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Master Thesis[1]

Prevention is Better than Cure: Old-Age Pension and Healthcare Utilization in India

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August 10, 2024

A thesis submitted in fulfilment of the requirements for the degree of Master of Science in Policy Economics.

[1] The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

Abstract

This thesis investigates the impact of the Indira Gandhi National Old Age Pension Scheme(IGNOAPS) on the health of the poor elderly in India. Using a Fuzzy Regression Discontinuity Design on data from the Indian Human Development Survey-II(IHDS-II), I analyse whether there are visible health improvements for pension recipients. The study exploits the quasi-experimental design created by the cutoff threshold of at least sixty years of age to be eligible for the pension. I find that recipients of the pension tend to see short-term health improvements. Pension recipients are 12.3 percentage points more likely to seek treatment for short-term causes. Additionally, they observed INR 237 lesser short-term health costs compared to non-beneficiaries. The results suggest that it is imperative to take into account the spending behaviour of the elderly and analyse if the pension is covering gaps in other policies. These findings contribute to the literature by empirically analysing the positive influence of pension on health outcomes, especially for those from the economically deprived sections of society

Contents

1 Introduction

Throughout the world, pension programmes play a crucial role in ensuring the economic stability of the elderly in the country. They provide additional disposable income to individuals in addition to their savings. This money can be used in any way the individual deems fit, but given that the elderly are often highly conscious about their health expenditure, a certain portion of the pension does go towards health (S. K. Mohanty, Chauhan, Mazumdar & Srivastava, 2014). This expenditure towards better health might be direct(purchasing medicines, doctor appointments, surgeries etc.) or indirect(better quality food, frequent physical activity, good housing conditions etc.). Pensions play a serious role in mitigating some of the pressure created financially by increased medical spending for the elderly.

Generally, pensions are contributory, but in a poverty-stricken country like India, some of the government's elderly pension policies are non-contributory. Given the country's large population, a small percentage of the elderly still amounts to a significant number. As India is relatively a young country in terms of demographics, the needs of the elderly can often be sidelined by various policies. Policies that are usually discussed in public forums and government manifestos focus on the troubles of the younger side of the population (Brosius & Mandoki, 2020). While that makes sense from the government's perspective given India's skewed demographic structure, it is also important to update and develop policies that look after the elderly, especially those in poverty and economically dire situations. If not well taken care of in terms of health, the elderly can later on also prove to be a strain on the already weak healthcare infrastructure of India (UNFPA India, 2023).

One such policy is the IGNOAPS, which provides a fixed monthly amount to elderly people who are officially below the poverty benchmark set up by the Indian government. It was introduced in 2007 to financially support elders who do not have any other means to support themselves. A program such as this enables the elderly to spend more money on their necessities and keep a frequent check on their health troubles. Especially for the deprived, every cash transfer can act as a significant step towards healthier lifestyle choices. Hence, IGNOAPS can play a crucial role in an elderly's life despite the monthly amount being pretty small compared to different policies.

Existing literature on pensions mainly looks at the impact of the policy on working incentives. They analyse how the labour supply has changed with changes in pension programmes. Some of them might look at the expenditure behaviour of the recipients, but very few papers observe the direct impact of a pension on the elders' health outcomes. Even if the papers do look at health outcomes, most of them focus on the elderly who were economically well-off and had private savings. While ideally, pension should better health outcomes, if not keep it unchanged, it is imperative to look at what exact factors are affected by it and what are the mechanisms behind these changes. Even research on IGNOAPS to date has mostly looked at the expenditure patterns of the recipients in terms of necessities and non-necessities. Hence, the paper seeks to understand if this pension leads to the betterment of the health of eligible individuals and what mechanisms can explain the said change. Therefore, the main question this paper attempts to answer is: Can pension schemes targeted towards the poor elderly have a positive influence on their health outcomes?

Beyond the main research question, the paper will also take a look at how the influence of the pension varies with different demographic categories such as gender, education etc. To answer this question, I will use the IHDS-II survey dataset and employ a Fuzzy Regression Discontinuity Design. The paper uses Fuzzy instead of a Sharp RDD because the pension policy has a lot of never-takers i.e. people eligible for the pension do not opt to enrol in it. The baseline results show that after receiving the pension, the elderly are 12.3 percentage points more likely to visit the doctor for short-term health concerns and 34.3 percentage points less likely for major morbidity concerns. However, the individuals who receive the pension also observe a significant fall in their short-term health costs such as medicines, health tests, etc. Given that I have three health parameters for the main model, the results do have discernible heterogeneity. The treatment effect of the pension program varies by religion, caste, gender and to a lesser extent, by literacy.

The paper is divided as follows: In Section 2, I will discuss the pension programme in detail. Section 3 will consist of a review of the prior research in the field of pension, elderly health and IGNOAPS. In section 4, I will discuss the nature of the survey dataset and more importantly, talk about the age-heaping issue prevalent in the sample selected from the survey data. Beyond this in section 5, the paper analyses the background behind RDDs and why Fuzzy RDD is the main model in the paper. In this section, the paper will also talk about the main assumptions behind the model and the local linear model that this study uses as the main specification. Section 6 is the most thorough as here I present the treatment estimates and discuss the results. I provide discussion for both homogeneous and heterogeneous treatment estimates. After this, I do additional robustness checks to analyse the sensitivity of the model to different settings. In section 7, the paper is concluded.

2 Indira Gandhi National Old Age Pension Scheme

IGNOAPS is one of the schemes under the National Social Assistance Programme (NSAP). NSAP is a set of schemes targeted towards the elderly, widows, and persons with disabilities who are below the poverty line. The Central Government of India funds the NSAP with mandatory support from the State Government. All the policies under NSAP are non-contributory, meaning the individuals eligible for it do not make any contribution towards it. Besides IGNOAPS, the NSAP has four other programs. They are the Indira Gandhi National Widow Pension Scheme (IGNWPS), Indira Gandhi National Disability Pension Scheme (IGNDPS), National Family Benefit Scheme (NFBS), and Annapurna Scheme. While some states match the amount from the Central government towards the benefits, other states often give much larger monetary support (Hindustan Times, 2017). This varies from state to state and also depends on alternative schemes of similar nature that might exist within a state. Hence there is considerable heterogeneity in the amount an individual can receive depending on their residency.

Coming back to IGNOAPS, there are two main requirements to be eligible for this policy. The first is that the person should be at least sixty years of age. The second condition is that the individual must be below the poverty line, which is the condition for all NSAPs. However, in India, the poverty line varies from state to state and region to region to account for differences in the cost of living. In addition to this, the poverty line is often considered to be very outdated and inadequate (Alkire & Seth, 2013). Hence, it seems that poverty line eligibility criteria might not be an effective one. But, despite the issues, this threshold is still used while targeting beneficiaries, so it cannot be overlooked.

The elderly receive a monthly pension of at least INR 300 (3.64 USD). Those above the age of 79, receive at least INR 500 (6.06 USD) a month. This amount is much lower than the World Bank's definition of poverty, where an individual earning less than 2.15 USD[2] a day is considered to be poor. As mentioned previously, the final amount can vary from region to region. However, this is the government-mandated minimum amount that the elderly must receive. Individuals receiving this pension can also be beneficiaries of other schemes depending upon their demographic status and state residence.

3 Literature Review

Unnikrishnan and Imai (2020)'s difference-in-difference analysis of IGNOAPS shows the importance of this scheme for the elderly in India. While the authors did not focus on healthcare outcomes specifically, their results showed that increased participation in this scheme led to more consumption of food and non-food goods and increased household assets. Most of this expenditure rise was focused on essential commodities. A similar study by Kaushal (2014) showed that the elderly under IGNOAPS and the National Pension Scheme in India had most of their expenditure towards their health and next of kin's education. The study looked at health outcomes through the lens of a change in household expenditures. Hence, Unnikrishnan and Imai (2020); Kaushal (2014) are crucial to my empirical research

[2]This value comes from the World Bank estimations at 2017 rates of the USD and inclusive of purchasing power parity.

as they show that IGNOAPS has played a significant role in increasing expenditure towards necessities such as health, necessity consumption, and education.

However, without downplaying its importance, it is essential to understand the major drawbacks of the pension policy. Kohli, Gupta, Banerjee and Ingle (2017)'s study of a small elderly care hospital in Delhi concluded that barely half of the people eligible for the policy opted for it. They mention administrative complications and a lack of general awareness behind the lack of policy take-up. A community-based survey in Uttarakhand gave similar results, elders were not well aware of the benefits and schemes available to them. Even if they were aware, they were choosing not to enrol in them (Bartwal, Rawat & Awasthi, 2016). This does not seem to be a state-specific issue as even Goswami et al. (2019)'s community-based survey in Delhi gave the same results. IGNOAPS also has problems that most welfare programs in India do, which is the issue of targeting people who need it while ensuring it does not go to the individuals who are not eligible for it (Narayana, 2019). Two aspects of the policy become clear from these papers, the first being that in its outcome, the policy is definitely welfare improving for the poor elders. The other aspect is the take-up issue of the policy. Surveys and primary research have outlined that elders are not always aware of the schemes they are eligible for, and even if they are aware, very few of them choose to apply for these schemes.

Now the paper takes a look at studies in other countries and the role of their old age programs on health outcomes.

A Regression Discontinuity Design study linking pension recipients with health outcomes in China observed that an increase in pension coverage and amount led to better health outcomes for the elderly in rural regions as it allowed them to spend more on over-the-counter drugs (Yan et al., 2023). This paper also concluded that amongst the bottom quartile income earners, this pension led to an increase in healthcare utilization. As my research will be focused on the elderly below the poverty line, it is important to know what mechanisms can improve or worsen health outcomes. Pega et al. (2022)'s meta-analysis also gives insight into understanding that unconditional cash transfers such as pensions, might be more effective than standard health insurance for specific health measurements. However, the authors were unsure about the effects of such transfers on direct healthcare utilization. Yang and Chang (2023)'s study on pension programs specifically made for Taiwanese farmers showed that both healthcare expenditure and outpatient visits increased for farmers after the program was implemented. In addition, expenditure on medicines was also observed to have increased post-pension. Most of these studies such as Yan et al. (2023); Yang and Chang (2023); Ma, Li, Sun and others (2021) exploit a variation in the eligibility of an existing pension scheme to establish the causal impact of pension income on different health parameters. Jensen and Richter (2004)'s work on paused payments in the Russian pension system also revealed the link between pension payments and healthcare outcomes. When pension was paused, people used healthcare services less and started consuming less nutritious meals due to a fall in disposable income. The paper also establishes that people who were in a state to work again dealt with this disruption better, especially compared to people who were poverty-stricken or could not work due to their physical limitations. This conclusion helps emphasize the importance of pension schemes for those who cannot afford to work again. Aguila, Kapteyn and Smith (2015)'s study on old-age pension in Mexico, also gives similar results as the prior papers. Healthcare access seemed to be accessible for people who were receiving this pension. In addition, the authors also found that health insurance usage increased for people who were part of the program. Hence, the above papers make it clear that pension - through direct and indirect mechanisms - have a positive influence on the health of their recipients.

While it's important to comprehend why the paper is examining the relationship between pension and the health of the elderly, it's equally necessary to not ignore how the timing of pension receipt —primarily during retirement — affects their health conditions at that stage of life. However, this aspect of pension seems to provide a more ambiguous relationship. Some papers show that retirement has positive effects on health mainly due to less work stress and physical exertion (Coe & Lindeboom, 2008; Bloemen, Hochguertel & Zweerink, 2017). On the other hand, certain studies show that retirement can worsen health outcomes and even burden the healthcare system of a country with higher health expenditure by the health-anxious elderly (Dave, Rashad & Spasojević, 2008; Behncke, 2011). So while the effect of retirement on health is hard to pinpoint, it is mainly because of the heterogeneity involved in its effects and also the differences in health indicators employed by authors (Eibich, 2015). Hence, in some papers, retirement can positively impact health outcomes, but in some, it can worsen them.

