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Epidemiology, Public Health: Review of Regression Discontinuity

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Abstract

A rigorous quasi-experimental technique for evaluating the causal effects of interventions on outcomes is regression discontinuity (RD) designs. RD can be used to estimate the causal effect of the treatment on health and other outcomes whenever a decision rule as- signs treatment, such as antihypertensive or antiretroviral therapies, to patients who score higher (or lower) than a specific cutoff value on a continuously measured variable, such as blood pressure or CD4 count. Similar to randomization, RD can address issues with confounding caused by unobserved factors and produce estimates of a treatment's causal effects that are free from bias. Due to the prevalence of treatments assigned using a cutoff rule, RD is a particularly helpful study design for medicine, epidemiology, and public health. Statins are prescribed by doctors using blood pressure cutoffs to decide how to manage hypertension, using mole size cutoffs as guidelines for mole removal, and recommending surgery for scoliosis when spinal curvature surpasses a specific threshold of severity. Additionally, RD possesses desirable practical traits. It may not be possible to conduct a randomised controlled trial (RCT) when a treatment has already become the norm, but RD can provide robust causal evidence on treatment efficacy when there is scant or no experimental evidence or when the evidence that is available has dubious internal or external validity.

Keywords: Epidemiology; Regression; Discontinuity; Antihypertensive

Introduction

Additionally, because RD may be implemented using data that is typically gathered in patient files and administrative data, it may be less expensive than experimental techniques. Cohort studies that gather data over time have an advantage over traditional research designs in that results may be easily presented graphically and communicated to policymakers and implementation groups. Thistlewaite and Campbell introduced RD to educational psychology for the first time in 1960. Rubin brought the design to statistics. Using ligistic models, Berk and Rauma expanded the model to include dichotomous variables. In a recent publication, RD was expanded to include survival analysis [1]. Since the 1990s, RD has been extensively utilised in economics. Studies on how incumbent status affects elections. Results, the impact of military conscription on wages, and the link between class size and student performance all shown that RD might produce significant effects in a variety of contexts. Numerous significant advances in the theory of RD have recently been found in the economics literature.

Materials and Method

In order to answer issues of relevance to epidemiologists and public health researchers, economists have also adopted RD designs. Almond, for instance, calculated the causal effect of intensive medical care given to babies with very low birth weight (less than 1,500 g) on 1-year mortality. Carpenter and Dobkin assessed how alcohol use affected mortality using the legal drinking age of 21 as a reference. The purpose of this article is to introduce the theory of RD, serve as a best practise implementation guide for medicine, epidemiology, and public health, and to carefully study and assess the usage of RD in various research domains, or the "current practise." We also go over potential applications and restrictions [2]. When a cutoff point on a continuous variable is utilised as the decision rule to determine a patient's eligibility for treatment or a programme, RD can be used. Any patient on one side of the cutoff value receives the treatment, while no patient on the other side does, and this rule's treatment assignment can either be deterministic or probabilistic (the probability of receiving the treatment is higher on one side of the cutoff value than on the other side). The first example is known as "sharp" RD, whereas the second is known as "fuzzy" RD. In the paragraph that follows, we present both examples [3].

Similar to an RCT, RD is more than just a way to analyse data; it's also a description of how data are produced. When a variable that is continuously measured has a cutoff value that identifies a treatment status. It is feasible to conclude, under some circumstances, that a variation in results is caused by the cutoff point of the assignment variable. Different assumptions have been used by researchers to pinpoint causal effects in RD designs. Early talks of RD prioritized impacts of global average treatments and called for very firm functional form assumptions. The majority of contemporary RD literature including this article focuses on local treatment effects "at the threshold." For this focus, continuity in potential outcome the absence of unobserved confounders at the threshold is the primary presumption. The patients in the two groups resemble one another more and more on both observable and unobservable qualities as we get closer to the cutoff value from above and below; in a narrow region around the threshold, the only variation is in treatment assignment [4]. It is amazing how effortlessly the continuity assumption is satisfied in some circumstances. Continuity in possible outcomes is ensured if measurements of the assignment variable exhibit random noise and cannot be precisely altered.

