ESSAYS ON ELDERLY DECISION MAKING

A Dissertation

Presented to

The Faculty of the Department

of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Doctor of Philosophy

By

Arpita Chakravorty

May 2018

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Abstract

The dissertation consists of two studies on decision making of the elderly in India and the United States. The first study uses data from the India Human Development Survey (IHDS), a nationally representative survey in India, to examine the effect of pension on the health and labor market decisions of individuals above 50 years. The study also examines its effect on the health of young children living with the pension beneficiaries. In particular, I examine the impact of the 2011 expansion of the Indira Gandhi National Old Age Pension Scheme on the labor and health outcomes of the elderly and co-residing grandchildren. The results suggest that elderly men and women work less as a result of pension from this program, with no detectable impact on their health status. I also compare the oldest individual above and below the state cutoff and those before and after the pension expansion, to find that children aged 0 to 5 years living with their grandmothers have better health than those living with grandfathers.

The second study explores the relationship between home equity and risk preferences of individuals above 50 year using the restricted panel dataset of the Health and Retirement Study between 1992 and 2014. Risk aversion is measured using hypothetical income gamble questions asked every two years between 1998 and 2006. I also examine the effect of home equity on portfolio allocation of these individuals. Following earlier literature, I define home equity as the difference between self-reported property value and mortgage, and use the zip code level housing prices to examine the causal relationship between home equity and risk aversion. The results suggest that an increase in home equity decreases risk aversion, but the effect is not significant.

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to Ma and Pa

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Chapter 1

Household Responses to Old Age Pension: Evidence from India

1.1 Introduction

With a significantly aging population across developing nations, there has been a steady rise in welfare programs targeting the elderly. Earlier studies find a decrease in the labor supply of the elderly (Juárez and Pfutze (2015) and de Carvalho Filho (2008)) with increased pension benefits. They also show an improvement in the health and education of children residing with pension beneficiaries (Edmonds et al. (2005), Bertrand et al. (2003), Duflo (2003)). Although evidence shows that social pension improves lives of the elderly across developing countries, the effects may not extend in the case of India. Few empirical studies examine the relationship between cash benefits to the poor elderly and well-being of the beneficiaries in Indian households (Kaushal (2014), Dutta et al. (2010), Asri et al. (2016), Pal and Palacios (2011) and Pal et al.

(2006), Gupta (2013)).

Do government cash transfers to the elderly translate into an improvement in their well-being and that of their family members? I answer this question by investigating the 2011 expansion of a means-tested, non-contributory national level pension program, called the Indira Gandhi National Old Age Pension Scheme (IGNOAPS), which targets poor individuals in India. This program's objective is to reduce poverty among individuals over 60 years. The welfare impacts of such policies can be quite large, since almost half the population of elderly in India live in poverty (Census, 2011) and the annual pension amount is equivalent to almost 30 percent of the per capita income of individuals below poverty line. So far, the total expenditure of this program has been about 150 million USD, with 33 million beneficiaries (NSAP, 2016). With the additional income through pensions, one could expect changes in the labor supply of the elderly and intergenerational transfer of resources in households with multiple generations.

I investigate the effects of pension income on work participation and health of the beneficiary, and also investigate changes in the nutritional status of grand-children co-residing with the elderly. It is common practice for poor elderly men and women in India to continue working beyond the typical retirement age since they are primarily employed in the informal sector, are agricultural workers or daily wage workers. This form of employment involves strenuous physical labor with adverse effects on the individuals. I hypothesize that benefits from this program should enable the elderly to withdraw from the workforce and stop participating in strenuous labor. This should lead to an improvement in health measures of the recipients. Some of the pension benefits could trickle down to other members of the households through intra-household redistribution of resources. These effects depend on the amount available to the elderly, since this benefit could act as an income addition or as a replacement of lost earnings conditional on their employment status.

I contribute to the existing literature in the following ways.[1] First, this study is directly related to the role of pension in labor market choices of aging men and women with stringent credit constraints. To the best of my knowledge, the only existing empirical study to estimate the causal impact of old age pension on labor supply in India is by Kaushal (2014). In her paper, Kaushal (2014) uses the 2007 expansion of the program but the dataset she uses cannot identify the pension recipients. I use the 2011 expansion of the program which reduced the eligibility age from 65 (in 2007) to 60, and am able to identify the beneficiaries of IGNOAPS.[2] Second, this study also speaks to the literature on inter-generational cash transfers in multi-generation households; specifically, the transfer of resources between grandparents and grandchildren. Third, the 2011 expansion of IGNOAPS reduced the age eligibility from 65 to 60 years for poor households. Although the federal mandate stated the new eligibility age to be 60, few states had already lowered the cutoff, and a few others continued to use the 65 year cutoff in 2011. This is the first study that uses this variation across states after the 2011 expansion of the program to explain the causal relation between pension receipt and elderly and child outcomes.

[1] In this paper, pension refers to the pension from IGNOAPS unless specified otherwise and is not conditional on employment of the individual.

