Research in Health Science
ISSN 2470-6205 (Print) ISSN 2470-6213 (Online)
Vol. 9, No. 2, 2024
www.scholink.org/ojs/index.php/rhs

Original Paper

Investigating the Application of Regression Discontinuity in the Field of International Health Economics

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Received: April 25, 2024 Accepted: May 23, 2024 Online Published: May 27, 2024

doi:10.22158/rhs.v9n2p91 URL: http://dx.doi.org/10.22158/rhs.v9n2p91

Abstract

As one of the most significant quasi-experimental research methods, with over eight decades of development, Regression Discontinuity Design (RDD) has garnered extensive attention within the field of international health economics. It has provided robust methodological support for causal inference in research conducted within this domain. This paper provides a comprehensive review and synthesis of the foundational concepts, origins, and evolutionary trajectory of the RDD. It systematically examines the relevant studies in the domain of international health economics, discusses the strengths and limitations of the RDD, and anticipates its future applications in the same field. The aim is to support the utilization of RDD in international health economic research. On a theoretical level, it has effectively enhanced the flexibility and applicability of research designs within the domain of international health economics, augmenting the economic efficiency and external validity of studies, and offering a versatile tool for related research on a global scale. On a practical level, RD accommodates the diverse policy needs of programs across various countries and regions. It provides a more robust and reliable empirical foundation for the formulation of pertinent health policies, aiming to improve the efficiency of health resource allocation and promote equity in health outcomes.

Keywords

Regression Discontinuity, Health Economics, Public Health Policy, Health Insurance, Health Behavior

1. Introduction

Causal inference, a central tenet of social science research, is tasked with the evaluation and analysis of the impact effects of policies or specific events to as accurately as possible reveal the underlying principles governing the operation of economic and social systems (Imbens, 2024). Randomized controlled trials, often regarded as the gold standard for causal inference, employ random assignment to generate experimental and control groups. This process allows for the construction of a rigorous framework of 'facts' versus 'counterfactuals' and controls for variables unrelated to the experimental manipulation, thereby identifying the net effect of the experimental intervention on the outcome variable. However, in the realm of social science research, constraints such as research costs and the particularities of the subjects under study often make it challenging to conduct inquiries within the stringent confines of a laboratory setting. Consequently, quasi-experimental designs, which mimic the effects of randomized interventions under natural conditions, have emerged as a viable alternative (Thistlethwaite & Campbell, 1960; Campbell & Stanley, 1963; Rubin, 1976).

As one of the critical methods in quasi-experimental research, Regression Discontinuity Design (RDD) focuses on the differences in outcomes for individuals before and after an intervention. In situations where randomized controlled trials are not possible, RDD serves as an alternative to estimate the causal relationship between the intervention and outcome variables (Trochim, 1984). Compared to other quasi-experimental design methods such as instrumental variables and difference-in-differences, RDD more closely approximates the experimental setting of a randomized intervention and operates under more lenient research assumptions, providing stronger control over endogeneity issues that arise during the research process and thus offering greater inferential power for causal effects (Lee & Lemieux, 2010). As one of the most credible quasi-experimental methods, it has been widely applied in various academic fields, including economics, health, education, environment, and public health (Angrist & Pischke, 2010; Khullar & Jena, 2021; Villamizar-Villegas et al., 2022). The core concept of RDD is basing on the assumption of a continuous variable X_i with a specific cutoff point C_0. All other variables are continuous across the cutoff point, but there is a treatment variable D_i that is discontinuous across it, with the assignment of samples to the left or right of the cutoff occurring randomly. This creates a quasi-experimental scenario at the cutoff point that mimics a randomized intervention experiment, specifically a localized random intervention experiment. Samples on one side of the cutoff do not receive the treatment, while those on the other side do, thus forming a naturally occurring experimental group and control group at the cutoff. By observing the outcome variable of these groups, the local average treatment effect (LATE) of the treatment variable at the cutoff can be estimated (Sacks & Ylvisaker, 1978; Hahn et al., 2001). The regression model is depicted as shown in Equation 1, where Y_i represents the outcome variable for the sample, X_i is the assignment variable, C_0 is the cutoff threshold, D_i is the treatment variable, and δ represents the local average treatment effect.