This paper has a twofold contribution to the literature. The first is that it looks at the impact of IGNOAPS on the direct health utilization parameters such as major and short-term morbidity conditions. This is different from the existing studies, which have mostly focused on expenditures related to education and consumption. The second contribution is the nature of the pension recipients. In this study, the pension recipients are elderly who are classified as being below the Indian poverty threshold. As prior research focused on pensioners as a whole, it is crucial to observe how this scheme supports elders who are poverty-stricken.

4 Data

4.1 Dataset

The dataset used in the study here is the India Human Development Survey II (IHDS-II)[3]. It is a nationally representative household survey conducted by researchers from the University of Maryland, the National Council of Applied Economic Research (NCAER), Indiana University, and the University of Michigan. It consists of data on health, education, employment, gender relations, village infrastructure, and more. 42,152 households were interviewed for this survey throughout 2011-12. More than forty-thousand of these households were the ones that were interviewed previously during IHDS-I in 2004-05. Hence this is a highly comprehensive database consisting of 14 different datasets (Desai et al., 2008). The fourteen datasets are the following: Individual, Household, Eligible Women, Birth History, Medical Staff, Medical Facilities, Non-Resident, School Staff, School Facilities, Wage and Salary, Tracking, Village, Village Panchayat and Village Respondent. Within these, my main focus is only on the individual and the household datasets. The household dataset is used mainly to observe the poverty status of households. The individual one is used to analyze the health outcomes of the interested demographic. Data in the analysis is cross-sectional because the focus is only on IHDS-II instead of merging it with IHDS-I and developing a panel structure.

4.2 Sample selection

As I am mainly interested in looking at individuals and their health outcomes, individual and household datasets are merged using household and personal identifiers. As mentioned before, two requirements exist to be eligible for IGNOAPS. Hence, the data will only include individuals whose households have been classified as being below the poverty line. In other words, if a household is classified as poor, all individuals in that household are given a Below Poverty Line (BPL) status. This sample selection is done to ensure that **variation in age** is the only factor determining IGNOAPS eligibility in the model. This leads to the final dataset having 69,612 individuals and over a thousand variables. However, the final count of individuals will be much smaller as the main focus will be people between the ages of 54 to 65 depending upon the requirement of the empirical analysis. Depending on the bandwidth of ages taken while estimation, this sample will change further in different specifications.

[3]IHDS II data files are publicly available at Data Sharing for Demographic Research program of ICPSR, the Inter-university Consortium for Political and Social Research.

Table 1: Descriptive Statistics for 5-Year Bandwidth

Variables	No. of Observations	Mean	SD	MIN	MAX
Health Outcome:					
Short-term morbidity treatment received	4044	0.18	0.39	0.00	1.00
Short-term morbidity health costs	4044	75.03	418.03	0.00	9000.00
Major Morbidity: Received treatment in the past year	4044	0.25	0.43	0.00	1.00
Covariates:					
Religion	4044	0.83	0.38	0.00	1.00
Assets	4043	13.38	5.82	1.00	31.00
Education	4035	2.43	3.64	0.00	16.00
Caste	4044	0.18	0.39	0.00	1.00
Benefits from other programs	4044	646.14	3278.85	0.00	80000.00
Annual household income	3260	67659.12	74020.86	240.00	852000.00

4.3 Age Heaping

Individuals across age groups exhibit a certain distribution. The individuals are concentrated in specific age groups. These ages are the ones that end in 0s or 5s. In brief, there is severe age heaping in the survey data. To verify this heaping, a density graph is presented below.

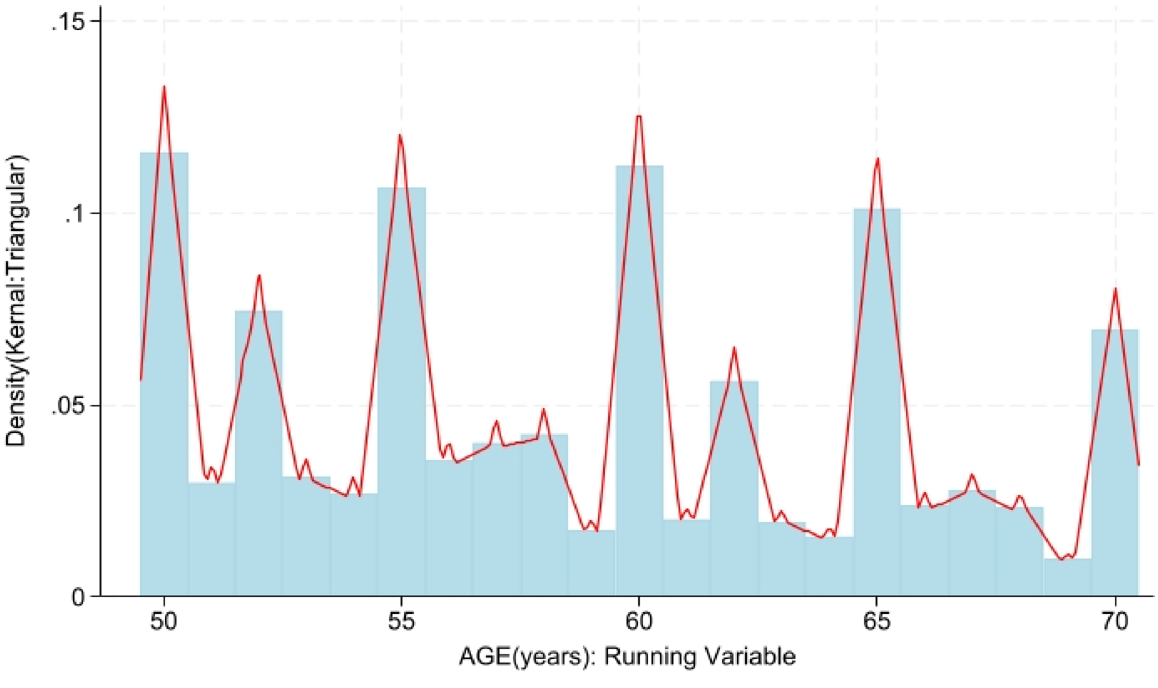


Figure 1: Graph showing heaping in the data

Note: This figure presents a histogram of the age values. Overlaid on the histogram is a discrete kernel density estimate (KDE) using a triangular kernel, displayed in red. The KDE provides a smoothed representation of the data distribution. The triangular kernel, used in this KDE, is used for assigning weights to data points linearly decreasing with distance from the point of estimation, resulting in a triangular shape that smooths the density estimate.

With this histogram density plot, it becomes clear that there is a concentration of individuals in ages that end in 0 or 5. There is a spike in the line plot at 50, 55, 60, 65, and so on. This concentration of individuals in this age category is not uncommon with survey datasets, especially with self-reported ages (Biemer, 1985). In addition, survey datasets from developing nations suffer from this data heaping more frequently than datasets from developed regions (Biemer, 1985).

To further verify this distribution of the data, Whipple's index is used[4]. This index is mainly used to look at whether there is age heaping across multiples of 5. A score above 125 means a problematic dataset (Shryock, 2013). For the age range of 50 to 70 years, the sample of this study has an index score of 252.71. This implies there is severe heaping across these ages.

Pardeshi (2010)'s study on a state in India to check for heaping in self-reported ages yielded similar results. The author found that people, especially the ones who were poor, often gave ages that ended with 0 or 5. People from deprived backgrounds do not often know their ages very well, so they tend to round off their ages to the most "well-rounded" numbers. Additionally, the author finds that, during survey rounds, if the specific individual is absent from the household, often their neighbours or family members are asked about them. These proxy respondents do not often know the exact age and hence provide their best guess.

Mis-reporting of age and age-related variables has often plagued survey datasets in different countries. China and Sub-Saharan Africa, to varying degrees, have reported mismeasurement in the ages of a certain percentage of people in their regions (Coale & Li, 1991; Lyons-Amos & Stones, 2017). Ideally, the solution would be to cross-check and verify respondents' claims in surveys with their official birth documentation.

However, poor people in India often do not get their or their children's birth registered. Given that every individual is below the poverty line in the dataset, it is not far-fetched to think that a significant percentage of them would not have exact documentation to verify their age claims. I. Mohanty and Gebremedhin (2018)'s study showed that economic stability, especially on the maternal side, is a significant determinant of birth registration in India. Unfortunately, even birth registration cannot suffice, as Pardeshi (2010) showed in her survey that about one-third of the individuals in her sample who claimed to be registered did not have any evidence to back this up.

Hence, this shows that heaping does exist in this data and is not a rare occurrence when focusing on individuals from deprived sections of society. While it does not mean that every individual whose ages end in 5 or 0 is not credible, it does show that in a country like India, even well-developed and comprehensive datasets, suffer from old fundamental problems of age mismeasurement in their surveys.

[4]The exact formula and calculation procedure for this index is in appendix A.3.

5 Empirical strategy

5.1 The model: Regression Discontinuity Design

The main aim of this paper is to analyze whether pension schemes can affect the health outcomes of the elderly. As the other eligibility criteria besides being below the poverty line are being above the age of 59, the paper will exploit this cutoff to study the impact of IGNOAPS. The paper seeks to understand if there is a clear causal link between the receipt of the pension and health outcomes. To test this, a Regression Discontinuity Design (RDD) is set up. RDDs exploit precise knowledge of rules determining treatment assignment. RDD observes "jump" across arbitrary or specific cutoffs (Angrist & Pischke, 2009). These cutoffs occur in a specific value of a variable called the running variable or assignment variable. Usually, if a person is above the cutoff, they are considered to be treated. Hence, the running variable determines if a person falls on the treated or the untreated side of the cutoff threshold. In brief, if a person is treated for no other reason than falling on either side of the cutoff, then a discontinuous jump in the outcome of an individual can be considered as treatment effect (Lee & Lemieux, 2010)

Two types of RDD are mostly commonly used (Angrist & Pischke, 2009):

- Sharp RDD: This model is used when the treatment assignment is determined discontinuously by the running variable. To give a small example, individual i receiving treatment, $D_i = 1$, is defined as:

$$D_i = \begin{cases} 1 & \text{if Age}_i \geq 60 \\ 0 & \text{if Age}_i < 60 \end{cases}$$

  where 60 is the cutoff age. The treatment is switched on when a person hits the age of 60.

- Fuzzy RDD: Where the sharp RDD model exploits discontinuity in outcome variables before and after treatment, Fuzzy RDD uses discontinuity in the probability of receiving treatment. So in this model, the discontinuity acts as an IV for treatment status instead of directly switching on or off the treatment. Let's take a look at the example of the discontinuity in the probability of receiving treatment: The probability of individual i receiving treatment, $P(D_i = 1|Age_i)$, is defined as:

$$P(D_i = 1|Age_i) = \begin{cases} g_1(Age_i) & \text{if Age}_i \geq 60 \\ g_0(Age_i) & \text{Age}_i < 60 \end{cases}$$

  where Age_0 is the cutoff age (60 in this case), and $g_1(Age_0) \neq g_0(Age_0)$. Assume $g_1(Age_0) > g_0(Age_0)$, indicating that individuals above the cutoff age are more likely to receive treatment.

A fuzzy RDD is used over a sharp one when the treatment has imperfect compliance. This is because IV can help in estimating the treatment effect despite a compliance issue (Imbens & Angrist, 1994). Compliance issue in this context means that people who should receive the treatment are not always the ones receiving it. When treatment is offered, there can be four possible groups of individuals (Imbens & Angrist, 1994):

- Always-takers: Irrespective of being offered the treatment or meeting its eligibility, these groups of people always receive the treatment.
- Never-takers: Unlike the always-takers, never-takers avoid treatment even if they meet the requirements or are eligible for it.
- Defier: Defiers are a group of individuals who will be in the control group if they are supposed to be in the treatment group and vice-versa.
- Compliers: Compliers are the individuals who only take the treatment when they are eligible for it.

