REGRESSION DISCONTINUITY DESIGN: AN APPLICATION IN ECONOMICS

REGRESYON SÜREKSİZLİK ANALİZİ: EKONOMİ ÜZERİNE BİR UYGULAMA

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- in case of using others Works, related studies have been cited in accordance with the scientific standards
- all cited studies have been fully referenced
- I did not do any distortion in the data set
- and any part of this thesis has not been presented as another thesis study at this or any other university.

25/05/2017

Neslihan ARSLAN

ÖZET

REGRESYON SÜREKSİZLİK ANALİZİ: EKONOMİ ÜZERİNE BİR UYGULAMA

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Yüksek Lisans, İstatistik Bölümü

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Regresyon Süreksizlik Analizi (RSA) ex-post facto deneylerine bir alternatif olarak geliştirilmiş ve genel anlamda, deneysel olmayan tasarımlarda deney etkisini nedensel olarak tahmin etmek için kullanılan bir yaklaşımdır. Regresyon Süreksizlik yöntemi birer deney ve kontrol gruplarına ek olarak bu grupları ayırmada kullanılacak olan ve önceden bilinen bir eşik değerinden oluşmaktadır. Verilerin deney ve kontrol gruplarına atanması sürecinin arkasında yatan mantık ise şu koşula dayanmaktadır: Eğer atama değişkenindeki bir gözlemin değeri kesme değerinden büyük ise o gözlem, deney grubuna; küçük ise kontrol grubuna atanmaktadır. Bir program değerlendirme veya deney söz konusu olduğunda verilerin atanması sürecinde ortaya çıkan farklılık ise bir süreksizlik veya bir sıçrama yaratmaktadır. Ortaya çıkan bu süreksizlik ise ana ve etkileşim etkilerinin tahminlerinde kullanılmaktadır.

RSA yöntemi, eşik değerine bağlı olarak dağıtılmış veri setini gösteren grafiksel açıklama bölümü ile başlamaktadır. Atama ve sonuç değişkenleri arasındaki ilişkide ortaya çıkan süreksizliğin yönü, istatistiksel analizler kısmı ile belirlenmekte ve sonrasında ise ana etki tahmini elde edilmektedir. RS tasarımları sadece ana etkinin tahmini için değil aynı zamanda etkileşim etkilerinin tahmini için de kullanılmaktadır. Grafiksel açıklama kısmından sonra, tahmin edilmek istenen etkilerin yönü istatistiksel modellerle bulunmakta ve RS ana ve etkileşim etkilerinin tahmini böylece elde edilmektedir.

Bu tez, temel olarak RSA’ya ilişkin teorik çerçeveyi açıklamayı, temel yaklaşımı, Türkiye’nin iktisadi kalkınmasını araştırmak üzere uygulama ile RSA’nın analizlerini örneklendirmeyi ve böylece il bazında terörizm ve iktisadi kalkınma arasındaki ilişkiyi açıklamayı amaç edinmiştir. Bu temel amaçlara göre, RSA literatür taraması ile değerlendirildikten sonra, grafiksel gösterim ile temel mantığı ve prensipleri detaylıca açıklanmıştır.

Anahtar Kelimeler: Regresyon Süreksizlik Analizi, Deneysel Tasarımlar, Parametrik Tahmin, Parametrik Olmayan Tahmin, Terörizm, İktisadi Kalkınma

ABSTRACT

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Regression Discontinuity Design (RDD) is developed as an alternative to ex-post facto experiments. It is an approach causally estimating treatment effects in non-experimental designs. The Regression Discontinuity Methodology comprises a treatment and a control group and a threshold value depicting a known cutoff criterion which is employed to separate treatment and control groups. The logic behind the assignment process depends on the condition that if the value of assignment variable for each observation is above the cutoff value, the observation is assigned to treatment group; otherwise, it is assigned to control group. The difference occurred during the assignment process creates a discontinuity or a jump in the estimation process.

The RDD methodology starts with graphical illustration revealing the distribution of data based on a cutoff criterion. Then, the direction of the discontinuity in the relationship between assignment and outcome variables is determined representing the main effect of the estimation process. The estimation process is supported by graphical illustration, parametric and nonparametric estimation methods. Furthermore, RD designs are used to obtain not only main effects but also interaction effects.

This thesis aims at explaining research design with a theoretical framework, evaluating this main approach through an application of economic growth of Turkey and hence analyzing the relationship between terrorism and economic growth at province level in Turkey. In line with this, a theoretical discussion, a descriptive analysis, and a case study related with the dynamics of terrorism and economic growth constitute the outline of this thesis.

Keywords: Regression Discontinuity Design, Experimental Designs, Parametric Estimation, Nonparametric Estimation, Terrorism, Economic Growth

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LIST OF ABBREVIATIONS

RSA	: Regresyon Süreksizlik Analizi
RS	: Regresyon Süreksizliği
RDD	: Regression Discontinuity Design
RD	: Regression Discontinuity
AIC	: Akaike Information Criterion
GTD	: Global Terrorism Database
RDWTI	: RAND World Terrorism Incidents
Growth	: Growth Rate of per capita Income
Terr	: Terrorism Index

1. INTRODUCTION

Regression Discontinuity Design have become popular recently in estimating causal treatment effects with non-experimental data. The term “regression discontinuity” comprises two negative connotations such that the term “regression” implies a moving backward or a reversion and the term “discontinuity” refers to a jump, a slump or a kink in the assignment process. Even though the term implies a negative meaning, it is proposed as a strong alternative methodology in dealing with randomized experiments. In Regression Discontinuity Design (RDD), treatment is solely based on the criteria such that whether an “assignment” variable (also termed as the “forcing” variable) which is greater than a known cutoff or threshold value.

The main logic behind this design is that the observations with score values below the cutoff or threshold value were better compared to those observations with score values above the cutoff value. In line with this logic, an observable covariate is employed to obtain the treatment effect. This covariate is named as the assignment variable. If the value of each observation under the assignment variable is above a known cutoff value, the observation is assigned to the treatment group; otherwise, it is assigned to the control group. The discontinuity or threshold value is set by the researcher and it is assumed to be publicly known.

RDD has several advantages. Treatment effect of RD estimate is unbiased at discontinuity point. In comparison with other nonexperimental methods, RDD can be performed with relatively weak assumptions however, it provides more credible results. Furthermore, RD analyses do not need ex-ante randomization. Well-executed RD analyses provide treatment estimates as good as those of randomized methods. In contrast to other quasi-experimental methods, since RDD is executed to identify the average treatment effect, it is not possible for treatment and control groups with the same score value unlike the other designs such as differences-in-differences or selection-on-observable approach.

Regression Discontinuity (RD), first proposed and studied by Thistlethwaite and Campbell in 1960, has originally aroused from the concept of random assignment and started to be widely accepted in line with the academic discussion in recent years. RD is an approach causally estimating treatment effects in non-experimental designs. Although RD originally dates back 1960s, this approach is of recent vintage and hence, this non-experimental approach has been of widespread interest lately. This approach, comprising various theories about RD, do not necessarily exclude each other, but rather tend to complement one another. Since the recent studies on RD design are growing substantially and since RD estimates are regarded as good as randomized methods, the scope and content of this thesis will focus on the concept of RD design.

Bearing in mind what has been stated above, this thesis has three purposes. First, it aims at explaining research design with a theoretical framework under which details of RDD are given. Second, it aims at propounding an analytical framework with an application on the economic growth since there is no study related with RDD in the existing Economics literature in Turkey. Third, it scrutinizes the connection between terrorist attacks and economic growth at province level in Turkey and to analyze the RD effect of the economic growth rate on the average terrorism index as an empirical analysis. Hence, this thesis is basically composed of a theoretical discussion, a descriptive analysis, and a case study related with dynamics of terrorism and economic growth.

Chapter 1 is an introduction to RDD outlining the overarching framework of this thesis. The remainder part is structured as follows. Chapter 2 highlights existing literature under two categories: theoretical and application literature. In this section, some crucial studies existed from 1960s until now were explained in detail for this thesis to be well-structured. Chapter 3 is the theoretical framework for RDD disclosing statistical model RDD incorporating its graphical illustration, parametric and nonparametric estimation methods and sensitivity analyses and validity tests. Furthermore, this chapter clarifies the difference between sharp RDD and fuzzy RDD. Chapter 4 sheds some light on the history of terrorism in Turkey and represents the relationship of terrorism and economic growth at the province level. Accordingly, sharp RD methodology has been applied to terrorism dataset to obtain average treatment effect and to see the impact direction. Chapter 5 concludes the thesis summarizing the main points and highlights disclosed and clarified throughout the study.

2. LITERATURE REVIEW

Literature review is divided into two parts as theoretical and application review and it will be reviewed chronologically starting from 1960s until the present time.

2.1. Theoretical Review

Most of the studies in recent years indicate that RDD is a non-experimental design that is mostly employed to estimate treatment effects by assigning a cutoff or threshold point in a two-group pretest-posttest model. From 1960s until now, RD approach was studied comprehensively. Although this approach was first studied in 1960s, it remained unpopular until 2008 since the recent studies created a crucial and distinct point of view in the literature. To exemplify them, various studies in different fields are reviewed below.

In year of 1960, the regression discontinuity design was pioneered by Thistlethwaite and Campbell through their article [1]. In their study, the authors described the analysis of RDD (Regression Discontinuity Design) by providing quasi-experimental test of a causal hypothesis. They explained the design through choosing two groups- treatment and control groups by random assignment process to obtain a quasi-experimental comparison. RD analysis was applied to the educational data and then interpreted compared to the ex-post facto design. By using educational data, the authors disclosed the effect of student scholarship on career plans under the condition that the scholarships were given only if the test scores exceed a threshold or cutoff point. Accordingly, the results of RD analysis suggested that achievements tend to increase the likelihood that the recipient will get the scholarship but the results did not support the inference that this tendency affects the student's career plans. Moreover, the results revealed that in ex-post facto experiment, assigning variables are inadequately controlled, however, in RD design, treatment and control groups are equated by matching the variables. In addition, main differences between the ex-post facto experiment and the RD design were explained along with a detailed evaluation.

After the introduction of RDD to the literature, this analysis started to be studied more frequently. In 1984, Trochim [2] illustrated basic methodology of regression discontinuity design within his book. Main assumptions underlying this design were expounded in detail in the scope of research design. By way of graphical illustrations, the logic of the RD design was explained coupled with its applications in different research areas. Accordingly, statistical models for RDD were introduced in line with previous studies in which pretest and posttest groups were represented by program and comparison groups, respectively. Given pretest and posttest variables, the model was described theoretically as well. Having explained necessary models with different polynomial degrees, model specification was determined for more appropriate and precise estimations. After theoretical chapters of the book, all analyses and mentioned theories were supported by applications in compensatory education programs. Not only sharp RDD but also fuzzy RDD was disclosed in detail along with their applications. Furthermore, steps to analyze RDD in MINITAB and SPSS were clearly expounded in the appendix part of this book. RD simulation exercises were shown as well.

More recently, Van der Klaauw [3] examined RD analysis by including a survey into their work related with current developments in economics in 2008. In his article, the author started with the section of elaborative introduction including a detailed history of RDD, a well-prepared literature review with a section explaining how useful this method in economics is. After this section, fuzzy and sharp RD designs were evaluated with respect to the treatment effects. Like other theoretical studies, steps of the implementation approach of the analysis were clearly explained coupled with parametric and semi-parametric methods. To investigate how sensitive the treatment effect estimates and to analyze how robust the parametric results, the author implemented sensitivity analysis and validity tests.

In another study published in 2009, Lee and Lemieux [4] introduced RDD in economics by publishing a “user guide” in which the basic theory behind the RDD was explained and the details of the RD analysis were given in addition to its validity tests. Why RDD is thought as a “quasi-experimental” design was evaluated and distinct estimation methods for RDD were interpreted with its main advantages and disadvantages. Through various examples, basic concepts of RDD were disclosed and fuzzy versus classic RD analyses were compared as a part of an empirical research. As to the regression methods of the RDD, parametric and non-parametric regressions were taken into consideration to determine the correct functional form of the model.

In 2011, Hann et al. [5] addressed unspoken questions regarding discussions and applications of RDD. Concerning identification sources and ways of estimating treatment effects under minimal parametric restrictions, the authors discussed the identifying conditions which are weakly disclosed in previous studies. This study contributed to the literature in the view of proposing a way of nonparametric estimation of treatment effects and offering an interpretation of the Wald estimator as an RD estimator. The goal of their study is to determine theoretically the effect of binary treatment variable x_i on the outcome y_i. In line with this goal, in the existence and absence of the treatment effect, outcome variable is denoted as y_{1i} and y_{0i} respectively. As to the treatment variable, it is denoted as $x_i = 1$ if the treatment is received and if not received, then $x_i = 0$. Based on these notations, the equation for the outcome variable was written as the following:

$y_i = \alpha_i + x_i\beta_i$; where $\alpha_i = y_{0i}$ and $\beta_i = y_{1i}$ (2.1)

In the theoretical part of this study, the comparison between fuzzy and sharp RD designs was reviewed and main differences among these two types of RDD were explained. Accordingly, in sharp RDD, the treatment variable, x_i is known in a deterministic way on an observable variable z_i such that $x_i = f(z_i)$; where this observable variable z_i takes continuous values and $f(z_i)$ is known and assumed to be discontinuous at the point z_0. In contrast, in fuzzy RDD, x_i is not known in a deterministic way rather it is random and it is given as z_i, bringing up the conditional probabilities. The conditional probability of $f(z) = E[x_i/z_i = z] = P[x_i = 1/z_i = z]$ is assumed to be known at point z_0. The only similarity between fuzzy and sharp RD designs is that the probability of receiving treatment $P[x_i = 1/z_i]$ is discontinuous at point z_0. Turning back to the content of the article, the focus is on the fuzzy RD design rather than the sharp one. Taking into consideration of constant and variable treatment effects, main assumptions, theories and their proofs were given along with their details in the study. In line with this, local known restrictions and known discontinuities were used in identifying treatment effects. In the estimation section of the study, it was theoretically shown that estimates derived from kernel regression under certain conditions based on one-sided uniform kernels are numerically equivalent to the Wald estimator.

In 2011, Porter and Yu [6] brought forward the question of whether the discontinuity point is always known by using bootstrap method to find the critical values for discontinuity in their paper. To clarify this question, Porter and Yu extended the applicability of RDD at an unknown discontinuity point. In reference to this, first, the critical points for the existence of discontinuity point were determined by the bootstrap method. Then, the presence of treatment effects was tested by a unified test statistic. In this scope, Monte Carlo simulation technique was performed and depending on the results, it has been found that existence of a discontinuity point does not impact the efficiency of treatment effect in the estimation process.