$$\begin{aligned} Y_i = \alpha + \beta_1 \cdot (X_i - C_0) + \beta_2 \cdot (X_i - C_0)^2 + \delta \cdot D_i \\ +\gamma_1 \cdot (X_i - C_0) \cdot D_i + \gamma_2 \cdot (X_i - C_0)^2 \cdot D_i + \varepsilon_i \end{aligned} \quad (1)$$

In 1984, Trochim, building upon Campbell's research, initially categorized regression discontinuity into two subtypes: sharp regression discontinuity and fuzzy regression discontinuity, based on varying assumptions (Trochim, 1984). Firstly, the distinction between the two lies in their underlying assumptions. The two assumptions for sharp regression discontinuity are as follows: first, the treatment variable is a deterministic function of the continuous forcing variable; and second, there is a strict jump in the value of the treatment variable from 0 to 1 on either side of the cutoff, as depicted in Figure 1. In contrast, the two assumptions for fuzzy regression discontinuity are: first, the treatment variable is not a deterministic function of the continuous forcing variable; and second, the value of the treatment variable ranges between 0 and 1 on both sides of the cutoff, with the treatment variable taking on lower values on one side compared to the other, as illustrated in Figure 2.

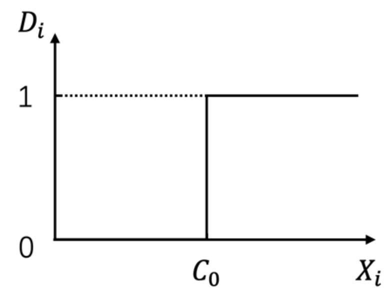

Figure 1. Sharp Regression Discontinuity

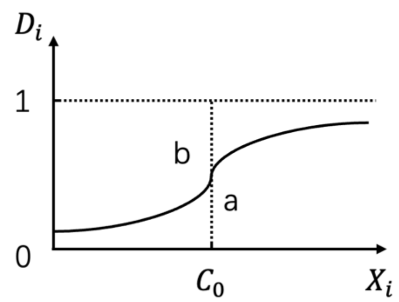

Figure 2. Fuzzy Regression Discontinuity

Secondly, sharp regression discontinuity (SRD) and fuzzy regression discontinuity (FRD) are applicable in different scenarios. On one hand, SRD is employed when the assignment of an experimental intervention to a sample is entirely contingent upon whether the value of an observed continuous variable exceeds a cutoff point. For instance, when a student's eligibility for higher education is determined solely by their admission test score relative to an established threshold, the cutoff score serves as the discontinuity point, that is, the critical value that delineates the receipt of the "higher education" intervention. If a student's score falls below the admission threshold, they are not admitted and are considered to have not received the "higher education" intervention, with a treatment probability of 0. Conversely, if their score exceeds the threshold, they are admitted and are considered to have received the "higher education" intervention, with a treatment probability of 1. The local average treatment effect (LATE) model for SRD is presented as Equation 2.

$$\begin{aligned} LATE_{SRD} &= \mathrm{E}(Y_1 - Y_0 | X = C_0) \\ &= \mathrm{E}(Y_{1i} | X = C_0) - \mathrm{E}(Y_{0i} | X = C_0) \\ &= \lim_{x \to c_0^+} E(Y_{1i} | X) - \lim_{x \to c_0^-} E(Y_{0i} | X) \end{aligned} \tag{2}$$

On the other hand, when the assignment of an experimental intervention to a sample is not solely dependent on the value of a continuous variable but is also influenced by other factors, the fuzzy regression discontinuity (FRD) approach is often utilized. In such cases, even if the value of the continuous variable exceeds the threshold, the probability of the sample receiving the experimental treatment is not 100%. For example, a policy may encourage eligible individuals to purchase a certain type of health insurance, yet the ultimate decision to purchase is not entirely determined by whether the eligibility criteria are met. Furthermore, each method has its own set of advantages and disadvantages, and the choice of method and experimental design should be based on the specific research objectives. Specifically, the sharp regression discontinuity provides a random assignment of the experimental treatment, which leads to more accurate estimation effects for the treatment variable and can more effectively reduce the impact of selective bias and other confounding factors on the research outcomes. On the other hand, due to its applicability in a broader range of research scenarios and closer resemblance to the natural state of the real world, fuzzy regression discontinuity often results in findings with stronger external validity and greater generalizability (Lee, 2005; Imbens & Lemieux, 2007; Bertanha & Imbens, 2014). Assuming X_i, $(Y_{1i} - Y_{0i}) \perp D_i | X_i$, the estimation equation for Fuzzy Regression Discontinuity (FRD) is presented as Equation 3:

