotheticals or Counterfactuals	A Well-specified Scientific Theory
2	Identifying Causal Parameters from Data	Mathematical Analysis of Point or Set Identification Joined With Estimation and Testing Theory

Policy Evaluation Problems and Criteria of Interest

P1

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

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- Objective evaluations
- Subjective evaluations
- Ex ante and ex post

P2

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

- This is the problem of *external validity*: taking a treatment parameter or a set of parameters identified in one environment to another environment.

P3

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

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- 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 (1951): Agents face two potential outcomes (Y_0, Y_1) with 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).

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- Roy model $\mathcal{S} = \{0, 1\}$.
- The Y_0, Y_1 depend on $X = (X_b, X_p)$,

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

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- In the program evaluation literature, this is called the **evaluation problem**.

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- In the original Roy model, an agent selects into sector 1 if $Y_1 > Y_0$.
- $$D = \mathbf{1}(Y_1 > Y_0), \tag{1}$$

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  (C is the cost of going from "0" to "1")

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- C can depend on cost shifters (e.g., Z)

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

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

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

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- The *ex ante* subjective evaluation is I_D.
- The *ex post* subjective evaluation is $Y_1 - Y_0 - C$.
- Agents may regret their choices because realizations may differ from anticipations.

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- Also, the 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, $Y_1 - Y_0$ does not reveal 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.

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- 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 ($\text{TT} = E(Y_1 - Y_0 \mid D = 1)$), or the effect of Treatment on the Untreated ($\text{TUT} = E(Y_1 - Y_0 \mid D = 0)$).

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

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- In measuring support for a policy in place, the percentage of the population that *ex post* perceives a benefit is also of interest: $\Pr(Y_1 - Y_0 - C > 0)$.

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- In the generalized Roy model, the margin is specified by people who are indifferent between “1” and “0”, i.e., those for whom $I_D = 0$.
- The mean effect of treatment for those at the margin of indifference is

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

Treatment Effects Versus Policy Effects

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- "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.

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- 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.

- Under one commonly invoked form of policy invariance, policies keep the potential outcomes unchanged for each person: $Y_0^a = Y_0^b$, $Y_1^a = Y_1^b$, but affect costs ($C^a \neq C^b$).

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- Such invariance rules out social effects including peer effects and general equilibrium effects.

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- Invoking invariance of potential outcomes, the observed outcomes under each policy regime are $Y^a = Y_0 D^a + Y_1(1 - D^a)$ and $Y^b = Y_0 D^b + (1 - D^b)$.

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- 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.

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

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- The treatment effect approach ("Rubin model") looks at *effects of causes*
- Does not investigate **mechanisms** of causation
- Framework is ill-suited to the study of personality psychology where causal mechanisms need to be developed

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)	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).

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- After explicating the "Rubin model," Holland makes a very revealing claim: 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.

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- 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.