THE DIFFERENCE-IN-DIFFERENCE DESIGN

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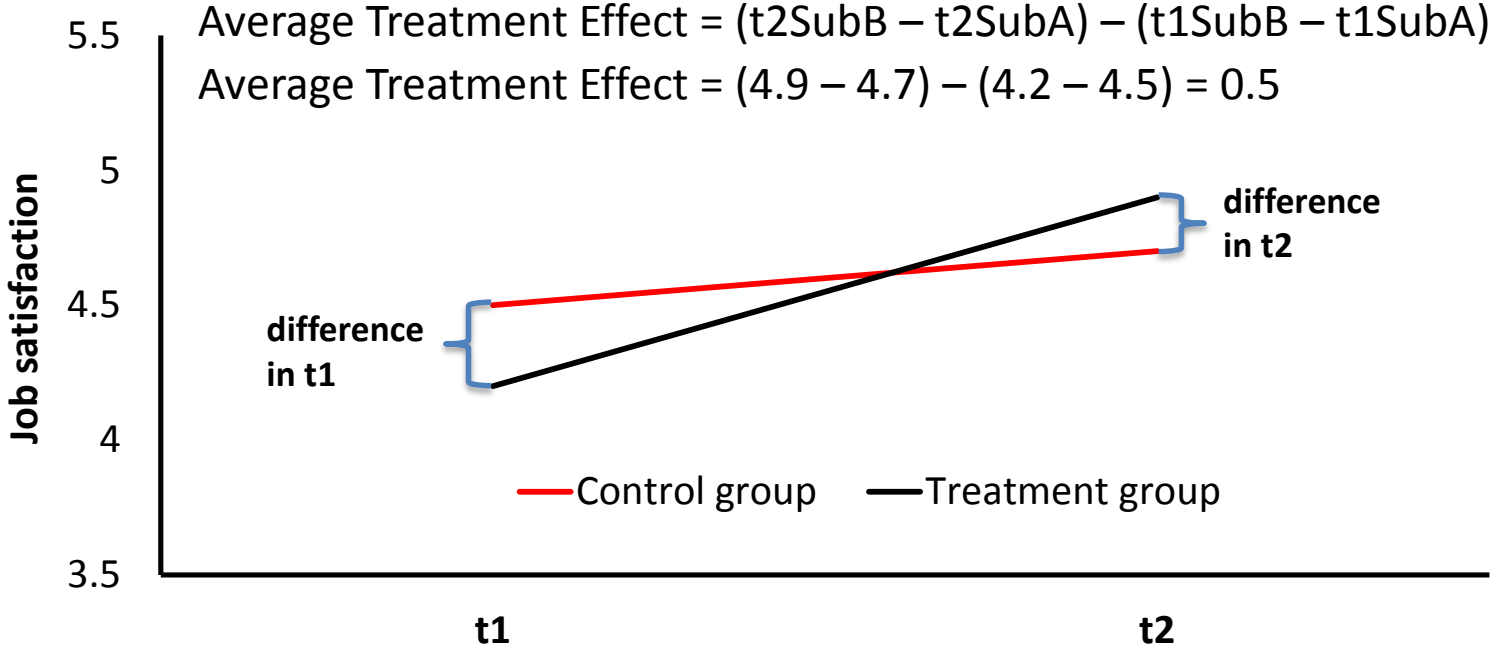
THE DIFFERENCE-IN-DIFFERENCE DESIGN

- The difference-in-difference (DID) design is probably the most frequently used design of natural experiments
- Often used to estimate the effects of policies or programs (e.g., gender quota in boards)
- Idea: Inferring causal relationships by comparing the pre-treatment to post-treatment changes in an outcome variable (e.g., job satisfaction) between a treatment group and a control group

EXAMPLE

Subsidiary A (control): Job satisfaction t1 = 4.5; t2 = 4.7
Subsidiary B (treatment): Job satisfaction t1 = 4.2; t2 = 4.9

Average Treatment Effect = (t2SubB – t2SubA) – (t1SubB – t1SubA)
Average Treatment Effect = (4.9 – 4.7) – (4.2 – 4.5) = 0.5



DIFFERENCE BETWEEN DID AND RANDOMIZED CONTROLLED TRIAL (RCT)