$$\begin{aligned} LATE_{FRD} &= \mathrm{E}(Y_1 - Y_0 | X = C_0) \\ &= \frac{\lim_{x \to c_0^+} E(Y_i | X) - \lim_{x \to c_0^-} E(Y_i | X)}{\lim_{x \to c_0^+} E(D_i | X) - \lim_{x \to c_0^-} E(D_i | X)} \end{aligned} \tag{3}$$

2. The Origins and Development of Regression Discontinuity Design

The Regression Discontinuity Design originated in the 1960s. In 1960, Thistlewaite and Campbell, in the absence of random assignment of experimental and control groups, employed a discontinuous regression analysis method to compare 5126 students who received academic honors in school with 2848 students who received commendations but no honors. They found that public recognition of students significantly increased their likelihood of receiving scholarships, while the lack of public recognition affected the students' attitudes and career planning. Subsequently, researchers re-analyzed the sample using a random assignment method and compared the results obtained from both analytical approaches. It was discovered that the Regression Discontinuity Design could provide a reliable estimation of causal effects in situations where randomized intervention experiments were not feasible (Thistlethwaite & Campbell, 1960). In 1963, Campbell and Stanley further elucidated the fundamental concepts and implementation processes of the regression-discontinuity (RD) design, a quasi-experimental method. They discussed how the RD approach could mitigate selection bias in experiments and enhance the internal and external validity of research studies, positing that the RD design is a reliable method for investigating causal effects under the constraints of real-world conditions. However, at that time, the research was characterized by a lack of rigorous statistical derivation on one hand, and on the other, researchers believed that the substitutive role of the RD method for randomized intervention experiments was only effective around the cutoff point, i.e., the critical value (Campbell & Stanley, 1963). In these two seminal studies, the RD method was systematically introduced for the first time. However, due to the lack of systematic proof by researchers at that time and the insufficient exploration of its applicable scenarios, the RD method did not garner widespread attention from the academic community.

During the 1970s to 1990s, the regression-discontinuity (RD) method made new theoretical advancements and became one of the three most important econometric methods in quasi-experimental research, alongside instrumental variable (IV) and difference-in-differences (DID), gradually gaining recognition in the academic community (Angrist & Pischke, 2010). In 1977, Rubin discovered in his research that when subjects are assigned to different experimental groups based on the values of covariates, the treatment effects could be estimated using the RD method, and he pointed out that the inferential results of RD are not only valid near the cutoff point (Rubin, 1976). In 1978, Sacks and Ylvisaker provided a brief statistical proof of the RD method through mathematical derivation, demonstrating that RD can reduce regression bias and improve the accuracy of regression estimations in the presence of nonlinear bias, and highlighted that its validity extends to the entire range of the variable, not just around the cutoff point (Sacks & Ylvisaker, 1978). In 1984, building upon Campbell's research, Trochim further explored the role of the RD method in program evaluation, systematically organizing the basic RD design, assumptions of RD, and the historical development of the RD method, and further categorized the cutoff into deterministic and fuzzy cutoffs, thereby further advancing the theoretical development of the RD method (Trochim, 1984).

Upon entering the 21st century, the regression-discontinuity (RD) method has received more rigorous academic validation and has been expanded upon more deeply, with its theory becoming more solid and its applications more extensive. As one of the most credible quasi-experimental methods, the RD method has rapidly permeated into research on policy effect evaluation, particularly evident in the field of microeconomics, with specific research areas encompassing education, political economy, public health, health, crime, and the labor market, among others (Lee & Lemieux, 2010). Hahn et al., in 2001, through rigorous theoretical analysis and mathematical derivation, demonstrated the effectiveness of the RD method in estimating causal effects, explored issues related to the general heterogeneity of the RD method, and provided a solid econometric theoretical foundation for the RD method (Hahn et al., 2001). Lee, in 2005, used the RD method to investigate the election outcomes in the U.S. House of Representatives from 1946 to 1998, further substantiating the effectiveness of the RD method in estimating causal effects (Lee, 2005). In 2007, Imbens and Lemieux conducted a more in-depth exploration of the econometric foundations of the regression-discontinuity (RD) method. In their study, they reviewed both the theoretical and practical issues encountered in the application of the RD method.

