The Causal Effect of Retirement on Health Condition: An Empirical Study on China

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Contents

Abstract

There is an ongoing debate in China about the adverse effect of the prolonged retirement age. To understand the potential costs of raising the retirement age, this paper examines the causal effect of retirement on health conditions by exploiting the China Health and Retirement Longitudinal Study (CHARLS. Using a fuzzy regression discontinuity design (RDD), I found that the effect of retirement on health was not significant for mental and physical health indicators. The results of this study provide important preliminary suggestive evidence for policymakers to increase the retirement age in China.

Key Words: *Retirement, Health ,RDD, CHARLS*

Preface

The motivation for this paper is to examine the causal effect of retirement on health conditions in China. The paper examines the impact from both mental health and physical health perspectives, and by applying the RDD methods, I find that the effect is not significant hence raising the mandatory retirement age in China will, to a certain extent, have no impact on the health of retirees. This finding provides valuable insights for political decision-makers in setting the retirement age. Moreover, the valid output of this study also stems from China's retirement age system and CHARLS' rich database of retirement pension tracking surveys.

1 Introduction

China is facing the issue of rapid ageing. According to the National Bureau of Statistics of China, the proportion of China's population aged 60 and up was 17.4 percent in 2020, compared with 7.5 percent in 1980. The increase in the elderly population is due to the decrease in fertility and increase in life expectancy. According to the World Bank indicators, the fertility rate was 2.94 births per woman, and the life expectancy was 65.86 in 1978 compared with 1.70 births per woman, and the life expectancy was 76.91 in 2019. People's life expectancy is increasing due to improved nutrition, hygiene, and medical care, and the decrease in fertility rate may be due to the One-child Policy. In China, the older society is rapidly growing, resulting in a reduction in the labor force and a rise in pension costs and health care expenditure.

The current retirement age policy in China was published in 1978, and the situation and social environment have changed dramatically. According to the lawful regulation of the statutory retirement ages(SRAs) setting in China, the SRAs are 60 years for men and 50 years for enterprises' women workers, or 55 years for women civil servants. Moreover, according to the newly issued document No.14 in 2015 by the Ministry of Human Resources and Social Security and Organization Department of the Central Committee of the Communist Party of China, the retirement of higher-ranking women in government service is delayed until age 60. Higher-ranking women denote female cadres and professional and technical staff with senior titles or at or above the deputy department level. Although with the adjustment, China's retirement age is lower than most developed countries. Most developed countries have set their SRAs at 65, according to the Organisation for Economic Cooperation and Development (OECD), and there is a global trend to raise the retirement age.

In this case, the Chinese government has begun to investigate altering the system in order to offset the significant reduction in the workforce and an overall increase in government expenditure. Arguments for setting the retirement age resulted in debate. The Chinese government might achieve its goal of growing the labor force while reducing the budget for paying pensions by raising the retirement age. While there are many political and economic aspects to consider the proper retirement age to be settled, one of the essential considerations is how retirement impacts people's physical and mental health.

Depression is one of the most common indicators of measuring mental health conditions. Depression has a physical impact on people's health and well-being. Suffering from depression has a negative effect. Depression can cause sleeplessness, impair the immune system, restrict blood vessels, increase the risk of heart attack, cause memory or decision problems, etc. Examining how retirement affects depression levels may thus help to reveal the effects on mental health.

Hypertension and blood sugar levels are two typical physical health indicators. The primary health concerns that contribute to the illness burden of older persons in China are hypertension and diabetes mellitus, among other things. Furthermore, there are many common causes and risk factors for hypertension and diabetes. Individuals who have one ailment are more likely to develop the other. People who have both diseases may also find that one aggravates the other. Aneurysms, heart failure, transient ischemic attack, kidney failure, and retinal vascular damage are only a few consequences that can arise from both disorders. Therefore, the inclusion of hypertension and blood sugar levels in the indicator of physical health can better reflect the health of the body.

Therefore, to understand the possible consequences of increasing the retirement age, I need to consider the causal effect of retirement. This paper aims to examine the consequence of mental health and physical health affected by retirement. The mental health condition is measured by depression level, and the physical health is measured by self-report health conditions, hypertension and blood sugar levels. The findings will aid policy development and implementation. For example, if retiring has a negative impact on mental health and physical health, raising retirement ages may raise healthcare expenses. If retiring has a positive or no significant effect on mental health and physical health, then raising retirement may not raise additional problems in the health sector.

This study uses SRAs as the exogenous variables of retirement. It utilizes RDD to assess the influence of retirement on health in China, based on the China Health and Retirement Longitudinal Study (CHARLS) from 2011 to 2018. I employ an appropriate retirement definition to limit the sample size for sample selection. I also create a horizontal merging of a cross-sectional dataset of four waves from 2011 to 2018 to increase the sample size to meet the RDD criteria. Specifically, I treated the same person in different waves as different people and combined the data to expand the dataset. I also conduct a sensitivity analysis for the effect of retirement on the mental and physical health of retirees of different gender groups using different bandwidths and higher polynomial terms. Finally, I check the manipulation test and balancing check to ensure robust findings. With respect to different bandwidths of RDD and different gender groups, the RDD results demonstrate that retirement has no significant effect on mental and physical health. Furthermore, the outcomes of this study give critical evidence for policymakers to adjust whether to raise the retirement age.

The remainder of the paper is organized as follows. Section 2 summarizes the literature reviews. The data and detailed data processing approaches are discussed in Section 3. The model and identification strategy are stated in Section 4. Section 5 reports the results, and Section 6 concludes. Some of the results tables are relegated to the Appendix.

2 Literature

Studies finding positive, negative or no effects of retirement on health have been inconsistent.

Research has indicated that retirement had a considerable positive significant impact on various either subjective or objective or both health indices in several developed countries. Charles (2004) examined a sample of males from waves 2 and 3 of the Health and Retirement Study (HRS) data and discovered a significant direct effect of retirement on well-being. By using early retirement window quotations to quantify retirement, Coe and Lindeboom (2008) showed no negative impact of early retirement on men's health using IV regression using data from the Health and Retirement Study(HRS). Neuman (2008) analyzed longitudinal data from the Health and Retirement Study (HRS) and used exogenous public and private pension changes to determine retirement status. Although nonsignificant results from objective health change models show that this protection may be more perceived than genuine, the authors discovered that subjective health change models suggest that retirement benefits both men's and women's health. According to Insler (2014), the health benefits of retirement are significant. According to studies using behavioral data such as smoking and exercise, retirement may affect health through various channels. Many retirees establish better behaviors as a result of their more free time. Eibich (2015) discovered that retirement improves subjective health status and mental health while reducing the usage of outpatient treatment, using RDD to detect financial incentives in the German pension system. Simultaneously, reducing work-related stress and tension, improving sleep length, and boosting physical activity appear to be essential methods by which retirement affects health. Kämpfen and Maurer (2016) used data from the American Health and Retirement Study to show that retirement had a significant positive impact on Americans meeting the federal government's 2008 physical activity guidelines through causal IV analysis. They also discovered that people with higher levels of education and money had a more significant impact on physical activity after retirement.