Jacob et al. [7] attracted attention in 2012 by publishing their study titled as "*A Practical Guide to Regression Discontinuity"*. In this guide, the authors started with the history and the background of regression discontinuity. The origin of this approach hinges upon the random assignment which is considered as "a gold standard in social sciences studies" like RDD in statistics. After giving detailed information about the history of RDD, the authors proceeded to the overview of the approach explaining the important part of the analysis which is the graphical illustration. Having disclosed the graphical presentation, the estimation process of RD analysis was unfolded in reference to the parametric and nonparametric strategies. In choosing the most appropriate model specification, these strategies were evaluated with diagnostics and robustness checks. Furthermore, the explanation of the notions of fuzzy and sharp regression discontinuities was included to this practical guide.

What Otsu et al. [8] intended to indicate in their recent article published in 2015, is the empirical likelihood depending on inference methods determined by the RDD approach. Empirical likelihood of confidence sets were constructed by identifying sharp and fuzzy RD designs. In addition, likelihood ratios of causal effects in RD designs are asymptotically distributed by chi-square. For the sharp RD design, asymptotic properties of empirical likelihood ratio were disclosed and Bartlett correction was shown for the confidence sets via bandwidth selection. Furthermore, conventional Wald-type methods have been compared with RD design under bandwidth selection criteria. In order to illustrate the methodology, the authors use the simulated data and empirical examples. In the end, the authors conclude and empirically find that likelihood statistics employs the Bartlett correction with high-order refinements.

2.2. Application Review

Although there are too many studies about RDD, the number of theoretical studies lags the number of applied studies as expected. Since RDD is of new vintage in recent times, applied studies are stuck into a few areas such as elections, program evaluations and educational fields. Examples of applied studies on RDD are given below.

After the first application and discussion paper introduced by Thistlethwaite and Campbell [1] in 1960, another article was published as an applied study by Berk and Rauma [9] in 1983. Berk and Rauma analyzed unemployment benefits to prisoners after their release from prisons in California and an ongoing crime control program was taken into consideration. The impact of legislation extending the eligibility for unemployment benefits to prisoners who became unable to take unemployment payments after their release was evaluated by employing RD analysis. Main question in the article was whether ex-offenders taking unemployment insurance will get lower incarceration rates than those who do not receive such benefits. After explaining the RD analysis in detail, data and methodology were disclosed and results were obtained. Accordingly, it was found that the decrease in the unemployment benefits after the release of the prisoners leads to a fall in the recidivism of the ex-offenders; that is, unemployment payments made to the ex-offenders expedites them to get acquainted to their life economically.

Although RDD approach has been around since 1960s, the concept has not been studied until relatively recently. In 1990s, an increasing number of studies were started to be published in a wide variety of economics context. To exemplify this variety, Van der Klauuw [10] published an article in 1997, which mainly focuses on the impact of financial aid offers on university enlistment decisions. As for the data set used in the analysis, students' financial aid forms and their enrollment decisions were used as the source. These provide annual information about students' age, gender, race, citizenship, their college grades and their SAT (Scholastic Assessment Test) scores. By performing RD design, preliminary estimates of the program at a cutoff point have been obtained by comparing the score values both below and above the cutoff point. After a forward, stepwise procedure, piecewise, linear, quadratic, cubic and higher degree polynomial functions were tested to determine which one is sufficient for the estimation. According to the relevant tests and analyses, quadratic enrollment function was found to be sufficient and the treatment effect estimate was found to be 0.0052 corresponding to the estimated enlistment elasticity on the subject of financial aid offer. Before concluding the article, sensitivity analyses and robustness checks were performed for the validity of treatment effect estimates.

The paper, published in 2011 by Dong [11] brought a new perspective to the RD approach and identified treatment effects without assigning a discontinuity point in the RD model. This identification was based on the intuition of L'hopital's rule and in explaining and investigating this new approach, a slope change meaning a kink rather than a discrete level change meaning a jump was used in the treatment probability of the model. In estimation process, instrumental variables were employed to evaluate the estimators which were tested in the presence and the absence of discontinuity to see a jump or a kink. In the empirical application section, the relationship between the retirement and food consumption was determined and the effect of retirement at age 62 on food consumption was estimated in the US. The time-period of dataset was from 1994 to 2007. Having done with relative analyses, the scatter plots of retirement rates and food consumption reveal that the retirement rate displayed both a jumpy and kinky structure; whereas, food consumption followed a kinky structure. To find the retirement effect estimator, the author used 2SLS to the following equation and obtained the treatment effect estimator given below:

$$Y = \alpha + \beta(X - c) + \tau T + e \tag{2.2}$$

$$\hat{\tau}(c) = \frac{\widehat{\beta_+} - \widehat{\beta_-} + \hat{w}(\widehat{C_+} - \widehat{C_-})}{\widehat{\beta_+} - \widehat{\beta_-} + \hat{w}(\widehat{q_+} - \widehat{q_-})} \tag{2.3}$$

The first equation represents a regression model yielding numerically equivalent estimators to the RD estimators. In this equation, α, β and τ are coefficients and T is treatment indicator. As for the second equation, $\hat{\tau}(c)$ represents the RD treatment effect, $\widehat{w}$ is used as the weight to minimize bootstrapped standard error. B, C, p and q are the constant regression coefficients and the subscripts + and – represent that the coefficients are estimated by using the data from above or below the cutoff point c. In addition to 2SLS method, other estimation alternatives were also given in the paper. According to the results of the estimation at both jumpy and kinky structures yielding approximately the same results, 15 % to 23 % of food consumption decreases when the retirement rates increase and the estimates were found to be substantially consistent.

In 2012, Crane et al. [12] put forth an article analyzing the effect of institutional ownership on payout policy by using RDD approach, which is also an example of the studies about RDD in the economics literature. Its main aim was to find the causal effect of institutional ownership on the tendency to pay more remittances and to buy out more shares by the firms; that is, to find the causal effect on proxy. As for the contributions of the article to the economics literature, it identifies whether the institutional ownership causes firms to pay more cash or not, whether the institutional ownership causes an increase in investment and equity issuances or not and whether the capital market frictions importantly affect the economic behavior of the firms or not. In reference to this, Russell 1000 and Russell 2000 indices were used from the time period of 1991 to 2008 among 8,193 firms and the dataset was retrieved from Compustat for the accounting data, Spectrum 13F for the institutional holdings data and CRSP for the stock return data. By assigning the observations randomly to treatment and control groups, the treatment effects were measured and accordingly a causal inference was made. In the conclusion section of the article, it is stated that the discontinuities in the Russell indices led to a discontinuity in the institutional ownership and it has been founded that there is a positive relation between institutional ownership and the dividends paid by the firms. In other words, the institutional ownership was found to cause the firms to pay more cash to shareholders on their payout policy. Moreover, increased institutional ownership was also found to lead the firms to increase their equity financing activity, investment in research and development sector and proxy-voting participation.

The other paper published by Coviello, and Mariniello in 2013 is another example of applied RDD studies in economics [13]. RDD Analysis was employed in this paper to indicate the effects of increased publicity on public procurement auctions. The logic behind the analysis is that the auctions with a value above the threshold determined via RDD were publicized in the Regional Official Gazette and in two Provincial newspapers so that if the auctions with the reserve price exceed 500,000 euro, they are publicized as mentioned but if they do not exceed the threshold value, then they are only publicized on the notice board in the public administration. By using the analysis with this logic, the causal effect of publicity on entry and the costs of procurement were identified. For this purpose, a large database about Italian procurement auctions retrieved from the Italian Authority Surveillance of Public Procurement System was used in the analysis between the years of 2000-2005. Point estimators and the standard errors of the effects of publicity on entry and winning rebate implying the procurement auctions were calculated by the RDD analysis. To consolidate the results, authors applied sensitivity analysis and robustness checks for the validity of estimation results since there was an apparent discontinuity between the auction outcomes and publicity procurement. At the end of all analyses, it was concluded in the article that there is a relationship between publicizing a procurement auction and the public procurement due to its effects on entry and the costs of procurement.

In 2013, Eggers et al. [14] examined the effects of election outcomes in the U.S. during different time periods starting from 1880 to 2010. By using RD design to estimate electoral effects, the authors analyzed Canada, Germany, France, Australia, India and Brazil and then compared their results. In the article, it was evaluated that in the elections, there is always a potential for imbalance near the cutoff point and thus, this makes the key RD assumption doubtful. However, details about why this important RD assumption becomes doubtful are not clearly disclosed. As for the application section of the article, election returns, mayoral and common election results, vote margins and incumbency status of the mentioned countries with respect to the part of the interest constitute the dataset for different election periods. After the application section, it was concluded that the U.S. displays different election pattern and thus it stands out as an anomaly among the mentioned countries.

In another perspective, Abdülkadiroğlu et al. [15] evaluated causal effects of peer characteristics in educational setting by employing fuzzy RD design within their paper in February, 2014. Not only peer achievements, but also ethnic arrangement of applicants to six exam schools functioning in Boston and New York was brought to the light. In this sense, admittance cutoffs at Boston and New York City's over-enrolled schools constitute the focus of the analyses. Exam schools' admission offers were used to construct instrumental variables for peer characteristics in the scope of fuzzy RD design. As for the data used in the RD and 2SLS analyses, enrollment and demographic information of Boston Public Schools' students was retrieved from Massachusetts Comprehensive Assessment System (MCAS) to determine how long a student was enlisted at a Boston exam school. In addition, a student file data containing student registration, test scores, and college outcomes; and a BPS exam school scholar folder based on ISEE scores and grades were taken into the analyses. As an instrumental variable in the fuzzy RD strategy, Z_{ik}, indicated scholars who clear the admittance cutoff at school k, described differently for each sample. Concerning this, it is asserted that Z_{ik} equals to 0 for a scholar who qualifies at k. After displaying graphical representation of the peer characteristics in the RD design, reduced form estimates were found before the 2SLS analysis applied. In this regard, parametric and nonparametric RD results represent the reduced form estimates since they show the overall effect. As the second analysis, 2SLS was performed in maximizing the precision of the estimates. Accordingly, 2SLS estimates were found consistent with the RD estimates.

To further extend the strands of literature, a recent paper published in February, 2014, Bastos et al. [16] assays the possible properties of a tariff schedule for Buenos Aires and estimates the short-term effect of price shocks on energy utilization by analyzing a non-linear relationship between accumulated energy utilization and unit prices implying exogenous price volatility. To define unit prices under accumulated energy utilization, a threshold point was defined at tariff discontinuity and accordingly to estimate the effects of price shocks on gas consumption, the left and right sides of cutoff point were built. Then, the demand impact of a price shock was estimated by using RD design with the comparison of gas consumption levels of household. Besides, strong evidence was shown statistically for the fact that the consumers have imperfect information about price determination system and consumers do not change their accumulated consumption. Concerning the main aim of the paper, the evidence on how fast energy utilization responds to price volatility was determined. In the empirical analysis, estimation sample contains 7190 households and the data set contains the variables about the amount of bills in May 2009, quantity of consumed gas, type of reading, dates of reading and issuance and the region and neighborhood residence of every consumer. To resolve the evidence about the price determination mechanism, a survey was performed to 353 households. Depending on this survey, information about basic socioeconomic characteristics of the households, their housing conditions, amount of bills and payment methods, the frequency of implemented tariffs and the consumption thresholds were obtained. Results of the survey supported basic assumptions and revealed that consumers tend to know their payments on gas consumption; however, they have scant information on this. That is, great majority of the consumers have imperfect information on price determination system. Under this assumption, short run impacts of price shocks were estimated by employing RD design with the following regression model:

$$C_{i,1} = \beta_0 + \beta_1 Treatment_{i,0} + f\left(\overline{AAC_{\iota,0}}\right) + w_{i,0} \tag{2.4}$$

In this model, gas utilization was compared in period 1 to the period 0.

$C_{i,1}$ refers to the utilization in period 1 for consumer i whereas $\overline{(AAC_{i,0})}$ refers to assignment variable for the normalized accumulated utilization in period 0. The parameter β_1 describes the average effect exceeding the cutoff value; so, any jump at the threshold point displays the discontinuity in the valid RD design.

Threshold point was determined as the value of 1500 cubic meters and the running variable was written in the following equation:

$$\overline{AAC_{\iota,0}} = AAC_{i,0} - 1500 \tag{2.5}$$

The logic behind the binary treatment variable was that:

$$Treatment_{i,0} = \begin{cases} 0, if\ \overline{AAC_0} \leq 0 \\ 1, if\ \ \overline{AAC_0} > 0 \end{cases} \tag{2.6}$$

Based on the comparison between treatment and control groups, there existed the tradeoff problem between precision and bias of the estimates. So, robustness and diagnostic checks came to the fore within the scope of choosing correct functional forms for the estimation process. In the analysis section of the paper, first local linear regressions were run to determine the existence of discontinuities at the threshold point. Then, consumption patterns were found. The results indicated that a price shock gives rise to a statistically significant decrease in gas utilization. Moreover, it has been found that there is a positive relationship between the gas consumption in period 1 and in period 0. At the threshold point, gas consumption falls discontinuously implying that consumers react a price shock by decreasing their gas consumption.

In 2015, the paper written by Barrientos and Villa [17] scrutinizes the effect of cash transfer programme on labor market circumstances in Colombia by employing RD estimation methodology in a different perspective. The authors start their paper by explaining not only dynamics of human development conditional cash transfer program but household resources dynamics as well. In that program, the authors also disclose labor supply effects of antipoverty transfers within a theoretical framework. Having explained data and RD methodology, local average treatment effect is obtained and it has been found that there is a positive and large impact of transfer program on labor market outcomes. Furthermore, the RD results suggested in the article that the antipoverty transfers help re-allocation of household resources enable among the households.

In summary, the origin of RD design lies in the root of random assignment studies. Since randomized experiments are not always feasible to be implemented, RD design came into the scene and it was pioneered by Thistlethwaite and Campbell (1960) [1] to evaluate social programs as an alternative to random assignment studies, which are concerned about assessing the effects of obtaining a National Merit Award on students' achievement in their career. After this pioneering work, the design has gained a considerable popularity among the academic society and various studies have been brought forward by econometricians and empirical economists. The development of this design has generated new econometric issues containing the academic derivation of causal inference and semi-parametric estimation methods have been introduced during the last two decades. In line with the improvement of RD design, many empirical studies extended the use of design and brought out the sensitivity and validity tests to evaluate the precision of RD effect estimates (Van Der Klaauw) [3].