[2] Other studies have conducted descriptive analysis using IGNOAPS. There have been state-specific surveys to study compliance of the program, and anecdotal evidence hinting at the benefits of pension to the elderly poor.

IGNOAPS is available to all poor elderly above the age cutoff, but participation in the program is voluntary. A host of individual, household and regional unobserved characteristics could simultaneously determine an individuals' selection into the program. Hence, naively comparing individuals with pension to those without would not explain the effects of pension since the two groups could be systematically different. To address this difficulty, I use the age eligibility criteria of the 2011 expansion of IGNOAPS in a regression discontinuity (RD) framework (Carpenter and Dobkin (2009); Hoekstra (2009)). An advantage of using the RD framework is its similarity to a formal randomized experiment wherein, the treatment assignment of the program is established according to the deterministic rule (eligibility criteria).

In a regression discontinuity framework, I compare individuals to the right of the cutoff to those to the left. Since not all non-eligible individuals receive pension on becoming eligible, i.e. the discontinuous increase in the probability of receiving pension is not exactly 1, but less than 1, I use a fuzzy regression discontinuity design to explain the effects of pension receipt as the ratio of the discontinuity in the outcome to the discontinuity in the probability of receiving pension. For example, I compare the labor supply of individuals just above the cutoff age to those who are just below the cutoff and rescale the same by the discontinuity in the probability of receiving pension to obtain the causal relationship between pension receipt and labor supply. The discontinuity at cutoff age becomes an instrument for the probability of receiving pension in a two stage least squares method. To ensure the validity of the regression discontinuity design, the discontinuity in covariates is examined graphically and empirically using a reduced form regression. I see that covariates vary smoothly across the threshold. Further, I am able to investigate the average change after the implementation of the revised policy using a difference-in-differences strategy. I compare individuals above and below the state cutoff in the given year, and those before and after the 2011 expansion of the policy.

Following is a summary of my findings. The estimates suggest that the likelihood of employment reduces by 6 percentage points for men just above the cutoff compared to those just below the cutoff. When the discontinuous decrease in employment of elderly male is rescaled by the discontinuous increase in pension receipt, the decrease in labor supply is almost 61 percent. This indicates that among those receiving pension, the likelihood of elderly men dropping out of the labor force increases by 61 percent. Conditional on being employed, I show that the annual earnings of elderly women reduces by a significant amount, with no change in the health status of either men or women. The difference-in-differences estimation indicates a decrease in the probability of acute malnutrition in children age 0 to 5 years living with their grandmother by 14 percentage points, but no change in children living with eligible grandfathers. The results imply that the bargaining power of elderly women increases when they become eligible for pension.

These impacts could be driven by two competing theories. The means-tested nature of the pension program could induce the elderly to reduce employment, and maintain their poverty status to reap benefits from the cash transfer (substitution effect). Alternatively, an increase in pension could relax elderly liquidity constraints, and make her/his retirement affordable (income effect). To disentangle these effects, I use a predetermined definition of poverty status, a below poverty line (BPL) card given out to households in 2002, to explain the impact of pension to be more of an income effect than a substitution effect. Also, the IGNOAPS program uses the same BPL card to identify individuals eligible for the program, which allows me to rule out the change in employment as a substitution effect.

This paper is organized as follows: Section 2 provides a brief summary of the existing literature on pensions and their effects in developing economies; section 3 explains the pension program and empirical methodology and section 4 provides a brief summary of the data. I explain the fuzzy regression discontinuity findings in section 5 and difference-in-differences findings in section 6. Section 7 provides robustness check measures and section 8 concludes.

1.2 Existing Literature

Over time, a plethora of studies have examined the effects of pension on the labor force participation (Gelman and Imbens (2017), Case and Deaton (1998), Maitra and Ray (2003), Posel et al. (2006), Tondini et al. (2017)) and health of the elderly (Ning et al. (2016), Cheng et al. (2016)).

Pension benefits to the elderly alter their retirement decisions in developed countries. The relative importance of pension in developing economies is different from that in developed countries. The source of these variations come from income levels, credit constraints, life expectancy and importance of the informal sector. de Carvalho Filho (2008) examines a universal old age pension program to find that access to old-age benefits is a strong determinant of retirement among rural workers in Brazil. Bertrand et al. (2003) and Duval (2003) explain the causal link between reduction in labor force participation and pension in South Africa and Mexico. In the Indian context, retirement decisions differ between the formal and informal labor markets. Government pension benefits on retirement are available to individuals in the formal labor market. With respect to IGNOAPS, it is not obvious for a change in labor force participation of the elderly to be driven by retirement from the formal sector, since majority of workers in these poor households are participants of the informal labor market. This makes it an important question to examine.

In India, most studies that evaluate IGNOAPS have been in particular states (Rajan (2007), Rajasekhar et al. (2016), Dutta et al. (2010), Alam (2009) and Gupta (2013)). Other studies investigating the program at the national level have explored its compliance and effects on income and consumption (Asri et al. (2016) and Garroway (2013)). The relation between pension through IGNOAPS and elderly labor supply for liquidity constrained households with agriculture as their primary occupation can pose an interesting question to explore, since pension benefits could either help them withdraw from the workforce, or induce them to reduce working to maintain their poverty status.