Correspondingly, many studies are showing the negative effects of retirement on health. Godard (2016) discovered that early retirement induced by discontinuous incentives in early retirement programs increased the probability of obesity in men by 12 percentage points over two to four years, based on the SHARE surveys from 2004, 2006, and 2010-2011. At the same time, retirement has a very nonlinear effect, affecting the right side of males primarily. Women, on the other hand, showed no significant results. Using the Health and Retirement Study (1992-2005), Dave et al. (2008) found that full retirement resulted in a 5-14 percent increase in mobility and daily activities issues, a 4-6 percent rise in sickness, and a 6-9 percent decline in mental health. At the same time, they discovered that being married, engaged in physical activity, or continuing to work part-time after retirement minimized the adverse health effects. Kuhn et al. (2010) calculated the causal effect of early retirement on blue-collar worker death. The findings revealed that the risk of dying increased by 2.4 percentage points for men but had no influence on mortality for women. Behncke (2012) employed nonparametric matching and instrumental variables (IV) methods to find the causal impacts of retirement on various health outcomes using the first three waves of the English Longitudinal Study of Aging (ELSA). Retirement appears to greatly increase the probability of being diagnosed with a chronic condition. Furthermore, retirement degrades self-assessed health and potential health inventories.

In early studies, Portnoi (1981) and Moen (1996) showed no significant effect of retirement on either physical or mental health.

Recent research in China on the impact of retirement on health has also been widely studied. Lei et al. (2018) revealed significant gender heterogeneity in the impacts of retirement on cognition in urban Chinese populations, with positive and significant effects on males but negative and not significant effects on women, based on the China Health and Retirement Longitudinal Study. Giles et al. (2021) use the same research data but account for couples' shared retirement. They find that creating incentives for women to retire later may promote longer working lives for both men and women, taking into account their husbands' wishes for joint retirement. Wang et al. (2021) found that the effect of retirement on health was nonsignificant for a variety of health indicators, different bandwidths of RDDs, and subsample groups using the China Health and Retirement Longitudinal Study (CHARLS) from 2011 to 2015. They used a fuzzy regression discontinuity design (RDD), and they proposed that minor differences in income and lifestyle could explain the outcome before and after retirement. Chen et al. (2020) measured the causal effect of retirement on stress using data from the China Health and Nutrition Survey in 2015 and a nonparametric regression discontinuity design (RDD), and the findings revealed that the effect of retirement on stress was nonsignificant on average. Retirement reduces stress in males but increases it in women, according to subgroup analysis. These gender-specific effects are high in magnitude but not statistically significant. Using the China Health and Retirement Longitudinal Study (CHARLS) in 2011, 2013, and 2015 with a fuzzy discontinuous design, Feng et al. (2020) investigated the causal impacts of retirement on body mass index (BMI) and body weight in China. Retirement boosts men's weight and BMI, according to the study, and the effect is significantly greater for men with poor educational attainment. Women's weight and BMI are unaffected by retirement. Different definitions of retirement, narrow retirement bandwidths, and excluding the rural hukou sample did not affect these results.

Overall, different selected samples, health assessments, identification procedures, retirement regulations, pension systems, and social and cultural variables between countries may all contribute to the conflicting findings and conclusions.

Because retirement decisions are not randomly made, it is challenging to estimate causal effects between retirement and health using simple ordinary least square(OLS) regression, as reverse causality and confounding factors exist. However, we could explore the causal relationship by using the RDD method. As Bloemen et al. (2017) pointed out, poor physical and mental health can cause people to retire, but unobservable and time-varying confounding factors can influence retirement and health. According to Insler (2014), the causal relationship between retirement and health can be investigated using instrumental variable regression or regression discontinuity design (RDD) with SRA as an exogenous retirement variable.

3 Data

The China Health and Retirement Longitudinal Study(CHARLS) provided the data for this study. The China Health and Retirement Longitudinal Study (CHARLS) gathers a nationally representative sample of Chinese people aged 45 and up. The baseline national wave of CHARLS was deployed in 2011, and it contains around 10,000 houses and 17,500 persons across 150 counties or districts and 450 villages or resident committees. Every two years, the participants will be followed. One year after the data collection ends, all data will be made public. CHARLS uses stratified multi-stage PPS sampling. This dataset contains detailed information on respondents' demographics, family structure, health insurance, retirement, and pension status.

The data in this paper comes from the survey's first four waves, which took place between 2011 and 2018. All of the samples in this study were between 30 and 90. To achieve the RDD sample size criteria, I created four waves of cross-sectional data from 2011 to 2018 and treated the same persons as distinct respondents' data in each wave.

After excluding observations with missing values on the selected variables, the remaining sample size is 56,780, with 26,631 males and 30,149 females. And I split the whole dataset into three groups as each group has different cutoff age values. The first group contains all male subjects whose SRA is 60 by regulation requirement. The second group is government females whose SRA is 55, and the third group is the non-governmental female group with SRA set as 50. And due to the data questions limit, there is no specific question that we can figure out the title of a government female; hence, we ignore the case when a government female with a high title could retire at 60 and keep it as 55.

3.1 Summary Statistics

Table 1 illustrates the fundamental data I used to do the main regression using the RDD. The running variable is age, and the cutoff values(SRAs) for each gender of the subjects are different. The cutoff point for males is 60, and for governmental females groups, it is 55, and for the remaining female groups, it is 50.

The dependent variables include depression level, self-reported health condition, hypertension condition, and high blood sugar condition. The mental health condition variable in the survey reveals how often the respondent felt depressed in the previous week. If the number is 1, it means that it happens rarely or never 1 day, 2 means that it happens some or a little 1-2 days, 3 means that it happens occasionally or a substantial amount of the time 3, and four means that it happens most or all of the time 5-7 days.

The self-reported health condition variable is the respondent's self-reported general health state, ranging from 1 to 5. Self-reported overall health status on a scale of Very Good to Very Poor is queried at the beginning or end of the Health module in Waves 1 to 3. Beginning with Wave 4, however, respondents were simply asked to self-report their current health condition at the start of the health module. One thing to be noticed is that for depression levels and self-reported health conditions, the least the number, the best the respondent's health is.

Hypertension variable and high blood sugar are indicator variables whether assigned to 0 or 1. A value of 0 indicates that the respondent has not been advised they have the disease by a doctor. A code of 1 indicates that the respondent has been diagnosed with the disease by a doctor.

Education and marital status are the covariate variables I chose since, according to the literature review section, they are associated with health. The education variable represents the respondents' educational level. 1 denotes a respondent who has completed less than a lower secondary education, 2 denotes upper secondary and vocational training, and 3 denotes tertiary education. The education variable is a categorical variable, so a greater value indicates a better level of education. The marriage variable is also a categorical variable. 1 denotes a respondent who has been married with their spouse present, 3 denotes a respondent who has been married but not living with their spouse temporarily for reasons such as work, 4 denotes a respondent who has been separated, 5 denotes a respondent who has been divorced, 7 denotes a respondent who has been widowed, and 8 denotes a respondent who has never been married. The integer value of the marriage variable is not continuous, as seen by the absence of values 2 and 6 in the descriptions.

	not retired (N = 38,045)	retired (N = 18,735)
Age		
min	30	32
max	90	90
mean (sd)	57.03 (8.50)	64.72 (10.10)
Gender		
Female(count)	18,473	11,676
Male(count)	19,572	7,059
Mental Health Condition		
min	1	1
max	4	4
mean (sd)	1.87 (1.05)	1.94 (1.12)
Education Level		
min	1	1
max	3	3
mean (sd)	1.12 (0.36)	1.14 (0.41)
Marriage		
min	1	1
max	8	8
mean (sd)	1.60 (0.01)	2.33 (0.02)
Self Reported Health Condition		
min	1	1
max	5	5
mean (sd)	2.88 (0.95)	3.16 (0.98)
Hypertension		
min	0	0
max	1	1
mean (sd)	0.26 (0.44)	0.41 (0.49)
High Blood Sugar Condition		
min	0	0
max	1	1
mean (sd)	0.07 (0.25)	0.13 (0.34)

Note: N represents the number of respondents and the bracket represents the value of standard deviation.