Although an increasing number of studies are related with RD designs, studies in the context of economics have started to appear over the last two decades. For example, labor supply of households in Bangladesh [18], financial aid offers on scholar enlistment [19], unionization within the context of wages and employment [20], the impacts of welfare-to-work-program on re-employment probability [21], social security payments on mortality [22], nationalization of private banks in India (Cole,2009) [23] and confinements on unemployment insurance [24] are those of studies evaluated within the context of economics in the growing literature over the last twenty years.

3. THEORETICAL BACKGROUND OF RDD

As a main discussion of recent developments, regression discontinuity design (RDD) became a thriving method for identifying and evaluating causal effects of treatments, programs and interventions. RDD attracts attention since this approach resembles to the formal experimental design. RDD is termed as a “quasi-experimental” design referring to its intuitive connection to randomized experiments. However, RDD is different from randomized assignment in the perspective that this design is not random and treatment and control groups differ from each other systematically. Treatment effects are captured by means of a discontinuity structure observed at the threshold value to explain the connection among the assignment and outcome variables. RD analyses provide less credible impact estimates than randomized experiments but, they provide more credible impact estimates than other quasi-experimental, non-experimental and observational studies. Therefore, this design is one of the strongest methodological alternatives to randomized experiments mostly used in social sciences. In briefly expressing the main distinctions between experimental, quasi-experimental and RD designs, the following table is illustrated below:

Table 1: Classification of Causal Hypothesis Testing Research Designs [2]

Type	**Experimental**		**Quasi-Experimental**	
Name	Randomized Experiments	Non-equivalent Group Design	Non-equivalent Group Design	RD Designs
Is assignment to the group random?	Yes		No	
Is assignment rule known?	Yes	No	Yes	
Assigned by cutoff on pretreatment measure?	No		No	Yes

According to Table 1, it is noteworthy to mention that RDD depends on the assignment criteria and more particularly hinges upon the existence of a cutoff value determined by a continuous pretreatment measure.

Quasi-experiments are considered inferior to randomized designs when internal validity is desired. However, under the situations that random assignment is not practical or feasible, quasi-experimental strategy may be preferred. Among these quasi-experimental designs, if the assignment criterion is known, RD designs can be used in the statistical analysis to obtain unbiased estimates of treatment effects. With this design, equivalence between the groups is not assumed, that is, pretest-posttest nonequivalent group design is allowed [25]. In this regard, RD designs which are the strongest approach of the quasi-experimental analyses are considered as a crucial alternative.

In addition to this, since random assignment requires a random selection prior to the application, it is not always feasible or practical to be implemented although it gives unbiased estimates. Performing an RD design has a significant and lower cost than random assignment methods. Moreover, RD designs eliminate drawbacks arising from the random assignment methodology since the selection process is completed on the basis of randomly generated number so this selection process couldn't be controlled by the analyst [7].

3.1. Introduction to RD Design

To clarify and demonstrate the RD design in detail, it is worthwhile to look at its definition firstly. RD design is defined as a quasi-experimental pretest-posttest design that estimates the causal effects of treatments by an assignment process depending on a cutoff or threshold point [4]. In estimating treatment effects, it is imperative to determine that the "assignment" variable (mentioned as "running", "rating" or "forcing" variable) falls above or below the cutoff point revealing a discontinuity in the likelihood of treatment at that value. As can be understood from its definition, RD designs are pertinent if there is a discontinuity relation between a continuous assignment variable and the treatment variable. In RD design, the assignment is solely made to the treatment and control groups based on a cutoff score. Thus, once a cutoff point has been determined, assignment is appointed on one side of cutoff point to one group (e.g. treatment group) and the other side to the other group (e.g. control group). Then, by comparing observations lying on these groups, it is possible to obtain treatment impact estimates.

In order to graphically illustrate the logic of RDD, in the absence or existence of treatment, the graphs given below indicate the distribution of data based on a cutoff point.

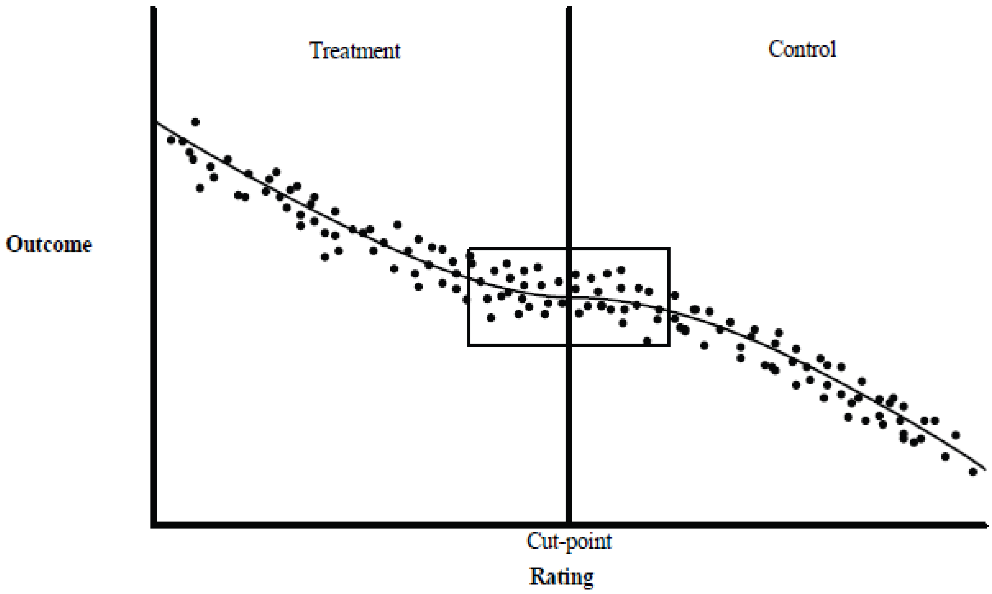

Figure 1. Pretest- Posttest (Rating-Outcome) Distribution in the Absence of Treatment [7]

In Figure 1, the relationship between rating and outcome variables are portrayed and the vertical line at a constant cutoff point represents the assignment process. This assignment is made depending on this constant cutoff point above which the datum is appointed to the treatment group and below which the datum is appointed to the other group. As can be clearly seen, the connection between the rating and outcome variables continuously passes the threshold value. This means that the outcomes above and below the threshold value are not different when there is no treatment evaluation.

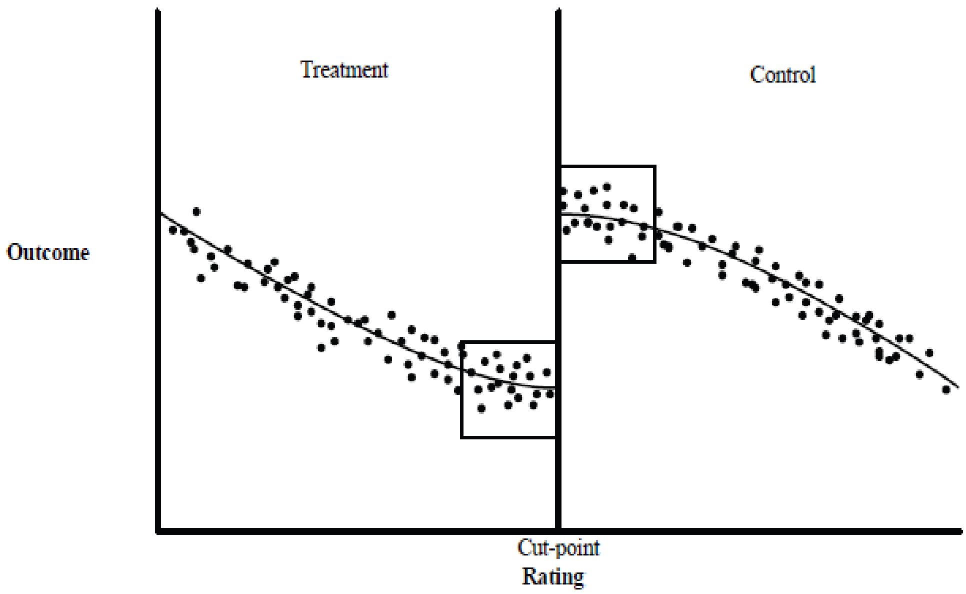

Figure 2. Pretest- Posttest (Rating-Outcome) Distribution in the Existence of Treatment [7]

Figure 2 shows what happens to the distribution of data under the existence of treatment. The vertical difference at the cutoff point indicates a sharp upward jump or discontinuity in the relationship between rating and outcome variables. This upward jump corresponds to the main effect between rating and outcome.

RD designs can also be used to determine the interaction effects in addition to the main effects. In this case, interaction effects reflect the degree to which the result is related with the outcome variable. To disclose this, how main and interaction effects within two groups are displayed on the regression lines in the existence of treatment is demonstrated in Figure 3.

Even though the regression lines under all five outcomes have the similar pattern, this does not mean the same thing and they are interpreted differently. Figure 3a, indicates the null case, that is, there is no discontinuity relation at the cutoff point between outcome and rating variables. Figure 3b reveals the case just mentioned in Figure 2 which is an upward positive effect since there is an upward jump at the cutoff. The inverse of this is illustrated in Figure 3c – a negative main effect. As to the interaction effects, Figure 3d indicates an interaction effect without main effects and finally in Figure 3e, both interaction and main effects are shown implying discontinuities in both level and slope of the regression lines between the treatment and control groups [2].

To sum up the logic of RD methodology, the selection depends on a threshold point under the pre-treatment case. The assignment process under the cutoff rule indicates that the datum on one side of the threshold value is appointed to one group and the datum on the other side of the threshold value is appointed to the other group. In doing so, a continuous calculable pre-treatment measure is needed. To determine main and interaction effects, the nature of the assignment variable should be known otherwise whether the effect is negative or positive couldn’t be found. A jump in regression lines reveals a treatment effect in the analysis as stated above. But the jump or discontinuity is not adequate to determine the direction of the effect. To make this determination clear, the assignment and the interpretation of scale values on the outcome variable should be known as well.

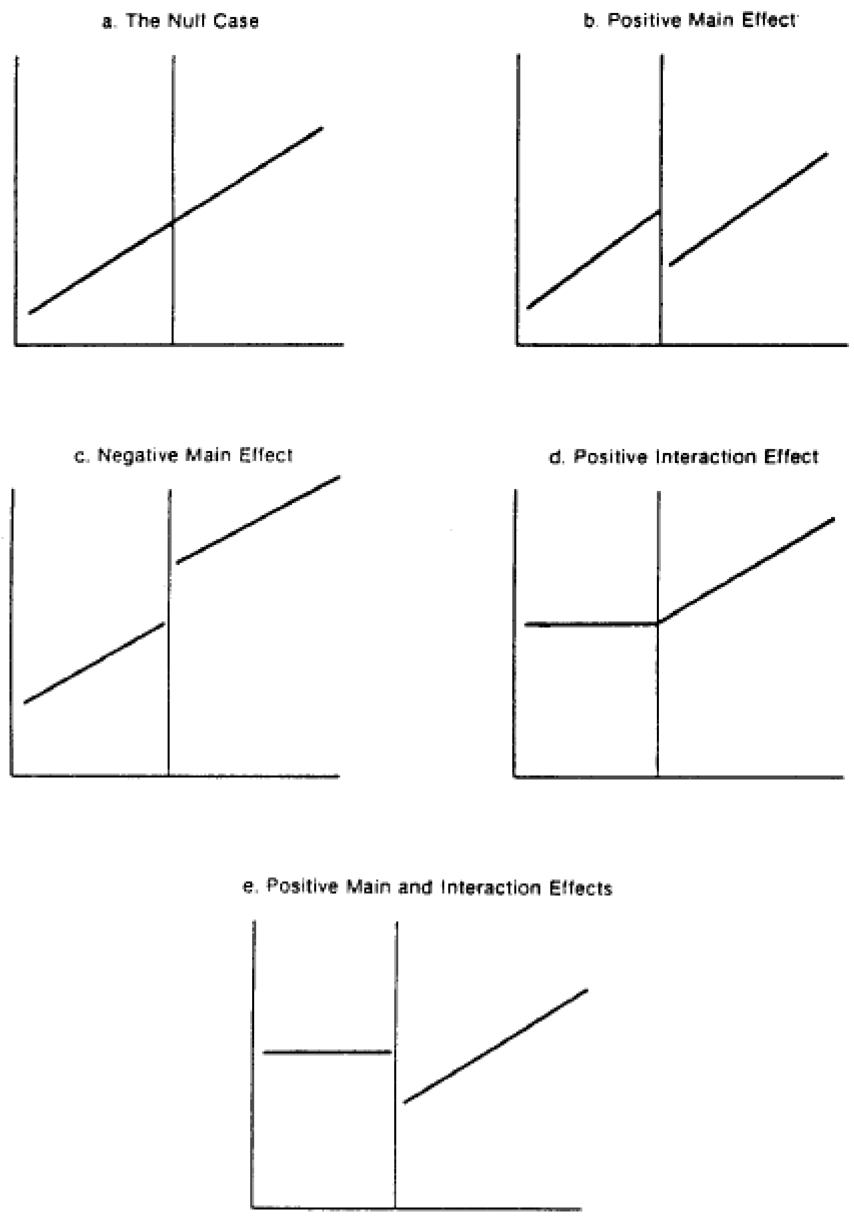

Figure 3. Hypothetical Regression Lines for RD Design [2]

3.1.1. Main Assumptions

Before analyzing statistical model of RD design, it is better to disclose its main assumptions and conditions which should be met to obtain unbiased impact estimates. As all research designs are based on some assumptions, RD designs should also be characterized with its main assumptions. These main assumptions are listed as the following:

- The assignment variable cannot be influenced by the treatment, that is, it is determined prior to the beginning of the treatment [7].

- The cutoff point is exogenously determined and the appointment to the treatment group depends on the cutoff point. This assumption further implies that there is no mis-assignment in terms of cutoff point [2], [7]. Because if there is mis-assignment around the cutoff value which is labelled as “fuzzy RD” by Campbell (1969), impact estimates are likely to be biased [25].
- Except treatment variable, all other variables are assumed to be continuous implying that there are no other ways in which observations are distributed to different pretest-posttest groups. In the absence of the treatment, all factors provide a continuous pretest-posttest relationship at the cutoff point [2], [7].
- There must be sufficient number of observations in treatment and control groups in order to estimate regression lines for each group. Both of these groups must be obtained from a single pretest distribution [2].
- The functional form depicting the connection among rating and outcome variables or between the pretest and posttest groups is continuous and specified correctly [7].
- The analytical model used to determine impact estimates precisely describes the true functional relationship. Selection of model specification or functional specification is important since misspecification may cause biased estimates. Trochim’s example in his book best explains this such that if the true relationship is in fact linear but if it is quadratic, cubic, logarithmic or others, then biased estimates would be likely to occur. To deal with this problem and to determine the correct model specification, one model (generally the basic one) should be tested against alternative models [2]. Selection of model specification will be explained in detail and analyzed in the following sections.

