

Impact Evaluation in Firms and Organizations

With Applications in R and Python

Chapter 8: Difference-in-Differences

8.1 Difference-in-Differences and the Impact in the Treatment Group

8.2 Behavioral Assumptions and Extensions

Requirements for difference-in-differences

- Requires outcome data before and after the intervention
- Requires a group that receives the intervention (treatment group) and a group that does not (control group)
- Requires a behavioral assumption known as common trends

Common trend assumption

- Potential outcomes without intervention would follow the same time trend in both groups
- Ensures comparability of before-after changes across groups

Assessing the intervention impact

- Compare before–after differences in outcomes between treatment and control groups
- Difference in these differences identifies the impact of the intervention

Interpreting before-after changes

- Treatment group's change in outcome over time reflects the time trend plus the intervention impact
- Control group's change in outcome over time reflects only the general time trend
- Subtracting the latter isolates the intervention effect

Role of common trends

- Assumes both groups would follow the same time trend without intervention
- Ensures differences in before-after changes in the outcome over time capture true impact
- Validity depends on equal time trends, not equal levels in the outcome

Differences-in-Differences

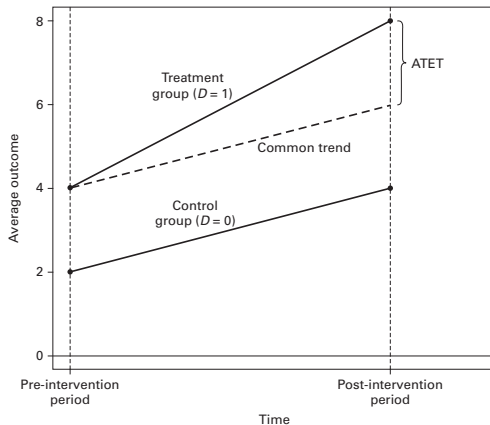


Figure 7.1: Differences-in-differences

Example

Difference-in-differences design

- New product line introduced only in some stores, and not in others
- Compare before-after change in weekly sales in treated stores
- Then subtract before-after change in control stores
- Identifies ATET under the common trend assumption

Interpreting the intervention effect

- Control stores experience a 3% increase in sales
- Treatment stores experience a 5% increase
- Impact of new product line equals $5\% - 3\% = 2\%$

Difference-in-Differences Example with Coupons

Example

Restaurant e-coupon example

- Some restaurants issue beverage e-coupons, others do not
- Impact assessed by comparing before–after sales changes across groups

Retail food coupon example

- Some households receive food coupons, others do not
- Impact assessed by comparing before–after purchasing changes across groups

Use of difference-in-differences framework

- Enables causal inference in nonexperimental settings
- Assumes common trends in absence of intervention

Violations of common trends

- Difference-in-differences fails if treatment and control groups do not share the same underlying trend in the outcome
- Regional factors, such as differing weather conditions, may create divergent trends, violating common trends

Dependence on outcome scaling

- Common trends may hold only for a specific scale of the outcome
- For example, it may apply to relative (percent) changes but not to absolute changes
- Choose a scale for which common trends are most plausible

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Formalizing the Common Trend Assumption

Notation

- Time index T : $T = 0$ before intervention, $T = 1$ after intervention
- Pre- and postintervention outcomes: Y_0 and Y_1
- Corresponding potential outcomes: $Y_0(1), Y_0(0)$ and $Y_1(1), Y_1(0)$

Common trend assumption

- Formally, expressed as

$$E[Y_1(0) - Y_0(0) \mid D = 0] = E[Y_1(0) - Y_0(0) \mid D = 1] \quad (8.1)$$

- Requires average change in potential outcomes without intervention to be equal across groups
- Ensures both groups share the same underlying trend in absence of treatment
- Allows identification of the intervention effect

No Anticipation Assumption in Difference-in-Differences

Definition of no anticipation

- Subjects in the treatment group should not change behavior before the intervention
- In other words, preintervention outcomes must not be affected by future treatment assignment
- For example, customers should not alter purchasing behavior before a new product line is introduced