Table 1: Summary Statistics of the Dataset

Table 1 shows that the mean of all variables appears to be different between the retired and non-retired groups. And a simple intuition of the dependent variables for the mental health condition, self-report health condition, hypertension, and high blood sugar are all worse in the retired group compared with the not retired group.

3.2 Retirement definition

Whether or not the respondent is retired is the leading independent variable of interest. There are three popular ways of defining retirement that has been utilized in past studies. First, I could apply the self-reported "processing retirement" to measure retirement according to the CHARLS survey. Second, retirement could be measured by leaving the workforce (Coe and Zamarro, 2011). Third, I could use the first two combinations, self-reported "processing retirement" and labor market exit, to determine the retirement status (Eibich, 2015; Wang, 2021).

However, the first two criteria are not ideal for this investigation due to two factors. On the one hand, some retirees may continue to work for a living after receiving their pensions. Some people, on the other hand, have never worked for compensation and have never "retired" from their occupations. I choose the last term because I believe it will produce more precise estimation results.

3.3 Data Processing

The age variable indicates the respondent's age in years at the current wave's interview. Because CHARLS conducts the tracking survey every two years, I utilize this information to fill in some missing values in the age variable.

The retirement variable indicates whether the respondent is retired. If the respondent reports doing agricultural work, non-agricultural employed work, non-agricultural self-employed work, or non-agricultural unpaid family business work, or if they are jobless or have never worked, the retirement variable is set at 0. The retirement variable is assigned 1 if the respondent is retired per their labor force status.

I include the variable of whether the respondent worked after they completed the retirement procedure to rule out the influence of working after retirement. If the respondent reports not working after the retirement procedure, the variable is set to 0. If the respondent reports working after completing the retirement process, the variable is set to 1. The labor force status, which is a variable, summarizes the respondent's labor force status as follows: 1 represents the agricultural employed, 2 represents the agricultural self-employed, 3 represents the non-agricultural employed, 4 represents the non-agricultural self-employed, 5 represents the non-agricultural unpaid family business, 6 represents the unemployed, 7 represents the retired, and 8 represents the never worked. Also, if a respondent reports doing two jobs in the last year, the non-agricultural work and paid work are given priority.

Therefore, by involving both of the variables above, we could rule out those people who have never worked for more than three months during their entire life, which the labor force status is 8, as well as those who still worked after finishing their retirement procedure which the variable for work after is equal to 1.

4 Identification Strategy

The causal effect between retirement and health is difficult to estimate empirically since numerous factors influence retirement decisions. Health concerns may directly cause retirement, and other complicating variables will affect both retirement and health at the same time. In this case, retirement and health will be affected simultaneously. A conventional OLS will not handle this issue, so one solution is to use the SRA as an exogenous variable for retirement and investigate the causal association between retirement and health indicators using the regression discontinuity design

(RDD). Based on the China Health and Retirement Longitudinal Study (CHARLS), the effect of retirement on mental and physical health in China was investigated using SRAs as the running variables of retirement and RDD. I employ depression as a mental health indicator and the self-report health status, hypertension, and high blood sugar levels as physical health indicators. Finally, I test the robustness of the findings by conducting various tests.

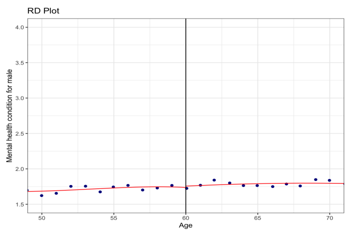
4.1 Visualization – RD plots

Through Figure 1, we could see a clear jump in the government female group, which indicates a positive impact of retirement on depression, and a slightly visible jump for the other two groups indicates the negative effect of retirement on the indicator of mental health condition.

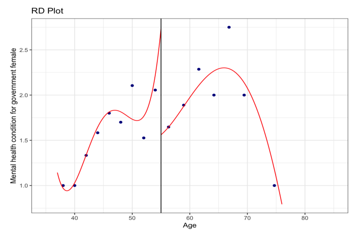
Through Figure 2, we could see a big jump in the government female group, which is a positive impact on retirement on self-reported health. There is a slightly small leap for the non-government female group, which indicates a negative impact of retirement on self-report health, and no noticeable jump for the male group for the self-report health.

Through Figure 3, we could see a big jump in the government female group, which indicates the positive impact of retirement on hypertension conditions. There is also a visible positive jump for both the male and non-government female groups, which shows the negative effect of retirement.

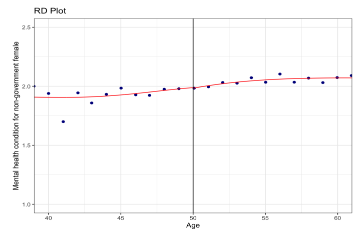
Through Figure 4, we can see a big jump for both the government female group and the male group, and for the male group, the leap is positive and negative for the government female group. The jump indicates that retirement harms high blood sugar and is positive for government females. Also, a slight positive jump corresponds with a negative retirement impact for the non-government female group.



(a) Male Group

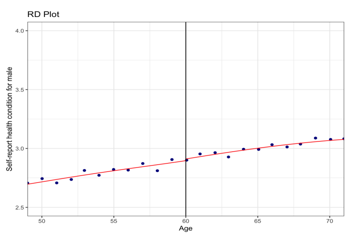


(b) Government Female Group

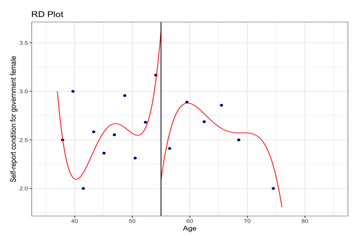


(c) Non-government Female Group

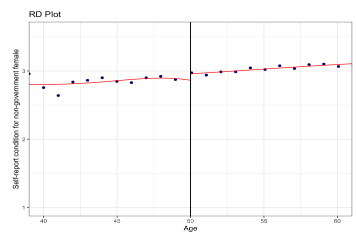
Figure 1: RD plot for Depression Condition



