The Economics of European Regions: Theory, Empirics, and Policy

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Potential Outcomes Approach: a brief history

- The approach to causal inference based on the definition of potential outcomes is the base of the modern approach to program evaluation.
- This modern approach comes from the *statistics literature* and is based on the work of Rubin (1974).
- However, it has important antecedents.
- The two most important are:
  - the introduction of potential outcomes in randomized experiments by Neyman (1923)
  - the introduction of randomization as the “reasoned basis” for inference by Fisher (1935).

Potential Outcomes Approach: a brief history (cont.)

- Although the basic idea that causal effects are the comparisons of potential outcomes may seem so obvious, the formal notation for potential outcomes was not introduced until 1923 by Neyman.
- Neyman begins with a description of a field experiment with m plots on which v varieties might be applied.
- Then, introduces what he calls "potential yield" U_{ik}, where i indexes the variety, $i = 1, ..., v$, and k indexes the plot, $k = 1, ..., m$.
- The potential yields **are not equal** to the actual or observed yield because i indexes all varieties and k indexes all plots, and each plot is exposed to only one variety.
- Then goes on to describe an urn model for determining which variety each plot receives
- This model is stochastically identical to the *completely randomized experiment* with $n = m/v$ plots exposed to each variety.

Potential Outcomes Approach: a brief history (cont.)

Neyman's formalism made three contributions:

1. explicit notation for potential outcomes;
2. implicit consideration of something like the stability assumption;
3. implicit consideration of a model for the assignment of treatments to units that corresponds to the completely randomized experiment.

However, "implicit is not explicit; randomization as a physical act, and later as a basis for analysis, was yet to be introduced by Fisher " (Neyman, 1923)

Potential Outcomes Approach: a brief history (cont.)

- Fisher, in 1925, takes the further step of proposing the necessity of physical randomization for credibly assessing causal effects.
- He proposed the physical randomization of units and furthermore developed a distinct method of inference based for this special class of assignment mechanisms, that is, randomized experiments.
- The "Fisher's exact P-values" are the accepted rigorous standard for the analysis of randomized clinical trials.
- In such a way, the concept of potential outcomes was used in the context of randomized experiments.

Potential Outcomes Approach: a brief history (cont.)

- Despite the almost immediate acceptance of randomized experiments, Fisher's p-values, and Neyman's notation for potential outcomes, these same elements were not used for causal inference in *observational studies*.
- It is only more recently, starting in the early seventies with the work of Rubin (1974), that the language and reasoning of potential outcomes was put front and center in observational study settings.
- Rubin (1974, 1975, 1978) make two key contributions:
  1. Rubin (1974) puts the potential outcomes center stage in the analysis of causal effects, irrespective of whether he study is an experimental one or an observational one;
  2. Rubin (1975, 1978) discuss the assignment mechanism in terms of the potential outcomes.

Potential Outcomes Approach: a brief history (cont.)

Rubin starts by *defining* the causal effect at the unit level in terms of the pair of potential outcomes:

Rubin, 1974, p. 639

. . . define the causal effect of the E versus C treatment on Y for a particular trial (i.e., a particular unit . . .) as follows: Let $y(E)$ be the value of Y measured at t_2 on the unit, given that the unit received the experimental Treatment E initiated at t_1; Let $y(C)$ be the value of Y measured at t_2 on the unit given that the unit received the control Treatment C initiated at t_1. Then $y(E) - y(C)$ is the causal effect of the E versus C treatment on Y . . . for that particular unit.

Potential Outcomes Approach: a brief history (cont.)

- This definition fits perfectly with Neyman's framework for analysing randomized experiments
- But shows that the definition has nothing to do with the assignment mechanism: it applies equally to observational studies as well as to randomized experiments.
- Rubin (1975, 1978) then discusses the benefits of randomization in terms of eliminating systematic differences between treated and control units and formulates the assignment mechanism in terms of potential outcomes.

$\Rightarrow$ For these reasons, the modern approach to causal inference and program evaluation is based on the "**Rubin Causal Model** (RCM)".

Lord's paradox

To illustrate the clarity of the potential outcomes interpretation of causality consider:

The Lord's paradox:

A large university is interested in investigating the effects on the students of the diet provided in the university dining halls and any sex differences in these effects. Various types of data are gathered. In particular, the weight of each student at the time of his arrival in September and his weight the following June are recorded.

Results:

- For the males the average weight is identical at the end of the school year to what it was at the beginning (the whole distribution of weights is unchanged, although some males lost weight and some males gained weight).
- The same thing is true for the females.
- Females started and ended the year lighter on average than the males.

