[MΞtHodo]

Fiche Technique

Quasi-experiments for public policy evaluation

Introduction

Evaluations of public programs and policies requires advanced techniques and protocols. Quasi-experiments are nowadays among the most frequently used methods. They aim at estimating the causal effect, if any, of a specific intervention in real-life situations (observational data). Typical applications relate to programs in education, public health, and economic policies.

The approach needs a comparison group, the so-called *counterfactual*, which resembles the treatment group in everything but the fact of receiving the intervention (Josselin and Le Maux, 2017). The core idea can be described as follows:

Estimated causal effect = Average outcome in the treatment group - Counterfactual

Definition: *The counterfactual relates to the outcome in the absence of intervention. It is a hypothetical situation that cannot be observed individually since the same unit (e.g. individual, patient) cannot be both exposed and unexposed to the intervention. The counterfactual is instead approximated with reference to a comparison group.*

Rationale for the approach

Quasi-experiments can address a number of challenges and concerns when evaluating a public program.

First, the approach can account for the various factors that may affect the environment of the program across time (longitudinal dimension of the program). For instance, it can be misleading to compare the outcome observed in the treatment group before and after the intervention takes place (*within-subjects estimate*). If such an approach is being used, measurements would encompass the true causal effect but also additional causes due to other variables changing through time (various events and shocks occurring during the period of observation). The analysis would suffer from an omitted-variable bias:

Within-subjects estimate = True causal effect + Omitted-variable bias

Second, the approach can deal with challenges related to the heterogeneity of participants (cross-sectional dimension of the program). Another erroneous way of estimating a causal effect is to compare the group that has been exposed to the intervention with the group that has not (*between-subjects estimate*). Individuals could differ in their characteristics (e.g., their productivity, motivation, health condition) thus generating a selection bias:

Between-subjects estimate = True causal effect + Selection bias

To avoid those biases, quasi-experiments identify a comparison group among the non-treated units (counterfactual estimates) that is as similar as possible to the treatment group.

Quasi-experimental methods

Four methods are frequently used to approximate the counterfactual:

Differences-in-differences. The approach uses panel data and calculates the effect of an intervention by comparing the changes in outcome over time between the treated and comparison groups. One of the first studies employing difference-in-differences is Ashenfelter and Card (1985).

Propensity score matching. This approach relies on the estimation of scores (probability of participating in the treatment) to select and pair subjects with similar characteristics and it computes the causal effect as the difference in means between the two selected groups. The method has been originally developed by Rosenbaum and Rubin (1983).

Regression discontinuity design. The method compares subjects in the vicinity of a cutoff point around which the intervention is dispensed. The underlying assumption is that subjects lying closely on either side of the threshold share similar characteristics. The first application of regression discontinuity design can be traced back to Thistlethwaite and Campbell (1960).

Instrumental variable estimation. This approach addresses the problem of endogeneity in individual participation and applies to situations where the exposure to a policy is determined to some extent by the decision of the units involved, in a process of self-selection. The idea that instrumental variables can be used to solve an identification problem was first introduced in Wright (1915).

Difference with experiments

In an experiment, the treatment group and the comparison group (usually referred to as *control group*) are randomly selected from the same population. It is considered the ideal way to estimate a causal effect. Yet, implementing a randomized controlled experiment is not always feasible given the many legal, ethical, logistical, and political constraints that may be associated with it (Josselin and Le Maux, 2017).

In a quasi-experiment, the analysis is instead based on observational data: units are not randomly assigned to comparable groups. A key issue is thus to find a proper comparison group that resembles the treatment group in terms of pre-intervention characteristics.

Pros and cons of quasi-experiments (based on Baslé et al., 2019)

Pros

Simplicity. The approach can be based on pre-existing information systems, yet data extraction is sometimes complex.

External validity. The approach uses observational data from the target population and evaluates causal effects in real life situations.

Cons

Lack of transparency. Quasi-experiments require sophisticated statistical techniques in order to isolate the effect of the intervention from other possible causes. For that reason, results are manipulable and not easily reproducible.

Lack of internal validity. The approach compares groups that are not randomly assigned. Potential biases have to be resolved.

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