The study most relevant to my paper is by Kaushal (2014). This paper uses the 2007 expansion of IGNOAPS to study its effects on the labor supply of older adults and consumption expenditure of households using a difference-in-differences mechanism. The author uses the National Sample Survey data from 2004 and 2007 to estimate causal effects of pension using state level age eligibility cutoffs as of 2006. My study distinguishes from this paper in various ways. First, I examine the 2011 expansion of the Indira Gandhi National Old Age Pension Scheme. The 2011 expansion was more inclusive, and increased the take up of this program with 60 to 64 year olds now eligible to receive pension.[3] Most states also increased pension generosity at the same time. While Kaushal (2014) uses the state level administrative rules to identify beneficiaries, I observe the pension recipients and the amounts they receive in my dataset. Using this information, I find a discontinuity in the probability of receiving pension from IGNOAPS in a fuzzy regression discontinuity framework. The expansion of the policy varies by state and time, and I am able to use this variation in a difference-in-differences set up as well, to study the long term change in outcomes. Second, as a proxy for poverty status, Kaushal (2014) uses the education level of the head of the household, while I use the measure of poverty as stated by the policy to define their eligibility criteria. And lastly, my analysis explores pension effects across generations which relates to existing literature on intergenerational transfer of benefits given to the elderly.

Few existing studies examine the benefits of cash transfers across generations. Edmonds (2006) and Duflo (2003) show that children benefit from living with the pension recipients. Edmonds (2006) and Juárez and Pfutze (2015) find an increase in school attendance and enrollment of young children living with grandparents. Further, gender of the recipient is also a significant factor to determine its effects on children. Duflo (2003) tests the unitary model of household decision making against a general model in South Africa, and finds that

[3] The increase in the number of beneficiaries across states between 2007 and 2011 is plotted in Figure 1 of the Appendix.

girls living with female recipients of pension have a higher nutritional status, while those with male recipients see no change. Ambler (2016) finds supporting results to indicate that pension earnings empower women to become primary decision makers in households. Women's bargaining power increases when they become eligible for social pension that adds to their income. The change in pattern of the use of income is visible in households where the male and female earn pensions at the same time. I add to the literature by investigating the nutritional status of children living with elderly men and women, to see if they respond differently. This is of particular interest in the Indian context since women have little decision making power in households.

1.3 Background of Indira Gandhi National Old Age Pension Scheme

This section provides a brief history of the Old Age Pension Program for the poor in India, drawing on Kaushal (2014), Dutta et al. (2010) and Asri et al. (2016). To address the lack of economic support to the elderly, the Indian Government introduced a pension program targeting the aging poor. This pension scheme was first launched by the Federal Government in 1995 with a modest amount of Rs. 75[4] to individuals above 65 years with little to no income or financial support from family members or other sources.[5] This scheme was first called the National Old Age Pension Scheme (NOAPS) and imposed a restric-

[4]Rs 75 is almost 1.5 USD at the current exchange rate

[5]Individuals with no source of income (destitutes), were difficult to identify which resulted in very low take up between 1995 to 2007.

tion on the maximum number of beneficiaries to be half the elderly population in each state. The federal government modified the eligibility criteria to include all individuals below the federal poverty line, and over 65 years in 2007, and increased the pension amount from Rs. 75 to Rs. 200.

Following the increase in enrollment from 8 million in 2004-05 to 14 million individuals in 2007-08, the federal government further lowered the age eligibility to 60 years from 65 years in 2011. My paper studies this 2011 expansion of the policy, which was renamed Indira Gandhi National Old Age Pension Scheme.[6] States responded to the change in age eligibility by implementing the federal age cutoff; while two states continued to follow the prior age eligibility of 65 years. All states were asked to provide an amount equal to or greater than the pension amount of 200 rupees provided by the federal government.[7]

The central program of IGNOAPS established a minimum pension amount of Rs 200, to all those who are below the poverty line and over 60 years of age. In entirety, the pension amount for individuals above 60 was a minimum of 200 rupees and could be a maximum of about 1200 rupees depending on the state of residence of the individual.[8]

Welfare scheme benefits targeting poor individuals can be availed by those in poor households, identified by ration cards.[9]. A ration card is a document issued under the authority of the State government, for the purchase of essential commodities from fair price shops and are of the following types:

[6]The central assistance under IGNOAPS is provided at the rate of Rs 200 per month per beneficiary for individuals in the age group 60 to 79 years. An amount of Rs 500 given out to individuals who are 80 years and above

[7]The expenditure and number of beneficiaries from this program are summarized in appendix Table A.20.