(a) Male Group

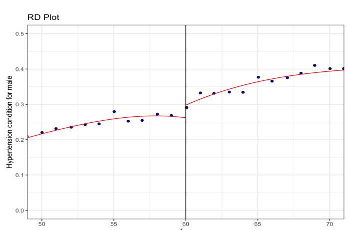


(b) Government Female Group

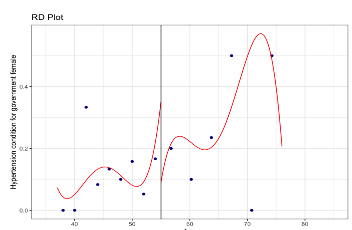


(c) Non-government Female Group

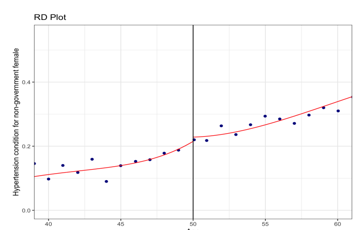
Figure 2: RD plot for Self-report Health Condition



(a) Male Group

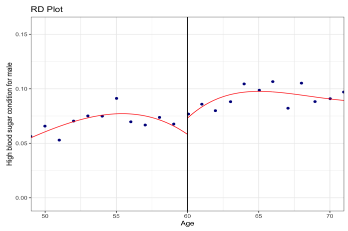


(b) Government Female Group

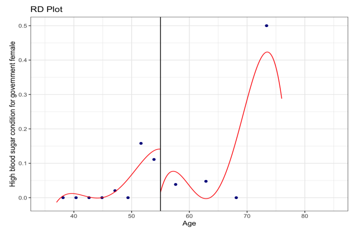


(c) Non-government Female Group

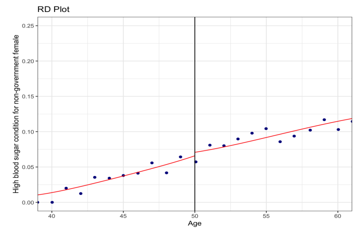
Figure 3: RD plot for Hypertension Condition



(a) Male Group



(b) Government Female Group



(c) Non-government Female Group

Figure 4: RD plot for High Blood Sugar Condition

4.2 Parametric Estimation with Sharp RDD

The parametric estimation of the RDD assumes the relationship between the outcome variable, which is the multiple health indices, and the running variable(age) is linear. According to Gelman and Imbens (2019), it is suggested to utilize polynomials up to the second degree in the majority of circumstances, and they prove this argument in three parts. First, the degree of the polynomial affects the estimated results. Second, polynomial terms impose "weights," which for higher polynomial terms could constitute noise. Third, for higher polynomial terms, the confidence interval's performance does not converge well. Hence in the regression setup, I only include the higher polynomial term up to the quadratic. Also, I added an intersection term for the treatment and the normalized age(age minus the corresponding cutoff value) because the treatment effect, which is retirement, depends on the age. And I also add the covariates, if the assumption holds, then all observed and unobserved covariates are balanced, and thus there is no need to include the covariates term. However, I involve the confounders to make the results more precise. And the formulation could be written as follows:

$$Health_{ik} = \beta_0 + \beta_1 D_{ij} + \beta_2 f(Age_i - c_j) + \beta_3 D_{ij} f(Age_i - c_j) + \mathbf{X_i}\beta_4 + \epsilon_i \tag{1}$$

$$D_{ij} = \begin{cases} 1, & \text{if } Age_i \geq c_j \\ 0, & \text{if } Age_i < c_j \end{cases} \tag{2}$$

where $Health_{ik}$ represents respondent i's health condition for indicator k, where $k \in \{\text{depression, self-report health condition, hypertension, high blood sugar}\}$. And β_0 represents the intercept for the regression, which captures the average health indicator level. $f(age)$ is a function about normalized age, and the function is up to the second polynomial term. And the normalized age is defined as $Age_i - c_j$. β_1 captures the treatment effect when $age_i = c_j$, which is also refer to the local average treatment effects(LATE). c_j is the SRA for group j, and $j \in \{1, 2, 3\}$, which refers to three different groups. And $\mathbf{X_i}$ is a vector that contains the covariates, which are the variable of education level and marriage status in our case. D_{ij} is an indicator function which equal to 1 if the respondent's age is higher or equal to the SRAs for the belonging group and 0 otherwise.

4.3 Nonparametric Estimation with Fuzzy RDD

I use a fuzzy RDD to assess the effect of retirement on health to address the inverse causal link between retirement and health. RDD is an ideal quasi-experimental approach for determining the causal effect of the treatment when SRA is used as an exogenous source of retirement status variation.

Another reason I utilize fuzzy RDD to assess the effect of retiring on health is that at the SRA, the retirement probability does not change from 0 percent to 100 percent directly. The treatment effect can therefore be calculated as the ratio of the increase in the outcome variable, which is the health indicator to the rise in the likelihood of retiring from the SRA. In the fuzzy RDD, the age at the cutoff value is a predictor of who will receive the treatment. It reflects the probability of receiving the treatment. Another way to put it is that there are noncomplier in our case where people who are older than the SRA requirement but have not retired, as well as people who are younger than the SRA but have retired early.

To formulate the model, I employ nonparametric estimation mixed with fuzzy RDD. The distinction between parametric and nonparametric estimation is that the former requires making assumptions about the shape of the regression line on both sides of the cutoff point. Nonparametric estimation, on the other hand, does not assume a fixed-function form based on the assumption; instead, the data drives the shape of the regression. The elements of the following equations are estimated using two-stage least square(2SLS) instrumental local linear regressions in nonparametric estimation. The following is the formula:

$$\hat{Retirement_i} = \alpha_0 + \alpha_1 D_{ij} + \alpha_2 f(Age_i) + \alpha_3 D_i f(Age_i) + \mathbf{X_i}\alpha_4 + \epsilon_{0ij} \tag{3}$$

$$Health_{ik} = \beta_0 + \beta_1 \hat{Retirement_i} + \beta_2 f(Age_i) + \beta_3 D_{ij} f(Age_i) + \mathbf{X_i}\beta_4 + \epsilon_{1ij} \tag{4}$$

$$D_{ij} = \begin{cases} 1, & \text{if } Age_i \geq c_j + \epsilon_{ij} \\ 0, & \text{if } Age_i < c_j + \epsilon_{ij} \end{cases}. \tag{5}$$

Where the estimated β_1 is the local average treatment effect(LATE), indicating the effect of retirement on health indicators around the cutoff point. $\hat{Retirement_i}$ represents the fitted values from the estimates of the first-stage equation, and it is the treatment variable whether individual i retires. $Health_{ik}$ is a measure of an individual i 's mental health condition(depression level), self-report health condition, whether have hypertension, and whether have high blood sugar diagnosed by a doctor. D_{ij} is an indicator variable equal to 1 for individuals that are older than the statutory retirement age plus an error term in that particular group, which represents a probability of whether assigned to the treatment group or not. $f(Age_i)$ is a up too second polynomial function for age. X_i is a vector of covariates, including the education level and marriage status that is likely associated with health indicators.

5 Results

5.1 Main Results

From the data processing part, I divided the whole sample size into three groups, the male group, the female government group, and the female non-government group. However, compared with the sample size, the government female group have a limited size with 189 observations compared with the other two groups, in which the male group has 26631 observations, and the non-government female group has 29960 observations. As the sample size is so limited, it is not valid to conduct the RDD on the government female group. Hence the results I have are mainly for the male and non-government female subgroups.