Whether or not an individual's value for the assignment variable exhibits random noise depends on it is essentially random for someone close to the cutoff whether they will fall above or below it. As a result, we can interpret the distinction in outcomes between those who fall slightly above and below the cutoff as a real causal effect of the treatment. Although not all RD designs have this interpretation of

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"local randomization," it is frequently justified in clinical contexts where blood pressure, CD4 counts, and blood glucose levels are recorded with significant inaccuracy [5].

In comparison to other quasi-experimental procedures, the constraints and presumptions required for causal inference in RD are more lax. Additionally, unlike most other quasi-experimental procedures, when the focus is on local treatment effects at the threshold, the crucial assumptions may be supported using the available data. Following are the three requirements for a valid RD:

- The cutoff value of the variable used to assign treatment—also referred to as the assignment variable—must be known to researchers. The assignment variable will be denoted by the letter Z throughout this section. Additionally, researchers need to understand if a medication is given when Z is above or below the cutoff. Knowing whether additional aspects (such as clinical judgement in addition to a laboratory measure representing Z) play a role in the decision to treat is also useful. To derive complier average causal effects (CACE) for individuals receiving treatment, the "fuzzy" variation of RD must be employed, in which intent-to-treat effects are calculated and scaled by the degree of compliance with the threshold criterion. Both the "fuzzy" and the "sharp" versions of RD, we calculate a causal impact that is specific to the population near the cutoff threshold.

- The assignment factor Any continuous variable, Z, that is assessed prior to therapy, is unaffected by the treatment, and, at some cutoff point, dictates the course of treatment, may be used. Sharp RD does not have an area of overlap where data with different treatment statuses have the same values of Z, in contrast to other quasi-experimental approaches that try to account for unobserved confounders (such as difference-in-difference analysis). According to Hahn et al., the absence of this overlap area makes continuity in Z near the cutoff adequate to produce accurate estimates of the TE [6-10]. Z is continuous at the cutoff, according to a visual examination of the data.

- Patients just above and below the threshold must be similar in order to identify causal effects. This is required to guarantee that their possible outcomes—that is, the results if all were treated or not—would be comparable right away on both sides of the threshold.

Discussion

Formally speaking, at the threshold, the conditional distributions of possible outcomes with regard to Z are continuous. If the precise cutoff point was chosen due to an underlying discontinuity in the relationship between Z and the result, the continuity assumption would be broken. Reverse causation might apply, for instance, if the threshold for antihypertensive therapy assignment was established because a physiological condition that is connected with the result of interest, such as cardiovascular mortality, happened precisely at the cutoff. could throw the analysis off. The result at the cut-off cannot have any unobserved confounders that are discontinuously related to it. The study may be complicated by other elements of the state policy environment, for instance, when assessing the impact of different cigarette taxes on smoking behaviour using distance from a state line as the assignment variable. To demonstrate that the discontinuity in Y is caused exclusively by the cutoff and not by another factor, plots of additional covariates around the cutoff and knowledge of how the cutoff rule is constructed can be helpful.

Conclusion

When measurements of the assignment variable (such CD4 counts, but not distance to an administrative boundary) contain random noise, the RD design is at its strongest. It frequently occurs in therapeutic applications. Assuming that patients have only sporadic control over the value of the assignment variable and are unable to accurately modify it, the assumption of continuity in prospective outcomes is in this situation trivially satisfied (in expectation). In the simplest scenario, patients cannot alter their treatment status because they have no control over Z (such as their birth date). However, as long as this control is insufficient, like in a case when patients have some degree of control over Z, RD can still be used in certain circumstances. Where medication compliance has a correlation with Z but is not a perfect predictor of Z. The degree to which patients and providers influence their measured value of Z will depend on the clinical and public health practises used in those contexts.

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