Hence, when there is a severe compliance issue, it is beneficial to exploit the discontinuity in the probability of receiving treatment instead of a Sharp RDD (Angrist & Pischke, 2009).

Now focusing back on IGNOAPS, this scheme has a compliance problem, although one-sided. The scheme has a lot of never-takers. In the dataset, 7513 individuals are eligible for the scheme, however, only 2773 receive this benefit. That means that the compliance rate is very low at 37 per cent. This low compliance implies that out of 7513 poor elders who can benefit from the pension scheme, less than half of them do. Hence, for my analysis, a Fuzzy RDD model will be employed. The number of people who receive the treatment will be less than the number of eligible people as the pension scheme has one-sided non-compliance due to the never-takers.

RDD estimates calculate the Local Average Treatment Effect (LATE). This is because the treatment effect is observed by looking at the differences in outcomes for units close to either side of the threshold. The number of units chosen on either side of the threshold is determined by the optimal bandwidth of the discontinuity design. As per Imbens and Kalyanaraman (2012) there is a variance-bias trade-off in determining the optimal bandwidth. If only units close to the threshold are considered while estimating the treatment effect then the estimate has high variance and low bias. Vice-versa, the more units are considered for estimations (larger bandwidth), the variance of the treatment effect is low but the bias is high. Therefore, the number of units involved while calculating the LATE is highly important.

ATE is estimated when you can compare the entire treatment and the control group. However given that RDD focuses on a specific subset of individuals within both the treated and the control group, the design estimates LATE. In the case of the Fuzzy RDD model, LATE will be estimated for the compliers.

When running a reduced form regression, which is the impact of being eligible for treatment on the outcome variable, it won't be estimating the treatment effect.

Rather, this will be the Intention to Treat (ITT) effect as shown in Ludwig and Miller (2007)'s study using a reduced form design[5]. Given that Fuzzy RDD is IV estimation, two-stage least squares (2SLS) will be used to estimate the RDD model. The first stage will involve regressing the treatment variable on the instrumental variable. The first stage will show the probability of receiving treatment given that an individual is eligible. In the second stage, the estimated treatment variable will be used as a regressor and health outcome as the dependent variable. This will give the treatment effect of the pension, more specifically, LATE for compliers. Before going into detailed estimation techniques, it is important to ensure that the identification strategy for the model is robust. For this, it is needed to ensure that the individuals before and after the threshold mimic a randomized experiment. As per Lee and Lemieux (2010), the two main assumptions required for any discontinuity design to have a valid identification are:

- **Imprecise Control over Assignment Variable**: The individual must not have precise control over the running variable. Because if they can control this, then they can self-select in and out of treatment. People can determine whether they want the treatment or not and opt in and out of it depending on its nature. This will cause selection bias to creep into the estimates. Hence, to ensure a truly randomized nature of the experiment, it is important that the people themselves cannot determine on which side of the cut-off threshold they will fall. In the next sub-section, this assumption will be discussed in more detail.
- **Continuity of baselines covariates**: To establish a causal link of a treatment, it is important that the treatment and control group are highly similar and the only difference is the treatment received by the treatment group. Hence, it is assumed that if observed baseline traits of both the treatment and the control group are similar at the cut-off, then the unobserved covariates are similar too. In other words, to ensure that the treatment estimates are causal, no other variable must have a jump across the threshold besides the outcome variable. If other covariates have a discontinuity across the threshold, that would bias the treatment estimates. This is because the estimate that is considered a direct effect of the pension scheme might have been caused by another covariate or control.

[5]Appendix A.7

5.1.1 RD Manipulation test

If individuals can manipulate the running variable, then they will be able to self-select in and out of treatment as per their benefit. This can cause problems with identification in a discontinuity design. Individuals must have imprecise control over their running variable to identify causal effects (McCrary, 2008). A more recent development in the density test has been Cattaneo, Jansson and Ma (2018)'s nonparametric density estimator based on local polynomial techniques. Similar to McCrary (2008)'s density test, this estimator also checks if there is bunching across the threshold of the discontinuity design.

In my study, as age is a running variable, ideally one would not expect any sort of bunching. People cannot control their age precisely. Those who are above 59 will be eligible for treatment and those below 60 won't be. To verify this assumption, Cattaneo et al. (2018)'s density test is used. The null hypothesis of the density test is that density is continuous across the threshold i.e. there is no self-selection or sorting[6].

The p-value of the test is 0.000 ($p<0.05$). It means the null hypothesis of no sorting is rejected. Statistically, this indicates self-selection and manipulation of the running variable. But given that age is the running variable, manipulation should not be possible. To check if the null hypothesis is rejected only at the cutoff age of 60 or at other nearby ages, I run the same density checks but for different age groups. In Appendix A.1, it can be observed that for age groups before and after the cutoff, the test is failing. This implies that at every age, there is bunching or self-selection. With the placebo density check, the concerns of real self-selection are reduced. But statistically, it is still a cause of concern as it can bias estimates.

The figure below plots the density graph using Cattaneo et al. (2018)'s density test. The discontinuity is much easier to understand graphically as there is a big surge near the cutoff point in the distribution of individuals. The two probable reasons for this statistical sorting might be: a)The age heaping in the sample or b)the discreteness of the running variable.

[6]While both the tests can be run in STATA and R, Cattaneo et al. (2018) provides a package for running the test using STATA and R.

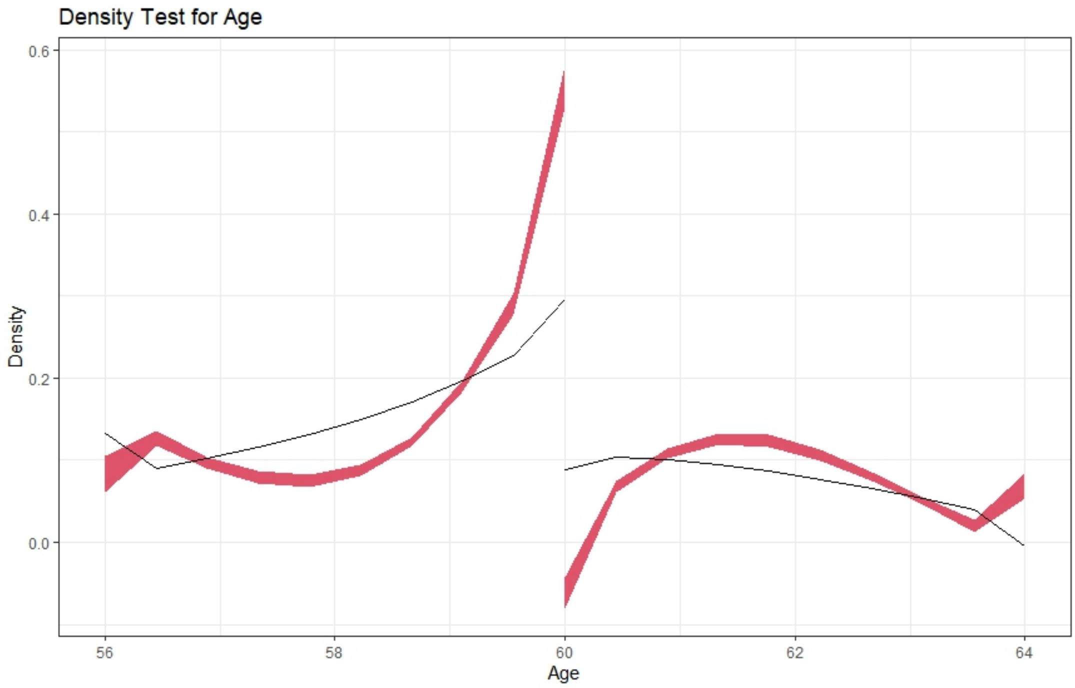


Figure 2: Density Test

Note: This density plot visualizes the distribution of the age variable. The data is divided using evenly spaced bins along the age variable, ensuring a uniform distribution of data points across the age range. The shaded regions around the density estimates represent 95% confidence intervals (significance level of 0.05), offering a visual measure of the uncertainty around these estimates.

As per Frandsen (2017), conventional tests for checking density such as McCrary (2008)'s and Cattaneo et al. (2018)[7]'s can perform poorly if the running variable is discrete. The paper states that general density checks can falsely reject the null hypothesis of no manipulation. So as a solution, Frandsen (2017) proposes an alternative test for manipulation when the forcing variable is discrete. After running the test[8], the p-value computed is very small, similar to the prior standard density check. Hence the null hypothesis of no manipulation is again rejected. Now, it is more clear now that age-heaping is causing a discontinuity in the density across the threshold.

As per Barreca, Lindo and Waddell (2016), heaping can bias estimates in an RDD estimation. However, it happens only when this heaping is non-random. Specifically, RD estimates can be biased when traits related to the outcome variable influence heaping in the assignment variables (Barreca et al., 2016). This can be a concern in this empirical set-up as the individuals who are in these heaped ages might be marginally less wealthy or well-read compared to those in other ages (I. Mohanty & Gebremedhin, 2018). Given that every individual in the sample is below the poverty line, these marginal differences should not cause large biases in

[7]This paper was a working paper when it was used as an example in Frandsen (2017).
[8]Appendix A.2

the estimates. An individual who is sure that they are fifty-four is similar in their economic status to the individual who is not sure about their age and claims to be fifty-five in this model. Hence, concerns of bias are not highly relevant in this context.

Hence, instead of discarding the entire discontinuity design due to heaping, the paper moves ahead with the aforementioned design. Donut-hole RDD will also be estimated as an additional check to account for the issue of heaping and a discrete running variable (Bartalotti, Brummet & Dieterle, 2021).

5.1.2 Balancing tests

As mentioned before, the covariates must not have a statistically significant discontinuity. This is to ensure that both the treatment and the control group are highly similar in observable characteristics and can be compared. To check for this, the second-stage regression estimates are used. Instead of using the outcome variable, it is replaced with the different covariates the study has[9]. Hence, the null hypothesis for each covariate is no significant discontinuity.

Table 2: Discontinuity test within the bandwidth of five years

Covariate	**Discontinuity**
Religion	-0.052*** (0.0106)
Assets	-0.88367* (0.519)
Education	-1.1313*** (.27686)
Caste	-0.01136 (0.0142)
Benefits from other programs	8.8028 (250.75)
Annual household income	-9548.5 (10970)

Note: Standard errors (SE) adjusted for clustering in age. Significance levels: * p< 0.1, ** p< 0.05, *** p< 0.01.

In the table above, I look at covariate discontinuity within a bandwidth of five years, which is the manually selected bandwidth. Out of the six covariates, religion and education show statistically significant discontinuity across the threshold. This means that when treatment effects are estimated, religion and education can explain some of the effects and not the pension itself.

This will bias the estimates if unaccounted for (Lee & Lemieux, 2010). Another thing the analysis makes clear is that the discontinuity is sensitive to polynomial orders and degree of bandwidth. Looking at section A.5.1 in the appendix, only the bandwidth of 5 years has similarly discontinuous covariates across both the quadratic and linear fit of the estimation. For polynomial order 1, both the bandwidth

[9]The detailed description can be found in Appendix A.4

of four and five years have similar discontinuities but when the estimation is quadratic, a bandwidth of four has more significant discontinuities. In both the fits, the bandwidth of six has the most number of covariates which are discontinuous across the threshold.