In Appendix A, the result tables sector, Tables 3-10, are the regression table results of the RDD by conducting the parametric estimation with Sharp RDD design. Tables 3-6 are the results for the male group on the dependent variables of depression, self-report health condition, hypertension, and high blood sugar condition. And Tables 7-10 show the results of the non-government female group with the same previous outcome variables. Generally speaking, among all the results table, the treatment effect of retirement on the health outcome variable is insignificant for all the subgroups. From Table 3-6, the sign of the treatment effect for the mental health condition and self-report health is negative, which are $-0,025$ and -0.019. It means that retirement has a positive impact that may increase mental health and self-report health condition. However, the sign of the treatment effect on diagnosing hypertension and high blood sugar are negative, which are 0.033 and 0.018 correspondingly. It means that retirement may affect the chance for the elder male group to diagnose these diseases increase. However, there is a completely different version for the female subgroups who will get worse mental health and self-report health condition after the retirement and will get a lower chance of diagnosing hypertension and high blood sugar after the retirement according to the signs of the treatment effect. Although the results are not significant, the finding of the different pattern that exists between genders is interesting to further discuss.

Table 2 shows the results of RDD using nonparametric estimation with Fuzzy RDD. I adopt three bandwidths for each group: the optimal bandwidth, twice the optimal bandwidth, and half of the optimal bandwidth, which is a common approach to doing the sensitivity analysis for the results. The choice of the bandwidth is important. If I estimate using small bandwidth will yield lower bias and higher variance, and if I use a large bandwidth, it will yield a higher bias but lower variance. Hence, I adopted the optimal bandwidth approach calculated by mserd, one common MSE-optimal bandwidth selector for the RD treatment effect estimator. And I use the triangular kernel function to give the different weights on the data within the bandwidth. As for the results for the male group and compared the treatment effect horizontally with different bandwidths, we could find that the value does not vary a lot, and hence the results pass the sensitivity analysis check, which yields robust and consistent results. The same situation also applies to the female subgroup. And overall, the treatment effect is not statistically significant.

Dependent Variables	Male Group			Female Non-Government Group		
	b = 5.219	2b	0.5b	b = 6.509	2b	0.5b
Mental Health Condition	-0.324	0.171	-2.010	-0.108	0.285	-0.347
	(0.845)	(0.663)	(2.566)	(1.230)	(0.684)	(1.362)
(Pr(>|z|))	0.702	0.796	0.434	0.930	0.677	0.799
[95% C.I.]	[-1.979 , 1.332]	[-1.128 , 1.471]	[-7.039 , 3.020]	[-2.519 , 2.303]	[-1.056 , 1.625]	[-3.016 , 2.321]
	b = 6.284	2b	0.5b	b = 5.351	2b	0.5b
Self-reported Health	0.245	0.373	-1.164	1.826	1.039	1.949
	(0.746)	(0.570)	(1.550)	(1.656)	(0.779)	(1.234)
(Pr(>|z|))	0.742	0.513	0.453	0.270	0.182	0.114
[95% C.I.]	[-1.216 , 1.707]	[-0.744 , 1.489]	[-4.201 , 1.873]	[-1.420 , 5.073]	[-0.488 , 2.566]	[-0.469 , 4.367]
	b = 5.792	2b	0.5b	b = 5.287	2b	0.5b
Hypertension Condition	0.568	0.563	0.747	0.532	0.520	0.305
	(0.387)	(0.300)	(0.991)	(0.610)	(0.329)	(0.453)
(Pr(>|z|))	0.142	0.061	0.451	0.383	0.113	0.501
[95% C.I.]	[-0.190 , 1.327]	[-0.025 , 1.152]	[-1.195 , 2.689]	[-0.663 , 1.727]	[-0.124 , 1.164]	[-0.583 , 1.194]
	b = 5.973	2b	0.5b	b = 5.889	2b	0.5b
High Blood Sugar Condition	0.224	0.170	0.415	-0.091	0.117	-0.359
	(0.212)	(0.161)	(0.556)	(0.307)	(0.165)	(0.322)
(Pr(>|z|))	0.290	0.290	0.456	0.768	0.476	0.264
[95% C.I.]	[-0.191 , 0.640]	[-0.145 , 0.485]	[-0.676 , 1.505]	[-0.693 , 0.512]	[-0.205 , 0.440]	[-0.990 , 0.271]

Note: b indicate the optimal bandwidth and the brackets below the coefficients indicate the standard error.

Table 2: Nonparametric Estimation of Fuzzy RD Results for Male and Female Subgroup

5.2 Validations of the RD design

There are three specifications and robustness checks to further examine the validation of the RDD:

First is the sensitivity analysis. The sensitivity analysis is used to examine the robustness of the results, specifically whether they are sensitive to different specifications. The sensitivity analysis was conducted in the above results section, and I used alternative bandwidths and higher polynomial terms to test the robustness of the results.

The second is the balance check. At the cutoff point, the balancing check to see whether there are any covariate variables jumps as well. If this is the case, the RDD is invalid since we can't tell whether the jump in the outcome variable is due to the treatment effect we're looking at or is caused by the effect of the covariates.

The third is the manipulation test. The manipulation test is used to see if the subjects were manipulated into receiving treatment. For example, some respondents may report a fake age to modify their eligibility status for retirement in the survey. However, as for the CHARLS was not used to determine retirement criteria, then there is no intention for respondent to misreport their retirement information, therefore manipulation was not a problem in this study.

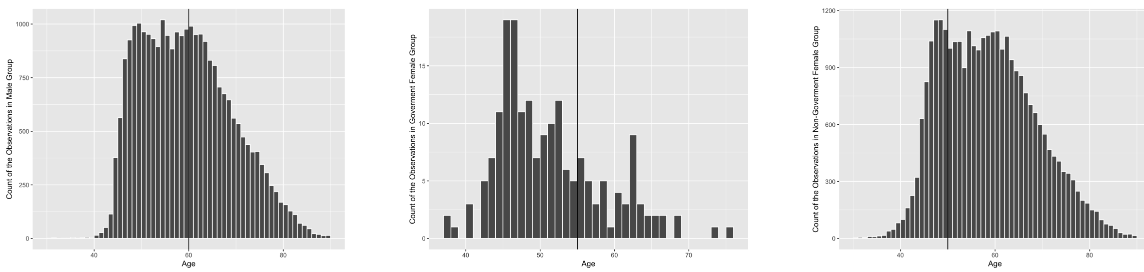
5.3 Robustness Check

We need to see if there was any manipulation in the running variable, which might make a lot of people bunched up around 60 years old for some reason. So we'll make a histogram of the running variable (the age variable) and see if there are any big jumps around the threshold.

To test for manipulation of the assignment variable, we used a visual examination of a histogram of age around the retirement threshold. In Figure 5, we could find that the gap for each group around the cutoff point is not significant. Hence, subjects below or above the cutoff point do not show a systematic difference in age. We could exclude the possibility that people may manipulate their age to self select the treatment is very unlikely to happen. Figure 7 shows the age density among all the subjects, including the government female group. The distribution around the cutoff is relatively balanced, which further excludes the possibility of manipulation during the treatment.

Figure 6 shows the probability of retirement for the male and female subgroup, and the shallow area is 95 percent of the confidence interval. And we could observe a significant jump at the cutoff point for both of the subgroups, which represents a discontinuity at the cutoff value. Hence, the prerequisite for applying the RDD is satisfied. Therefore, we could use the RDD method to examine the causal effect of retirement on health.