3.1.2. Statistical Model of RDD

Since Thistlethwaite and Campbell’s pioneering work in 1960s, there have been many studies regarding the statistical models of RDD. In 1971, Sween [26] promoted the calculation of regression equations for the pre-test and post-test groups and estimated treatment effects by performing t-test of the difference between regression lines of each group. In 1974, Boruch [27] and in 1975 Boruch and DeGracie [28] proposed a variety of useful statistical models and separated the RD design as fuzzy RDD and sharp RDD depending on the cases where pretest variable is random or fixed. In 1979 Reichardt [29] and Campbell, Reichardt and Trochim [30] discussed the general analytical model of RDD which was suggested in Chow's work (1960) [31] and was consolidated in Gujarati's work (1970) [32]. After these works, a similar approach was summarized by Judd and Kenny [33] in 1981 and in 1983, Berk and Rauma [9] reconsidered the analytical models of RDD and presented RD analysis in the area of criminal justice. With these supportive works of RD design, its analytical model has taken its final shape as the following:

Given a pretest variable x_i and posttest variable y_i, a general model for RDD is formally written as [2]:

$$y_i = \beta_0 + \beta_1 x_i^* + \beta_2 z_i + \beta_3 x_i^* z_i + \cdots + \beta_{n-1} x_i^{*s-1} z_i + \beta_n x_i^{*s} z_i + e_i \qquad (3.1)$$

Where;

x_i^* = pre-treatment variable for individual *i* minus the cutoff value, x_0,

($x_i^* = x_i - x_0$),

y_i = post-treatment variable (outcome variable) for individual *i*,

z_i = assignment variable (1, if the observation is in treatment group; 0, otherwise),

s= the degree of the polynomial for x_i^*,

β_0 = parameter of control group intercept at cutoff point,

β_1 = linear slope parameter,

β_2 = RD effect estimate,

β_n= interaction term parameter for the s^{th} polynomial,

e_i = random error.

In this model, main hypothesis is to test whether RD effect estimate is statistically significant or not, that is:

Null hypothesis: $H_0: \beta_2 = 0$ (3.2)

Alternative hypothesis: $H_1: \beta_2 \neq 0$ (3.3)

This general equation provides both main and interaction effect estimates in line with the discontinuities at the threshold value. By deducting the threshold value from each pretreatment score, x_i^* is obtained. So, by means of this transformation, it might be possible to increase the interpretability of β_0, $\beta_2$and $\beta_3$parameters which represent the main and interaction effects. To see how this process operates, it is beneficial to clearly show the steps of the mechanics of the model.

So, the true model, the basic one is written as:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i \qquad (3.4)$$

The definitions for the terms in this simple model are same with the model given above.

By using general model, the control group line is obtained as:

$$y_c = \beta_0 + \beta_1 x_i^* \qquad (3.5)$$

In which z_i will take the value of “0” since the observations are distributed to the control group.

$y_c = \beta_0$ is the point where the control regression line intersects at the cutoff point since $x_i^* = 0$ at the cutoff.

By putting the value of “1” into z_i variable, the observations are distributed to the treatment group and then, treatment regression line is obtained as:

$$y_t = \beta_0 + \beta_1 x_i^* + \beta_2 \qquad (3.6)$$

In this case,

$y_t = \beta_0 + \beta_2$ is the intersection point of the regression line at the cutoff value.

The main effect is captured by the vertical difference between the regression lines of treatment and control groups at the cutoff point:

$$y_t - y_c = (\beta_0 + \beta_2\ ) - \beta_0 = \beta_2 \qquad (3.7)$$

So the amount of β_2 reflects the main treatment effect.

In addition the main effect model, if the interaction effects are included to the model, then the following model is used:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + \beta_3 x_i z_i \tag{3.8}$$

Similar to the calculations shown above, regression lines for control and treatment groups are given below successively:

$$y_c = \beta_0 + \beta_1 x_i^* \tag{3.9}$$

$$y_t = \beta_0 + \beta_1 x_i^* + \beta_2 + \beta_3 x_i^* \tag{3.10}$$

The difference between these lines gives both main and interaction effects as can also be retrieved from the following equation:

$$\begin{aligned} y_t - y_c &= (\beta_0 + \beta_1 x_i^* + \beta_2 + \beta_3 x_i^*) - (\beta_0 + \beta_1 x_i^*) \\ &= \beta_2 + \beta_3 x_i^* \end{aligned} \tag{3.11}$$

Here, β_2 represents the main treatment effect and $\beta_3$represents the interaction effect which is interpreted as the dissimilarity among the slopes of treatment and control groups. β_0 is where the control regression line hits the vertical line of the cutoff point whereas β_2 displays the treatment group cutoff intercept. Similarly, β_1 is the linear slope of control group while β_3 is the slope of treatment group.

These models can be extended to the higher order polynomials. For example, if a more complex model is considered, the true function will be given below as:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + \beta_3 x_i^3 + \beta_4 x_i^3 z_i \tag{3.12}$$

Control group regression line is:

$$y_c = \beta_0 + \beta_1 x_i^* + \beta_3 x_i^{*3} \tag{3.13}$$

While the treatment group regression line is:

$$y_t = \beta_0 + \beta_1 x_i^* + \beta_2 + \beta_3 x_i^{*3} + \beta_4 x_i^{*3} \tag{3.14}$$

By taking the difference of these two regression lines, the following is obtained:

$$\begin{aligned} y_t - y_c &= \left(\beta_0 + \beta_1 x_i^* + \beta_2 - \ + \beta_3 x_i^{*3} + \beta_4 x_i^{*3}\right) - (\beta_0 + \beta_1 x_i^* + \beta_3 x_i^{*3}) \\ &= \beta_2 \ + \beta_4 x_i^{*3} \end{aligned} \tag{3.15}$$

In this case, the main effect is again β_2, however, the interaction effect is represented by the parameter of β_4 displaying a cubic interaction effect rather than a linear one since the difference of two groups' regression lines exhibits a third order function.

The significance of the main and interaction effects are tested by means of confidence intervals which are constructed at 95 % significance level. For example, a 95 % confidence interval for the main effect β_2 is [2]:

$$CI_{95\%} = \beta_2 \pm 2SE(\beta_2) \tag{3.16}$$

If it is necessary to use multiple cutoff points in some situations, the treatment condition must be divided into the multiple groups. For instance, if one wishes to use two treatment groups, then two cutoff points would be needed. In this case, two assignment variables and two treatment groups must be used. To clarify this, if the true function is linear and if there is no interaction effect, then the analytical model becomes:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 z_{1i} + \beta_3 z_{2i} + e_i \tag{3.17}$$

Where the assignment variable z_i is defined as:

z_{1i} = 1 if assignment is to the first treatment group, 0 otherwise

z_{2i} = 1 if assignment is to the second treatment group, 0 otherwise

In this model, β_2 reveals the difference between the first treatment group and the control group whereas β_3 indicates the distinction between the second treatment and the control groups.

However, in multiple cutoff situations, the interpretation of the regression models and the model specification selection become more complex which makes the analysis more difficult. Thus, this case is not preferred and is not included to the scope of RDD [2].

One of the most important part of RDD is the selection of true functional form which is known as the selection of model specification. This refers to the selection of correct subset of variables, specifically, polynomial and interaction terms which best describe the functional form of data. Since the primary goal of RD design is to obtain unbiased and statistically efficient treatment estimates, the correct subset of variables must be selected from the general model which exactly describes the true functional form. This can be achieved by five computational procedures according to Hocking (1976) [34]: all possible regressions; stepwise regression methods (forward and backward selections); optimal subset procedures; suboptimal methods and ridge regression techniques. Although RD design requires the exact specification, in real life it is really hard to reach exactly specified true model. Therefore, simple models are generally preferred to the complex ones since simple models are more likely to provide unbiased and more efficient estimates than the complex ones. Furthermore, if the true function includes an extra and unnecessary variable (over-specification), the estimation of this function will yield biased and inefficient treatment effects whereas if the true function excludes an important variable (under-specification), then the estimation of this model will create biased estimates as well. However, if the true function is exactly specified; if the true function includes the correct subset of variables, then its estimation will create biased but efficient estimates. Optimal model selection will be disclosed in detail in the estimation section.

3.1.3. RDD Modelling Strategy

Given the discussion of correct model specification of RD design, an over-specified model is chosen at the beginning of the analysis. By gradually removing higher-order terms until obtaining an unbiased and efficient impact estimate or until the model diagnostics indicate that the model best fits the data. Accordingly, RDD has a modeling strategy involving five steps [2]:

1. The RD analysis starts with the transformation of pretest score which is done by deducting the threshold value from each treatment score. By doing so, the changed pretest value will be equal to 0 which is the original cutoff value. When x=0, y-value represents the cutoff intercept point.
2. To visually examine the relationship between pretest and posttest variables, one can examine the discontinuity in the pretest-posttest graph. This discontinuity can be a vertical change representing the main effect and a slope change representing the interaction effect. Furthermore, to determine the pre-post relationship, one can look at the number of flexion points, which is an approach to determine the functional specification of the model as well.

3. Based on the number of flexion points across two groups, the degree of polynomials is determined. If the model does not display a flexion point, then this means that a linear relationship should be assumed. In addition, previous experience of modeling data should also be taken into consideration while determining the degree of polynomials of the model specification.
4. The posttest scores are regressed on pretest scores, the outcome variable, and all higher-order transformations and interactions. The regression coefficient linked with the assignment variable is the main effect estimate which is the vertical discontinuity at the threshold value. On the other hand, the regression coefficient associated with the treatment and pretest variables referring an interaction term is the estimate of the interaction effect, which is the slope change at the cutoff. Significance of these coefficients is tested by constructing a standard t-test approach.
5. Based on the steps mentioned above, to minimize the possibility of bias, the treatment effect can be re-estimated with a greater efficiency by removing unnecessary terms in the model. In accomplishing this, the degree of the polynomials in the model should be determined carefully. To determine how to clarify the model is to start the analysis by analyzing the highest-order terms and its interactions in the model. If model coefficients are not statistically significant, but if the related tests indicate a good fit, the terms should be dropped successively and the resulting models should be re-estimated. To sum up, it is important to refine the model in the final step depending on the results of previous steps.

3.2. Illustration of RDD

Graphical representation of RDD is important and informative since a simple graph visualizes the identification strategy and indicates the connection between forcing and outcome variables. The quality of RD design depends on the ability to determine true functional form of the model. So, to find out the true model, graphical representation is of great importance and thus it is integral part of RDD. In line with this, Riecken et al. (1974) [35] state that *“one should distrust the results if visual inspection makes plausible a continuous function with no discontinuity at the cutting point”*.

Graphical visualization of RD Analysis has mainly three advantages. First of all, graphical representation gives an easy way describing the relationship between outcome and assignment variables revealing the functional form of model on each side of cutoff point. Secondly, by analogizing the mean outcomes in each group left and right side of threshold value, one can grasp the magnitude of discontinuity or jump in the model at that point. If the graph doesn't display a jump or discontinuity, then it is unlikely to obtain statistically precise and unbiased treatment effects. Thirdly and finally, the graph shows other possible points at which there exists a jump or discontinuity. If there is a discontinuity at a point other than the cutoff, then, one can infer that there are other factors influencing the pre-post relationship (Lee& Lemieux) [36], [7].

To create graphical tools in the implementation of RDD, there are four types of graphs, each of which represents the pre-post relationship [7]:

1. A graph revealing the probability of treatment as the function of assignment variable, from which one can get an idea about the type of the analysis such as fuzzy or sharp RDD,
2. Graphs indicating the connection between non-outcome variables and the rating variable,
3. Graphs plotting the density of the assignment variable which shows whether there is a manipulation of the assignment variable around the cutoff point,
4. A graph displaying the relationship between assignment and outcome variables, from which one can clearly see the magnitude of the treatment effect and the functional form of the model.

   Although all these graphs are seen in the literature, the fourth graph is mostly used one. To effectively display the data without the loss of information, the plot of outcome on the assignment variable is presented mostly. To create such a graph, following steps are taken into account [7]:

1. Separate the assignment variable into "bins", which are defined as equal-sized intervals.
2. Define the bins at the cutoff point and be sure that there is no other bin containing treatment and control groups.

3. Compute the mean value and midpoint value of assignment and outcome variables for every bin and calculate the number of the observations in every bin.
4. By using the number of observations in every bin, graph the mean values on the vertical line against the midpoint assignment values on the horizontal line.
5. Impose the regression lines for each treatment and control groups to better visualize the pre-post relationship.

These steps are useful for plotting the pre-post relationship; however, this procedure brings out the problem of “bin width selection”, referring to how to select the extent of the intervals or bins. Optimal bin width (also named as bandwidth in the literature) selection is imperative since if the bin size is low, then the related graph will be noisy and thus the relationship between assignment and control variables will be difficult to be seen. Moreover, in this case, the estimates will be highly imprecise. In contrast, if the bin size is too large, then the discontinuity at the cutoff will be hard to be observed. In this case, the estimates will be biased since the slope of regression lines will fail to explain the treatment effects [36], [7].

3.2.1. Bin Width Selection

For appropriate bin width selection, there are two types of formal tests suggested in the literature [36]. Both tests depend on the F-test and start with the assumption that the bin size is too large and using lower bin widths will give a better fit to data. The first one includes the steps given below (Imbens& Kalyanaraman) [7], [37]:

1. For a known bin size h, K separate indicators are created.
2. Outcome variable is regressed on the set of K separate variables (labelled as regression 1).
3. Every bin is divided into two equally-sized bins which raises the bin size from K to 2K and reduces the bin size from h to h/2.
4. 2K indicators are created for every bin with a low size.
5. Outcome variable on the new set is regressed on 2K indicators (regression 2).
6. For both regressions 1 and 2, their R-squared values are obtained and symbolized as R_1^2 and R_2^2 successively.
7. An F-statistic is calculated by the formula given below:

$$F\ statistic = \frac{(R_2^2 - R_1^2)/K}{(1-R_2^2)/(n-K-1)} \tag{3.18}$$

Here, *n* represents the number of observations in the equation and by using *K* and *n-K-1*, p-value of this F-statistic is calculated and compared to determine the acceptance or rejection of the hypothesis.

