Regression discontinuity design

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Disclosure

I have nothing to disclose

Gerandomiseerde vs. observationele data

Schatten van behandeleffecten:

- RCT unmeasured confounders in balans (door randomisatie)
- Observationele data unmeasered confounders (confouning by indication)

- IEMO project ouderen

Recente publicaties regression discontinuity

COMMENTARY

Regression Discontinuity Design

Let's Give It a Try to Evaluate Medical and Public Health Interventions

Jan P. Vandenbroucke[a] *and Saskia le Cessie*[a,b]

The regression discontinuity design has been described as the next best thing after a randomized trial: it may produce valid causal inferences, at least under some assumptions,[1–4] and can do this without randomization and even without having a real-life control group that is comparable in all relevant respects (or made comparable by adjustment). In principle, the regression discontinuity design is able to estimate effects of interventions in all health care situations in which a treatment is given to persons above a threshold of some continuous prognostic measurement and not given to those below the threshold. The basic idea is that the counterfactual outcomes of the persons who were treated(ie, their expected outcome if they had not been treated) are derived by extrapolation from a model based on those who did not qualify for treatment.[3] In their review article in this issue of EPIDEMIOLOGY, Bor et al[5] explain the background theory: for the limiting situation (ie, for

thebmj

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RESEARCH METHODS & REPORTING

Regression discontinuity designs: an approach to the evaluation of treatment efficacy in primary care using observational data

Regression discontinuity designs use observational data to examine treatment efficacy. This article uses the example of statin prescription in primary care to explain the concept of the method and how it can be used

Aidan G O'Keeffe *lecturer in statistics*[1], Sara Geneletti *lecturer in statistics*[2], Gianluca Baio *lecturer in statistics*[1], Linda D Sharples *professor of statistics and director of CHRD*[3], Irwin Nazareth *professor of primary care and population science*[4], Irene Petersen *reader in epidemiology and statistics*[4]

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ORIGINAL ARTICLE

OPEN

Regression Discontinuity Designs in Epidemiology

Causal Inference Without Randomized Trials

Jacob Bor,[a,b,c] *Ellen Moscoe,*[c] *Portia Mutevedzi,*[b] *Marie-Louise Newell,*[b,d] *and Till Bärnighausen*[b,c]

Abstract: When patients receive an intervention based on whether they score below or above some threshold value on a continuously measured random variable, the intervention will be randomly assigned for patients close to the threshold. The regression discontinuity design exploits this fact to estimate causal treatment effects. In spite of its recent proliferation in economics, the regression discontinuity design has not been widely adopted in epidemiology. We describe regression discontinuity, its implementation, and the assumptions required for causal inference. We show that regression discontinuity is generalizable to the survival and nonlinear models that are mainstays of epidemiologic analysis. We then present an application of regression discontinuity to the much-debated epidemiologic question of when to start HIV patients on antiretroviral

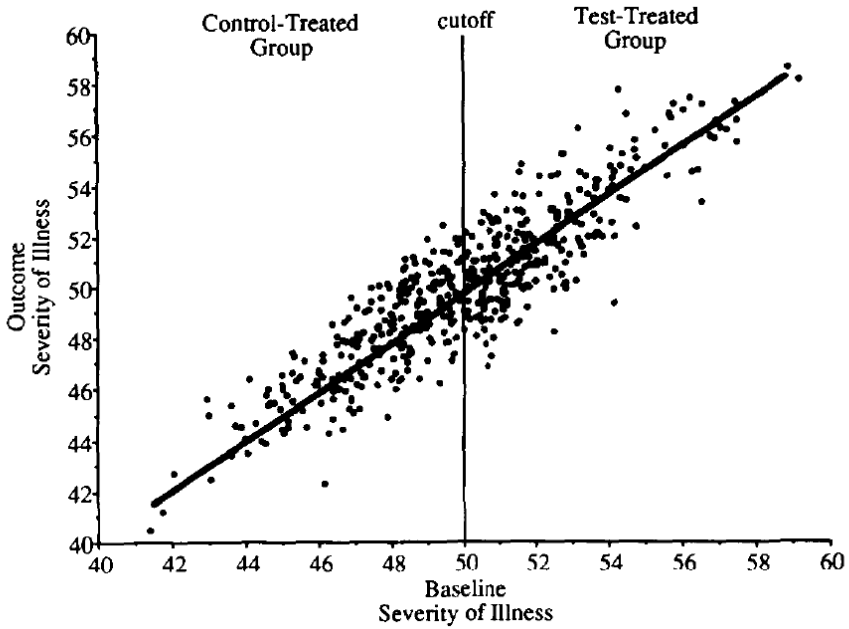
Causal inference in nonexperimental studies typically requires a strong, untestable assumption: that no unobserved factors confound the relationship between the exposure and the outcome.[1] Violations of this assumption will lead to biased estimation of causal effects. The regression discontinuity design is one important quasi-experimental study design in which this assumption is not required for causal inference. Regression discontinuity designs can be implemented when the exposure of interest is assigned—at least in part—by the value of a continuously measured random variable and whether that variable lies above (or below) some threshold value. Provided that subjects cannot precisely manipulate the value of this variable, assign-