Figures 8 and 9 show that the covariates variable is continuous at the cutoff point for all the subgroups. Hence the jump in the outcome variables could not be caused by the covariates variables, which further examines the validation of the RDD method and guarantee that the casual effect is from retirement rather than other confounding factors.



(a) Male Group

(b) Government Female Group

(c) Non-government Female Group

Figure 5: Frequency of the observations for different groups

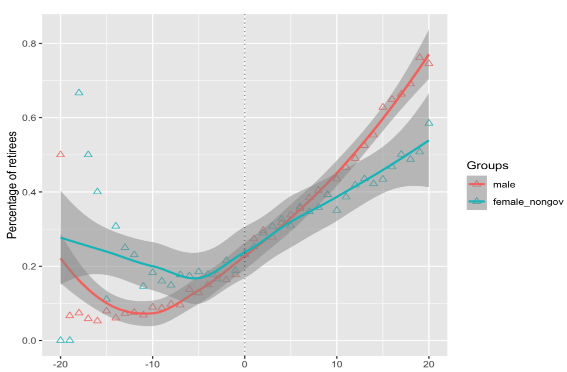


Figure 6: Probability of the retirement for male and non-government female

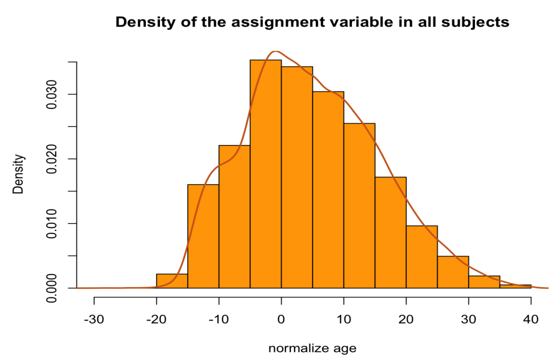
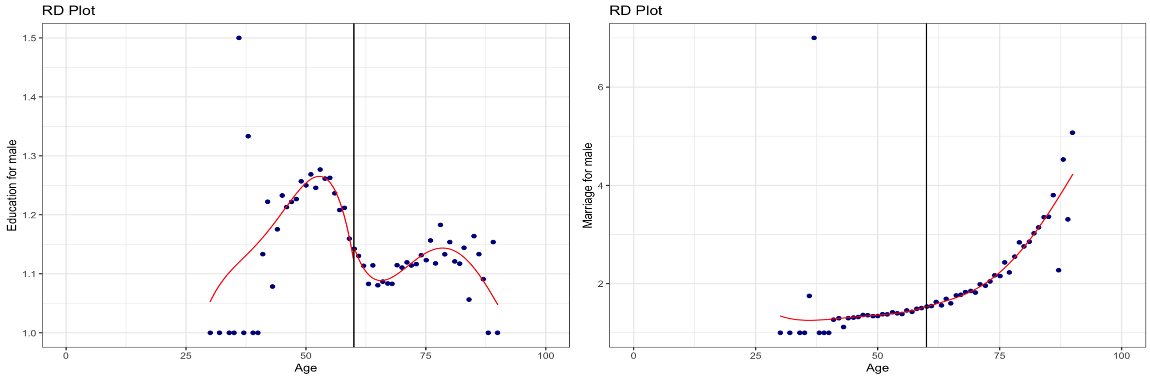
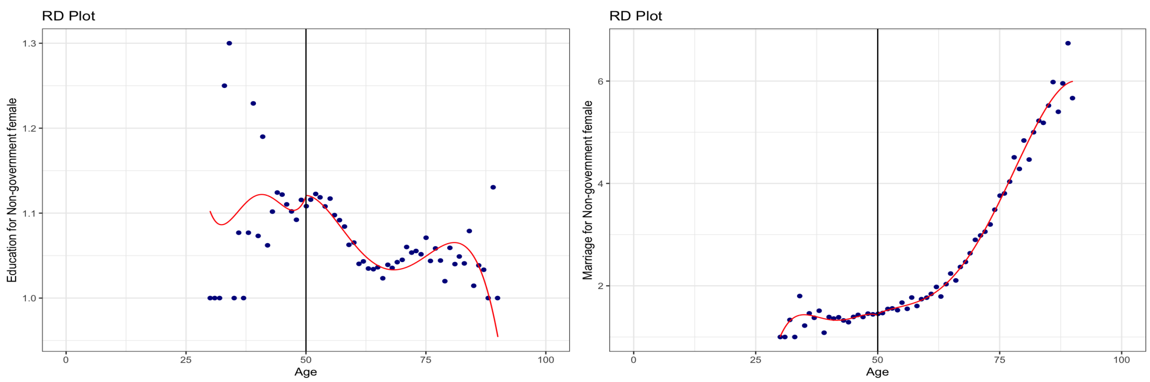


Figure 7: Density of the age variable in all subjects



(a) RD plot of education level for male group (b) RD plot of marriage status for male group

Figure 8: Balance check for covariates in male group



(a) RD plot of education level for female subgroup (b) RD plot of marriage status for female subgroup

Figure 9: Balance check for covariates in non-government female group

6 Conclusion

This study aims to explore the effect of retirement on the health of Chinese older people. This study indicates that retirement has a non-significant impact on China's mental and physical health. These results are robust across different health indices, RDD bandwidths, and sub-groups.

This study contributes to the literature on the effect of retirement on health by providing more evidence from China. In this study, I use the newly released dataset from China Health and Retirement Longitudinal Study(CHARLS) from 2011 to 2018.

I use multiple health indicators to measure physical health. I also use a more enlarged sample size by treating the same person in different waves as a different person and combining the four waves as a harmonized sample size. Finally, I test the causal effect of retirement on health for gender-specific.

There are some limitations to this study and need to be further improved in the future. It would be worth looking more at the health edges for an impact beyond the conditional means. Also, the mechanisms determining health outcomes should be further discussed as there may exist lags in certain chronic diseases such as hypertension. Usually, people do not expect that outcomes to change right around the cutoff, but rather on average, some periods later. I should involve a long-term effect for examining the retirement effect to get a more concrete measure. At the same time, chronic diseases have correlated with the lifestyle, as it may be the case that after retirement, people change their lifestyle in order to change their health condition. That means retirement may affect the health condition through the channel of it changing people's lifestyles. That is the case I need to test further. Furthermore, the impact of changing the mandatory retirement age is so enormous that there would be cultural and macroeconomic effects that themselves affect health in unclear ways. Also, due to differentiation in the local and global setting, the decision of whether to raise the mandatory retirement age could not be generalized.

This study provides preliminary findings on the effect of retirement on health conditions in China and may help policymakers make the decision. The results of this study have value for policymakers in China who are considering raising the retirement age. Raising the retirement age could further help release the burden of government expenditure. In terms of future study, one intriguing way is to look at more health indices to examine the impact of retiring in China. Also, because the dependent variable accepts limit values, the binary choice or ordered logistic regression model might be used to investigate the treatment effect on the outcome variables. It is also intriguing to find the causative influence of the couple's retirement treatment on their health status.

