	Method	Description	What assumptions are required, and how demanding are the assumptions?	Required data
Randomization	Randomized Evaluation/ Randomized Control Trial	Measure the differences in outcomes between randomly assigned program participants and non-participants after the program took effect.	*The outcome variable is only affected by program participation itself, not by assignment to participate in the program or by participation in the randomized evaluation itself.* Examples for such confounding effects could be information effects, spillovers, or experimenter effects. As with other methods, the sample size needs to be large enough so that the two groups are statistically comparable; the difference being that the sample size is chosen as part of the research design.	Outcome data for randomly assigned participants and non-participants (the treatment and control groups).
Basic Non-Experimental Comparison Methods	Pre-Post	Measure the differences in outcomes for program participants before the program and after the program took effect.	*There are no other factors (including outside events, a drive to change by the participants themselves, altered economic conditions, etc.) that changed the measured outcome for participants over time besides the program*. In stable, static environments and over short time horizons, the assumption might hold, but it is not possible to verify that. Generally, a diff-in-diff or RDD design is preferred (see below).	Data on outcomes of interest for program participants before program start and after the program took effect.
	Simple Difference	Measure the differences in outcomes between program participants after the program took effect and another group who did not participate in the program.	*There are no differences in the outcomes of participants and non-participants except for program participation*, and both groups were equally likely to enter the program before it started. This is a demanding assumption. Non-participants may not fulfill the eligibility criteria, live in a different location, or simply see less value in the program (self-selection). Any such factors may be associated with differences in outcomes independent of program participation. Generally, a diff-in-diff or RDD design is preferred (see below).	Outcome data for program participants as well as another group of non-participants after the program took effect.
	Differences in Differences	Measure the differences in outcomes for program participants before and after the program *relative* to non-participants.	*Any other factors that may have affected the measured outcome over time are the same for participants and non-participants, so they would have had the same time trajectory absent the program*. Over short time horizons and with reasonably similar groups, this assumption may be plausible. A "placebo test" can also compare the time trends in the two groups before the program took place. However, as with "simple difference," many factors that are associated with program participation may also be associated with outcome changes over time. For example, a person who expects a large improvement in the near future may not join the program (self-selection).	Data on outcomes of interest for program participants as well as another group of non-participants before program start and after the program took effect.

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	Method	Description	What assumptions are required, and how demanding are the assumptions?	Required data
More advanced statistical non-experimental methods	Multivariate Regression/OLS	The "simple difference" approach can be—and in practice almost always is—carried out using multivariate regression. Doing so allows accounting for other observable factors that might also affect the outcome, often called "control variables" or "covariates." The regression filters out the effects of these covariates and measures differences in outcomes between participants and non-participants while holding the effect of the covariates constant.	Besides the effects of the control variables, *there are no other differences between participants and non-participants that affect the measured outcome*. This means that any unobservable or unmeasured factors that do affect the outcome must be the same for participants and non-participants. In addition, the control variables cannot in any way themselves be affected by the program. While the addition of covariates can alleviate some concerns with taking simple differences, limited available data in practice and unobservable factors mean that the method has similar issues as simple difference (e.g., self-selection).	Outcome data for program participants as well as another group of non-participants, as well as "control variables" for both groups.
	Statistical Matching	Exact matching: participants are matched to non-participants who are identical based on "matching variables" to measure differences in outcomes. Propensity score matching uses the control variables to predict a person's likelihood to participate and uses this predicted likelihood as the matching variable.	Similar to multivariable regression: *there are no differences between participants and non-participants with the same matching variables that affect the measured outcome*. Unobservable differences are the main concern in exact matching. In propensity score matching, two individuals with the same score may be very different even along observable dimensions. Thus, the assumptions that need to hold in order to draw valid conclusions are quite demanding.	Outcome data for program participants as well as another group of non-participants, as well as "matching variables" for both groups.
	Regression Discontinuity Design (RDD)	In an RDD design, eligibility to participate is determined by a cutoff value in some order or ranking, such as income level. Participants on one side of the cutoff are compared to non-participants on the other side, and the eligibility criterion is included as a control variable (see above).	*Any difference between individuals below and above the cutoff (participants and non-participants) vanishes closer and closer to the cutoff point*. A carefully considered regression discontinuity design can be effective. The design uses the "random" element that is introduced when two individuals who are similar to each other according to their ordering end up on different sides of the cutoff point. The design accounts for the continual differences between them using control variables. The assumption that these individuals are similar to each other can be tested with observables in the data. However, the design limits the comparability of participants further away from the cutoff.	Outcome data for program participants and non-participants, as well as the "ordering variable" (also called "forcing variable").
	Instrumental Variables	The design uses an "instrumental variable" that is a predictor for program participation. The method then compares individuals according to their predicted participation, rather than actual participation.	*The instrumental variable has no direct effect on the outcome variable. Its only effect is through an individual's participation in the program*. A valid instrumental variable design requires an instrument that has no relationship with the outcome variable. The challenge is that most factors that affect participation in a program for otherwise similar individuals are also in some way directly related to the outcome variable. With more than one instrument, the assumption can be tested.	Outcome data for program participants and non-participants, as well as an "instrumental variable".