Lord's paradox (cont.)

The paradox is generated by considering the contradictory conclusions of two statisticians asked to comment on the data.

Statistician 1

There is no evidence of any interesting effect of diet (or of anything else) on student weight. In particular, there is no evidence of any differential effect on the two sexes, since neither group shows any systematic change.

Statistician 2

After "controlling for" initial weight, the diet has a differential positive effect on males relative to females because for males and females with the same initial weight, on average the males gain more than the females.

Lord's paradox (cont.)

- Such gain scores are **not causal effects** because they do not compare potential outcomes at the same time post-treatment; rather, they compare changes over time.
- If both statisticians confined their comments to *describing* the data, both would be correct.
- For causal inference, both are wrong!

Lord's paradox (cont.)

- The units are the *students*.
- The time of application of active treatment (the university diet) is *September*.
- Time of the recording of the outcome Y is *June*.
- Let us accept the stability assumption.
- The potential outcomes are June weight under the university diet $Y_i(1)$ and under the "control" diet $Y_i(0)$.
- The covariates are sex of students, male versus female, and September weight.
- But the assignment mechanism has **assigned everyone to the new treatment**! There is **no one**, male or female, who is **assigned to the control** treatment.

$\Rightarrow$ there is absolutely no purely empirical basis on which to compare the effects, either raw or differential, of the university diet with the control diet!

Advantages of POA

The potential outcome approach (POA) has a number of advantages over the framework based directly on realized outcomes.

1. The POA allows to define causal effect **before** specifying the assignment mechanism and **without** making functional form or distributional assumption.

   The most common definitions of causal effect at unit level is the difference $Y_i(1) - Y_i(0)$ or the ratio $Y_i(1)/Y_i(0)$.
   • Such definition do not require to take a stand on whether the effect is constant or varies across the population.
   • Moreover, does not require to assume endogeneity or exogeneity of the assignment mechanism.
   • Allows researcher to first define the causal effect of interest without considering probabilistic properties of the outcome.

Advantages of POA (cont.)

2. The POA **links** the analysis of causal effects to *explicit manipulations*: considering two potential outcomes forces the researcher to think about scenarios under which each outcome could be observable, that is to consider the kind of experiment that could reveal the causal effects.

Causal effect of ethnicity on outcome of job application

- Simple comparisons of economic outcomes by ethnicity are difficult to interpret.
- Are they the result of discrimination by employers, or are they the result of differences between applicants, possibly arising from discrimination at an earlier stage of life?
- We can obtain unambiguous causal interpretation by linking comparisons to specific manipulations.
- Bertrand and Mullainathan (2004): compare call-back rates for job applications submitted with names that suggest African-American or Caucasian ethnicity.
- The clear manipulation is the name change!

Advantages of POA (cont.)

3. The POA **separates** the modelling of the potential outcomes from that of the assignment mechanism.

Causal effect of job training program on earnings.
• The outcome, earnings, in the absence of the program $Y_i(0)$ can be modelled in terms of individual characteristics and labour market histories.
• Similarly, the outcome, earnings, given enrolment in the program can be modelled again conditional on individual characteristics and labour market histories.
• The probability of enrolling in the program given the earnings in both treatments can be modelled conditional on individual characteristics.
• This *sequential* modelling will lead to a model for realized outcome in a easier way with respect to directly specifying a model for the realized outcomes.

Advantages of POA (cont.)

4. The POA **allows** to formulate probabilistic assumption in terms of *potentially observable* variables, rather than in terms of *unobserved* components.

   • In this approach many of the critical assumption will be formulated as (conditional) independence assumptions involving the potential outcomes.
   • Assessing their validity requires the researcher to consider the dependence structure if all potential outcomes were observed.
   • By contrast, models in terms of realized outcomes often formulate the critical assumptions in terms of errors regression functions.
   • In the regression function $Y_i = \alpha + \tau W_i + \epsilon_i$ the independence assumption between W_i and ϵ_i implicitly bundle also functional-form assumptions.

Advantages of POA (cont.)

5. The POA **clarifies** where the uncertainty in the estimator comes from.

• If we observe the *entire population* (increasingly common with the growing availability of administrative dataset) we would be able to estimate population averages with no uncertainty.
• However, causal effect will be *uncertain* because for each unit at most one of the two potential outcomes is observed.