Formal expression

- No anticipation requires

$$E[Y_0(1) - Y_0(0) \mid D = 1] = 0 \quad (8.2)$$

- Implies zero treatment effect in the pretreatment period

Causal effect of interest

- Causal effect of interest in the DiD approach: ATET after the implementation of the treatment
- ATET is denoted as

$$\Delta_{D=1} = E[Y_1(1) | D = 1] - E[Y_1(0) | D = 1] \quad (8.3)$$

$$= \underbrace{E[Y_1 | D = 1] - E[Y_0 | D = 1]}_{\text{before-after change among treated}} - \underbrace{\{E[Y_1 | D = 0] - E[Y_0 | D = 0]\}}_{\text{before-after change among nontreated}}$$

- Difference in before–after changes isolates the effect among treated units and thus identifies the ATET

Placebo tests

- Outcomes measured in several periods before intervention are used to assess validity of common trends
- Apply difference-in-differences to two preintervention periods, treating the later as a placebo-treatment period
- True effect is zero because the intervention has not yet occurred
- Estimated effect should be close to zero if common trends hold

Interpreting violations

- Large or significant placebo effects signal differing trends across groups
- Indicates that the common trend assumption is likely violated
- Suggests that treatment and control outcomes evolve differently even without intervention

Staggered treatment introduction

- Intervention is introduced to different groups at different times
- Allows defining treatment groups by their intervention start period

Assessing heterogeneous effects

- Enables comparison of impacts across groups and time periods
- Effects may differ depending on when groups receive the intervention

Short- and long-term impacts

- Can estimate effects shortly after intervention (e.g., one week post-introduction) but also long-term outcomes (e.g., one year after introduction)
- Helps determine persistence or decay of intervention effects

Improving plausibility with covariates

- Common trend assumption may be more plausible when groups are made comparable in observed covariates X
- Example: Common trends may be more plausible when comparing only areas with similar economic conditions

Conditional common trend assumption

- Common trend assumption is modified to include covariates:

$$E[Y_1(0) - Y_0(0) \mid D = 0, X] = E[Y_1(0) - Y_0(0) \mid D = 1, X]$$

- Requires the average change in potential outcomes without intervention to be equal across groups conditional on X

No anticipation assumption

$$E[Y_0(1) - Y_0(0) \mid D = 1, X] = 0$$

- Among treated units with the same X , pretreatment outcomes are unaffected by the future intervention

Common support

$$\Pr(D = 1, T = 1 \mid X, (D, T) \in \{(d, t), (1, 1)\}) < 100\%$$

for all $(d, t) \in \{(1, 0), (0, 1), (0, 0)\}$

- For any value of X in the group with $D = 1, T = 1$, there must be subjects with the same value of X in the remaining three groups

Conditional ATET

- Based on the modified behavioral assumptions, the conditional ATET can be identified

$$E[Y_1(1) - Y_1(0) \mid D = 1, X] = E[Y_1 \mid D = 1, X] - E[Y_0 \mid D = 1, X] \\ - \{E[Y_1 \mid D = 0, X] - E[Y_0 \mid D = 0, X]\} \quad (8.5)$$

ATET

- To obtain the ATET, take the average of the conditional ATET in the treatment group during the posttreatment period

$$\Delta_{D=1, T=1} = E[E[Y_1 \mid D = 1, X] - E[Y_0 \mid D = 1, X] \\ - \{E[Y_1 \mid D = 0, X] - E[Y_0 \mid D = 0, X]\} \mid D = 1, T = 1] \quad (8.6)$$

Why observations may be related

- The outcome of one observation may depend on the outcomes of other observations
- Panel data: repeated observations create within-subject dependence over time
- Repeated cross-sections: different subjects may share contextual factors, such as institutions or regulations

Implications for variance estimation

- Ignoring such dependence can lead to incorrect variance estimates
- Cluster-robust methods account for dependence among related observations
- Clusters group subjects that share related unobserved characteristics