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

Dipartimento di Economia e Management



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- 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).

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- 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.

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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)

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- 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.

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  - 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.

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#### 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.

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

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- Females started and ended the year lighter on average than the males.

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#### 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.

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- For causal inference, both are wrong!

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- 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.
- ⇒ 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!

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- 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.

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- The clear manipulation is the name change!



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- 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.

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  - 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  $\epsilon_i$  implicitly bundle also functional-form assumptions.

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- 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.

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  - a specific selection/assignment mechanism, i.e. choosing the treatment with the highest potential outcome.

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- 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.

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

#### 1. Randomized experiments (cont.)

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- 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

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

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 Sensitivity analysis: where robustness of estimates to specific limited departures from unconfoundedness are investigated (Rosenbaum and Runin, 1983; Rosenbaum, 1995).

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- 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).

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- 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).