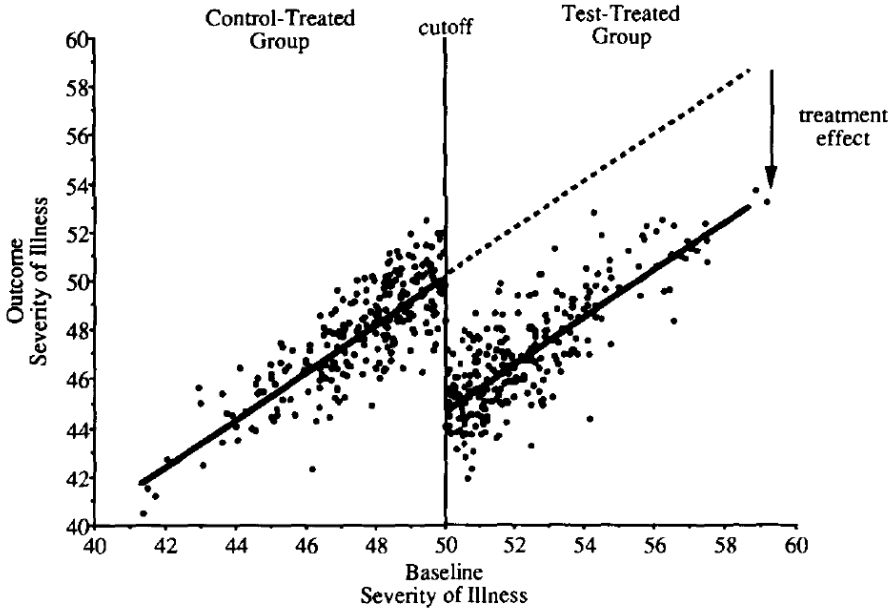
Regression discontinuity design

- Quasi-experimenteel design

- I.p.v. randomiseren, patiënten behandeling toewijzen op basis van assignment variabele

Regression discontinuity design





** Trochim & Cappelleri, 1992*

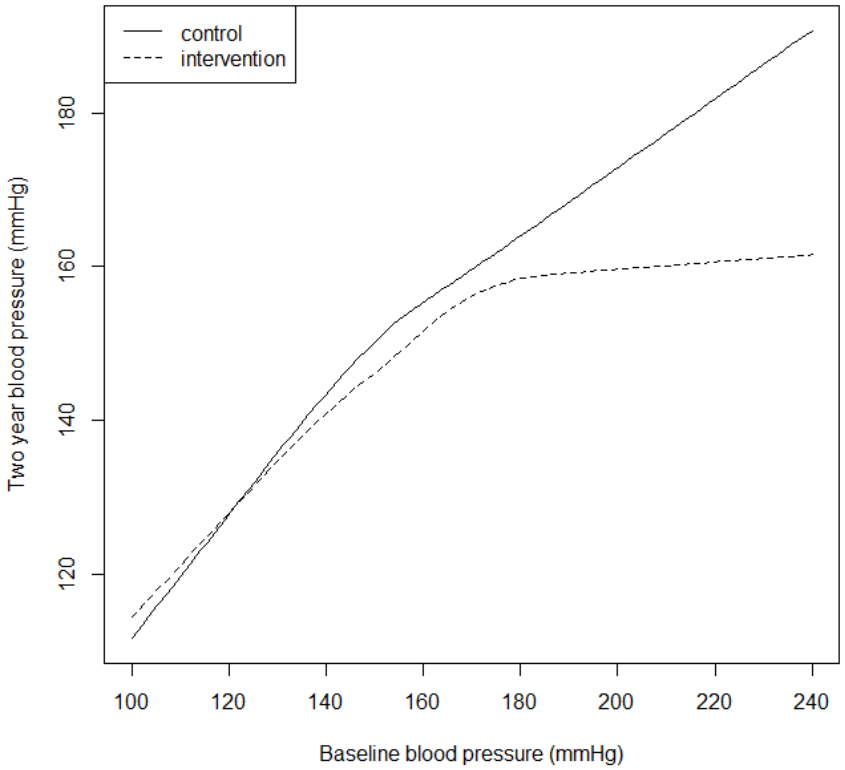
Validatie studie

- "Prevention of Dementia by Intensive Vascular Care" study (preDIVA) **(n = 2346)**
- RCT effect als "gouden standaard"
- 4 hypothetische scenario's (cut-offs BP en age)
- Regression discontinuity (RD):