[8]State variation in age eligibility and pension amounts are explained in the Appendix

[9]Welfare schemes include programs for households below the poverty line - like the Public Distribution System, childcare, vaccination centers, etc

- BPL - Below Poverty Line
- APL - Above Poverty Line
- Antyodaya - Poorest section of the population

The below poverty line (BPL) cards are distributed by the state government representatives after identifying households based on population surveys in each state in accordance with the guidance provided by the ministry of rural development. There have been four BPL surveys so far- 1992, 1997, 2002 and 2011 (Ram et al. (2009)).[10]. A plethora of studies examine the definition of poverty in India and the need for the use of BPL cards versus the use of consumption expenditures to define poor households. As of 2014 (Planning Commission Report, 2014), the federal definition of poverty measured any household failing to meet the minimum consumption expenditure of Rs 4860 in rural areas and Rs 7035 in urban areas for a family of five at 2011-12 prices was noted as a below poverty line household (poor). Given these variations in defining poverty status I account for variations in poverty line across states and urban-rural regions using the type of ration cards owned by households to proxy for their poverty status. I combine households with BPL and Antyodaya cards as "Poor" and the remaining households as "NonPoor". The pension eligibility program is determined by the assignment variable, age in this scenario, and the poverty status of the household. As mentioned earlier, the definition of 'poverty' varies by states and could cause imperfect take-up by eligible individuals, hence fur-

[10]The latest round of the survey between 2011-13 used a score based ranking technique indicating the quality of life and a set of 13 socio economic indicators which included the type of house, size of land holdings, food security, sanitation, ownership of consumer durables, etc. The total score ranged from 0 to 52 and the states were given flexibility of deciding the cut-off points

ther analysis is restricted to poor households only as defined by the ration cards they hold. The use of poverty status to identify the affected elderly has two major concerns which I address here:

1. BPL card status: As mentioned earlier, the BPL cards were last revised and provided to households in 2005. This definition of poverty status is predetermined and any threats regarding an increase in poor individuals due to the policy is resolved using their predetermined poverty status. Also, to ensure there is no increase in the proportion of poor elderly due to the policy, I report results for households and individuals using the 2004 definition of BPL cards provided in the 2004-05 IHDS sample.

2. Concerns about misuse and improper allocation of households to poor and non-poor status are dealt with using a wealth index to group households based on the consumer durables they own. The quartiles are defined in decreasing order of poverty status, with the lowest quartile defined as the poorest section of the population.

1.4 Data

1.4.1 India Human Development Survey

The primary dataset used in this analysis is the India Human Development Survey (IHDS) data, a nationally representative survey conducted in two waves - 2005 and 2012. All states and union territories of India were surveyed with the exception of Andaman and Nicobar Islands, and Lakshadweep Islands. [11]

[11]The first round, India Human Development Survey (IHDS) is a survey of 41,554 households conducted in 2004-05 while the second round,India Human Development Survey

The second wave was surveyed between December of 2011 and December of 2012. This provides me with an acceptable time frame to analyze the short term effects of pension, since the policy was implemented on June 30 2011. I use the household and individual level data from the 2012 wave of IHDS (IHDS-II) for the regression discontinuity design and IHDS I and II for the difference-in-differences strategy.

An advantage of using the IHDS is that I can identify individuals participating in the old age pension program and also the amount of pension provided by the program. The dataset also includes pension amounts available to individuals from other sources (private employers, government job retirement benefits). As per the eligibility criteria defined by IGNOAPS, individuals above the cutoff age are eligible, provided they belong to households below the poverty line. The primary results of this paper are based on individuals who are above or below the cutoff age by 5 years (bandwidth). Of the total number of individuals in the selected bandwidth receiving pension income from IGNOAPS, approximately 82 percent belong to poor households.

Table 1 reports descriptive statistics of poor individuals and households where an elderly beneficiary is five years from the cutoff age. After tracking the age criteria followed by each state in India, my analysis segregates states by the varying eligibility age of 58, 60 and 65 years. In my sample, 75 percent of men and 33 percent of women between 55 and 65 years report being employed.[12] The

(IHDS), re-interviewed 83 percent of these households, and an additional 2134 households replaced.

[12]The question on employment status varies in the two rounds. Round 1 measures employment by an individual working less than or greater than 240 hours a year. Round 2 reports employment as (a) None (b)Working less than 240 hours (c) Working more than 240 hours, (d)part-time or full-time. Using both definitions, I define employment equals 1 if greater than 240 hours or work per year and 0 otherwise.

earnings used are hourly and annual earnings, conditional on being employed.[13]

1.4.2 Evidence on take-up

Figure 1 presents the first stage with a discontinuity in the probability of receiving pension. This eligibility criteria varies by states, and I use this variation by normalizing age as (Age-C), where C is the state age cutoff. Being eligible (above state's cutoff) increases the likelihood of a poor individual receiving pension. Although pension eligibility is determined by the age cutoff and poverty status, Figure 1 indicates some non-poor individuals (ineligible group) also receiving pension benefits from IGNOAPS. This invalidates the use of non-poor individuals/households as a comparison group. Hence, further analysis is only restricted to poor households.