If the calculated F statistic is found to be statistically insignificant, then, it is concluded that further dividing the bins doesn't provide a better fit to data, the narrower one should be selected; thus, the narrower bin significantly increases the explanatory power of bin indicators. By testing different bin sizes, the largest and appropriate bin size is found.

The second test proposed in the literature is also an F-based test and the null hypothesis is again that the bin width is too large. In implementing this test, the steps given below are followed [7], [37]:

1. For a known bin size h, K separate variables are created for every bin.
2. Outcome variable is regressed on the set of created indicators (regression 1).
3. Interaction terms are created from the set of the assignment variable and K separate variables.
4. Outcome variable is regressed on these interaction terms as well as the indicators in the bin (regression 2).
5. An F-test is again constructed with the formula given above. If the interaction terms are found to be jointly significant, then it is concluded that the tested bin width is too large and it should be reduced.

Although two types of these F-tests include the mentioned steps, appropriate bin width is selected more easily by using statistical data package programs since they provide various bin widths with the p-values of F-tests.

3.3. Estimation

Estimation of regression lines in RDD is mainly based on parametric and nonparametric methods. Although both methods are mentioned widely in the literature, parametric methods are mostly used in the estimation of RD design since in estimating RD impact, nonparametric methods pose a "boundary problem" at the cutoff. Before covering both in detail, the distinction between parametric and nonparametric methods should be clarified. For this, background information of these methods would be helpful.

Parametric methods use observations in data set to determine the pre-post relationship model as a function of assignment variable in the existence of treatment. This method includes distinct functional forms of the assignment variable to minimize the amount of bias. These functional forms consist of six models which include the simplest linear form, linear form with the interaction term, quadratic form, quadratic interaction form, cubic form and cubic interaction form. In estimating treatment effect, these functional forms are tested starting with the simplest linear form against one-step higher order functional form by performing F-tests and AIC approach [7].

As for the nonparametric method, local linear polynomial regressions and kernel regressions constitute the basis of the method. In this case, functional form of the model is closer to the linear one and in estimating treatment effects; local randomization is employed within the close vicinity of cutoff point which implies the bandwidth. In nonparametric method, choosing the appropriate bandwidth is crucial and its selection can be made via graphical visualization of the distribution of assignment variable. After the selection of bandwidth, regression lines on each side of the cutoff point are estimated. This approach is called as local linear regression. If polynomial terms are used in local linear regression, then, it is called as local polynomial regression [7].

In nonparametric method, kernel regression is a local method which is suitable to estimate regression function at a particular point. However, this poses a problem since estimating the regression equation at the threshold point causes a boundary issue. Kernel regressions do not perform well due to this boundary problem and thus invalidate the RDD [36]. Moreover, kernel regression treatment estimates tend to have a systematic bias. Within finite samples, bandwidth should be selected largely to obtain more precise treatment estimates. In this method, to reduce the bias, it would be better to shrink the bandwidth. However, this doesn’t work if the bandwidth is not large enough causing extremely noisy estimates instead of the precise ones (Imbens & Lemieux [5], [38]. To refrain from such a problem, several authors suggest that local linear or local polynomial regressions should be employed to reduce this potential bias of the treatment effect estimate since kernel regression method provides estimates with boundary bias. Indeed, Fan and Gijbels [40] propounds using local linear or polynomial regression as a practical solution to the bias problem.

As Black et al. (2007) [41] states that parametric methods fall behind the nonparametric methods in estimating treatment effects. In nonparametric method, selection of optimal bandwidth reflects how its estimates perform well. On the other hand, the parametric method is substantially sensitive to the functional form of the outcome equation.

These two methods should be compared to grasp which method is better than the other one. So, it should be clarified that parametric method tries choosing the best model to estimate treatment effect for a pre-determined data set; while, nonparametric method selects the best data set to estimate treatment effect for a given model. Parametric method tries selecting the most suitable functional form among the rating and outcome variables given the large data set. However, nonparametric method focuses on the optimal and narrower data set in which local linear or polynomial regression provides a consistent treatment effect. In this regard, one should decide on the tradeoff between the precision and the bias of the effect estimates in considering which model to choose in the analysis. Parametric method in RDD uses all data in estimating treatment impacts; hence, this treatment effect estimate has more precision than that of nonparametric method. However, the potential bias in estimates increases since it is not so easy to determine the correct functional form of the model in parametric method. In contrast, in nonparametric method, the probability of an estimate to be potentially biased decreases in conjunction with the precision [7]. So, it can be clearly deducted that one should decide on the tradeoff between bias and precision of impact estimates in choosing between these two methods.

3.3.1. Parametric Estimation

As stated above, parametric method estimates treatment effects by specifying the relationship between assignment and outcome variables. In order to eliminate any erroneous inference in estimating treatment effects, model should be specified correctly. For this purpose, the following regression equation represents parametric RDD model for single treatment and control groups (Lee&Munk) [42].

$$Y_i = \alpha + \beta_0 T_i + f(r_i) + \varepsilon_i \tag{3.19}$$

α= mean value of outcome in the treatment group after controlling the assignment variable,

Y_i = outcome variable for the ith observation,

T_i= 1 if the ith observation is appointed to the treatment group and 0 otherwise,

r_i = assignment variable for the ith observation centered at the threshold value which is also known as score variable,

$f(r_i)$= function of r_i.

ε_i= independently and identically distributed random error term for the ith observation.

In this model, the coefficient of β_0 stands for the RD impact estimate since the amount of this coefficient represents a jump, drop or discontinuity at the cutoff value. The assignment variable r_i is added into the equation to eliminate bias coming from the functional form selection. In this scope, assignment variable is centered on the cutoff point by generating a new score variable via the formula of $r_{icutoff-score} = (r_i - cutoff - score)$ (3.20)

This new score variable is used in the model instead of r_i. By doing so, the value of assignment variable becomes zero and it makes the interpretation of results easier (Heckman & Robb) [43]. Moreover, function of r_i stands for the relationship between outcome and assignment variable. Various models given below are tested in parametric method to determine the optimal functional form which best fits the whole data [7]:

1. Linear model:

$$Y_i = \alpha + \beta_0 T_i + \beta_1 r_i + \varepsilon_i \tag{3.21}$$

2. Linear Model with interaction:

$$Y_i = \alpha + \beta_0 T_i + \beta_1 r_i + \beta_2 r_i T_i + \varepsilon_i \tag{3.22}$$

3. Quadratic model:

$$Y_i = \alpha + \beta_0 T_i + \beta_1 r_i + \beta_2 r_i^2 + \varepsilon_i \quad (3.23)$$

4. Quadratic model with interactions:

$$Y_i = \alpha + \beta_0 T_i + \beta_1 r_i + \beta_2 r_i^2 + \beta_3 r_i T_i + \beta_4 r_i^2 T_i + \varepsilon_i \quad (3.24)$$

5. Cubic model:

$$Y_i = \alpha + \beta_0 T_i + \beta_1 r_i + \beta_2 r_i^2 + \beta_3 r_i^3 + \varepsilon_i \quad (3.25)$$

6. Cubic model with interactions:

$$Y_i = \alpha + \beta_0 T_i + \beta_1 r_i + \beta_2 r_i^2 + \beta_3 r_i^3 + \beta_4 r_i T_i + \beta_5 r_i^2 T_i + \beta_6 r_i^3 T_i + \varepsilon_i \quad (3.26)$$

In these models, assignment variable is centered at the cutoff point as mentioned above. All notations and variables are the same as defined before.

In the first, third and fifth models, slope of the relationship between outcome and assignment variables are the same around the threshold value, however, in the other three models, interaction terms are included as different polynomial functions of assignment variable indicating that this will affect both slopes and intercepts of regression lines and thus they vary on both sides of the threshold value. By adding interaction terms, model becomes more complex and the slope coefficients vary on either side of the cutoff, thus, the power of the analysis diminishes. Indeed, this problem becomes very important especially in smaller data sets [7].

In parametric method of RD estimation, the most challenging problem is to find the most appropriate functional form which fits the data best. To solve this problem, Lee and Lemieux (2010) [36] suggested an F-Test approach. Six models given above are tested against the model best describing the data. This F-Test approach has the following steps [7], [36]:

1. A set of indicators are created for K-2 bins. These bins are utilized to describe the data visually. 2 bins are excluded from K number of bin indicators to refrain from the collinearity problem.
2. One of the six models is regressed and Regression 1 is obtained.
3. A second regression is run by including bin indicators created in step 1, which is regression 2.

4. R-squared values are obtained from each regression as R_r^2 and R_u^2 successively.
5. An F-statistic is calculated by the formula given below:

$$F\ statistic = \frac{(R_u^2 - R_r^2)/K}{(1-R_u^2)/(n-K-1)} \tag{3.27}$$

   n represents the total number of observations in the equation line and K is the number of created band indicators.

6. P-value of this F-statistic is calculated by using the degrees of freedoms of the mentioned R-squares, that is, *K* and *n-K-1*. If the F-statistic is found to be statistically insignificant, then it is concluded that the data from each bin don't add further information into the system, thus the model is not specified correctly[1].

It is noteworthy to mention that in implementing this approach, a simple linear model is considered and is tested against the higher order functional form model. For example, linear interaction model is tested against the linear model. If the tested model is not found to be statistically significant, then this implies that the simplest linear model is enough to explain the relationship between assignment and outcome variables. Then, it can be concluded that this simplest model is regarded as a suitable choice for the analysis. Nevertheless, if the F-test reveals that the simplest model is not specified correctly, then interaction terms should be included to the functional form of the models and a new F-test should be implemented to check whether the higher order polynomial model is statistically significant or not. This process is carried forward until the F-test is found statistically insignificant [7], [36]. In addition to F-Test approach, one can also find the appropriate model by simply running the simple model and then testing the significance of added interaction terms.

Another approach in determining the appropriate functional form is AIC approach. Akaike Information Criterion abbreviated as AIC is a measure of goodness of fit capturing the tradeoff between bias and precision in a more complex model. The following formula stands for AIC:

[1] Statistical software programs provide these F-test results automatically and thus compare the specified model with a null one.

$$AIC = Nln\left(\widehat{\sigma_b^2}\right) + 2p \tag{3.28}$$

$\widehat{\sigma_b^2}$ is the estimated residual variance of the model with p parameters where p is the number of parameters including intercept[2].

As can be understood from its formula, when the estimated residual variance or the number of the parameters in the model increases, AIC also increases. Therefore, AIC depicts the tradeoff between the variance and the bias. As the model becomes more complicated, then the number of the parameters in the model rises, but the estimate’s residual variance decreases with more complex models. So, these two factors move in opposite direction.

In implementing AIC to the model selection, all these six models are taken into account and their corresponding AIC values are calculated. A model providing the minimum AIC value is regarded as the optimal model for the parametric estimation. However, it is important to say that AIC show whether a model fits data better than the other one or not. Thus, one cannot test the goodness of the model by just looking at the AIC value of the models. Therefore, in the literature, it is said that one should first look at the F-Test results to determine the appropriate functional form and after F-Test, selected model should be approved by comparing AIC values. In this sense, F-Test should be the first step and AIC should be the second [7], [36].

3.3.2. Non-parametric Estimation

Use of nonparametric and semi-parametric methods in RD estimation came into the literature after RD analysis was reborn. Nonparametric regression is performed depending on the information obtained from data set. Nonparametric methods try to estimate functional form of the model rather than estimating the parameters in the model. To consistently obtain estimated treatment effects, nonparametric method mainly uses local linear regressions. In this context, the simplest approach is to choose small neighborhood to the left and right sides of the threshold point. This small neighborhood is called as “bandwidth or discontinuity sample” in the literature [7], [36].

[2] Statistical software programs provide AIC results automatically as well.

Local linear regressions as a general discussion estimate linear regression functions within a distance *h* adjacent to right and left sides of the cutoff point. In this context, the followings are tried to be minimized [40]:

$$\min_{\alpha_1 : \beta_1} \sum_{i:c-h \leq X_i < c} \left(Y_i - \alpha_1 - \beta_1 (X_i - c)\right)^2 \tag{3.29}$$

and

$$\min_{\alpha_r : \beta_r} \sum_{i:c-h \leq X_i < c+h} \left(Y_i - \alpha_r - \beta_r (X_i - c)\right)^2 \tag{3.30}$$

The value of $\mu_1(c)$ is obtained as:

$$\widehat{\mu_1(c)} = \widehat{\alpha_1} + \widehat{\beta_1}(c - c) = \widehat{\alpha_1} \tag{3.31}$$

And the value of $\mu_r(c)$ is obtained as:

$$\widehat{\mu_r(c)} = \widehat{\alpha_r} + \widehat{\beta_r}(c - c) = \widehat{\alpha_r} \tag{3.32}$$

So, the estimated treatment effect is captured by the difference between estimated means such as $\widehat{\alpha_r} - \widehat{\alpha_1}$.

In addition to local linear regression approach, another way to predict treatment effects is to subtract mean outcomes of both treatment and control group bins. However, this simple approach creates biased estimators in the neighborhood of the cutoff point which also refers to the boundary bias. The Figure 4 best depicts this situation.

In Figure 4, points A and B represent expected mean outcomes for the control and treatment bins successively whereas A' and B' are the intercepts for the control and treatment regression lines successively as well. When using distinct expected mean outcomes for the treatment and control groups, the estimated treatment effect becomes biased since this difference is positive even though there is no treatment effect. Therefore, the approach of difference of means for the two bins provides biased estimator within the neighborhood of the cutoff point. Although the bandwidth (h) is decreased, this boundary bias couldn't be decreased to the smaller amounts.