The existence of such discontinuities tends to bias treatment estimates. Cattaneo, Idrobo and Titiunik (2024)'s suggestions for dealing with discontinuities are to use a parametric form of RDD. However, given the narrow bandwidth the study employs, a parametric form may not provide reliable estimates compared to Cattaneo et al. (2024)'s local polynomial estimations.

5.2 Estimation

5.2.1 Model Specification

These are two main equations I am interested in estimating:

$$treatment_i = \beta_0 + \beta_1 eligibility_i + \beta_2 \text{Age}_i + \beta_3(\text{Age}_i \cdot eligibility_i) + \beta_4 \mathbf{X_i} + \epsilon_i \quad (1)$$

$$\text{healthoutcome}_i = \alpha_0 + \alpha_1 \hat{treated}_i + \alpha_2 \text{Age}_i + \alpha_3(\text{Age}_i \cdot eligibility_i) + \alpha_4 \mathbf{X_i} + \nu_i \quad (2)$$

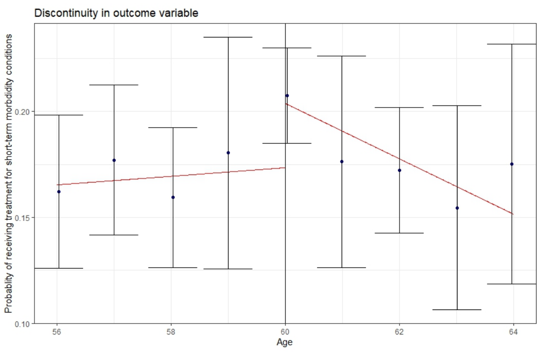
Equation 1 here is the first stage in the 2SLS estimation. $treatment_i$ is the variable which shows if the person actually receives treatment or not. In other words, it is the main treatment variable. $eligibility_i$ is the instrument which shows eligibility for the treatment. Given that the treatment has severe one-sided non-compliance, the number of people who receive the treatment is much lower than the number of people who need to receive it. $treatment_i$ is estimated in the first stage and then this estimated $treatment_i$ is used to observe LATE in the second equation, which is the second stage. Therefore, α_1 is the estimated treatment effect in this model. The model also includes the interaction term between $eligibility_i$ and Age_i, which is to account for age trends. Including the interaction term reduces the bias in the estimates that might be present due to the effect of age on the health of individuals. $\mathbf{X_i}$ is the vector of covariates in the model. Even though covariate inclusion might not help in dealing with covariate discontinuity, it reduces bias and increases the precision of estimates (Cattaneo et al., 2024)

The errors in the model here are clustered with age to account for similar traits of individuals who are the same age. The variable healthoutcome_i is the placeholder for the health outcome indicators.

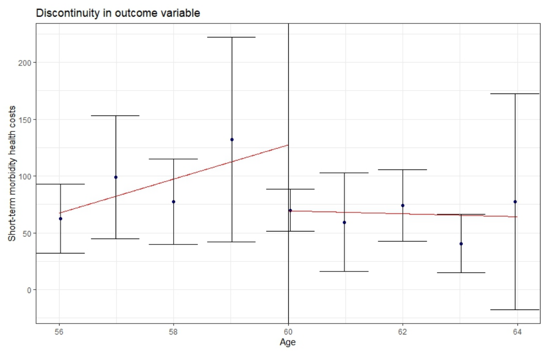
For the main results, Cattaneo et al. (2024)'s local polynomial estimators fit on both sides of the threshold. Initially, the local linear fit will be the optimal model to analyse treatment estimates. These treatment estimates will also be checked with the inclusion of covariates and interaction to observe the variation in the effects.

Hence, I estimate the equations using Cattaneo et al. (2024)'s local polynomial estimators. In this method, the estimation fits a polynomial regression locally around the defined bandwidth. This fit can be of any specific order but it will still be considered non-parametric because the linear or the quadratic fit will be locally around the bandwidth. I will employ a triangular kernel in the model. This kernel provides more weight to the observations near the cutoff and reduces the weight of the observations linearly as the distance between the data point and the cutoff increases. For this study, a linear local polynomial fit is robust and provides the main treatment estimates. Further specifications of the model will be presented in section 6.2 under robustness checks.

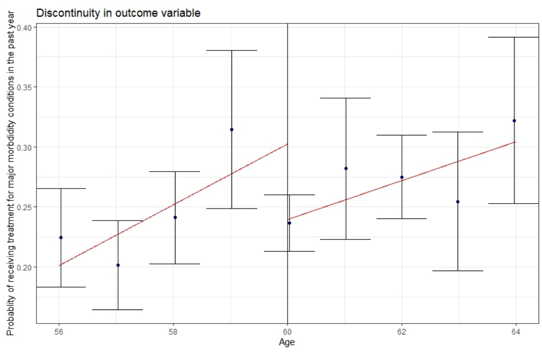
5.2.2 Discontinuity in Outcome Variable



(a) Panel A



(b) Panel B



(c) Panel C

Figure 3: Outcome across the threshold.

Note: These figures illustrate the relationship between age and the outcome variables using RDD. The plot is centred around a cutoff value of 60, with a linear polynomial fit applied on either side of this cutoff. A 95 % confidence interval is shown around the regression line to indicate the range within which the true relationship is expected to lie. The x-axis is limited to ages between 56 and 64 to highlight the region near the cutoff. Data points at the cutoff are adjusted for clarity.

The model deploys multiple outcome variables:

- Short-term morbidity treatment received (Yes-1, No-0): This is a question in the survey which asks the individuals if they have received any treatment for a short-term health concern in the past 30 days. The health concerns are mainly fever, cough, and diarrhoea.
- Short-term morbidity health costs: Individuals who did receive treatment(answered yes to the above question), were asked about the total cost of the treatment. This total cost included both in-patient and out-patient services.
- Major Morbidity: Received treatment in the past year (Yes-1, No-0): This question asks the respondent if they have received any treatment for any major morbidity condition. The options of major morbidity conditions provided were: Cataract, Tuberculosis, High Blood Pressure, Heart Disease, Diabetes, Leprsoy, Cancer, Asthma, Polio, Paralysis, Epilepsy, Mental Illness, STD/AIDS and Accidents in the past year.

I am using wide parameters of healthcare utilization to ensure that if some treatment effect is detected, how robust it is with different parameters. Especially with increasing age, health conditions worsen (Thomas, 2016). Hence, having multiple health parameters can be a useful way to get a more precise impact of the pension rather than just the effect of age itself. I also focus on the short-term health costs to analyse if there are any significant immediate effects of the pension on health decisions.

Before I start the estimation process, I want to ensure that there is a jump or discontinuity in these outcomes after the age of sixty. This jump is necessary because it provides evidence of a causal effect of the pension on health outcomes. In an RDD, the presence of a discontinuity at the cutoff allows for comparison of elderly just below and just above the threshold, who are assumed to be similar in all factors except for the treatment eligibility (Imbens & Lemieux, 2008; Lee & Lemieux, 2010; Cattaneo et al., 2024). The evidence of this jump helps to isolate the effect of the pension from other confounding factors. In short, I want to show statistically that these jumps in the outcome variable across the age of sixty, within the bandwidth, were due to the pension and not any other factor.

In Figure 3, for the selected health outcomes, there is a big jump or discontinuity after the age of 60.

6 Results and Discussion

In this section, the paper mainly discusses the results of the above-mentioned specifications. Section 6.1 will analyze the main treatment effects and the mechanisms behind them. In section 6.2, I will do various robustness checks to ensure that the treatment effects are stable across varying specifications.

As mentioned prior in section 5.1 there is a tradeoff between variance and bias while choosing the bandwidth for the LATE. Given that the forcing variable is age and the paper is observing health outcomes of the elderly, looking at broad bandwidth can cause endogeneity. As people's health worsens over age (Hoang Van Minh & Wall, 2010), taking a bigger bandwidth can cause bias in the estimates. Hence, the empirical analysis sticks with bandwidths of 4, 5 and 6 years of age on both sides of the cutoff. A narrower bandwidth of three years was not included due to the lack of sufficient observations on either side of the threshold. Further robustness checks will show that a bandwidth of 5 years provides the most consistent and robust results compared to the alternatives. For completeness's sake, the results with all three bandwidths have been included in Table 4.

6.1 Treatment Effects

Table 3: First Stage Estimates

Fuzzy RDD at Age 60	**BW 4** (1)	**BW 5** (2)	**BW 6** (3)
Probability of receiving treatment	0.255*** (0.004)	0.256*** (0.005)	0.256*** (0.005)
Effective Observations	3,466	4,044	6,380

Standard errors (SE) in parentheses. Adjusted for clustering in age.
*** p<0.01, ** p<0.05, * p<0.1

In Table 3, the estimates for the first stage are provided. This estimation was done using Equation 1 in section 5.2, however, covariates were excluded from the model[10]. If the first stage is insignificant or the effect is not strong, then it suggests that this assignment rule-being above the age of 59-is not sufficient to bring about a change in the probability of taking the treatment. In brief, if the first stage is weak, inference from treatment effect will be severely limited (Cattaneo et al., 2024).

For all the bandwidths, the first stage is highly significant[11]. They are significant at a 1 per cent level. These estimates show that a person eligible for the pension has a 26 percentage points chance of actually receiving this benefit. The first-stage estimate is highly consistent and significant across different bandwidths in the model.

[10]Even with its inclusion, the first stage stays significant.

[11]After running only the first stage regression separately, the F-value is above 20, higher than the minimum recommended amount by Cattaneo et al. (2024) for the first-stage to be strong.

6.1.1 Homogenous Treatment Estimates

Table 4: Treatment Estimates

Treatment Effect	**BW 4** (1)	**BW 5** (2)	**BW 6** (3)
Panel A: Short-term morbidity treatment received	0.123* (0.065)	0.123** (0.051)	0.113* (0.061)
Panel B: Short-term morbidity health costs	-255.2** (127.8)	-237.0** (102.5)	-177.0 (114.7)
Panel C: Major Morbidity treatment received	-0.492*** (0.0604)	-0.343** (0.136)	-0.188 (0.135)
Effective Observations	3,466	4,044	6,380

Standard errors (SE) in parentheses. Adjusted for clustering in age.
*** p<0.01, ** p<0.05, * p<0.1

Now, I look at the main treatment estimates. As mentioned, the focus will be on the bandwidth of 5 years, but all the other bandwidth results are also provided in Table 4. Results from the three parameters are provided[12] in each of the three panels in the table.

In the first panel, it is observed that people who are beneficiaries of this pension will be 12.3 percentage points more likely to have received health treatment and advice in the past thirty days compared to non-beneficiaries. This estimate is statistically significant. On the other hand, in panel B, the health costs of the treated group are on average 237 rupees lower than the control. Despite being poverty-stricken, individuals receiving the pension are on average spending less on healthcare services. In other words, this implies that people who were receiving the pension were more likely to have received treatment or advice for their needs but would spend less on these treatments. Given the statistical significance, it seems like in the short-run, the pension can improve the health conditions of the elderly. Moving on to Panel C, the probability of having gone for treatment for major health issues in the past years falls by thirty percentage points after receiving the pension.

Aguila et al. (2015)'s study of a direct cash transfer program in Mexico yielded similar results. For short-term health outcomes, the study found that the elders who received the transfer improved their food habits and visited doctors more frequently. In addition, they spend most of their cash transfer on expenditures that directly or indirectly improve their health. This is similar to Unnikrishnan and Imai (2020); Kaushal (2014)'s studies where they showed that IGNOAPS recipients spent most of their pension amount on necessities such as food and hygiene products. The fear or the idea that these funds might misused for other non-necessary purchases is highly unfounded (Aguila et al., 2015). Deprived elderly when given pensions, seem to increase their necessities expenditure. Gaarder, Glassman and Todd (2010)'s

[12]While the IHDS-II dataset had several other health parameters, such as fever, dengue, diabetes and more, the data was lacking for the individuals within the bandwidth. Given the lack of observations in an already narrow bandwidth, these health outcomes were not considered.

research shows that when individuals are poverty-stricken, they spend on other commodities only after reaching their minimum sustenance level in terms of food. This can be one of the mechanisms through which pension recipients did much better than their non-beneficiary counterparts.