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Appendix A Result Tables

Mental Health	**Full data**	**Bandwidth = 10**	**Bandwidth = 5**	**Bandwidth = 2**	**Bandwidth = 1**
(Intercept)	1.934	1.876	1.944	1.963	1.951
	(0.032)	(0.044)	(0.077)	(0.117)	(0.081)
D	-0.025	0.048	-0.075	-0.099	-0.087
	(0.033)	(0.045)	(0.076)	(0.104)	(0.079)
age_centered	0.013	-0.022	0.045	0.066	0.042
	(0.007)	(0.016)	(0.054)	(0.128)	(0.046)
I(age_centered^2)	0.001	-0.003	0.008	0.013	
	(0.000)	(0.001)	(0.009)	(0.040)	
education	-0.155	-0.163	-0.164	-0.160	-0.147
	(0.014)	(0.017)	(0.025)	(0.037)	(0.048)
marriage	0.020	0.020	0.030	0.028	0.019
	(0.004)	(0.005)	(0.006)	(0.009)	(0.012)
D × age_centered	-0.009	0.018	0.014	-0.037	
	(0.008)	(0.020)	(0.061)	(0.206)	
D × I(age_centered^2)	-0.001	0.004	-0.020		
	(0.000)	(0.002)	(0.010)		
Num.Obs.	26631	18522	10380	4826	2912
R2	0.007	0.008	0.007	0.008	0.004
R2 Adj.	0.007	0.007	0.007	0.006	0.003
AIC	75442.4	52546.3	29670.5	13880.2	8339.3
BIC	75516.1	52616.7	29735.8	13932.0	8375.2
Log.Lik.	-37712.205	-26264.137	-14826.268	-6932.087	-4163.651
F	28.730	20.524	11.169	6.084	3.266

Note: The brackets below the coefficients indicate the standard error.

Table 3: Parametric estimation for Male Group with Mental Health Condition as dependent variable

Self-report Health	**Full data**	**Bandwidth = 10**	**Bandwidth = 5**	**Bandwidth = 2**	**Bandwidth = 1**
(Intercept)	3.102	3.084	3.087	3.090	3.079
	(0.031)	(0.042)	(0.074)	(0.112)	(0.078)
D	-0.019	0.016	-0.023	-0.053	-0.059
	(0.032)	(0.044)	(0.073)	(0.099)	(0.076)
age_centered	0.020	0.013	0.049	0.024	0.052
	(0.007)	(0.015)	(0.052)	(0.123)	(0.044)
I(age_centered^2)	0.000	0.000	0.006	-0.022	
	(0.000)	(0.001)	(0.008)	(0.038)	
education	-0.174	-0.177	-0.149	-0.126	-0.109
	(0.014)	(0.017)	(0.024)	(0.035)	(0.046)
marriage	0.010	0.012	0.014	0.005	0.003
	(0.003)	(0.005)	(0.006)	(0.009)	(0.012)
D × age_centered	0.003	-0.002	-0.033	0.049	
	(0.008)	(0.019)	(0.058)	(0.197)	
D × I(age_centered^2)	-0.001	0.001	-0.007		
	(0.000)	(0.002)	(0.010)		
Num.Obs.	26631	18522	10380	4826	2912
R2	0.029	0.019	0.008	0.006	0.003
R2 Adj.	0.029	0.018	0.008	0.005	0.001
AIC	73590.2	51287.9	28836.2	13454.7	8092.8
BIC	73663.9	51358.4	28901.4	13506.6	8128.7
Log.Lik.	-36786.093	-25634.966	-14409.079	-6719.357	-4040.414
F	113.225	50.015	12.234	4.665	1.847

Note: The brackets below the coefficients indicate the standard error.

Table 4: Parametric estimation for Male Group with Self-report Health Condition as dependent variable

Hypertension	**Full data**	**Bandwidth = 10**	**Bandwidth = 5**	**Bandwidth = 2**	**Bandwidth = 1**
(Intercept)	0.247	0.239	0.248	0.170	0.274
	(0.014)	(0.020)	(0.035)	(0.053)	(0.037)
D	0.033	0.034	0.006	0.067	-0.019
	(0.015)	(0.021)	(0.035)	(0.047)	(0.036)
age_centered	0.003	0.000	0.027	-0.065	0.042
	(0.003)	(0.007)	(0.024)	(0.058)	(0.021)
I(age_centered^2)	0.000	0.000	0.005	-0.021	
	(0.000)	(0.001)	(0.004)	(0.018)	
education	0.023	0.021	0.032	0.044	0.030
	(0.006)	(0.008)	(0.011)	(0.017)	(0.022)
marriage	0.001	0.004	0.007	0.003	0.001
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
D × age_centered	0.009	0.013	-0.015	0.128	
	(0.004)	(0.009)	(0.027)	(0.092)	
D × I(age_centered^2)	0.000	0.000	-0.005		
	(0.000)	(0.001)	(0.005)		
Num.Obs.	26631	18522	10380	4826	2912
R2	0.029	0.016	0.008	0.005	0.004
R2 Adj.	0.028	0.016	0.007	0.004	0.003
AIC	33191.5	23375.7	13228.5	6147.6	3706.9
BIC	33265.2	23446.1	13293.7	6199.4	3742.8
Log.Lik.	-16586.758	-11678.850	-6605.252	-3065.798	-1847.468
F	111.988	43.173	11.639	4.181	2.922

Note: The brackets below the coefficients indicate the standard error.

Table 5: Parametric estimation for Male Group with Hypertension Condition as dependent variable

High Blood Sugar	**Full data**	**Bandwidth = 10**	**Bandwidth = 5**	**Bandwidth = 2**	**Bandwidth = 1**
(Intercept)	0.021	0.013	0.020	-0.025	-0.004
	(0.009)	(0.012)	(0.021)	(0.030)	(0.021)
D	0.018	0.014	-0.004	0.027	0.001
	(0.009)	(0.012)	(0.021)	(0.027)	(0.021)
age_centered	-0.001	-0.005	0.015	-0.024	0.010
	(0.002)	(0.004)	(0.015)	(0.033)	(0.012)
I(age_centered^2)	0.000	-0.001	0.003	-0.007	
	(0.000)	(0.000)	(0.002)	(0.010)	
education	0.046	0.045	0.057	0.071	0.073
	(0.004)	(0.005)	(0.007)	(0.010)	(0.013)
marriage	-0.003	-0.002	-0.002	-0.004	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
D × age_centered	0.003	0.014	-0.010	0.041	
	(0.002)	(0.005)	(0.016)	(0.053)	
D × I(age_centered^2)	0.000	0.000	-0.003		
	(0.000)	(0.001)	(0.003)		
Num.Obs.	26631	18522	10380	4826	2912
R2	0.010	0.007	0.009	0.013	0.012
R2 Adj.	0.010	0.007	0.008	0.011	0.011
AIC	4974.5	4274.3	2534.8	882.6	538.0
BIC	5048.3	4344.7	2600.0	934.4	573.9
Log.Lik.	-2478.272	-2128.143	-1258.395	-433.287	-262.998
F	40.312	18.816	12.867	10.307	8.961

Note: The brackets below the coefficients indicate the standard error.