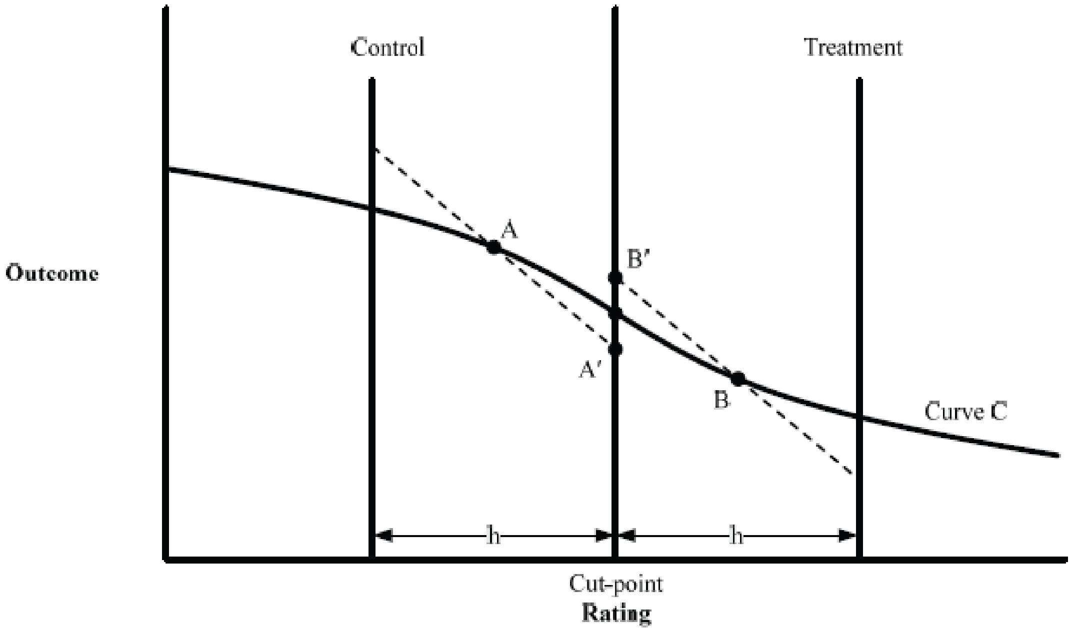

Figure 4. Boundary Bias from Comparison of Means in Treatment and Control Groups [7]

Since it is difficult to eliminate boundary bias, it is advised in the literature that the local linear regression should be employed rather than the approach of difference of mean outcomes [5]. The logic of local linear regression is to estimate two different regression lines on treatment and control groups with distinct intercept and slope terms on both sides of the cutoff point. Local linear regression employs the following regression model to estimate treatment impacts within a chosen bandwidth in the neighborhood of the cutoff point:

$$Y_i = \alpha + \beta_0 T_i + \beta_1 r_i + \beta_2 r_i T_i + \varepsilon_i \qquad (3.33)$$

In this regression, the rating variable is also centered at the threshold value similar to the models in parametric method. As can be also seen from Figure 4, (B'-A') represents the discontinuity between two regression lines, indicating that the treatment impact estimate is nonzero and thus biased. However, the bias coming from the local linear regression is much smaller than the boundary bias coming from the difference of expected mean outcome. That is why local linear or local polynomial regression is suggested to be used in the literature relative to the other approach.

In estimating local linear or local polynomial regression within the neighborhood of cutoff point, it is important to choose optimal bandwidth *h*. Selection of optimal bandwidth in nonparametric method refers to deciding optimal tradeoff between bias and precision. Because using larger bandwidth creates more precise treatment effect estimates while increasing their bias. In line with the optimal bandwidth selection, two procedures are suggested for nonparametric regressions used for RDD [7]. The first one is "Cross Validation" and the second one is "Plug-in" Procedure. Both focus on the logic of mean square error (MSE), a measure to decide on the balance between precision and the bias of the estimates. As the bin size gets larger, then the estimated impacts get more precise however, they become potentially more biased as well.

As for the first procedure to determine optimal bandwidth selection, Cross Validation Procedure yields an optimal bandwidth on which the data is fitted in a regression over the set of data. This procedure is widely used in the RDD literature and also known as "leave-one-out cross validation" procedure (Ludwig & Miller) [38], [44]. Main steps and graphical visualization of this procedure are given [7]:

1. A bandwidth h_1 is selected.
2. An observation A is appointed to treatment group with a rating score r_A and an outcome Y_A.
3. Outcome variable is run on rating score variable by using all observations in the left side of observation A within the bandwidth h_1. By this way, a rating is obtained which ranges from $h_1 - r_A$ to r_A.
4. From the regression in step 3, predicted value of the observation A, $\widehat{Y_A}$ is obtained.
5. Bandwidth h_1 is shifted to the left slightly and then the process mentioned in the steps above is repeated to obtain the predicted value of the outcome variable for observation B.
6. Then, this process is repeated for all observations on the right side of the cutoff point until there are fewer than two observations in the interval of $r_i - h_1,\ r_i$.
7. Cross Validation Criterion, CV is calculated by using the following formula:

$$CV(h_1) = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \widehat{Y_i}\right)^2 \qquad (3.34)$$

Here, N represents the whole number of observations and the other terms are the same as defined before.

8. The steps given above are repeated for the bandwidths of h_2, h_3,...
9. After having completed these steps, all CV values are obtained for each bandwidth size[3]. Then the bandwidth with the minimum CV value is selected as the appropriate and optimal bandwidth since CV exhibits the mean square error.

Another procedure to determine optimal bandwidth size is the Plug-In procedure which also provides an analytic solution in determining the tradeoff between precision and bias of the estimates. Plug-In procedure minimizes a particular function by using the following mathematical formula which is adapted and modified in the context of local linear regressions (DesJardins & McCall) [37], [45]:

$$\hat{h}_{opt} = C_K \left(\frac{2.\frac{\hat{\sigma}^2(c)}{\hat{f}(c)}}{\left(\hat{m}_+^{(2)}(c) - \hat{m}_-^{(2)}(c)\right)^2 + (\hat{r}_+ - \hat{r}_-)} \right)^{\frac{1}{5}} N^{-\frac{1}{5}} \tag{3.35}$$

In this formula, C_K represents a constant which is special to the weighting function[4]. c represents the cutoff value, $\hat{\sigma}^2(c)$ is the estimated conditional variance of the assignment variable at the cutoff point. $\hat{f}(c)$ represents the estimated density function of the rating indicator at the cutoff value. $\hat{m}_+^{(2)}(c)$ and $\hat{m}_-^{(2)}(c)$ represent the derivatives of the relationship between outcome and assignment variables. $\hat{r}_+$ and $\hat{r}_-$ are the regularization terms used to adjust for the low precision in obtaining estimated second derivatives. N represents the whole number of observations as given before.

In implementing this formula, all calculations are obtained successively and they are plugged in to the formula to obtain the optimal bandwidth[5]. These two procedures may provide different bandwidth sizes however; the treatment effect estimates in these different bandwidths don’t tend to quantitatively differ from each other [37].

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[3] This can also be accomplished by using statistical software or data package programs.
[4] In this case, weighting function is a rectangular kernel.
[5] Although the calculations are computationally complex, statistical software or data package programs provide the results of this procedure.

After the optimal bandwidth is determined, treatment effect estimates are obtained in line with the bandwidth selection depending on the first four models given in the section of parametric estimation.

3.3.3. Estimation in the Fuzzy RDD

In fuzzy RDD, the assignment to treatment is made stochastically, not deterministically. In a deterministic model, variables are determined by parameters in the model, however, in a stochastic model, randomness becomes important and thus, variables are depicted by probability distributions. RD design mainly consists of two types: sharp and fuzzy RD designs. Sharp RDD is covered in the former sections in detail. In both fuzzy and sharp RD designs, probability of treatment displays a discontinuity at the threshold value as mentioned in previous sections. However, these two types of RD designs differ from each other. Under sharp RD design the probability of treatment shows a discontinuity from 0 to 1. In contrast, fuzzy RDD doesn't follow such a 0-1 step function. Based on this, the discontinuity starts with 0, but not jumps to 1, that is; it takes a value by less than 1 at the cutoff point [3]. Therefore, fuzzy RDD stands for a smaller discontinuity in the probability of treatment. The existence of a tiny discontinuity in the probability of treatment causes the relationship between rating and outcome variables not interpreted as an average treatment effect [4].

As to the implementation and interpretation of fuzzy RD design, the estimation of treatment effect at the threshold value is equivalent the estimation of instrumental variable (IV) estimator since the probability of treatment doesn't follow 0-1 step function. Under the IV approach, treatment impact estimate is further interpreted as a local average treatment effect (LATE) (Marmer et. al.) [46].

The probability of treatment is written as [36]:

$$P(D = 1 \mid \; X = x) = \gamma + \delta T + g(X - c) \tag{3.36}$$

where;

$T = 1[X \geq c]$ shows that the rating indicator is greater than the cutoff point c.

D is the treatment dummy.

Similar to the previously mentioned graphical illustration, it is worth recommending a graph representing the relationship between the treatment dummy and the assignment variable to visually grasp the amount of discontinuity in the probability of treatment symbolized as δ.

Estimation in Fuzzy RD design is depicted by two equation system [36]:

$$Y = \alpha + \tau D + f(X - c) + \varepsilon \tag{3.37}$$

$$D = \gamma + \delta T + g(X - c) + v \tag{3.38}$$

Depending on these two equations, the treatment effect estimate is obtained by using instrument of dummy with T. Having substituted equation (3.38) into the equation (3.37), the following reduced form equation is obtained [36]:

$$Y = \alpha_r + \tau_r T + f_r(X - c) + \varepsilon_r \tag{3.39}$$

where, $\tau_r = \tau\delta$ which is interpreted as the fuzzy treatment effect.

Estimation in fuzzy RDD can be done by using local linear or local polynomial regressions as well. Two- Stage Least Squares (2SLS) method is employed in this case whose estimation results are equivalent to the ratio of reduced form coefficient, $\frac{\tau_r}{\delta}$ [36]. As for the bandwidth choice, it is recommended by Imbens and Lemieux (2008) [38] that in choosing the optimal bandwidth, it should be firstly focused on the outcome equation and accordingly, the selected bandwidth should be employed in the treatment equation identically since the optimal bandwidth for the treatment equation is considered to be less than the other one for the outcome equation.

3.4. Sensitivity Analyses and Validity Tests

The implementation and identification of RD designs have been clearly disclosed with respect to main assumptions. The focus of this section is the validity and precision of RD effect estimates by means of several robustness checks. First of all, it is recommended that RD analysis should start with a graphical representation of data to grasp the existence of a discontinuity in the probability of treatment. A similar graph for the outcome variable also provides a first insight to whether there is a non-zero treatment or not (Lemieux & Milligan) [20], [47]. Secondly, it is imperative to analyze the sensitivity of the RD estimates. For this, higher-order terms in polynomial functional specifications can be added and the existence of polynomial splines can be investigated. Thirdly, the effect estimates are analyzed in the context of robustness by restricting the sample of observations within the close vicinity of the cutoff point. By this way, the approximation of true functional form is probable to be obtained. Alternative to the mentioned approach, local “Wald” estimates can be employed for different bandwidth sizes by which the influence of the data points is decreased and thus the bias coming from misspecification and the loss of efficiency can be eliminated [3].

In assessing the quality of RD design is to test the precision of RD effect estimates. According to Jacob and Zhu (2012) [7], the precision of estimated treatment effects is tested by means of a minimum detectable effect (MDE) or a minimum detectable effect size (MDES). This measure implies the minimum true effect which has an acceptable chance of detecting the treatment effect. Typically, MDE produces statistically significant treatment effect with 80 % chance at 5 % significance level. MDE is calculated with a multiplier of 2.8 and standard error of the estimated treatment effect (Bloom) [48].

In the context of RD analysis, MDE is calculated by using the following formula [7]:

$$MDE \approx 2.8\sqrt{\frac{(1-R_Y^2)\sigma_Y^2}{NP(1-P)(1-R_T^2)}} \tag{3.40}$$

$$MDES \approx 2.8\sqrt{\frac{(1-R_Y^2)}{NP(1-P)(1-R_T^2)}} \tag{3.41}$$

where;

R_Y^2 = The ratio of variation in the outcome (Y) anticipated by the rating and other variables included in the model,

R_T^2 = The ratio of variation in the treatment (T) anticipated by the rating and other variables included in the model,

N =All number of the observations in the sample,

P =The ratio of the sample assigned to the treatment group,

σ_Y^2 = The variance of the outcome variable.

MDE and MDES results are obtained for several RD models depending on the distribution of the assignment variable. Depending on the MDE or MDES results, the more precise RD effect estimate can be found out for the given functional forms or models mentioned in the previous sections. It is noteworthy to say that as the complexity of the estimation model increases, then the precision of the RD effect estimate decreases.

4. DATA AND METHODOLOGY

4.1. Situation of Terrorism in Turkey

Over half a century, Turkey has been competing against terrorism and political violence at both national and international level. This painful period of terrorism cost Turkey more than 35,000 lives and a massive burden to its economy.

Terrorism history in Turkey dates back to 1960s until recently. Late 1960s and 1970s were two decades flagged as political and social upheaval due to a considerable modernization process. Several factors created volatility and nourished the instability which are rapid urbanization due to the migration from rural areas to urban cities; less employment causing financial slowdown due to increasing urban population; bureaucratic turmoil in the southeastern part of Turkey; burgeoning radical Islamist and leftist student movements and the legislation of the Constitution of 1961 guaranteeing Turkish citizens the right of political protest which then caused the government to have difficulty in controlling violence attacks (Toprak) [49]. Having struggled a lot for the terrorism activities during decades, unfortunately, the number of killings and casualties had increased substantially. The regional distribution of terrorism index and deaths is given in the following figures.