They provided mathematical derivations for the fuzzy and sharp RD designs, as well as for the assumptions underlying the RD method. They introduced the use of graphical analysis to assess the validity of the RD method and conducted sensitivity analyses (Imbens & Lemieux, 2007). In 2010, Lee and Lemieux explored the origins of the RD design, its substitutability for randomized intervention experiments, the specific operational methods of the RD approach, the rules of discontinuity, practical issues in special contexts, the current scope of application, and the future for the RD method's development (Lee & Lemieux, 2010). Subsequently, researchers in the fields of health economics and health economics have increasingly turned their attention to the RD method, gradually beginning to apply this novel method of causal inference to empirical studies on health and the evaluation of policy intervention effects.

3. Application of Regression-Discontinuity in International Health Economics Research

3.1 Public Health Policy

In the field of health economics, researchers often seek to investigate the effectiveness and benefits of specific health policies or medical assistance policies. The goal is to provide effective policy recommendations for improving public health quality in areas such as preventive healthcare, disease control, and health promotion for an entire nation. Therefore, the regression-discontinuity (RD) method, being one of the most effective methods for policy evaluation, has been widely applied in the exploration of the impact effects within this domain.

In studies within this field, researchers frequently use age and date of birth of the subjects targeted by the policy as the cutoff points for the RD design. They compare samples who are just eligible for the policy with those who are not, in the vicinity of the critical age. Additionally, many studies also consider the policy's eligibility threshold as the cutoff point, examining the differences in outcome variables between samples that qualify for the policy and those that do not. This approach allows for a nuanced understanding of the policy's impact on various demographic groups and contributes to the development of more targeted and effective public health strategies.

For instance, Bernal et al. in 2024 explored the impact of a non-contributory social pension scheme introduced in Peru in October 2011 on the nutrition-related health outcomes of individuals over the age of 65. This policy provided a monthly stipend of $33 to eligible elderly individuals. The study, conducted between 2012 and 2015, categorized the elderly into three groups—extreme poverty, non-extreme poverty, and non-poverty—based on their household-weighted welfare index. Elderly individuals in extreme poverty were eligible for the program, while those slightly above the threshold and in non-extreme poverty were not entitled to the subsidy. The study selected the extreme poverty line as the cutoff point, including elderly individuals within 0.3 standard deviations above and below the extreme poverty line, who constituted a very similar group of elderly individuals near the threshold for receiving the pension. The findings revealed that the social pension scheme significantly improved the nutritional status of the elderly and had a positive impact on their food expenditure and utilization of healthcare services. However, the program had a significant impact on improving anemia among women but not among men, and the effects were notable only within the first 24 months of receiving the subsidy, with diminishing impact thereafter (Bernal et al., 2024).

In 2023, Yaylali similarly utilized age as a cutoff point to conduct a regression analysis on a free health insurance policy in Jordan. To achieve universal health coverage, Jordan introduced a policy in 2002 that provided free health insurance to children under the age of six, with the eligibility for free insurance ceasing once children surpassed this age threshold. The researchers selected the age of six as the cutoff and found that the free health insurance policy increased the likelihood of children's health insurance participation by 17%, thereby improving the utilization of healthcare services and the well-being of children. This improvement manifested in more frequent medical visits and an increased use of private hospital services provided to children, especially in areas where the public healthcare system was less efficient. Concurrently, the study discovered that the free health insurance policy did not significantly reduce healthcare expenditures for children. The possible reason for this could be attributed to the relatively low efficiency of Jordan's public healthcare system, leading residents to prefer private medical institutions (Yaylali, 2023).

In a related topic, Mata in 2012 conducted a causal analysis on the impact of eligibility thresholds for Medicaid on the utilization of healthcare services and children's health outcomes. Specifically, a U.S. Medicaid program for children determines eligibility for medical assistance based on the economic status of the child's household within the jurisdiction. When a child's family economic situation falls below a certain percentage of the federal poverty line, the child becomes eligible for assistance. Using this threshold as a cutoff point, the researchers found that eligibility for Medicaid did not have a significant positive effect on various health conditions of children, including obesity rates and rates of school absences due to illness (De La Mata, 2012).