Figures 2 and 3 indicate a jump in pension receipt and amounts among poor males and females, with those below the cutoff also receiving some benefits. This discontinuity in the probability of receiving pension does not change from 0 to 1, but a number smaller than 1. This discontinuity in pension receipt is used in a fuzzy regression discontinuity framework (Lee and Lemieuxa (2010) and Imbens and Lemieux (2008) elaborate on the method of fuzzy regression discontinuity). The intuition is that households with at least one eligible individual over the cutoff can be compared to those who are just below the cutoff, as their characteristics would be similar. Any discontinuous jumps in the outcomes observed at the threshold could be interpreted as the causal effect of the

[13]Earnings reported in the dataset are imputed by the Survey and are conditional on working.

program. Hence, the relationship between the outcome and pension income can be explained using the discontinuity in age, determined by the state administrative rule which defines the age eligibility, to instrument for the probability of receiving pension in a two stage least squares method (2SLS). The difference in mean outcome of the groups on either side of the cutoff gives the reduced form impact of the policy rule. I use the discontinuity to estimate the local average treatment effects that is equivalent to the difference in mean outcomes for the treatment and comparison groups divided by the difference in treatment receipt rates for both groups within a close neighborhood around the cutoff. This is estimated through a two stage least squared IV approach.

For this methodology to be valid, it is imperative that individuals are not able to manipulate the eligibility criteria. One drawback of using the IHDS data is that age is self reported. In this dataset, individuals do not report their age accurately, but tend to round off their age to the nearest multiples of 5 or 10 causing age heaping, or bunching at regular intervals of 5. If there exists a relation between the attributes of the outcome variable that could predict heaping in age, which is the running variable, the results obtained using heaped data would be biased. Age heaping in this study would be a problem if individuals chose to report their age as that eligible for the pension, heaping at 60 years, leading to an attenuation bias. For example, some individuals who are 59 or 61 might report their age as 60. Since RD involves comparing individuals who are 59 to those who are 61, this rounding off of age could lead to attenuation bias causing an underestimation of the true effects of pension.

Figure 4 shows the distribution of age using IHDS II. Figure 4 exhibits heaping across age groups at all ages in multiples of 5, but there is no observed discontinuity in age distribution at the eligibility of 60 years. To test the presence of manipulation in age formally, I also use the McCrary method to test for bunching at the cutoff. The null hypothesis of a discontinuity at the age cutoff is rejected.

Using the IHDS data, I find a few states have not reported any pension amounts from IGNOAPS. Since the FRD is sensitive to every individual receiving the treatment, I drop 8 states and 2 Union territories from further analysis. In support of these states not having reported pension amounts, I provide evidence from administrative data showing very few number of beneficiaries in these states[14].

1.5 Regression Discontinuity Estimation

My main approach in identifying the effects of pension on elderly labor supply and child health is a regression discontinuity design. This approach involves comparing, for example, the health of poor elderly individuals who were just below the state eligible age cutoff with the health of those just above the age cutoff.

Corresponding to Figures 2 and 3, the regression discontinuity estimates are presented in Table 2 using the following specification.

For individual i in household h in state s

[14] Arunachal Pradesh, Mizoram, Manipur, Meghalaya, Sikkim, Tripura, Puducherry, Daman and Diu, Chandigarh, Goa account for 2.5 percent of the households and are dropped from my analysis. Lakshadweep and Andaman Nicobar Islands are not included in the survey data

$$D_{ihs} = \alpha_0 + \alpha_1 Eligible_{ihs} + \alpha_2 f(Age_{ihs} - C_s) + \alpha_3 Eligible_{ihs} * f(Age_{ihs} - C_s) + \gamma X_{ihs} + \eta_s + \epsilon_{ihs} \tag{1.1}$$

η_s gives state fixed effects, X_{ihs} controls for individual characteristics like caste, religion, education and family size.

D is a dummy indicating if an individual receives pension or not, and takes the value 1 for those who receive pension and 0 for those who don't. Here, the two comparable groups are those eligible and those not eligible for the pension program, where *Eligible* is a dummy which takes the value 1 if the individual is above the cutoff age (eligible) and 0 otherwise (non-eligible). If there is an already existing age trend, the impact of the pension could be confounded with the impact of age if age trend is not accounted for. *f(Age-C)* is a polynomial allowing for age trends to differ on both sides of the threshold by including them individually and by interacting them with the dummy *Eligible*. State time invariant characteristics are controlled using state fixed effects. The reduced form is given by the following specification:

$$Y_{ihs} = \beta_0 + \beta_1 Eligible_{ihs} + \beta_2 f(Age_{ihs} - C_s) + \beta_3 Eligible_{ihs} * f(Age_{ihs} - C_s) + \gamma X_{ihs} + \eta_s + \epsilon_{ihs} \tag{1.2}$$

where, Y_{ihs} denotes the outcome variable, which can be labor supply and health of the elderly.

The coefficient β_1 gives the change in outcome for individuals who are above the cutoff age relative to those below the cutoff age, thereby giving the size of the discontinuity at the cutoff.