However, the probability of receiving treatment for major morbidity conditions falls after the receive of pension. Ideally, treatment for health conditions should increase after a rise in disposable income (Dabla-Norris, Kochhar, Suphaphiphat, Ricka & Tsounta, 2015). Two mechanisms can explain the lack of increased utilization of healthcare services for major conditions after the pension receipt. The first mechanism is the lack of healthcare infrastructure in India. Gaarder et al. (2010) explains that cash transfers can be ineffective when there are no proper health facilities to be utilized. Selvaraj, Karan, Mao et al. (2021)'s research on government healthcare interventions in India suggested that despite attempts at improvements, a lot of the newer and developed infrastructure is out of reach for the poor and rural Indians. This might explain why there was no visible rise in the probability of receiving treatment for serious conditions. However, this mechanism fails to explain the strong decrease in using said facilities despite the higher income. The second mechanism seems to explain the results better. If an elderly individual is treated properly for their short-term health troubles and also spend their pension on necessities, they are less likely to develop long-term major morbidity ailments (Elston et al., 2019). Riumallo Herl, Kabudula, Kahn, Tollman and Canning (2022)'s longitudinal study in South Africa showed the increased likelihood of delaying age-related disabilities if the exposure to old-age pensions was long-term. Hence, the authors expect that, if the pension persists, the recipients will live a healthier life on average. This can explain the fall seen in the probability of having used healthcare services for major morbidity causes.

In brief, IGNOAPS leads to more short-term healthcare utilization but lower treatment costs. This probably indicates that the expenditure habits of the recipients enable them to live healthier lives compared to non-recipients and treatments used for their health are not expensive. This increase in healthcare utilization in the short term also leads to positive long-term effects. Individuals despite having marginally more money to spend, seem to reduce health care use for more serious conditions. Optimal spending habits and better short-term health outcomes decrease their probability of having conditions that require more intensive healthcare. Elderly on average need healthcare more than others (Abdi, Spann, Borilovic, de Witte & Hawley, 2019). In addition, the poor in India are mostly deprived of healthcare access and resources (Iyengar & Dholakia, 2012). So, for this study, especially considering the individuals are at the intersection of being extremely poor and elderly, even a small benefit in health status becomes considerable.

6.1.2 Heterogeneous Treatment Estimates

Table 5: Treatment Estimates by Demographic Categories

	Short-term Morbidity Treatment (1)	Short-term Health Costs (2)	Major Morbidity Treatment (3)	Take-up rate (%) (4)	Observations (5)
Homogeneous Effect	0.123**	-237.0**	-0.343**		
	(0.051)	(102.5)	(0.136)		
Religion					
Hindu	0.166***	-309.4***	0.260	29.04	3,346
	(0.043)	(104.5)	(0.006)		
Muslim	0.300	331.6	0.461	19.11	431
	(0.399)	(215.3)	(0.290)		
Caste					
Upper Castes: Brahmins	0.421	-2,114	-0.743	26.15	105
	(0.686)	(1,809)	(0.682)		
Upper Castes/General	0.128	-62.41	0.027	22.31	629
	(0.091)	(191.0)	(0.186)		
Other Backward Castes (OBC)	0.146***	-255.9***	-0.658***	27.83	1,735
	(0.043)	(88.1)	(0.208)		
Scheduled Castes (SC)	0.329***	132.1	-0.036	34.22	982
	(0.119)	(115.5)	(0.083)		
Education					
Non-Literate	0.223***	-100.4*	-0.148	31.11	2,513
	(0.073)	(60.9)	(0.093)		
Literate	-0.179***	-495.3	-0.696***	22.10	1,525
	(0.030)	(327.7)	(0.230)		
Gender					
Men	-0.220*	-549.8***	-0.351**	21.89	1,919
	(0.127)	(193.4)	(0.165)		
Women	0.304***	-64.48	-0.373**	33.23	2,125
	(0.027)	(52.9)	(0.152)		

Standard errors (SE) in parentheses. Adjusted for clustering in age.
*** p<0.01, ** p<0.05, * p<0.1

In Table 5, the paper looks at heterogeneous treatment effects. Up until now, the paper has mostly focused on the implications of homogeneous treatment effects. However, in a country like India, religion, caste, gender, and education can determine an individual's health (Borooah, 2010). Even "minor" castes and religions can represent millions of people (Thorat & Ahmad, 2015). Therefore, it becomes necessary to see how the effect of the pension varies from one demographic category to another. In the first row, the general homogeneous treatment effect is given to make it convenient to compare to heterogeneous effects.

- **Religion**[13]: In India, there is a wide gap between religions in terms of economic power and wages. Despite India's growth story, the gaps between Hindus and Muslims haven't reduced significantly (Bhattacharjee & Chaudhuri,

[13]Following religion categories were not included due to lack of observations around the bandwidth: **a)**Buddhist, **b)**Jain, **c)**Tribal,**d)**Others and **e)**No religion. While some estimates could be computed, the low level of observations would not warrant their inclusion. There was a tendency to over-fit the data due to the small number of observations.

2023). Christians and Sikhs are the third and fourth biggest religions in India, but in absolute numbers are still very small compared to Hindus and Muslims. For Hindus, short-term parameters are mostly in line with the general treatment effects. In the case of column 3, the pension does not seem to have a significant impact on their major morbidity health issue. For Muslims however, there does not seem to be any impact of the pension on their health outcomes. This is contrary to the general treatment effects. Compared to Hindus, the number of individuals who identify as Muslims is much lower in the bandwidth. While the direction of the effect is in line with expectations, they do not have a significant impact. Hindus, despite being more in absolute numbers have a higher take-up rate for the policy compared to Muslims. Within the selected bandwidth of five years, only 19.11 per cent of eligible Muslims take up the policy whereas almost 30 per cent of eligible Hindus benefit from it. In brief, these results suggest that Muslims seem not to benefit as positively as Hindus from the pension.

- **Caste[14]:** Despite popular notions that caste discrimination in India does not exist or exists in a very small sphere, education and health status often vary considerably by caste (Johri & Anand, 2022). However, these estimates do not suggest a major effect of the pension policy on the health outcomes of the upper castes. All the estimates are highly insignificant. OBCs and SCs seem to benefit a lot more from these pension policies compared to the upper castes. Their short-term health parameters are in line with the estimated LATE. The Upper Castes and the Brahmins generally tend to be very well off financially compared to other castes (Aslany, 2020). The sample representation from them is also small and can to a certain extent explain the insignificance of the pension on their health parameters. However, the health costs for SCs do not have a significant reduction, compared to the OBCs. This might be because on average Scheduled Castes are highly discriminated against economically and socially (Gupta & Coffey, 2020). As evidenced by Thapa, van Teijlingen, Regmi and Heaslip (2021)'s research, caste-based structural inequality increases health risks for those at the lower rungs of it. So, given the structural inequalities present, it should not be surprising that a small pension amount is not bringing about a significant reduction in health costs. Johri and Anand (2022)'s study also establishes that scheduled castes score much lower on life satisfaction and social protection compared to the other castes. On the other hand, OBCs have a much lower proportion of economically backward people compared to the SCs (Alkire & Fortacz, 2021). Hence, the pension amount is not large enough to account for structural inequalities that SCs have to face for access to healthcare. It is to be noted that while SCs have to face institutional difficulties in the country, their take-up rate for the pension

[14]The Scheduled Tribes were excluded from the caste category because of the lack of observations.

policy is much higher than others. This shows that while economically SCs might be backward, their access to this pension scheme is not hindered by this inequality.

- **Education:** Now, I take a look at how the treatment estimates vary with education. Surprisingly, the non-literate individuals seem to have a much higher take-up rate for the policy despite being larger in absolute numbers. In addition, the literate group of individuals has a reduced probability of treatment or advice for both short-term and major morbidity causes. So, the healthcare utilization for the literate gets reduced post the pension benefit. On the other hand, healthcare utilization, at least for short-term issues, increases for the non-literate. They also observe a reduction in their short-term health expenditure. DeWalt, Berkman, Sheridan, Lohr and Pignone (2004)'s systematic review of existing research explores the relationship between literacy and health outcomes. On average, more literate individuals were less likely to be hospitalized and more likely to have healthy practices. Low educational literacy often leads to low health literacy. This, in turn, can cause bad health practices which explain the increased healthcare utilization (Shahid et al., 2022). This mechanism might show why literate individuals might not have been as incentivized as the non-literate to take up the policy and also why they did not increase their utilization of healthcare.
- **Gender:** Finally, I study how the treatment effect varies with gender. Women have a much higher take-up rate of the pension policy than men. In addition, women have a higher probability of receiving treatment for short-term morbidity compared to men and similarly reduced probability of taking up treatment for major morbidity. Rather, men significantly reduce their utilization of healthcare facilities for both short-term and major morbidity conditions. This results in a much larger and statistically significant fall in health costs for men compared to women.
  Women in India are generally much more anaemic and are also burdened with menstrual disorders and worse nutritional intake (Zodpey & Negandhi, 2020). On average, women's healthcare needs are usually less prioritized compared to men (Zodpey & Negandhi, 2020). If a woman in a household still decides to go for treatment or regular check-ups, she might not have the means to do so. This causes women to self-medicate and self-diagnose their health problems which makes matters worse for them (Madhiwalla, Sinha & Nandraj, 2000). In short, women's healthcare needs are neglected socially and financially. As this pension is for individuals and not household-based, it grants women the freedom to deal with with major and short-term morbidity conditions. Given that women might be more reliant on pensions for their health compared to men and might need it more, the probability of treatment rises for them whereas men observe a large fall in their health costs.

Hence, after looking at both the heterogeneous and homogeneous treatment estimates, it becomes clear that the pension does lead to better health outcomes. However, the effects in terms of significance are highly heterogeneous. Muslims respond much less to the extra pension benefit compared to Hindus. On the other, people from lower castes benefit more from the pension compared to general/upper castes. Similarly, the non-literate increase their healthcare utilization to a much higher degree in contrast to falling healthcare use by the literate individuals. It is the same for women, as they increase their healthcare use whereas men reduce their healthcare costs. There has been considerable prior research to show why and how health status varies across these categories. While the effects were mostly in line with the homogeneous estimates, not all demographic groups showed significant effects, despite them being economically mostly similar. Even though the overall effects are positive, it is important to look at whether targeting the literate and upper-caste individuals with the scheme is highly effective.