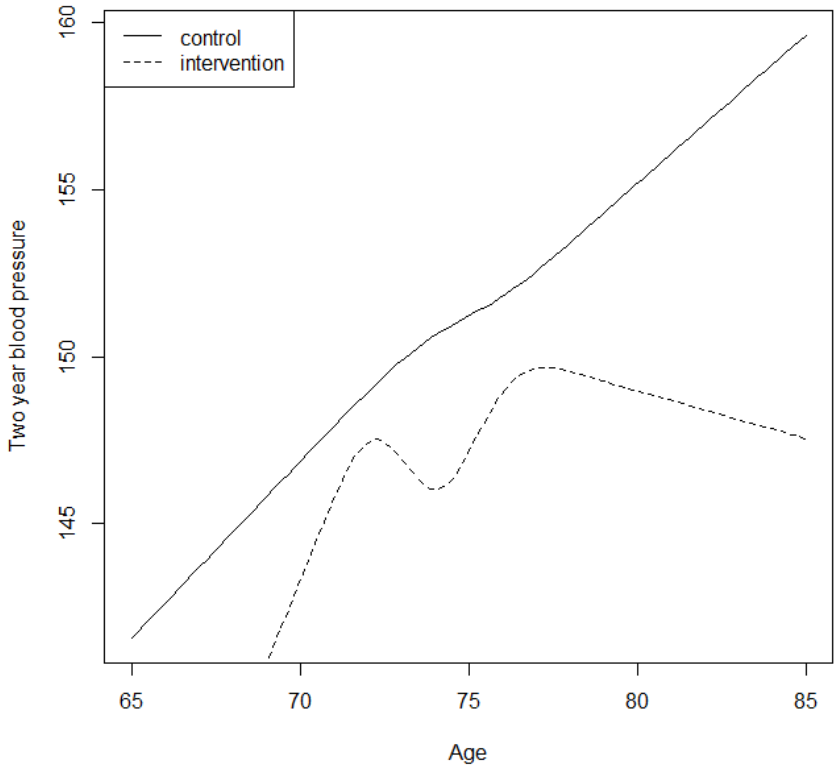
1) Local linear regression
2) Restricted cubic spline (RCS) adjustment

RD effect estimate in preDIVA (RCT data)

Assignment on BP



Assignment on age



RD vs RCT in preDIVA – assignment on blood pressure

Analysis	Treatment effect estimate (95% CI) for two year blood pressure (mmHg)	Standard error (SE) of treatment effect estimate
RCT		
Linear adjustment	-4.0; (-5.4; -2.6)	0.7
RD – assignment on blood pressure > *140 receiving treatment*		
RCS adjustment	-5.9 (-10.8; -1.0)	2.5
Local linear regression	-9.3 (-18.5; -0.1)	4.7
RD – assignment on blood pressure > *160 receiving treatment*		
RCS adjustment	-5.9 (-11.4; -0.3)	2.8
Local linear regression	-10.2 (-21.0; 0.6)	5.5

RD vs RCT in preDIVA – assignment on age

Analysis	Treatment effect estimate (95% CI) for two year blood pressure (mmHg)	Standard error (SE) of treatment effect estimate
RCT		
Linear adjustment	-3.2 (-5.5; -0.9)	1.2
RD – assignment on age > *72 receiving treatment*		
RCS adjustment	-0.7 (-6.4; 5.1)	3.0
Local linear regression	2.4 (-3.7; 8.5)	3.1
RD – assignment on age > *74 receiving treatment*		
RCS adjustment	-2.5 (-9.2; 4.2)	3.4
Local linear regression	-2.8 (-8.2; 2.7)	2.8

Voor- en nadelen?

- Assumpties lokaal vs. globaal effect
- Minder efficiënt dan RCT

- Uitvoeren RD sluit aan bij klinische praktijk
- Bredere patiëntenpopulatie (generaliseerbaarheid)

Conclusie

- Regression discontinuity kan vergelijkbare behandeleffecten schatten als een RCT, maar vereist de aanname van een globaal behandeleffect over de hele range van de assignment variabele

Vragen / discussie