The measure of discontinuity as reported in Table 2 uses the group of individuals who are above or below the cutoff age by 10 years. To check for robustness, I also include individuals 5 years from the cutoff.[15]The first stage point estimates from Table 2 suggest that the likelihood of an eligible individual receiving pension is 10 percentage points higher than a non-eligible individual. Due to imperfect targeting of individuals by the policy, where the government fails to identify all eligible individuals, not all non-eligible individuals receive pension on becoming eligible at the cutoff. The discontinuity in receiving pension at the cutoff amounts to 416 rupees annually (Table 2). On average, individuals just above C receive 416 rupees more than those just below the cutoff. Using the results obtained, the effect of the pension on the treated group amounts to Rs 4,160 annually. Given the federal amount of Rs 200, the annual amount should be a minimum of about Rs 2,400. When estimating equation 1 by gender, I find men and women to be almost equally likely to be receiving pension if they are eligible.

To identify the effects of pension income distinctly from other confounding factors affecting the individuals decision to participate in the pension program, I exploit this discontinuity in the probability of receiving pension from IGNOAPS and a corresponding discontinuity in the amount of pension received at the age defined by states for poor individuals. Using the change in income induced by IGNOAPS, the causal relation between individual outcomes and pension receipt

[15]Table 22 in the appendix shows results for discontinuity in pension using a bandwidth of 5 years.

is estimated in a fuzzy regression discontinuity set-up with the discontinuity at the cutoff age as an instrument for the probability of receiving pension as seen in the following equations:

$$Y^{*}_{ihs} = \gamma_0 + \gamma_1 PensionReceipt_{ihs} + \gamma_2 f(Age_{ihs} - C) + \gamma X_{ihs} + \nu_{ihs} \qquad (1.3)$$

The coefficient of interest is γ_1,a measure of the change in the outcome at the cutoff age as a result of pension receipt. The coefficient γ_1 is a ratio of the jump in outcome (β_1) to the jump in pension receipt (α_1) at the cutoff. The ratio of the discontinuities in the outcome variable to the probability of receiving pension gives the estimate of the causal relation between the pension income and the outcome of interest. For outcomes of family members living with a pension beneficiary, I estimate equation 3 using the age of the oldest male (oldest female) of the household as the running variable.

1.5.1 Validity of RD Design

I use the discontinuity in probability of receiving pension through IGNOAPS to identify the effects of pension on elderly and children outcomes. The key identifying assumption of the RD design is that assignment to the treatment is as good as random immediately around the cutoff. Given the nature of the pension program there is no reason to expect discontinuities in predetermined individual and household characteristics at the state specific cutoffs. I use a parametric RD specification to test whether the instrument predicts observable characteristics of individuals around the cutoff:

$$Y_{ihs} = \gamma_0 + \gamma_1 Eligible_{ihs} + \gamma_2 f(Age_{ihs} - C) + \gamma_3 Eligible_{ihs} * f(Age_{ihs} - C) + \epsilon_i hs \tag{1.4}$$

where, Y_{ihs} is a covariate for individual i in household h of state s; $Eligible_{ihs}$ is a dummy for individual above state cutoff; and $f(Age_{ihs} - C_s)$ is a flexible polynomial of one's age normalized to zero around the state cutoff, which is allowed to take different functional forms on either side of the cutoff. I use a linear and quadratic specification to allow for age to vary on either side of the cutoff.

As Table 3 presents, covariates are imbalanced at the cutoff under the linear specification but balanced under the quadratic specification. Since my study involves understanding how men and women respond to pension separately, I exmaine the discontinuity in the observable characteristics by gender. Under the linear specification, the point estimates for religion is significant, and the F-test rejects the null hypothesis of covariate balance. In contrast, the quadratic specification indicates a strong balance on covariates and the F-test fails to reject the null hypothesis.[16] These results suggest that the covariates vary smoothly at the cutoff for pension, while there is a discontinuity in the probability of receiving pension at the respective state cutoffs.

Based on the covariate balance tests, I choose the quadratic RD specification but report point estimates of the linear and quadratic specifications for individuals 10 years from the cutoff. Standard errors are clustered at the state

[16]The imbalances under the linear specification are similar in direction to the quadratic specifications for all but caste of the individual.

level for my analysis.

Threat to Identification

To ensure that my analysis is identifying effects through pension from old age benefits, I examine discontinuities in pension receipt from other sources. Other sources of pension can either be from the government or from the private sector and both are contributory amounts. In India, those employed in the public sector receive pension on retirement, wherein, the age of retirement varies depending on the form of occupation.[17] Another form of pension, private pension, is from the private sector where individuals contribute a share of their income to a pension fund every month and receive the same with interest on retirement. I compare pension take up of poor and non-poor households using various sources of pensions, as reported in Table 4. I find a significant increase in pension from other government sources for non-poor households, and no significant effect on the poor households. The non-poor individuals are more likely to be employed in the formal sector and are eligible to receive pensions from government and private sources, unlike the poor individuals who are mostly employed in the informal sector.

[17]Typically, teachers are expected to retire at 58, government officials at 60; some individuals are given an extension to retire at 62.