Earlier, Card and Shore-Sheppard employed age as a cutoff to investigate the effects of two medical assistance policies in the United States. One of the medical assistance policies targeted children under the age of six from families with incomes between 100% and 133% of the poverty line, where children aged five were eligible for medical assistance, but those aged six were not. Another policy targeted children born before October 1983, with those born one month later ineligible for the policy. The researchers compared these children, who were fundamentally similar, using the regression-discontinuity method with the date of birth as the cutoff to explore the impact of eligibility for medical assistance on children's overall insurance coverage. The study found that eligibility for medical assistance significantly increased the number of medical visits children made in the past year (Card & Shore-Sheppard, 2004).

3.2 Health Insurance

Health insurance, as an essential health safeguard for individuals and families, has consistently been a focal point of research in health economics. Driven by concerns for the accessibility of medical services and health equity, the regression-discontinuity (RD) method has also been widely applied globally within this domain. Age, as one of the critical indicators for obtaining health insurance, provides a natural cutoff threshold for the RD method. Researchers from various countries observe the differences between samples on either side of a specific age point to explore the relationship between health insurance and people's health status, medical expenditures, and health-related decision-making.

For instance, Kettlewell and Zhang, in 2024, utilized extensive administrative data from Australia to analyze how the cost of health insurance related to age influences people's choices regarding private health insurance. In Australia, if residents do not purchase health insurance before the age of 31, they are subject to a 2% annual surcharge when they do so after turning 31. Therefore, the study used 31 years old as the cutoff point to estimate the impact of the cost of health insurance on people's choices of private health insurance. The findings indicated a significant increase in the purchase of private health insurance at the age cutoff of 31, and the effect of this increased insurance cost on the propensity to purchase health insurance diminished over time. This study provided empirical support for enhancing participation in the health insurance market through the regression-discontinuity method (Kettlewell & Zhang, 2024).

Coincidentally, in 2015, Mata and Gaviria utilized data from a national survey conducted in Colombia between 2010 and 2013 to investigate the impact of losing health insurance on residents' physical health status and utilization of medical services through a fuzzy regression-discontinuity (RD) design. According to a Colombian health insurance policy, dependents lose their health insurance coverage upon reaching 18 years of age. The study selected 18 years old as the cutoff point and compared the medical service choices and health levels of the samples before and after the loss of health insurance. The findings revealed that the loss of health insurance led to a deterioration in the self-assessed health status of residents turning 18, and it also resulted in a significant increase in the utilization of private medical institutions' services among those residents (De la Mata & Gaviria, 2015).

Card and colleagues also focused on the causal relationship between health insurance and the utilization of medical services. In 2008, they conducted an effectiveness evaluation of the U.S. health insurance policy to explore the impact of health insurance coverage on the utilization of healthcare services. The study revealed that nearly one-fifth of low-income non-elderly individuals in the United States were uninsured. However, according to U.S. health insurance policies, individuals become eligible for Medicare when they reach the age of 65, resulting in less than 1% of elderly individuals being uninsured. The researchers used age as a cutoff point, selecting 65 as the critical threshold, and compared samples before and after the age of 65. They found that having health insurance significantly increased the frequency of utilization of low-cost medical services, that is, the number of medical visits. Additionally, having health insurance along with supplementary insurance increased the utilization rate of high-cost medical services among the elderly, such as joint replacement surgeries and coronary artery bypass surgeries (Card et al., 2008).

3.3 Health Behavior

Health behaviors play a significant role in improving the overall health status of populations, optimizing the allocation of medical resources, and identifying and reducing health inequalities. The alteration of health behaviors itself serves as a natural breakpoint, creating a quasi-randomized intervention experiment, thereby making the regression-discontinuity (RD) method one of the optimal approaches for investigating health economics-related issues such as individual health behaviors. Empirical studies in this field often focus on personal health decisions regarding alcohol consumption, smoking, and health education.

