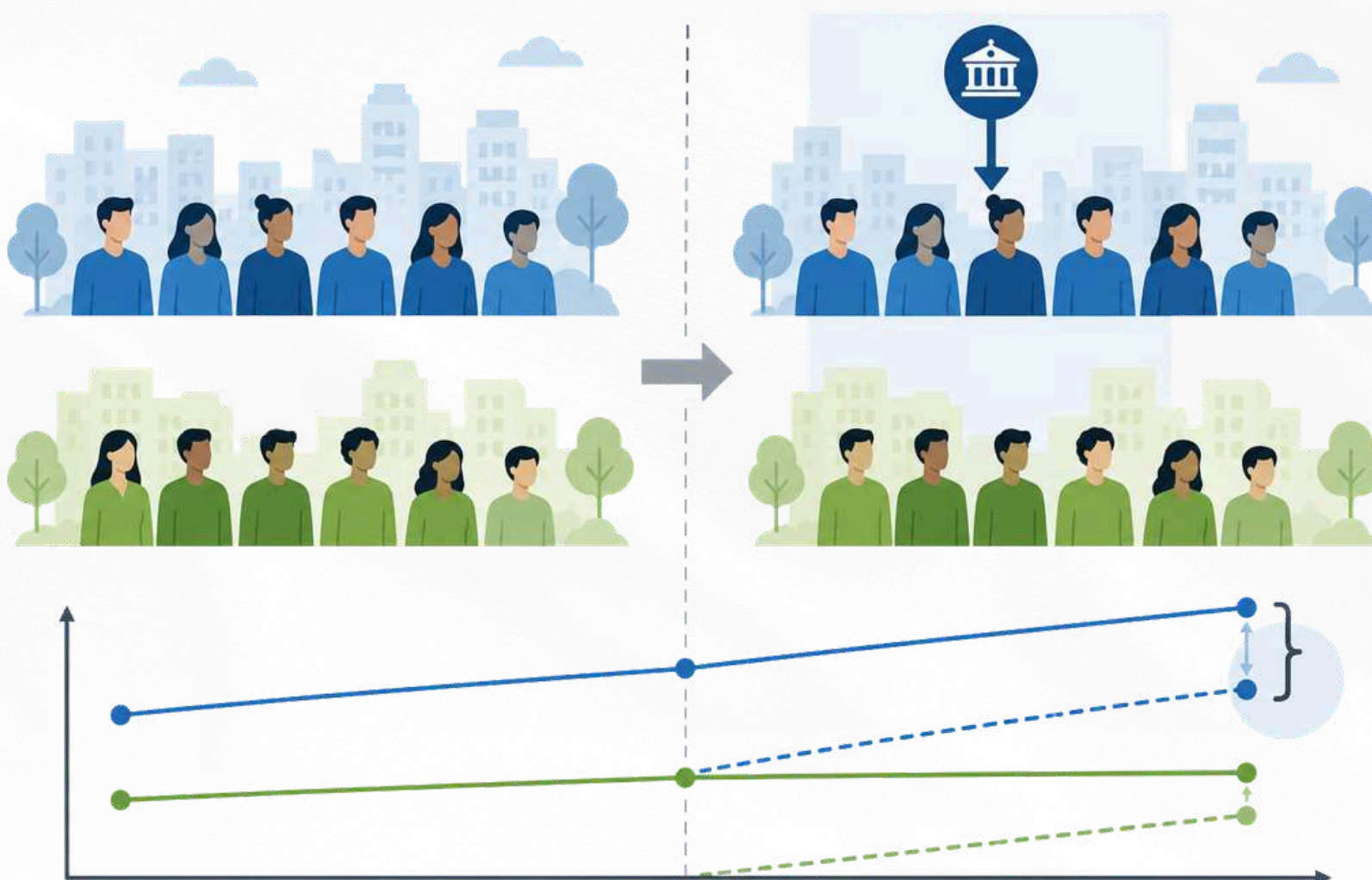


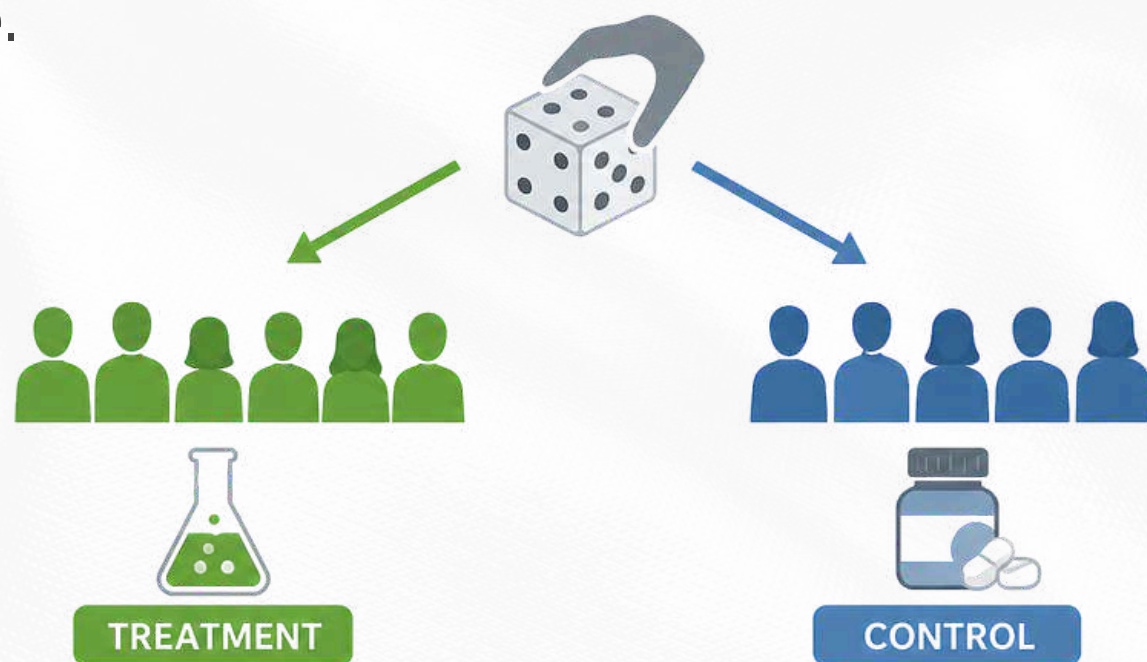
Difference-in-Differences (DiD):

how to measure impacts
when there are no experiments



The problem of causal identification

- As we saw in a previous post, distinguishing correlation from causation is fundamental in economic and legal analysis.
- An ideal method for estimating causal effects is the randomized controlled experiment: randomly assigning who receives the treatment and who does not.
- The problem: in economics, controlled experiments are rarely possible.



What is Difference-in-Differences?

DiD is a statistical method that estimates the causal effect of an intervention (an event, treatment, policy, or shock) by comparing two simultaneous differences:

- **First difference (before vs. after):** how did the treated group change?
- **Second difference (treated vs. control):** how much did the treated group change relative to a comparable group that did not receive the treatment?

The key: the control group makes it possible to isolate what would have happened anyway, removing shared trends and external factors. In simple terms, it works as a benchmark.

An example: impact of a new regulation on sales

Suppose that in 2022 a new regulation is applied only to firms in Region A. Firms in Region B are not affected. We want to know:
how much the regulation affected sales?

Average sales (hypothetical index):

- **Region A (treated):** 100 before 2022 → 85 after 2022.
Difference: –15.
- **Region B (control):** 100 before 2022 → 92 after 2022.
Difference: –8.

DiD estimate = $(-15) - (-8) = -7$

The 8-point drop in Region B reflects shared external factors (a recession or trend). The effect attributable to the regulation is only –7, not –15 as one might mistakenly assume.