1.5.2 Regression Discontinuity Results

Elderly Labor and Health

Figure 9 provides a graphical representation of the discontinuity in labor supply of men and women in poor households. The estimation corresponding to this figure is reported in Table 5 (equation 2 estimated). Table 5 Panel 1 reports the reduced form results. I find that male employment of those eligible for pension reduces by 3.8 percentage points in comparison to the non-eligible males in poor households. The quadratic fit estimates a bigger effect of almost 6.6 percentage points. A back of the envelope calculation shows the monthly pension income to amount to almost 20 percent of the monthly earnings of poor individuals. Hence, this could trigger a change in the employment of workers. On re-scaling the discontinuity of employment by the discontinuity in an individual receiving pension at the cutoff, I obtain the local average treatment effects of the pension program on employment which is about 60 percentage points. The large 2SLS estimates using the eligibility criteria for pension as an instrument for pension receipt are a result of lower magnitudes in the first stage and are consistent with a bandwidth of 5 years (Appendix Table 22). Column (1) indicates no significant change in the employment of women. In support of the findings of employment changes, point estimates of earnings suggest that pension affects men on the extensive margin, and women on the intensive margin. These results suggest that men and women reduce working as a result of the pension.

Next, I examine if a change in labor force participation is followed by changes in the health of elderly men and women. Since almost 85 percent of the poor are employed in the informal sector, pension benefits could help these individuals withdraw from the workforce. Given that males reduce their work hours and have more time for leisure, I would expect an improvement in their health. The direction of change in women's health is expected from the pension income they earn, helping them address personal needs better. Table 8 presents the impact of pension on the health of the elderly. To examine significant changes in their health, I use the WHO definitions of underweight and overweight calculated from body mass index, in addition to the number of days they have been ill. Point estimates from table 8 indicate no significant change in the health status of poor individuals. This indicates that pension income in the short run does not translate into a source of better nutrients and life style sufficiently. It is also possible that the duration between the program and survey data is too short to observe a change in the health status of individuals.

Earnings and Pension

Changes in income and consumption are potential channels that affect pension beneficiaries. To explain the effects of pension, I explore changes in household income and consumption and find that having an eligible male or female has no significant effect on these household measures. Since I find that individuals are working less, pension benefits should have a significant impact on the total income of individuals. Findings from table 6 show no significant changes in the sum of annual earnings and pension of males or females. Since men and women reduce working, but on different margins, I examine the share of total individual income to household income for males and females separately.[18] I

[18] Individual income here is calculated as a sum of annual earnings and annual pension. Share of income is calculated as ((Individual Earnings + Pension)/(Household earnings +

find some evidence of an increase in the income share of women relative to men. Conditional on the elderly being employed, the share of pension income and earnings to household income indicates that elderly women might have a higher bargaining power within the household.

Child Health and Education

The multi-generation household structure in India enables me to explore the effects of the additional pension income on younger generations living with the elderly. I use the same discontinuity in pension amount to examine the effect on child outcomes. I expect there to be a discontinuous improvement in the nutritional status using stunting, wasting and underweight measures of young children who are more susceptible to environmental and nutritional shocks. Duflo (2003) finds a direct transfer of benefits from grandmothers to granddaughters. Ambler (2016) also finds women to have a higher bargaining power in households with the pension income, with no change in the decision making status of women. Following this literature, I use the oldest male's and oldest female's age to determine eligibility of the household of the child to establish the transfer of benefits from grandparents to children. The age of the oldest male and female is restricted to 5 years above and below the cutoff age. I find no significant evidence within the bandwidth of my study. To explain this channel better, I investigate the discontinuity in household expenditure. I find a discontinuous increase in the education expenditure of households, but no evidence of an increase in the share of food or medical expenditure in poor

Pension))

households. Further, the effects could vary depending on who the pension earner in the household is.

1.6 Difference-in-Differences Estimation

While the fuzzy regression discontinuity estimation examines the effects of the pension within the bandwidth of choice and acts like a randomized experiment, I use a difference-in-differences methodology to understand the long run impacts of pension income to poor households. I compare 50 to 79 year old individuals above and below the state cutoff in the given year, and those before and after the 2011 expansion of the policy,.

1.6.1 Difference-in-Differences Estimation Strategy

There are two advantages to using the difference-in-differences approach in addition to the regression discontinuity design. Firstly, it addresses the issue of a delay in payment of pension funds and delay in receiving the amount that could translate in to benefits for the household. Second, health of the children and elderly individuals could take time to respond to the increased inflow of cash into the household. This strategy enables us to measure the long term effects (period of one year) to explain how pension incomes for those eligible after the 2011 expansion of the policy affects the outcome. The difference-in-differences specification is built on the assumption that the underlying trends in the outcome variables between those who did and did not receive pension would have been similar in the absence of the pension program, i.e, there exist parallel trends in outcomes between the treatment (eligible) and comparison (not eligible) groups. I exploit the panel nature of the IHDS data with the two waves in 2005 and 2012 and use household fixed effects in all specifications to account for time invariant household characteristics. I also use age fixed effects of the oldest male and female in all specifications. This helps separate the effect of aging from the policy impact.