6.2 Robustness checks

In a discontinuity design, it is necessary to check the robustness of the results. To ensure that the treatment effect is correctly attributed to the intervention or policy, the results should stay robust in different model specifications and settings (Lee & Lemieux, 2010). To a certain extent, the paper already did a robustness check in Table 4, where I looked at treatment estimates with multiple bandwidths. Most of the estimates stayed relatively robust. They were significant in a consistent manner and had similar treatment effects. Now, in this section, I will look at other major robustness checks, namely:

- Covariate Inclusion
- Alternative Specification of the Model
- Disconintuity at Plaecbo cutoffs
- Donut-hole Estimation

6.2.1 Sensitivity of Results to Covariates

Table 6: Robustness Check: Covariate Inclusion

Treatment Effect	**BW 4** (1)	**BW 5** (2)	**BW 6** (3)
Panel A: Short-term morbidity treatment received			
No Covariates	0.123* (0.065)	0.123** (0.051)	0.113* (0.061)
Interaction	-1.261*** (0.173)	0.123** (0.051)	0.113* (0.061)
Covariates + Interaction	0.094 (0.100)	0.115 (0.082)	0.085 (0.076)
Panel B: Short-term morbidity health costs			
No Covariates	-255.2** (127.8)	-237.0** (102.5)	-177.0 (114.7)
Interaction	-860.1*** (331.7)	-237.0*** (102.5)	-177.0 (114.7)
Covariates + Interaction	-191.3* (98.7)	-168.6** (82.4)	-82.2 (108.9)
Panel C: Major morbidity: Received treatment in the past year			
No Covariates	-0.492*** (0.060)	-0.343** (0.136)	-0.188 (0.135)
Interaction	-2.058*** (0.195)	-0.572*** (0.135)	-0.189 (0.136)
Covariates + Interaction	-0.541*** (0.102)	-0.353** (0.178)	-0.179 (0.170)
Observations (Effective)	3,466	4,044	6,380

Standard errors (SE) in parentheses. Adjusted for clustering in age.
*** p<0.01, ** p<0.05, * p<0.1

Ideally, covariates inclusion should make the treatment estimates more precise and reduce the standard errors. However, they should not change the treatment effect significantly. In Section 5.1.2, it was discussed how in the model, certain covariates show discontinuity across the cutoff. This leads to biased estimates. However, in bandwidth 5, only two out of the six covariates showed significant discontinuity. As far as this paper is concerned, for the bandwidth of 5, the estimates should not vary by much when including covariates.

In column 2, treatment estimates stay relatively robust compared to alternative bandwidths after incorporating covariates in the model. The magnitude of the treatment effects falls after their inclusion. Even though Panel B and Panel C show significant results, the effect is much lower than without covariates.

The pension has had a positive impact on health outcomes, but some proportion of this effect can be attributed to observed covariates such as differences in education and religion.

6.2.2 Functional specification sensitivity

Table 7: Estimates for Different Local Functional Estimations

Health Outcome	**Linear Specification** (1)	**Quadratic Specification** (2)
Panel A: Short-term morbidity treatment received		
No Covariates	0.123** (0.051)	0.059 (0.085)
Interaction	0.123** (0.051)	-24.43*** (2.35)
Covariates + Interaction	0.115 (0.082)	-0.036 (0.119)
Panel B: Short-term morbidity health costs		
No Covariates	-237.0** (102.5)	-409.2** (160.6)
Interaction	-237.0*** (102.5)	-12031*** (2404)
Covariates + Interaction	-168.6** (82.4)	-329.2*** (125.0)
Panel C: Major morbidity: Received treatment in the past year		
No Covariates	-0.343** (0.136)	-0.802*** (0.037)
Interaction	-0.572*** (0.135)	-10.93*** (1.117)
Covariates + Interaction	-0.353** (0.178)	-0.949*** (0.008)

Standard errors (SE) in parentheses. Adjusted for clustering in age.
*** p<0.01, ** p<0.05, * p<0.1

Up until now, all the reported estimates were local linear polynomial fit. To check if these treatment estimates stay consistent with a different specification, I look at the model but in a quadratic setting. Instead of a local linear fit, the model here in column two estimates a local quadratic fit on both sides of the threshold. The estimates are very different compared to those in column 1. In addition, they are very highly sensitive to the addition of covariates and interaction terms. Further, the estimates that the local quadratic fit yields are very high compared to the linear estimates. In all the panels, with the inclusion of interaction terms, the estimates increase drastically compared to the linear fit. In Panel C, the estimated probability is almost equal to 1, if not exceeding it. This means that the quadratic form is considerably overfitting the data. Instead of capturing the actual trends in data, it is capturing the noise in the model and making it overly complex. This unnecessarily complicated model makes these estimates less generalizable and robust (Lee & Lemieux, 2010).

Hence, the linear specification of the model is appropriate and robust for my analysis purposes.

6.2.3 Placebo Discontinuity

Table 8: Placebo Discontinuity Tests at 57.5 and 62.5 Years

Health Outcome	**57.5 Years** (1)	**62.5 Years** (2)
Panel A: Short-term morbidity treatment received	0.178 (0.252)	0.0616 (0.218)
Panel B: Short-term morbidity health costs	82.62 (366.1)	101.4 (357.3)
Panel C: Major Morbidity: Received treatment in the past year	-0.816*** (0.286)	0.0285 (0.212)
Effective Observations	5,499	4,909

Standard errors (SE) in parentheses. Adjusted for clustering in age.
*** p<0.01, ** p<0.05, * p<0.1

The main aim of conducting this placebo discontinuity test is to ensure that the outcome discontinuity due to the eligibility criteria of the pension policy at the age of 60 is not present at any other age. The discontinuity at the other age cutoffs must be insignificant so that the causal link between receiving pension benefits and better health outcomes is credibly established. The placebo cutoffs I use for the analysis are the median ages on either side of the sample[15] (Imbens & Lemieux, 2008).

Looking at the results in Table 8, there is a significant discontinuity at 57.5 years for Panel C. This signals that the treatment effects of the pension on the probability of receiving treatment for major morbidity will not be unbiased. The estimates so far calculated for this parameter were probably biased by some other factor or policy and cannot be causally attributed to the pension. As some other factor might be causing a jump in this outcome variable other than the pension, it becomes difficult to establish a causal link. However, for Panels A and B, the discontinuity is not significant at the placebo cutoffs. So, the treatment effect of the pension can be causally linked with the health improvements in these parameters.

Hence, besides Panel C, the other two variables had no discontinuity or jump at the placebo ages, meaning the treatment effect estimated would be attributed to only the receipt of the pension.

[15] Given the chosen bandwidth of 5, the median age on either side is 57.5 and 62.5

6.2.4 Donut-hole RDD Estimation

Table 9: Treatment Effect with "Donut"-hole RDD

Health Outcome	Donut-hole Estimates (1)	Standard Estimates (2)
Panel A: Short-term morbidity treatment received	0.0226 (0.0447)	0.123** (0.051)
Panel B: Short-term morbidity health costs	-201.6* (104.5)	-237.0** (102.5)
Panel C: Major Morbidity: Received treatment in the past year	-0.166 (0.131)	-0.343** (0.136)
Effective Observations	2,781	4,044

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Given that the data had severe age heaping and the running variable is discrete, I ran a donut hole RDD estimate as an additional robustness check. Barreca et al. (2016) suggested looking at treatment estimates after removing the heaped values from the running variables to deal with rounding off or heaping in the data. This method of estimation is also suitable to correct for mismeasurement in the running variable (Bartalotti et al., 2021).

If self-selection or sorting is suspected in the running variable, a donut-hole RDD model is recommended. In this specification, a certain number of individuals, usually those near the bandwidth, are not included in the estimation process. The treatment effect is only calculated after removing these individuals near the bandwidth. Hence, in such cases, the RDD graphs have a "hole" near the bandwidth due to absent observations.

I attempt to do something similar for this paper's specification. Even though it is not an exact donut-hole RDD, it closely resembles one. Instead of removing all the observations close to the bandwidth, all the individuals in the heaped ages are removed. That is, I take away all the individuals whose ages end in 0 or 5 within the five-year bandwidth. The treatment estimates thus computed are reported in column 1 in Table 9. There is a huge fall in the number of observations within the bandwidth. Previously it was 4,044 individuals in the estimation. But now that is reduced to 2,781. Besides short-term morbidity health costs, the other outcome variables are statistically insignificant in the donut-hole model. With these comparative estimates in the table, it is visible that the observations in the heaped values drive quite a major proportion of these treatment estimates. Despite that, the fall in short-term morbidity health costs is still significant, even if marginally. In all the specifications there is always a significant reduction in short-term health costs for those who receive the pension.

After looking at all the robustness checks, the model that best suits this study is the one with 5 years of bandwidth and a linear specification. These estimates are in line with existing studies and are much more robust to the inclusion of covariates.

However, a point of concern remains over the extent to which estimates for Panel C can be interpreted as causal given that it shows a significant discontinuity at an age other than the cutoff.

6.3 Policy Implications

In this study, IGNOAPS has led to an increased probability of receiving treatment for short-term health concerns and at the same time a fall in short-term health costs. The probability of treatment for major morbidity conditions is much harder to link causally, hence I will focus on mainly the short-term benefits of the pension scheme. Such pensions increase the disposable income for the poor elderly and it is important to know how their spending impacts their health. Having this higher disposable income enables them to visit doctors for smaller issues which often acts as a preventive measure against a bigger health scare (Aguila et al., 2015). In addition, this cash transfer enables these individuals to purchase food rations, clothes, and other necessities (Aguila et al., 2015). This indirectly reduces the probability of having more serious health concerns, at least in the short run. Short-term morbidity issues can often be dealt with by maintaining a healthier lifestyle (Rippe, 2018). However, despite the improvements in health, the pension policy has several problems.

Firstly, the low compliance issue of the policy. Only 37 per cent of the eligible individuals make use of the policy and its benefits. This policy, similar to other policies by the Central Government of India is plagued by awareness issues surrounding its benefits and eligibility (Bartwal et al., 2016; Kohli et al., 2017; Goswami et al., 2019; Narayana, 2019). Secondly, there is also the targeting of the policy. In the results, Upper Caste and Muslim individuals did not benefit from the policy as much as other categories. It might be the case that these individuals already benefit from other State-sponsored schemes or other programs under NSAP. In such a situation, more regional targeting might be more effective (Grosh, Leite, Wai-Poi & Tesliuc, 2022). If individuals in some states already receive more benefits compared to individuals from other states, then targeting the ones in poor states will be more useful. The other reason can also be the incentive to take up the policy because of the bureaucratic process involved which increases the effort of taking up the policy compared to the reward of the pension benefit.

While this pension scheme is very old, it needs to be improved upon instead of being ignored. The Indian Government's efforts towards better public health have been considerable, but despite the large number of schemes, their coverage amongst rural and poor individuals has been very low (Hooda, 2020). Ideally, health insurance schemes are expected to improve the health outcomes of individuals. But, analysis has shown that these insurance schemes have a much worse coverage rate than the old age pension for the poor in India. In the survey dataset, of all individuals above 59 years of age, only 12 per cent of them had any government healthcare insurance. On the other hand for IGNOAPS, over 37 percent of the eligible individuals had access to the benefits. Despite, the low take-up rate of the policy, it still has wider coverage than alternative health insurance policies. Schemes like pensions can allow individuals to take up healthier lifestyle practices which automatically betters their health, which is different from general healthcare policies. Even though both serve different purposes, it seems like due to the lack of coverage of the health policies by the government, the pension policy might have been compensating for the failure of effective insurance policies, at least for short-term conditions. This is in no way a call to reduce insurance coverage, but rather how to distinguish between the behaviour of recipients while being under these schemes. It is also important to recognise that if the desired programmes do not reach the people, they use alternative policies as a replacement which reduces their capacity to spend on other commodities beyond necessities.

The health effects of the pension scheme have not been taken into consideration while deciding its monthly payments and coverage. As the poor elderly rely on government support highly for their survival, it will not be futile to make changes to this existing scheme taking into account the expenditure pattern of the beneficiaries and analyzing if the pension amount has been stretched too thin to cover up for failure for other schemes.

7 Conclusion

The paper has studied the impact of the pension on the health outcomes of the elderly below the poverty line. It has used the Fuzzy RDD model to study the effect of the pension on parameters such as short-term health usage, short-term health costs and treatment for major morbidity. Using data from IHDS-II, I find a significant fall in short-term health costs and a higher probability of visiting doctors for healthcare needs. In addition, a significant fall in the probability of using healthcare facilities for major morbidity treatment falls. The paper discusses that the reason behind the fall in visiting doctors for major health concerns could be an increase in quality of life, which will have mitigated or delayed the more serious concerns. The policy implication of these results suggest that the Indian Government should realise the unintended health benefits of this minor policy and look at ways to update it. As this policy is old, it has been a while since it has received updates to its structure and payments. More recent health-specific policies have not had the coverage of this pension. Hence, attention should be paid to providing upgrades to existing policies that might be doing the work of other programs. This is the main contribution of the paper as prior research on India's health policy has not focused on pensions as a means of dealing with health troubles for the elderly.