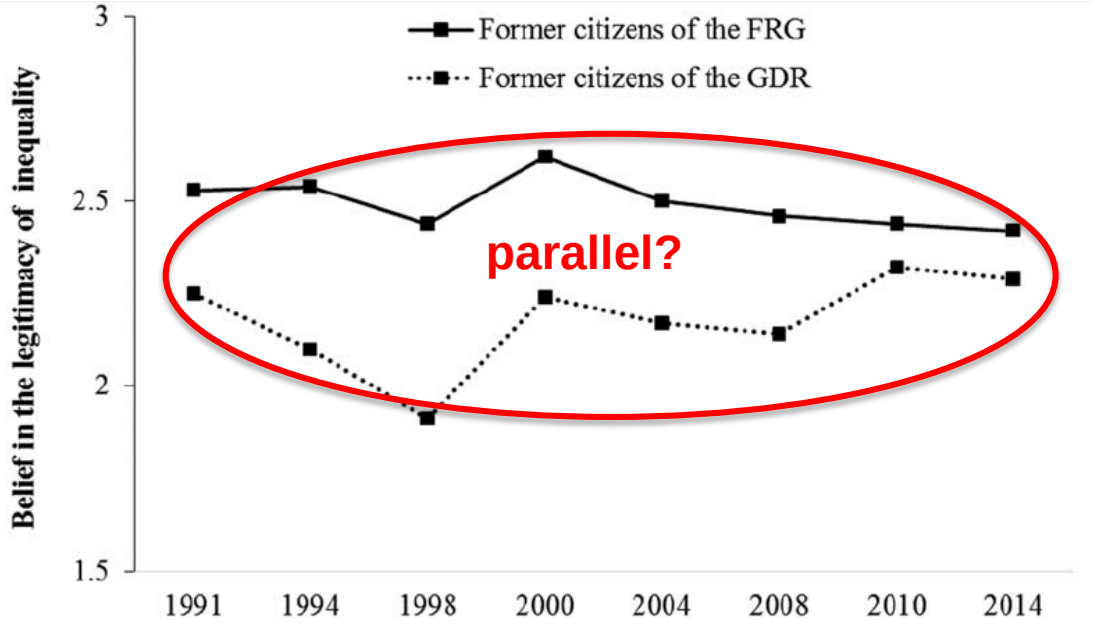
	DID	RCT
Well-defined study population	Yes	Yes
Treatment group and control group	Yes	Yes
Treatment randomly assigned	No	Yes

ASSUMPTIONS OF THE DID DESIGN

1. Common trend assumption
   a) Group varying confounders are time invariant (e.g., no changes in the management of subsidiary A and B that can affect job satisfaction)
   b) Time varying confounders are invariant across groups (e.g., management changes in the company headquarter affect both subsidiaries similarly)

TESTING THE COMMON TREND ASSUMPTION

1. Graphical check
   a) Visual inspection of the lines for the treatment and control group; should be almost parallel (only applicable if time periods > 2)



Haack, P. & Sieweke, J. (2018): The legitimacy of inequality: Integrating the perspectives of system justification and social judgment. Journal of Management Studies, 55, p. 502

TESTING THE COMMON TREND ASSUMPTION

2. Group-specific linear trend
   a) Statistical analysis: Regress the outcome variable on time-invariant group effects (a_g), group-invariant time effects (b_t), an interaction between the group and time effects ($beta_g*(a_g*t)$), and the treatment variable (D_{gt}).

$$Y_{gt} = a_g + b_t + beta_g*(a_g*t) + D_{gt} + \varepsilon_{gt}$$

If the estimated treatment effect D_{gt} is similar to the estimated treatment effect in the model excluding the group x time interaction (a_g*t), the common trend assumption is not plausible.

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2. Strict exogeneity
   a) The treatment is not due to changes in the outcome variable (e.g., comapnies implement work-life policies as a response to a decrease in job satisfaction)
   b) Treatment exposures in t1 are not anticipated by outcomes measured at t0 (e.g., companies implement changes in anticipation of a new regulation)

"TESTING" THE EXOGENEITY ASSUMPTION

1. Granger-type causality test
   a) Check whether current outcomes are correlated with future exposure to treatment

2. Collecting qualitative data about the event
   a) Interviews with managers, policy makers etc. to check the decision process regarding the treatment
   b) Document analyses to learn about the event (e.g., why was a new policy introduced?)

CONCLUSION

- The difference-in-difference design can be applied to answer many questions in management research (e.g., effect of regulations on firm performance)
- If assumptions of the DID are violated, the treatment effect is biased
- It is important to have good knowledge of the event

REFERENCES

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Wing, C., Simon, K., & Bello-Gomez, R. A. 2018. Designing difference in difference studies: Best practices for public health policy research. ***Annual Review of Public Health***, 39(1): 453-469.