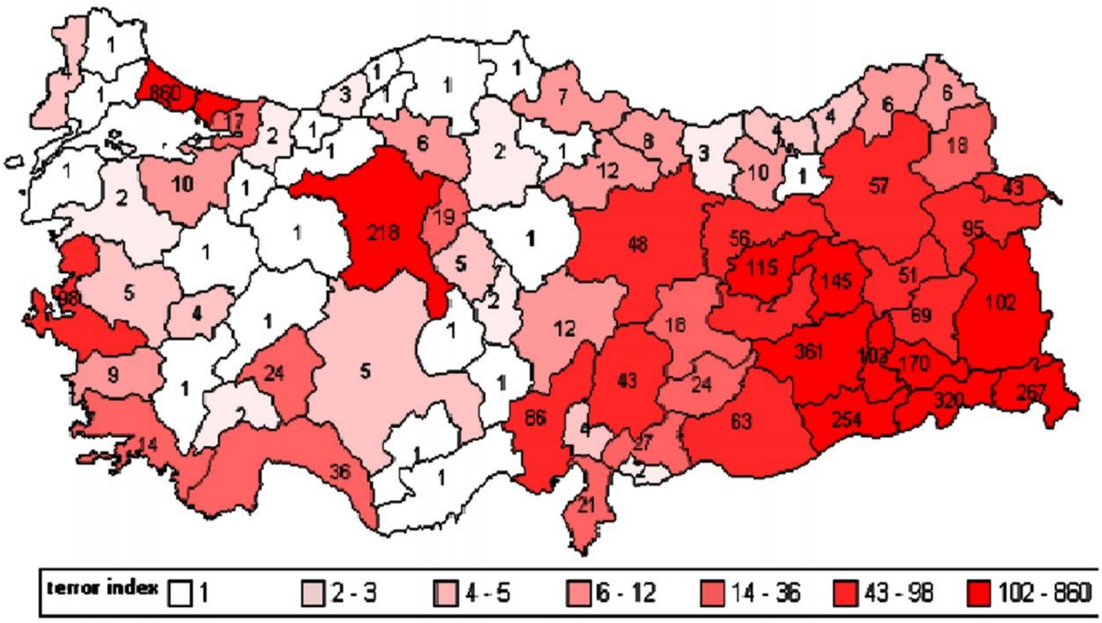

Figure 5: Regional Distribution of Terrorism Index (Polat & Uslu) [50]

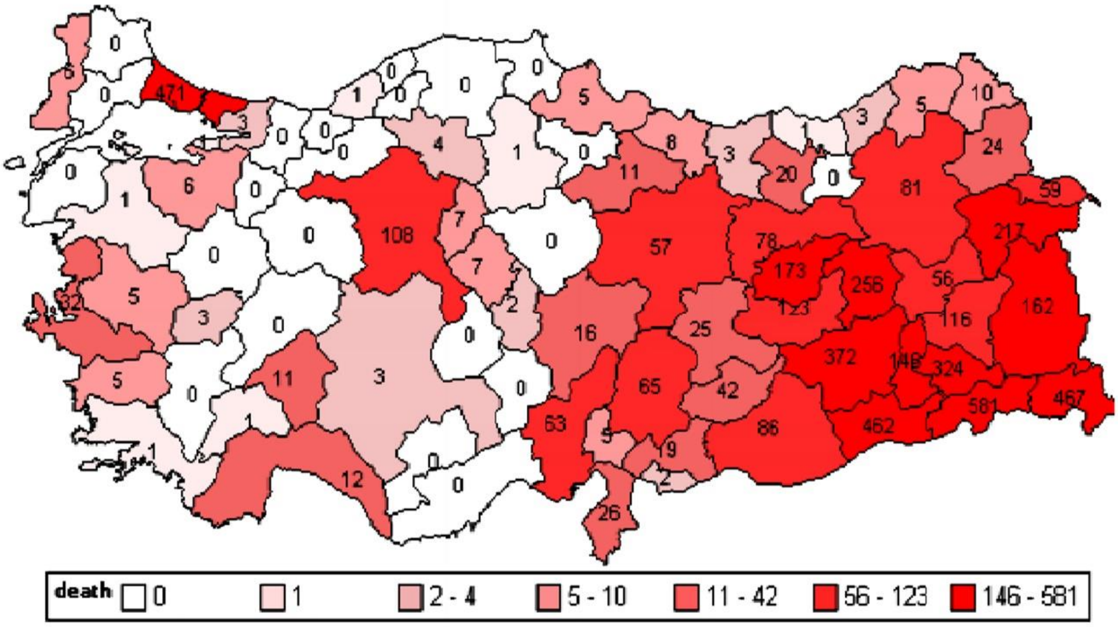

Figure 6: Regional Distribution of Deaths from Terrorist Attacks [50]

Figure 5 and 6 indicate terrorism index and deaths respectively at province level in Turkey for the time period of 1970-2010 which proves that the main characteristic of terrorism in Turkey is its regional dimension. Figure 1 reflects regional distribution of terrorism index whereas Figure 2 indicates regional distribution of deaths due to terrorist attacks from which one can easily see that the most terrorist incidents and thus deaths have been mainly focused in Eastern and Southeastern Turkey. In addition to eastern and southeastern cities, Istanbul and Ankara have also been exposed to terrorist attacks due to their large population density.

4.2. Summary of Data

Rising number of terrorist attacks provokes the anxiety of economic growth of Turkey since terrorist attacks affect and are affected by economic development. In measuring how terrorist attacks are affected by economic growth at the province level, sharp RDD will be performed in this chapter and its results will be evaluated accordingly.

The empirical part of this paper hinges on a dataset compiled from various data providers[6]. Data is retrieved for the year of 2014 which is the latest time that available data permits. Dataset includes province level two basic variables: Growth

[6] Global Terrorism Database (GTD), RAND Database of World Terrorism Incidents (RDWTI), and Turkish Statistical Institute

rate of per capita income (Growth) and average terrorism index (Terr) calculated by the number of killings due to terrorism attacks.

Table 2 Descriptive Statistics and Correlation

Variable	Terr	Growth
Mean	3,682	0,059
Std. Dev.	3,243	0,107
Min	2,718	-0,573
Max	27,807	0,2583

Table 3 Correlation Matrix

Variable	Terr	Growth
Terr	1	
Growth	-0,171	1

Table 2 and 3 provides descriptive statistics for all variables in addition to the correlation matrix. It is seen from the table that the mean value of terrorism index is very high and so its standard deviation, indicating higher volatility of terrorism attacks. The maximum value of average terrorism index indicating the maximum average number of killings occurred in Turkey during the period of 1974-2014 is 27,81. High value of terrorism index indicates that not only precious human lives and properties were lost but the growth process was decelerated as well. The correlation matrix of the variables reveals that terrorism index has a weak and negative correlation with growth rate, which is 17,1%[7].

[7] RDD analysis results are obtained by employing STATA data package program.

4.3. Visual Illustration

Before implementing to the RD analysis, it is beneficial to start with graphical illustration to see the discontinuity type in the relevant data.

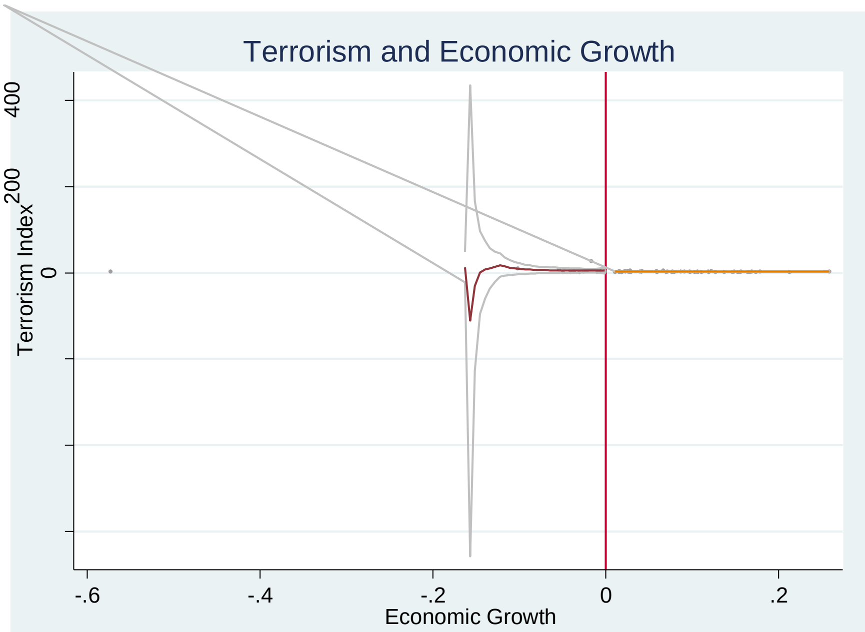

Figure 7: Scatter Plot of Terr and Growth at the cutoff value=0

According to the Figure 7, the running or the assignment variable specified as the economic growth is on the horizontal line whereas the terrorism index specified as the outcome variable is on the vertical line. This graph indicates that all provinces in Turkey are distributed to the treatment and control groups at the cutoff value being equal to zero. The provinces with the economic growth rate lower than 0 is appointed to the treatment group and the other provinces with the growth rate higher than 0 are distributed to the control group.

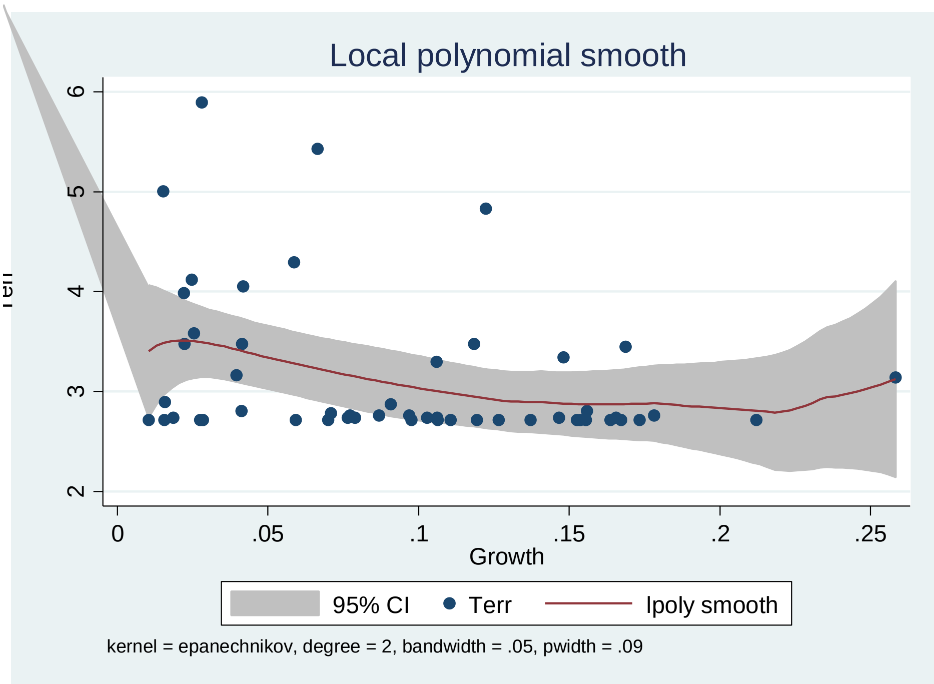

Figure 8: Local polynomial smoothing function for Terr and Growth

In another perspective, local polynomial smoothing graph of Terr and Growth variables is given in the following graph, from which one can clearly see the type of the approximation. In the graph below, the good approximation for the regression fit between Terr and Growth variables seems to be 2^{nd} degree polynomial fit.

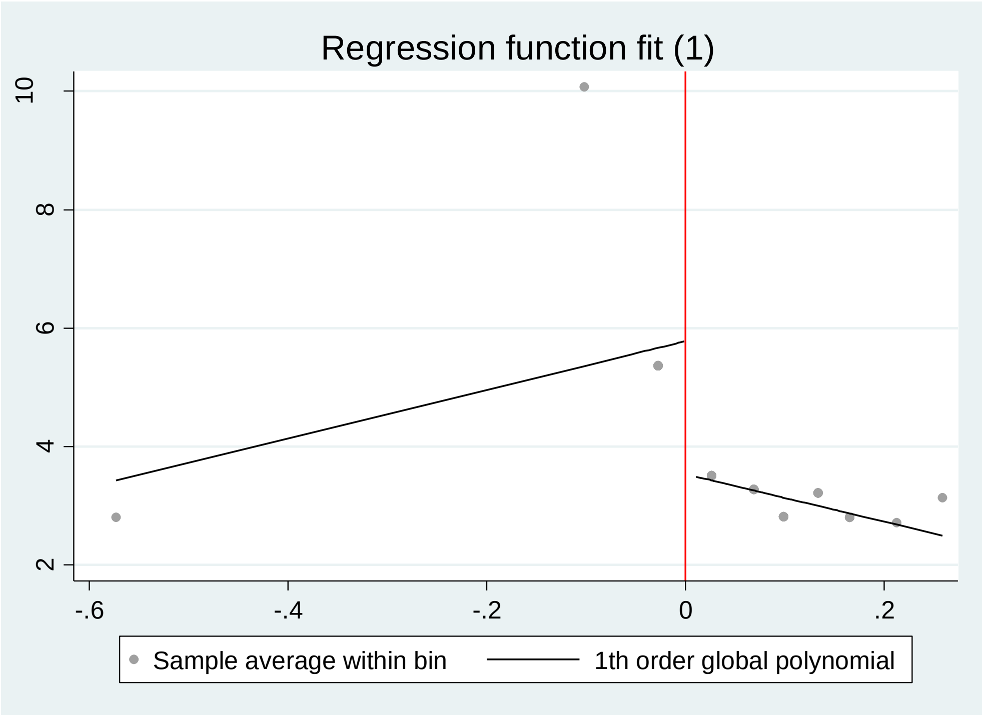

Figure 9: Regression function fits for different polynomial degrees, Part (a)

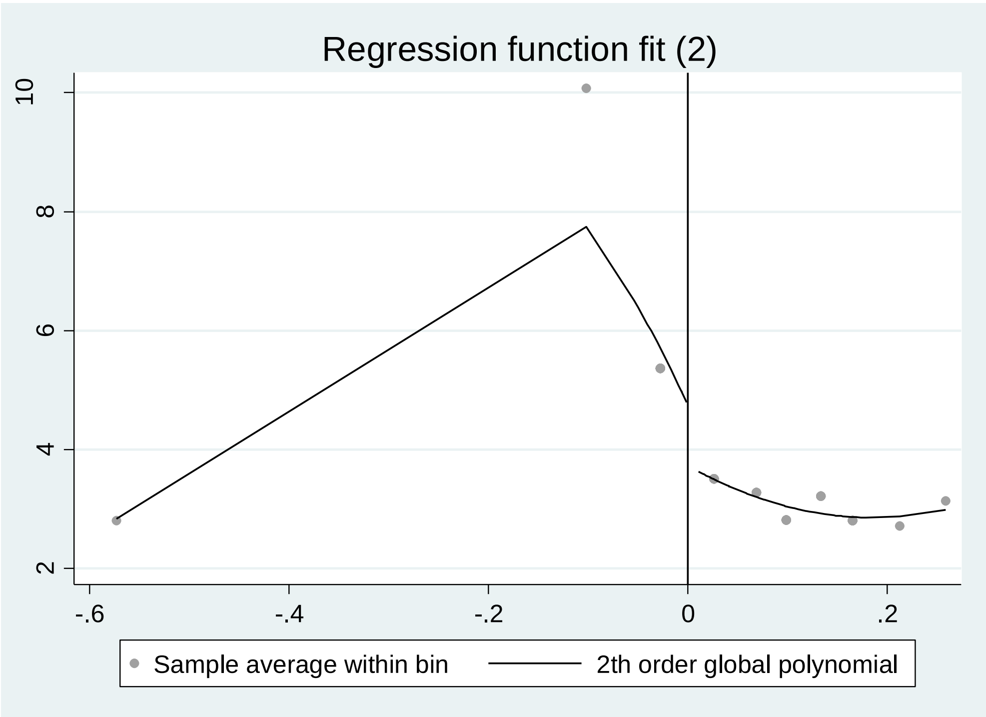

Figure 10: Regression function fits for different polynomial degrees, Part (b)