The empirical specification is robust to covariate inclusion and different bandwidths, even though the estimates themselves have marginal changes in the percentage and costs. However, as the bandwidth is very narrow, using a polynomial fit of order 2 around the cutoff leads to a major over-fitting of the regression fit to the data. The estimates cannot be interpreted logically. Hence, the model is only slightly sensitive to bandwidth and covariates but very sensitive to the order of polynomial fit.

Despite the significant impact the pension has on receiving treatment and advice from doctors and reducing healthcare costs, the study has several limitations. Firstly, the quality of the survey dataset is rough as there is a mis-measurement of the age of individuals, which is the forcing variable. This is prevalent in survey datasets related to people from poor or developing countries. This measurement issue has led to a heaping of individuals in ages that end in 0 or 5. In turn, this heaping caused significant density discontinuity across the threshold, denoting "self-selection" in the treatment group. Secondly, given the direct negative relationship between age and health, the study could only focus on narrow bandwidths. Despite the narrow bandwidths, the paper cannot completely discount age-related biases in the treatment effect. The true treatment effect will be smaller than the reported effect for short-treatment probability because as people get older, they usually visit doctors and clinics more often. On the other hand, the short-term health cost effects will be downward biased, because the decrease observed would have been higher if people as they grew older had similar healthcare costs compared to people on the left side of the threshold.

Nevertheless, the paper can establish a causal link between the pension and short-term health betterment. However, high-quality survey data or the planned population survey in the future by the Indian Government might give a clearer picture of IGNOAPS, its coverage and its effect on the health of the elderly. Until then, research should be done in India for the poor and deprived to understand if certain programmes and their benefits compensate for the failure of other policies.

References

Abdi, S., Spann, A., Borilovic, J., de Witte, L. & Hawley, M. (2019). Understanding the Care and support needs of older people: A scoping review and categorisation using the who International Classification of functioning, disability and Health Framework (icf). *BMC geriatrics*, *19*, 1–15.

Aguila, E., Kapteyn, A. & Smith, J. (2015). Effects of income supplementation on health of the poor elderly: The case of Mexico. *Proceedings of the National Academy of Sciences*, *112*(1), 70-75.

Alkire, S. & Fortacz, A. (2021). Insights for Policymaking from the Multidimensional Poverty Index. *Great*, 169.

Alkire, S. & Seth, S. (2013). Identifying BPL households: A comparison of methods. *Economic and Political Weekly*, 49–57.

Angrist, J. D. & Pischke, J.-S. (2009). *Mostly harmless econometrics: An Empiricist's companion.* Princeton University Press.

Aslany, M. (2020). Contested Capital: Rural Middle Classes in India: Rural Middle Classes in India. Cambridge University Press.

Barreca, A. I., Lindo, J. M. & Waddell, G. R. (2016). Heaping-induced bias in regression-discontinuity designs. *Economic inquiry*, *54*(1), 268–293.

Bartalotti, O., Brummet, Q. & Dieterle, S. (2021). A correction for regression discontinuity designs with group-specific mismeasurement of the running variable. *Journal of Business & Economic Statistics*, *39*(3), 833–848.

Bartwal, J., Rawat, C. S. & Awasthi, S. (2016). Awareness and utilization of geriatric Welfare services among elderly in Nainital District of Uttarakhand. *National Journal of Community Medicine*, *7*(09), 727–731.

Behncke, S. (2011). Does retirement trigger ill health? *Health Economics*, *21*(3), 282–300.

Bhattacharjee, S. & Chaudhuri, A. R. (2023). Religion in the labor market: evidence from India. *Applied Economics*, *55*(41), 4781–4816.

Biemer, P. P. (1985). *Evaluating Censuses of Population and Housing.* US Department of Commerce, US Census Bureau, Statistical Training Document.

Bloemen, H., Hochguertel, S. & Zweerink, J. (2017). The causal effect of retirement on mortality: Evidence from targeted incentives to retire early. *Health economics*, *26*(12), e204–e218.

Borooah, V. (2010). Inequality in Health Outcomes in India: The Role of Caste and Religion. In *Blocked by Caste: Economic Discrimination in Modern India* (pp. 179–207). Oxford University Press.

Brosius, C. & Mandoki, R. (2020). *Caring for old age: Perspectives from south asia* (Vol. 8). Heidelberg: Heidelberg University Publishing.

Cattaneo, M. D., Idrobo, N. & Titiunik, R. (2024). *A Practical Introduction to Regression Discontinuity Designs: Extensions*. Cambridge University Press.

Cattaneo, M. D., Jansson, M. & Ma, X. (2018). Manipulation Testing Based on Density Discontinuity. *The Stata Journal*, *18*(1), 234–261.

Coale, A. J. & Li, S. (1991). The effect of age misreporting in China on the calculation of mortality rates at very high ages. *Demography*, *28*(2), 293–301.

Coe, N. B. & Lindeboom, M. (2008). Does retirement kill you? Evidence from early retirement windows. IZA discussion papers no. 3817. *Institute for the Study of Labor (IZA), Bonn.*

Dabla-Norris, M. E., Kochhar, M. K., Suphaphiphat, M. N., Ricka, M. F. & Tsounta, M. E. (2015). *Causes and consequences of income inequality: A global perspective.* International Monetary Fund.

Dave, D., Rashad, I. & Spasojević, J. (2008). The effects of retirement on physical and mental health outcomes. *Southern Economic Journal*, *75*(2), 497–523.

Desai, S., Dubey, A., Joshi, B., Sen, M., Shariff, A. & Vanneman, R. (2008). India human development survey. *College Park, Maryland: University of Maryland*.

DeWalt, D. A., Berkman, N. D., Sheridan, S., Lohr, K. N. & Pignone, M. P. (2004). Literacy and health outcomes. *Journal of General Internal Medicine*, *19*(12), 1228–1239.

Eibich, P. (2015). Understanding the effect of retirement on health: Mechanisms and heterogeneity. *Journal of Health Economics*, *43*, 1–12.

Elston, J., Gradinger, F., Asthana, S., Lilley-Woolnough, C., Wroe, S., Harman, H. & Byng, R. (2019). Does a social prescribing 'holistic' link-worker for older people with complex, multimorbidity improve well-being and frailty and reduce health and social care use and costs? A 12-month before-and-after evaluation. *Primary Health Care Research 38; Development*, *20*, 135.

Frandsen, B. R. (2017). Party bias in union representation elections: Testing for manipulation in the regression discontinuity design when the running variable is discrete. In *Regression discontinuity designs: Theory and applications* (pp. 281–315). Emerald Publishing Limited.

Gaarder, M. M., Glassman, A. & Todd, J. E. (2010). Conditional cash transfers and health: unpacking the causal chain. *Journal of development effectiveness*, *2*(1), 6–50.

Goswami, A. K., Ramadass, S., Kalaivani, M., Nongkynrih, B., Kant, S. & Gupta, S. K. (2019). Awareness and utilization of social welfare schemes by elderly persons residing in an urban resettlement colony of Delhi. *Journal of Family Medicine and Primary Care*, *8*(3), 960–965.

Grosh, M., Leite, P., Wai-Poi, M. & Tesliuc, E. (2022). *Revisiting targeting in social assistance: A new look at old dilemmas*. World Bank Publications.

Gupta, A. & Coffey, D. (2020). Caste, religion, and mental health in India. *Population Research and Policy Review*, *39*(6), 1119–1141.

Hindustan Times. (2017, January). Delhi govt increases monthly pension of elderly, widows and disabled. *Hindustan Times*. Retrieved from `https://www.hindustantimes.com/delhi/delhi-govt-increases-monthly-pension-of-elderly-widows-and-disabled/story-GM5KeCQHxdBgk62EyQ5CfK_amp.html`

Hoang Van Minh, N. T. K. C., Peter Byass & Wall, S. (2010). Patterns of health status and quality of life among older people in rural Vietnam. *Global Health Action*, *3*(1), 2124.

Hooda, S. K. (2020). Penetration and coverage of government-funded health insurance schemes in India. *Clinical Epidemiology and Global Health*, *8*(4), 1017-1033.

Imbens, G. W. & Angrist, J. D. (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica*, *62*(2), 467–475.

Imbens, G. W. & Kalyanaraman, K. (2012). Optimal Bandwidth Choice for the Regression Discontinuity Estimator. *The Review of Economic Studies*, *79*(3), 933–959.

Imbens, G. W. & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, *142*(2), 615–635.

Imbens, G. W. & Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences.* Cambridge university press.

Iyengar, S. & Dholakia, R. H. (2012). Access of the rural poor to primary healthcare in India . *Review of Market Integration*, *4*(1), 71-109.

Jensen, R. T. & Richter, K. (2004). The health implications of social security failure: evidence from the Russian pension crisis. *Journal of Public Economics*, *88*(1), 209–236.

Johri, A. & Anand, P. V. (2022). Life satisfaction and Well-being at the Intersections of caste and Gender in India. *Psychological Studies*, *67*(3), 317–331.

Kaushal, N. (2014). How public pension affects elderly labor supply and well-being: Evidence from India. *World Development*, *56*, 214–225.

Kohli, C., Gupta, K., Banerjee, B. & Ingle, G. K. (2017). Social security measures for elderly population in Delhi, India: Awareness, utilization and barriers. *Journal of clinical and diagnostic research: JCDR*, *11*(5), LC10.

Lee, D. S. & Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature*, *48*(2), 281–355.

Ludwig, J. & Miller, D. L. (2007). Does Head Start Improve Children's Life Chances? Evidence from a Regression Discontinuity Design. *The Quarterly Journal of Economics*, *122*(1), 159-208.

Lyons-Amos, M. & Stones, T. (2017). Trends in Demographic and Health Survey Data Quality: An Analysis of Age Heaping over Time in 34 Countries in Sub Saharan Africa between 1987 and 2015. *BMC Research Notes*, *10*(1), 760.

Ma, C., Li, Z., Sun, Z. & others. (2021). The Role of Pensions in Alleviating the Medical Burden of Rural Residents—Why Subsidizing Income Is Better Than Subsidizing Medical Insurance. *China Industrial Economy*, *2021*(4), 43–61.

Madhiwalla, N., Sinha, R. & Nandraj, S. (2000). *Health, Households, and Women's Lives: A Study of Illness and Childbearing Among Women in Nasik District, Maharashtra.* Centre for Enquiry into Health and Allied Themes, Research Centre of Anusandhan Trust.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, *142*(2), 698-714.

Mohanty, I. & Gebremedhin, T. A. (2018). Maternal autonomy and birth registration in India: Who gets counted? *PLOS ONE*, *13*(3), 1-19.

Mohanty, S. K., Chauhan, R. K., Mazumdar, S. & Srivastava, A. (2014). Out-of-pocket expenditure on health care among elderly and non-elderly households in India. *Social indicators research*, *115*, 1137–1157.

Narayana, M. R. (2019). Old age pension scheme in India: distributional impacts. *South Asia Research*, *39*(2), 143–165.

Pardeshi, G. S. (2010). Age heaping and accuracy of age data collected during a community survey in the Yavatmal district, Maharashtra. *Indian Journal of Community Medicine*, *35*(3), 391–395.

Pega, F., Pabayo, R., Benny, C., Lee, E.-Y., Lhachimi, S. K. & Liu, S. Y. (2022). Unconditional cash transfers for reducing poverty and vulnerabilities: effect on use of health services and health outcomes in low-and middle-income countries. *Cochrane Database of Systematic Reviews*(3).