The first key assumption: parallel trends

DiD rests on two central assumptions.

The first: in the absence of treatment, the treated and control group would have followed a parallel trajectory.

- Both groups don't need to be identical, only that they would have evolved in a similar way had the intervention not occurred.
- This assumption cannot be directly verified for the post-treatment period, but it can be assessed by examining the prior historical trend of both groups.

Its violation is one of the main arguments used to challenge a DiD estimate.

The second key assumption: exclusivity of the treatment

The second assumption is equally important: **the only thing that should have changed at the time of the treatment is the treatment itself.**

- If another simultaneous event affects the treated or control differentially, the DiD estimate will confound that effect with the effect of the treatment.
- For example: if, alongside the regulation from the previous example, Region A also launched a marketing campaign aimed at boosting sales, DiD would incorrectly attribute part of the campaign's effect to the regulation.

DiD in arbitration and impact evaluations

DiD is widely used to quantify damages in contexts where it is not possible to randomly assign a treatment.

It is commonly used to quantify the impact of a breach of contract, an anticompetitive practice, or early termination of a business relationship on a firm's sales, margins, or value.

The control group can be built using comparable companies not affected by the event or using the claimant company's own trajectory in sales of other unaffected products. This can allow for a robust estimate of the counterfactual scenario that would have existed in the absence of the alleged event.