For instance, against the backdrop of a high prevalence of metabolic diseases in Spain, Gaggero et al. in 2022 examined the impact of health information on individual health decision-making and lifestyle changes, using continuous longitudinal survey data from eight Spanish medical institutions between 2004 and 2010. They explored the influence of the diagnosis of one of the most prevalent chronic diseases globally—Type 2 diabetes—on lifestyle changes and BMI values among populations, including smoking cessation, alcohol abstinence, and weight loss. During the study, researchers employed the glycated hemoglobin (HbA1c) values used for diagnosing Type 2 diabetes as the cutoff point, applying a fuzzy regression-discontinuity design to compare the short-term and long-term differences in BMI and lifestyle factors, such as weight loss, smoking, and alcohol consumption, between populations just above and below the diagnostic threshold. The findings indicated that after the diagnosis of Type 2 diabetes, patients' BMI values significantly decreased, particularly among those with complications and those living alone; additionally, the study found that the diagnosis of Type 2 diabetes significantly reduced patients' body weight but had no impact on their alcohol and tobacco consumption behaviors (Gaggero et al., 2022).

Additionally, some researchers have shifted their focus to the relationship between educational behaviors and health behaviors. Against the backdrop of the expansion of university education in Sweden, Heckley and his colleagues in 2022 explored the causal relationship between university education and health to understand the potential health benefits of higher education. The study particularly focused on students who just met the university admission criteria and those who just failed to meet them, using the university admission threshold as the cutoff point. The researchers employed Swedish administrative data from 2003 to 2015, along with outpatient and inpatient data, to investigate the impact of university education on students' health status and the use of healthcare services through a regression-discontinuity approach. The study found that a 10% increase in university admission rates might lead to a 1% increase in hospital admissions for male students on the edge of admission eligibility, with the underlying reason being mental illnesses related to alcohol and narcotics. However, an opposite phenomenon was observed among female students, where university education reduced the probability of hospitalization due to mental health issues for female students (Heckley et al., 2022).

In the realm of maternal health behaviors, Edoka et al. in 2016 utilized data from two nationwide, large-scale surveys to investigate the impact of Sierra Leone's 2010 free healthcare initiative, which waived medical fees for specific groups, on the utilization rates of health services for children under five years old, maternal health services for pregnant women, and out-of-pocket medical expenditures.

Employing a fuzzy regression-discontinuity design during the study, they designated children aged 0-4 as the experimental group and children aged 5-10 as the control group, with the age of 5 serving as the critical threshold. The findings revealed that the free healthcare initiative had a negative impact on the utilization of medical services for children under five and reduced the likelihood of their health expenditures, with no effect on out-of-pocket medical costs. Concurrently, the initiative led to an increase in the utilization rate of maternal health services for pregnant women (Edoka et al., 2016).

Additionally, as one of the significant health-related behaviors, the academic community has frequently employed the regression-discontinuity (RD) method to investigate issues surrounding alcohol consumption. In 2009, Carpenter and Dobkin used the legal minimum drinking age as the critical threshold to address the endogeneity of policy through the RD method, examining the impact of alcohol consumption on mortality rates in the United States. The study found that when the legal minimum drinking age is set at 21 years, obtaining eligibility to drink leads to a substantial increase in the consumption of alcoholic products and the number of drinking days. This increase in alcohol consumption results in a significant rise in the mortality rate among 21-year-olds, with the leading causes of death being motor vehicle accidents involving alcohol, alcohol overdose, and suicide. Furthermore, the study discovered that a 1% increase in the number of drinking days corresponds to a 0.4% increase in the mortality rate, marking the first time such a direct numerical estimation has been made in the field of related research (Carpenter & Dobkin, 2009).

4. Discussion

Since the 1990s, the theory of the regression-discontinuity (RD) method has developed rapidly and has garnered widespread attention from economists, with its application experiencing explosive growth in fields such as health economics and health economics. By reviewing the fundamental ideas, main content, and developmental history of the regression-discontinuity theory, as well as by conducting a retrospective and analytical examination of research in related areas of health economics, it can be observed that the RD method possesses several advantages over other methods of causal inference.

Firstly, compared to randomized intervention experiments, the RD method offers a higher cost-effectiveness. Conducting randomized intervention experiments often requires the construction of a strict laboratory environment to control for extraneous variables beyond the experimental variables. This approach is not only economically costly but also subject to ethical constraints in health economics research, which involves human subjects and all factors related to their health, thereby limiting the scope of the research. In contrast, the RD method typically utilizes an existing health policy as the experimental intervention variable, which is already in reality. This approach incurs lower implementation costs, requires fewer demands on the external research environment, and is less likely to encounter ethical issues, thus enhancing the external validity of the research.