Rippe, J. M. (2018). Lifestyle Medicine: The Health Promoting Power of Daily Habits and Practices. *American Journal of Lifestyle Medicine*, *12*(6), 499–512.

Riumallo Herl, C., Kabudula, C., Kahn, K., Tollman, S. & Canning, D. (2022). Pension exposure and health: Evidence from a longitudinal study in South Africa. *The Journal of the Economics of Ageing*, *23*(C).

Selvaraj, S., Karan, A. K., Mao, W. et al. (2021). Did the poor gain from India's health policy interventions? Evidence from benefit-incidence analysis, 2004–2018. *International Journal for Equity in Health*, *20*(1), 1–11.

Shahid, R., Shoker, M., Chu, L. M., Frehlick, R., Ward, H. & Pahwa, P. (2022). Impact of low health literacy on patients' health outcomes: a multicenter cohort study . *BMC Health Services Research*, *22*(1).

Shryock, H. S. (2013). *The methods and materials of demography.* Academic Press.

Thapa, R., van Teijlingen, E., Regmi, P. R. & Heaslip, V. (2021). Caste Exclusion and Health Discrimination in South Asia: A Systematic Review. *Asia Pacific Journal of Public Health*, *33*(8), 828–838.

Thomas, R. K. (2016). Demographic Factors Associated with Morbidity. *In Sickness and In Health: Disease and Disability in Contemporary America*, 117–145.

Thorat, S. & Ahmad, M. (2015). Minorities and poverty: Why some minorities are more poor than others? *Journal of Social Inclusion Studies*, *1*(2), 126–142.

UNFPA India. (2023). Public Health Care Utilization by Elderly in India: An Analysis of Major Determinants from LASI Data. *UNFPA India Analytical Paper Series*(7).

Unnikrishnan, V. & Imai, K. S. (2020). Does the old-age pension scheme improve household welfare? Evidence from India. *World Development*, *134*(C).

Yan, P., Li, F., Nicholas, S., Maitland, E., Tan, J., Chen, C. & Wang, J. (2023). Impact of Pension Income on healthcare utilization of Older Adults in rural China. *International Journal for Equity in Health*, *22*(1).

Yang, F.-A. & Chang, H.-H. (2023). Impact of a Pension Program on healthcare utilization among Older Farmers: Empirical Evidence from health claims data. *World Development*, *169*(C).

Zodpey, S. & Negandhi, P. (2020). Inequality in health and social status for women in India long-standing bane. *Indian Journal of Public Health*, *64*(4), 325–327.

A Appendix

A.1 Density Test

Table 10: RD Manipulation Test Results

Bandwidth	Cutoff	P-value (Order 1)	P-value (Order 2)
4	56	0.0000	0.0000
	57	0.0000	0.0000
	58	0.0152	0.0000
	59	0.0000	0.0000
	60	0.0000	0.0000
	61	0.0000	0.0000
	62	0.0000	0.0000
	63	0.0000	0.0000
	64	0.0000	0.0000
4 (Dropped)	60	0.0000	0.0000
5	56	0.0000	0.0000
	57	0.0000	0.0000
	58	0.0000	0.0000
	59	0.0000	0.0000
	60	0.0000	0.0000
	61	0.0000	0.0000
	62	0.0000	0.0000
	63	0.0000	0.0000
	64	0.0000	0.0000
5 (Dropped)	60	0.0000	0.0000
6	56	0.0000	0.0000
	57	0.3697	0.0000
	58	0.0000	0.0000
	59	0.9671	0.9671
	60	0.0040	0.0040
	61	0.0000	0.0000
	62	0.0163	0.0000
	63	0.0000	0.0001
	64	0.0000	0.0000
6 (Dropped)	60	0.0000	0.0000

Notes:

- The `rddensity` package assumes an unrestricted model with a triangular kernel and jackknife estimation of the vce matrix of standard errors.
- Dropped units are those dropped indiviuals with ages that are multiples of 5 within the bandwidth.

A.2 Frandsen(2017)'s Density Test for Discrete Forcing Variable

Table 11: Test for Manipulation of the Running Variable at the Threshold

Statistic	**Value**
Chi-Square Test Statistic	1316.595
p-value	1.27e-286

The test uses a Chi-square goodness-of-fit test to compare the observed distribution of the running variable near the cutoff to an expected distribution under the null hypothesis of no manipulation.

A.3 Whipple's Index

$$W = \left(\frac{N_0 + N_5}{0.2 \cdot N_{\text{total}}} \right) \times 100 \quad (3)$$

where:

- N_0 is the number of people whose reported age ends in 0,
- N_5 is the number of people whose reported age ends in 5,
- N_{total} is the total number of people in the given age range.

The value of Whipple's Index ranges from 100 (indicating no age heaping) to 500 (indicating extreme age heaping).

A.4 Covariates Description

The table contains the list of covariates that the paper aimed to deal with. Other covariates such as region of residence, state of residence and occupation did not have large enough samples to check for discontinuity.

Table 12: Variable Descriptions

Variable	Type	Description
Education	Integer	Years of education completed
Assets	Integer	Total assets of an individual's household
Religion	Dummy	Dummy variable: 1 for Hindus, 0 for Non-Hindus
Caste	Dummy	Dummy variable: 1 for upper castes (including General Category), 0 for lower castes (Scheduled Castes, Tribes, Other Backward Castes)
Benefits from other programs	Integer	Total money received from other means (e.g., NSAP programs, charity)
Annual household income	Integer	Total household income from salaries, wages, and bonuses

A.5 Covariate Balancing

A.5.1 Discontinuity Test Results

Table 13: Covariate Discontinuity Across the Threshold (Polynomial Order 1)

Covariate	BW 4	BW 5	BW 6
Religion	-0.0576*** (0.0149)	-0.0519*** (0.0107)	-0.0209 (0.0186)
Assets	-1.024* (0.604)	-0.884* (0.520)	-1.059*** (0.404)
Education	-1.409*** (0.135)	-1.131*** (0.277)	-1.160*** (0.191)
Caste	-0.0112 (0.0190)	-0.0114 (0.0143)	-0.0293** (0.0145)
Benefits from other programs	111.2 (276.1)	8.803 (250.8)	56.61 (193.5)
Annual household income	-9,839 (14,427)	-9,548 (10,970)	-15,140* (8,627)

Note: SE adjusted for clustering in age. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 14: Covariate Discontinuity Across the Threshold (Polynomial Order 2)

Covariate	BW 4	BW 5	BW 6
Religion	-0.0522** (0.0236)	-0.0943*** (0.0290)	0.0005 (0.0015)
Assets	-1.863*** (0.690)	-0.876 (0.763)	-3.410*** (0.0285)
Education	-2.011*** (0.0475)	-1.255*** (0.366)	-1.932*** (0.0167)
Caste	-0.0281 (0.0264)	0.0093 (0.0287)	-0.0869*** (0.0002)
Benefits from other programs	547.9* (293.9)	78.1 (339.8)	1,207*** (7.0)
Annual household income	-24,062 (19,238)	-6,330 (18,054)	-66,989*** (297.4)

Note: SE adjusted for clustering in age. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

A.5.2 Comparison of Means Test

Table 15: Covariate Balance Tests Across Threshold

Covariate	**Below Cutoff Mean**	**Above Cutoff Mean**	**Test Statistic**
Religion	0.439	0.456	$\chi^2 = 0.1935$
Assets	13.739	12.969	$t = 5.2983^{***}$
Education	2.658	1.996	$t = 7.3999^{***}$
Caste	0.183	0.172	$\chi^2 = 1.1519$
Benefits from other programs	683.97	704.91	$t = -0.2555$
Annual household income	74,134.51	62,034.36	$t = 5.8747^{***}$

Note: Continuous variables were compared using t-tests, while dummy variables were compared using Chi-squared tests. The null hypothesis states no significant difference in means between individuals above and below the cutoff. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.6 Pension Take-Up Rate

Table 16: Take-up Rate by Demographic Categories

Category	Eligible (1)	Received (2)	Percentage (3)
Religion			
Hindu	2,090	607	29.04
Muslim	272	52	19.11
Caste			
Upper Castes: Brahmins	65	17	26.15
Upper Castes/General	372	83	22.31
Other Backward Castes (OBC)	1,103	307	27.83
Scheduled Castes (SC)	637	218	34.22
Education			
Non-Literate	1,651	514	31.11
Literate	864	191	22.10
Gender			
Male	1,160	254	21.89
Female	1,360	452	33.23

A.7 Intention-to-Treat Effect

Table 17: ITT Estimates

Health Outcome	**Treatment Effect**
Panel A: Short-term morbidity treatment received	0.0316** (0.0130)
Panel B: Short-term morbidity health costs	-60.68** (26.22)
Panel C: Major Morbidity: Received treatment in the past year	-0.0878** (0.0348)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As mentioned before in Section 5.1, the ITT effect is calculated by estimating the impact of being eligible for the pension rather than the pension benefit itself. It means that ITT will estimate the effect of being above the age of 59 on the health parameters. This is the reduced form version of 2SLS where $elgibility_i$ replaces the instrumented variable ($treatment_i$) in the main treatment equation.

In the above table, I calculate the ITT effect with Cattaneo et al. (2024)'s local polynomial estimators but within a Sharp RDD model with a bandwidth of 5 years on each side. The ITT estimate is similar to the Sharp RDD estimation this paper would have had, had there not been severe compliance issues with the treatment.

The estimates in the table show that being above the age of 59 increases the probability of short-term treatment by 3.2 percentage points. The short-term health costs fall by almost sixty-one rupees for the month and the probability of taking treatment for major conditions falls by 8.8 percentage points. These estimates are highly significant and very similar in direction to the main 2SLS treatment estimates. As the reduced form estimates here are significant it shows that the eligibility of the treatment itself leads to positive health outcomes, even though much smaller.

A.8 MSE Optimal Bandwidth

Table 18: Optimal Bandwidth Estimates

Health Outcome	**Bandwidth**	**Treatment Effect**
Panel A: Short-term morbidity treatment received	10.1	0.0913* (0.0534)
Panel B: Short-term morbidity health costs	7.8	-159.3* (91.78)
Panel C: Major Morbidity: Received treatment in the past year	7.8	-0.112 (0.123)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Minimising mean squared has been widely used in RDD literature as a means of deciding the optimal bandwidth (Imbens & Rubin, 2015). This method was introduced and developed by Imbens and Kalyanaraman (2012). This is a data-driven estimator, that chooses that bandwidth which takes into consideration both the variance and bias of the bandwidth. The general formula for this bandwidth estimator is:

$$\min MSE(h^*) = \arg\min_h \left(\text{Bias}^2(h) + \text{Variance}(h)\right)$$

Here, **h** refers to the optimal bandwidth. Given that I have used Cattaneo et al. (2024)'s local linear estimation for the treatment effects, I use the same software package to determine the optimal bandwidth using the above-mentioned formula. The results are given in Table 18. The optimal bandwidth varies quite a bit depending on the health outcome. However, they range between 7-10 years on each side of the threshold. Only Panel A and Panel B show significant results for the data-driven bandwidth. While the short-term results are significant, the probability of visiting a doctor for major morbidity becomes insignificant. Intuitively, it can be speculated that the long-run effects of the pension wear off.

However, this was the main reason the paper chose the optimal bandwidth manually. When age is a assignment variable, it was bound to happen that increasing the bandwidth would cause estimates to include worsening of health due to age-related factors. If one looks at the health outcomes of individuals who might have been receiving pensions for eight to ten years, the treatment estimates would not have been significant. Other policy changes might have taken place, health worsened due to age and so on. Given the strong relationship between the running and the outcome variable, I choose a narrower bandwidth of 5 years across the threshold to get more precise and less biased estimates, even at the cost of a higher standard error.