Table 6: Parametric estimation for Male Group with High Blood Sugar Condition as dependent variable

Mental Health	**Full data**	**Bandwidth = 10**	**Bandwidth = 5**	**Bandwidth = 2**	**Bandwidth = 1**
(Intercept)	2.241	2.184	2.249	2.218	2.164
	(0.044)	(0.054)	(0.080)	(0.121)	(0.085)
D	0.017	0.004	-0.080	-0.031	-0.010
	(0.041)	(0.052)	(0.078)	(0.105)	(0.080)
age_centered	0.013	0.006	0.080	0.043	0.012
	(0.015)	(0.024)	(0.057)	(0.133)	(0.047)
I(age_centered^2)	0.000	-0.001	0.013	0.011	
	(0.001)	(0.003)	(0.010)	(0.042)	
education	-0.267	-0.251	-0.251	-0.262	-0.233
	(0.022)	(0.025)	(0.029)	(0.042)	(0.053)
marriage	0.029	0.052	0.060	0.060	0.061
	(0.003)	(0.006)	(0.008)	(0.011)	(0.015)
D × age_centered	-0.004	0.015	-0.047	-0.041	
	(0.015)	(0.026)	(0.063)	(0.213)	
D × I(age_centered^2)	-0.001	-0.001	-0.017		
	(0.001)	(0.003)	(0.011)		
Num.Obs.	29960	17073	10963	5438	3252
R2	0.010	0.013	0.014	0.013	0.012
R2 Adj.	0.009	0.013	0.013	0.012	0.010
AIC	91566.3	51484.0	32902.5	16320.2	9745.1
BIC	91641.1	51553.8	32968.2	16373.0	9781.6
Log.Lik.	-45774.171	-25733.022	-16442.255	-8152.086	-4866.546
F	41.912	32.417	21.660	11.782	9.576

Note: The brackets below the coefficients indicate the standard error.

Table 7: Parametric estimation for Non-Government Female Group with Mental Health Condition as dependent variable

Self-reported Health	**Full data**	**Bandwidth = 10**	**Bandwidth = 5**	**Bandwidth = 2**	**Bandwidth = 1**
(Intercept)	3.151	3.150	3.123	3.181	3.156
	(0.038)	(0.047)	(0.070)	(0.107)	(0.076)
D	0.050	0.064	0.099	0.056	0.127
	(0.035)	(0.045)	(0.068)	(0.092)	(0.071)
age_centered	0.008	-0.008	-0.037	0.081	-0.032
	(0.013)	(0.020)	(0.049)	(0.117)	(0.042)
I(age_centered^2)	0.000	-0.002	-0.009	0.041	
	(0.001)	(0.002)	(0.008)	(0.037)	
education	-0.230	-0.255	-0.254	-0.251	-0.283
	(0.018)	(0.022)	(0.025)	(0.037)	(0.047)
marriage	0.007	0.012	0.012	0.010	0.002
	(0.003)	(0.005)	(0.007)	(0.010)	(0.013)
D × age_centered	0.008	0.030	0.046	-0.153	
	(0.013)	(0.023)	(0.055)	(0.189)	
D × I(age_centered^2)	0.000	0.001	0.010		
	(0.001)	(0.002)	(0.010)		
Num.Obs.	29960	17073	10963	5438	3252
R2	0.018	0.016	0.014	0.010	0.013
R2 Adj.	0.017	0.016	0.013	0.009	0.012
AIC	81943.3	46594.9	29919.6	14981.3	8976.8
BIC	82018.0	46664.6	29985.4	15034.1	9013.3
Log.Lik.	-40962.635	-23288.446	-14950.821	-7482.632	-4482.407
F	76.728	40.553	21.464	9.541	10.708

Note: The brackets below the coefficients indicate the standard error.

Table 8: Parametric estimation for Non-Government Female Group with Self-reported Health Condition as dependent variable

Hypertension	**Full data**	**Bandwidth = 10**	**Bandwidth = 5**	**Bandwidth = 2**	**Bandwidth = 1**
(Intercept)	0.174	0.199	0.202	0.241	0.191
	(0.018)	(0.021)	(0.030)	(0.045)	(0.032)
D	-0.001	0.009	0.016	-0.025	0.035
	(0.017)	(0.020)	(0.029)	(0.039)	(0.030)
age_centered	0.013	0.019	0.015	0.082	-0.002
	(0.006)	(0.009)	(0.021)	(0.050)	(0.018)
I(age_centered^2)	0.000	0.001	0.001	0.024	
	(0.000)	(0.001)	(0.004)	(0.016)	
education	0.021	0.012	0.004	0.011	0.001
	(0.009)	(0.010)	(0.011)	(0.016)	(0.020)
marriage	0.002	-0.002	-0.002	-0.006	-0.004
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
D × age_centered	0.004	-0.006	-0.009	-0.108	
	(0.006)	(0.010)	(0.024)	(0.080)	
D × I(age_centered^2)	-0.001	-0.001	0.001		
	(0.000)	(0.001)	(0.004)		
Num.Obs.	29960	17073	10963	5438	3252
R2	0.058	0.020	0.013	0.006	0.002
R2 Adj.	0.058	0.020	0.012	0.005	0.000
AIC	37458.2	18771.5	11417.0	5690.1	3369.5
BIC	37532.9	18841.2	11482.7	5742.9	3406.1
Log.Lik.	-18720.079	-9376.770	-5699.482	-2837.053	-1678.767
F	262.228	50.300	20.508	5.227	1.268

Note: The brackets below the coefficients indicate the standard error.

Table 9: Parametric estimation for Non-Government Female Group with Hypertension Condition as dependent variable

High Blood Sugar	**Full data**	**Bandwidth = 10**	**Bandwidth = 5**	**Bandwidth = 2**	**Bandwidth = 1**
(Intercept)	0.057	0.078	0.096	0.083	0.127
	(0.012)	(0.013)	(0.019)	(0.027)	(0.020)
D	-0.003	0.002	-0.010	-0.006	-0.031
	(0.011)	(0.013)	(0.018)	(0.024)	(0.019)
age_centered	0.008	0.005	0.011	-0.014	0.024
	(0.004)	(0.006)	(0.013)	(0.030)	(0.011)
I(age_centered^2)	0.000	0.000	0.001	-0.012	
	(0.000)	(0.001)	(0.002)	(0.009)	
education	0.012	-0.012	-0.021	-0.020	-0.035
	(0.006)	(0.006)	(0.007)	(0.009)	(0.012)
marriage	-0.001	-0.001	-0.001	0.001	0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
D × age_centered	-0.001	0.004	0.002	0.050	
	(0.004)	(0.006)	(0.015)	(0.048)	
D × I(age_centered^2)	0.000	0.000	-0.002		
	(0.000)	(0.001)	(0.003)		
Num.Obs.	29960	17073	10963	5438	3252
R2	0.012	0.009	0.008	0.004	0.004
R2 Adj.	0.012	0.009	0.007	0.003	0.003
AIC	11818.3	3088.7	995.2	130.2	213.4
BIC	11893.1	3158.4	1060.9	183.1	249.9
Log.Lik.	-5900.148	-1535.362	-488.608	-57.121	-100.684
F	51.484	22.811	12.464	4.032	3.284

Note: The brackets below the coefficients indicate the standard error.

Table 10: Parametric estimation for Non-Government Female Group with High Blood Sugar Condition as dependent variable

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