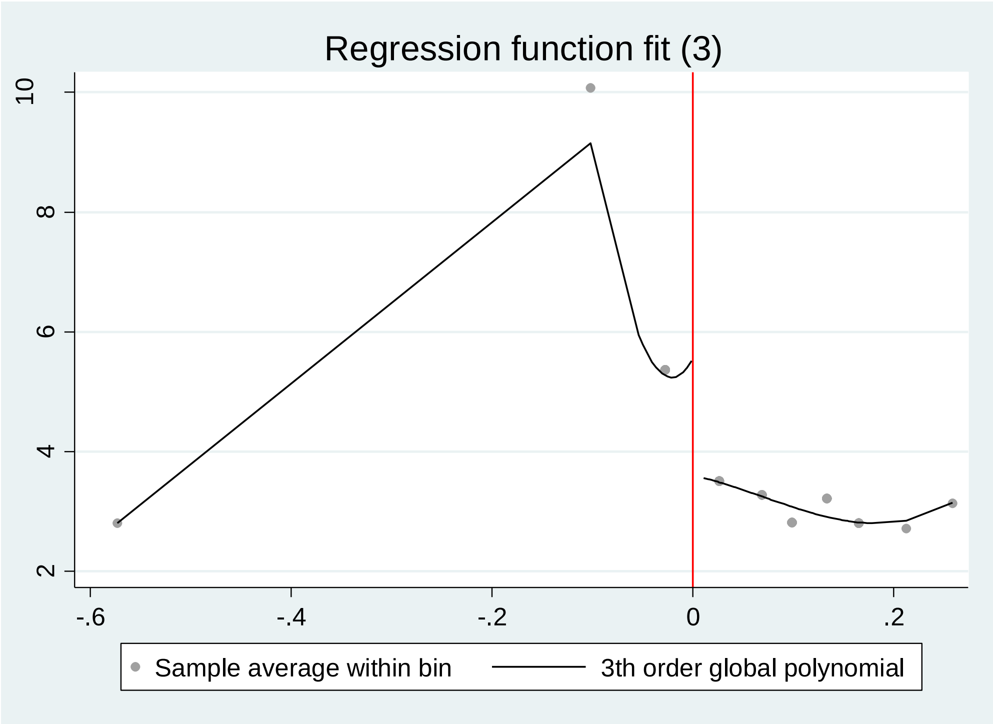

Figure 11: Regression function fits for different polynomial degrees, Part (c)

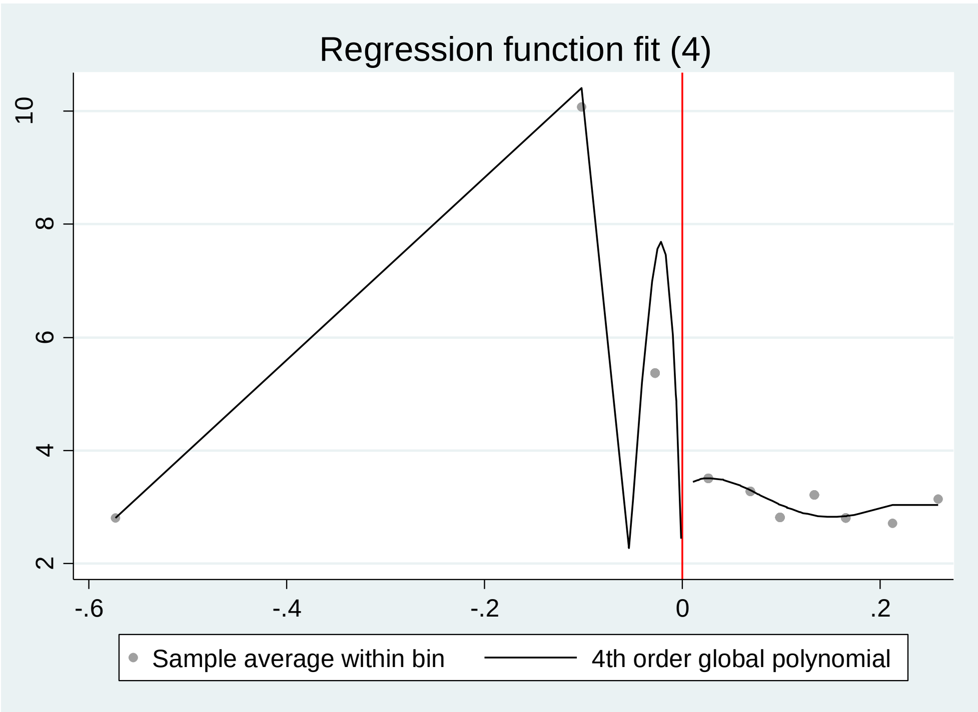

Figure 12: Regression function fits for different polynomial degrees, Part (d)

In Figure 9, the part (a) indicates the RD plot between terrorism index and economic growth by employing 1st order polynomial in the regression fit. Terrorism index and the economic growth of provinces in the treatment group are positively related as clearly seen from Figure 9; however, there is a negative relationship in the control group. This creates a slump, thus a discontinuity at the cutoff point. The more the economic growth of provinces there occurs in the treatment group, the more the terrorist attacks happen to eliminate the economic growth. However, in the control group, this is not the case, that is, the more economic growth takes place in the provinces, the less terrorist attacks happen.

Part (b) of Figure 10 reveals the regression fit by using 2^{nd} order polynomial in the RD plot. In treatment group, the relationship between terrorism index and economic growth is increasingly positive until a level, however; after that level, the function slumps sharply and turns to a negative relationship. On the other hand, in the control group the relationship becomes a little bit wavy implying both positive and negative relationship but this time the fluctuations are flexible substantially. The RD function of the treatment group in Part (c) resembles as in the RD function of part (b) however, the regression fit in the control group remains exactly the same as in the Part (c).

Part (d) of Figure 12 shows a much more complex relationship between terrorism index and economic growth since the 4^{th} order polynomial is used in the regression fit function. In this graph, one can easily see that the RD function in the treatment group fluctuates three times with sharp slumps. In contrast, the RD function in the control group doesn’t change a lot, it remains much more stable as in the graph of part (b). The more order of polynomial is used in the regression fit, the more complex function is obtained in the treatment group. Nevertheless, the same thing is not the case for the control group.

4.4. RDD Estimation Results

In estimation section, due to data availability and data compatibility, sharp RD has been employed to obtain treatment effect of economic growth rate on the average terrorism index. The table given below summarized optimal bandwidth along with the average treatment effect, its standard deviation and its p-value. The RD estimation is done by data package program of STATA and the estimation is performed by employing Triangular Kernel.

Table 4: Sharp RD Estimation Results

	Order of Polynomial 1	Order of Polynomial 2	Order of Polynomial 3	Order of Polynomial 4
Order loc. Poly. (p)	1	2	3	4
Order Bias (q)	2	3	4	5
BW loc. Poly. (h)	0,031	0,030	0,071	0,063
BW Bias (b)	0,071	0,075	0,696	0,313
Treatment Effect (p-value)	-2,425 (0,067)	2,901 (0,594)	3,2606 (0,659)	1,1689 (0,900)
BW Bias Corrected Treatment Effect (p-value)	-2,1647 (0,024)	3,166 (0,561)	2,467 (0,739)	0,664 (0,943)

According to Table 3, RD estimation results for the order of polynomial degrees 1, 2, 3 and 4 along with the optimal bandwidth, bandwidth and order bias values and the treatment effect for each polynomial degrees are given. The results indicate that the optimal regression function fit has been captured at the 1st polynomial degree. The more complex the regression function becomes, the less significant results there exist. So, the optimal bandwidth at the 1st local polynomial is found to be 0,031. The order bias is found to be 2 whereas the bandwidth bias is found to be 0,071.

Depending on the results, the treatment effect for the order of polynomial degree 1 is statistically significant at 10% significance level since its p-value is 0,067 being lower than 0,1. The treatment coefficient is found to be -2,425 meaning that if the economic growth of the provinces is increased by 1 %, average terrorism index falls by 2,425 points. As for the bandwidth bias corrected treatment effect of economic growth rate on the average terrorism index, only the 1st order polynomial estimate is statistically significant with the treatment effect of -2,1647 meaning that 1% increase in the economic growth rate lowers the terrorism index by 2,1647 points. So, it can be clearly concluded that the relationship between economic growth and the average terrorism index is negative such that the more economic growth happens in the provinces, the less terrorism attacks occur in Turkey.

5. CONCLUSION AND IMPLICATIONS

Regression discontinuity design is basically performed to obtain causal treatment effects with nonexperimental data and it is developed as a strong alternative methodology in dealing with randomized experiments. The main logic behind this design is that if the value of the assignment variable for each observation is above a known cutoff value, the observation is assigned to the treatment group; otherwise, it is put in the control group. The RD estimate is unbiased at the discontinuity point and the analysis can be performed with relatively weak assumptions providing credible results. Furthermore, RDD does not require ex-ante randomization and disposes of ethical issues of random assignment. Well-implemented RDD provides estimates for treatment effect as good as those of randomized methods.

Going through the literature, Regression Discontinuity (RD) first proposed and studied by Thistlethwaite and Campbell in 1960 has originally aroused from the concept of random assignment and started to be widely accepted in line with the academic discussion in recent years. After this pioneering work, the design has gained a considerable popularity and generated new econometric concepts containing the academic derivation of causal inference and the semi-parametric estimation methods. In line with the improvement of RD design, a large number of empirical studies extended the use of design and brought out the sensitivity and validity tests to evaluate the precision of RD effect estimates. Especially in economics, labor supply of households in Bangladesh [18], financial aid offers on school enlistments [19], unionization within the context of wages and employment [20], the impacts of welfare-to-work-program on re-employment probability [21], social security payments on mortality [22], nationalization of private banks in India [23] and confinements on unemployment insurance [24] are the examples of growing number of studies.

In line with the main purposes of this thesis, research design has been tried to be explained with a theoretical framework in detail. Having visually displayed the graphical representation, the estimation methodology of RDD has been disclosed within the perspective of both parametric and nonparametric techniques. The difference between Fuzzy and Sharp RDD has also been explained in the theoretical framework. In addition, the sensitivity analysis and validity tests have been propounded in the last section of theoretical background of RDD.

In the empirical study of this thesis, the relationship between the average terrorism index and the economic growth rate has been analyzed to obtain the treatment effect of economic growth rate on the terrorism index and to see how the economic growth rate of provinces affect the terrorist attacks in Turkey. In doing so, the graphical illustration has been displayed first and then the sharp RD estimation has been performed. The fuzzy RD analysis is not implemented since it is not in the scope of main purposes of this thesis.

According to the empirical results, the optimal regression fit has been captured at the 1st polynomial degree, which is also supported by the graphical illustration. The more complex the regression function becomes, the less significant results there exist. So, the optimal bandwidth at the 1st local polynomial is found to be 0,031. The order bias is found to be 2 whereas the bandwidth bias is found to be 0,071.

Depending on the results, it has been found that the treatment effect for the order of polynomial degree 1 is statistically significant at 10% significance level since its p-value is 0,067 being lower than 0,1. The treatment coefficient is found to be -2,425 meaning that if the economic growth of the provinces is increased by 1 %, average terrorism index falls by 2,425 points. As for the bandwidth bias corrected treatment effect of economic growth rate on the average terrorism index, only the 1st order polynomial estimate is statistically significant with the treatment effect of -2,1647 meaning that 1% increase in the economic growth rate lowers the terrorism index by 2,1647 points. So, it is concluded that the relationship between economic growth and the average terrorism index is negative such that the more economic growth happens in the provinces, the less terrorism attacks occur in Turkey.

As for the policy implications, crucial and effective measures should be taken by policy makers to cope with terrorist organizations and to lessen drastic impacts of attacks. To struggle against attacks, the policy makers and the government should focus on the Eastern and Southeastern Turkey since the clear majority of terrorist organizations wreathe in this region. To eliminate the welfare heterogeneity and inequality across regions, the government should incentivize investment opportunities in these regions by compensating businessmen through granted privileges with higher security measures and fiscal support. By encouraged investments and establishments, firms will use more capital and thus hire more people creating more employment opportunities. Then, the education level will increase when more people become employed and relatively richer. And thus, higher education will bring higher awareness and less willingness to work with terrorist organizations. Since the welfare gap across regions creates a fertile environment for terrorist organizations to disseminate, welfare realization would make headway in dealing with terrorism.

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APPENDIX

APPENDIX 1: RDD Commands

- import excel "C:\Users\neslihana\Desktop\dataset.xls", sheet("Sheet1") firstrow
- ssc inst rd, replace /* installs the package */
- net get rd /* loads example data from web */
- rd Terr Coastal Growth, c(0)
- rd Terr Growth, gr mbw(100) /* scatterplot and wald stat*/
- rd Terr Growth, mbw(100) gr line(`"xline(0)"')
- net install rdrobust, from(http://www-personal.umich.edu/~cattaneo/software/rdrobust/stata) replace
- ssc install binscatter
- findit rdrobust /*force installing, click the link and get the package*/
- rdplot Terr Growth c(0)
- rdplot Terr Growth, binselect(es) ci(95) /* plot with confidence interval*/
- rdplot Terr Growth, p(2) ci(95) shade /*2nd order polynomial*/
- rdplot Terr Growth c(0) p(2), graph_options(title(RD Plot of Terrorism and Economic Growth)) /*RD plot with title*/
- rcspline Terr Growth, nknots(3) showknots title(Cubic Spline) /* Cubic Spline with knots*/
- tw (scatter Terr Growth, mcolor(gs10) msize(tiny)) (lpolyci Terr Growth if Growth<0, bw(0.05) deg(2) n(100) fcolor(none)) (lpolyci Terr Growth if Growth>=0, bw(0.05) deg(2) n(100) fcolor(none)), xline(0) legend(off)
- lpoly Terr Growth if Growth<0, bw(0.05) deg(2) n(100) gen(x0 s0) ci se(se0) /*smoothed grap in CIs*/
- lpoly Terr Growth if Growth>=0, bw(0.05) deg(2) n(100) gen(x1 s1) ci se(se1) /*smoothed grap in CIs*/
- cmogram Terr Growth if Growth>0 & Growth<10, cut(0) scatter line(0) qfitci /*change values*/
- rdrobust Terr Growth, deriv(0) /*Estimation for Sharp RD designs*/
- rdrobust Terr Growth, deriv(1) /* Estimation of Kink RD Designs*/

- rdrobust Terr Growth, fuzzy(T) /*Estimation for Fuzzy RD designs*/
- rdrobust Terr Growth, fuzzy(T) deriv(1) /*Estimation for Fuzzy Kink RD designs*/

CURRICULUM VITAE

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GRADUATE SCHOOL OF SCIENCE AND ENGINEERING
THESIS/DISSERTATION ORIGINALITY REPORT

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