Econometric literature

- The potential outcomes framework also has important antecedents in econometrics.
- Haavelmo (1943) discusses in the framework of simultaneous equation models (SEM) identification of supply and demand models.
- He makes a distinction between "any imaginable price π" as the argument in the demand and supply functions, $q^d(\pi)$ and $q^s(\pi)$, and the "actual price p", which is the observed equilibrium price satifying $q^s(p) = q^d(p)$.
- The supply and demand functions play the same role as the potential outcome in Rubin's approach, with the equilibrium price similar to the realized outcome.

Econometric literature (cont.)

- Potential outcome are also used explicitly in labour market setting by Roy (1951).
- Roy models individuals choosing from a set of occupations.
- Individuals know what their earning would be in each of these occupations and choose the occupation (treatment) that maximizes their earnings.
- In Roy's model there is:
  - an explicit use of the potential outcomes;
  - a specific selection/assignment mechanism, i.e. choosing the treatment with the highest potential outcome.

Econometric literature (cont.)

- The econometric literature on causality was primarily motivated by application to evaluation of labour market programs in **observational settings** (see e.g., Ashenfelter, 1978, Ashenfelter and Card, 1985, Lalonde, 1986 and Manski, 1990).
- Observational data generally create challenges in estimating causal effects with respect to randomized experiments.
- The focus in the econometric literature is traditionally on *endogeneity* or *self-selection*, etc.
- Individual who choose to enrol in a training program are by definition different from those who choose not to enrol.
- These differences, if they influence the response, may invalidate causal comparison of outcomes by treatment status.

The assignment mechanisms

The **assignment mechanisms** is defined as the conditional probability of receiving the treatment, as a function of potential outcome and observed covariates.

We can distinguish three classes of assignment mechanism:

1. Randomized experiments
2. Unconfounded assignments
3. Assignment mechanisms with some dependence

1. Randomized experiments

In **randomized experiments** the probability of assignment to treatment **does not depend** on potential outcomes and is a **known** function of covariate.

• Consider a population of N units. In a *completely randomized experiment* $N_1 < N$ randomly chosen units are assigned to the treatment and the remaining $N_0 = N - N_1$ units are in the control group.

• In *pairwise randomization* initially units are matched in pairs and, successively, one unit in each pair is randomly assigned to the treatment.

• In *general stratified experiment* the randomization takes place within a finite number of strata.

1. Randomized experiments (cont.)

- There are *in practice* few experiment in economics, and most of them are completely randomized experiments.
- The use of formal randomization has become more widespread in the social science in recent years.
- In randomized experiments estimators for the average effect of the treatment are usually given by the difference in means by treatment status.

2. Unconfounded assignments

The **unconfounded assignments** mechanisms maintains the restrictions that the assignment probability **does not depend** on potential outcomes:

$$W_i \perp (Y_i(0), Y_i(1)) \,|X_i.$$

However, the assignment are **no longer** assumed to be a **known** function of the covariates.

The unconfounded assumption (Rosembaum and Rubin 1983) is not tied to functional form or distributional assumption.

2. Unconfounded assignments (cont.)

Unconfoundedness is also referred in the literature as selection on observables, exogeneity and conditional independence.

All these labels refer to some for of the assumption that *adjusting treatment and control groups* for differences in observed covariates (or pre-treatment variables), remove all biases in comparisons between treated and control units.

Without unconfoundedness there is no general approach to estimate the treatment effects.

Various methods have been proposed for special cases.

3. Assignment mechanisms with some dependence

The third class of assignment mechanisms contains all remaining assignment mechanisms with **some dependence** on potential outcome.

There are two general methods that relax the unconfoundedness without replace it with additional assumption:

- **Sensitivity analysis**: where robustness of estimates to specific limited departures from unconfoundedness are investigated (Rosenbaum and Runin, 1983; Rosenbaum, 1995).
- **Bounds on estimands**: where ranges of estimands consistent with the data and the limited assumptions the researcher is willing to make, are derived and estimated (Manski, 1990; 2003; 2007).

3. Assignment mechanisms with some dependence (cont.)

Many of the possible dependence create substantive problems for the analysis except in some special cases:

- **Regression discontinuity designs**: it applies to settings where overlap is completely absent because the assignment is a deterministic function of covariates, but comparisons can be made exploiting continuity of average outcomes as a function of covariates (see Cook, 2007).
- **Differences-in-differences**: it relies on the presence of additional data in the form of samples of treated and control units before and after the treatment (e.g., Ashenfelter and Card, 1985; Athey and Imbens, 2006).
- **Instrumental variables**: it relies on the presence of additional treatments, the so-called instruments, that satisfy specific exogeneity and exclusion restrictions (Imbens and Angrist, 1994; Angrist, Imbens and Rubin, 1996).