Secondly, the regression-discontinuity (RD) method offers higher accuracy in estimating causal effects, with results that closely approximate those of randomized controlled trials, making it one of the most credible quasi-experimental research methods. Specifically, the difference in treatment effects on either side of the cutoff closely resembles the setup of a randomized intervention experiment. It naturally creates a localized random intervention around the cutoff point, allowing for the random assignment of the experimental treatment variable and effective control over external interference factors, thereby addressing issues of endogeneity.

Thirdly, compared to other quasi-experimental design methods such as instrumental variables and difference-in-differences, the RD method requires milder assumptions, has a broader range of applicable scenarios, and a wider scope of research applicability. Specifically, according to the fundamental principles of the RD method, the conditional distribution functions on either side of the cutoff are continuous. That is, before and after the experimental intervention, all variables other than the experimental treatment variable are continuous. However, instrumental variable and difference-in-differences methods often require the assumption that all other variables are continuous before and after the experimental intervention. This is also one of the key elements that distinguish the regression-discontinuity method from other quasi-experimental methods.

However, it is also possible to identify some drawbacks associated with the use of the regression-discontinuity (RD) method. The most critical issue is that when individuals are aware of the group assignment rules in advance, they can manipulate or alter the cutoff variable at their discretion, choosing to join either the experimental or control group. This threatens the validity of the RD method's estimations. Specifically, in health economics research, the subjects of study are often the health behaviors and health-related decisions of populations. When individuals can choose whether to meet the cutoff threshold themselves, the assignment between the experimental and control groups is not random. The RD cannot create the effect of random assignment of the treatment variable at the cutoff, leading to an endogenous group assignment problem within the experiment, which affects the final estimation of the causal effect. Therefore, it is crucial to test the conditional density functions of the distribution variables on either side of the cutoff. The RD method can only be used when the densities are similar, indicating the absence of an endogenous group assignment issue.

Secondly, when there are variables in the model, other than the experimental treatment variable, that can affect the outcome variable, these variables need to be included in the regression model. However, if these variables also exhibit a discontinuity at the cutoff threshold, it is not possible to attribute all changes in the estimated coefficients of the local average treatment effect to the experimental treatment variable alone, leading to a potential bias in the experimental estimation results. Thus, before conducting a regression-discontinuity analysis, it is necessary to examine whether the conditional densities of other variables that can affect the outcome variable are continuous at the cutoff point.

5. Conclusion

The regression-discontinuity (RD) method, as an effective quasi-experimental research design, is primarily advantageous for its ability to harness natural experiment cutoffs to simulate the environment of randomized controlled trials, thereby providing more accurate causal inference outcomes. Within the international health economics community, the exploration of public health policies aimed at medical assistance and the enhancement of health equity, the focus on medical accessibility and health economics within the field of health insurance, and the investigation into the improvement of health quality and the efficiency of health decision-making in the realm of health behavior research, all provide an excellent context for the implementation of the RD method. As the field of health economics continues to expand and deepen, the RD method, with its flexibility, practicality, and high credibility and feasibility as an experimental design approach, is expected to have a broader application in the future. This will significantly contribute to the scientific development and practical application of the international health economics.

Theoretically, the evolution of the Regression Discontinuity Design (RDD) has significantly enhanced the flexibility of research design and the reliability of research conclusions within the field of international health economics. Its unique research design has reduced the cost of studies and expanded their scope, leveraging naturally occurring, localized random interventions to bolster the credibility of causal inferences. Additionally, RDD serves as a versatile policy evaluation tool for related global research endeavors.

Practically, the application of RDD in the field of international health economics has provided crucial methodological support for the achievement of high standards of health worldwide. By offering robust and reliable estimates of causal effects, it has optimized the efficiency of health resource allocation, improved public health, and elevated the overall health standards.

In the future, the regression-discontinuity method will continue to shine through its theoretical development and expansion of application scopes, exerting a long-term impact on the investigation of effects within the international health economics community. It will provide direct evidence of causal effects in areas such as policy evaluation, health intervention research, the allocation of limited medical resources, the integration of health and behavioral economics, and addressing emerging global health challenges like population aging and epidemic diseases. The RD method will offer more robust methodological support for policy formulation and the assessment of policy and program effectiveness.

Acknowledgements

The authors are supported by Natural Science Foundation of Shaanxi Province (2023-JC-QN-0784).

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