Eligibility for old age pension is defined by the respective state rules (Appendix Table 24 for program details). I estimate the following specification to examine the effect of the old age pension policy for household h in state s at time t:

$$\begin{aligned} Pension_{hst} = \alpha + \beta_1(Eligible_{hst} * After2011_t) + \beta_2 Eligible_{hst} + \\ \beta_3 After2011_t + \eta_h + \eta_a + \epsilon_{hst} \end{aligned} \tag{1.5}$$

Pension is defined as total pension amount for household h of state s at time t. Eligibility is defined as the oldest female (oldest male) above state cutoff in the given year. After2011 is a dummy for the time period (2011=1 and 2004=0). η_a gives age fixed effects. η_h are household fixed effects.

The comparison groups in the regression are individuals below the cutoff age or in the pre-treatment period. In this equation β_1 is the coefficient of interest and represents the difference-in-differences estimator of the effect of the expansion of the policy for a household with an eligible individual after the expansion of the policy in 2011. β_2 explains the change in the pension amount of the eligible group relative to the non-eligible group in the base year, 2004.

β_3 gives the estimated change of the non-eligible group between 2004 and 2011.

I use the cutoff age by states for old age pension in 2011-12 to identify the change in old age pension amounts received by households where the oldest individual was between 50 and 79 years, between 2004-05 and 2011-12. I find the pension amount to be significantly higher for households with at least one eligible individual after the implementation of the revised policy of 2011.

Elderly Labor and Health

As discussed before, I find a decrease in the employment and earnings of elderly men and women respectively. One of the concerns about the reduction in employment of individuals, is that it could be driven by retirement from the organized sector. In my study, this is not necessarily true, since the poor households comprise of individuals who are primarily occupied in the informal/unorganized sector and are daily wage workers or construction workers. Also, retirement in India is restricted to the public sector jobs - such as officers, janitors, low or high ranked jobs. However, to address the question of reduction in employment due to retirement from the job or effects of the income flow, I exploit the panel structure of the data to identify individuals employed in the public sector in 2004. Following them over time, they would most likely retire from the labor force. Hence, I identify individuals employed in the public sector in 2004, and exclude them to examine effects of pension on elderly employment. Estimates suggest a reduction in the employment and earnings of these individuals, but, the effect is not significant.

Child Health

In my analysis, I find households with eligible grandmothers spending more on food and education, with no evidence of an increase in household expenditure on consumption of food or education in the presence of a male beneficiary. Conditional on households with an eligible female increasing their consumption of food, an increase in nutrient intake of households indicates an improvement in the nutritional status of children. Using the anthropometric z scores of children to measure wasting, stunting and underweight children, I find that for children living with an elderly female, wasting in children reduces by 14 percentage points. However, this effect is not significant when I look at health measures of boys and girls separately. Although the direction of the change indicates that both boys and girls can benefit from living with a grandmother, low power of the data limits the study for now. The same analysis on children living with their grandfathers shows no change in their health measure. As seen earlier, there is a reduction in earnings of men but no change in womens employment or earnings. This is indicative of women having more power within the household, since the pension income adds to their average annual earnings, and increases their decision making power in the household.

The effects of additional income in poor households is not necessarily restricted to the targeted individuals, but can be extended to those living in the same eligible households. I use the eligibility of the oldest male and female in every household to define the eligibility of the household and its impact on the labor supply of prime age individuals living with the elderly.

1.7 Robustness Check

The federal mandate changed the eligibility for pension in 2011 from 65 to 60 years for poor individuals. To examine the effects of the pension program using the federal rule, I restrict my analysis to states that strictly followed the 60 year cutoff in 2011, for individuals in the age group 55 to 64. The size of the discontinuity in pension receipt using these six states is similar to the analysis including various state cutoffs. On an average, individuals just above 60 receive 522 rupees more than those just below 60 years. Using the results obtained, the effect of the pension on the treated group amounts to Rs 3,720 annually and a monthly pension of Rs 310. This validates the results from section 6.2.

1.7.1 Donut Regression using District Level Household Survey

I also use District Level Household Survey (DLHS4) to examine the health of children and the elderly as a robustness check. The reproductive and child health survey is designed to cover the areas of antenatal care and immunization services, family planning, utilization of government health services, contraceptive prevalence. The DLHS has been carried out in four phases starting in 1998-99. The most recent phase was carried out in 2012-13 and covered 26 states. The remaining nine poorest states were surveyed separately under the Annual Health Survey (AHS). The advantage of using this dataset is having the date of birth - month and year, of the elderly in the dataset which helps with the regression discontinuity design. However, accuracy of the dataset is questionable as age heaping is observed in the dataset. To obtain unbaised estimates, I use a donut regression discontinuity, dropping all individuals at age 50, 55, 60, 65 and 70 as needed for the analysis. The estimated equations are the same as equation 2, with reduced form estimates reported. Donut regression results confirm my findings from the fuzzy regression discontinuity results. Pension income does not affect the health of beneficiaries in the short run, and my results again show that there is no change in the nutritional status of children living with grandparents, as observed in the fuzzy regression discontinuity design.

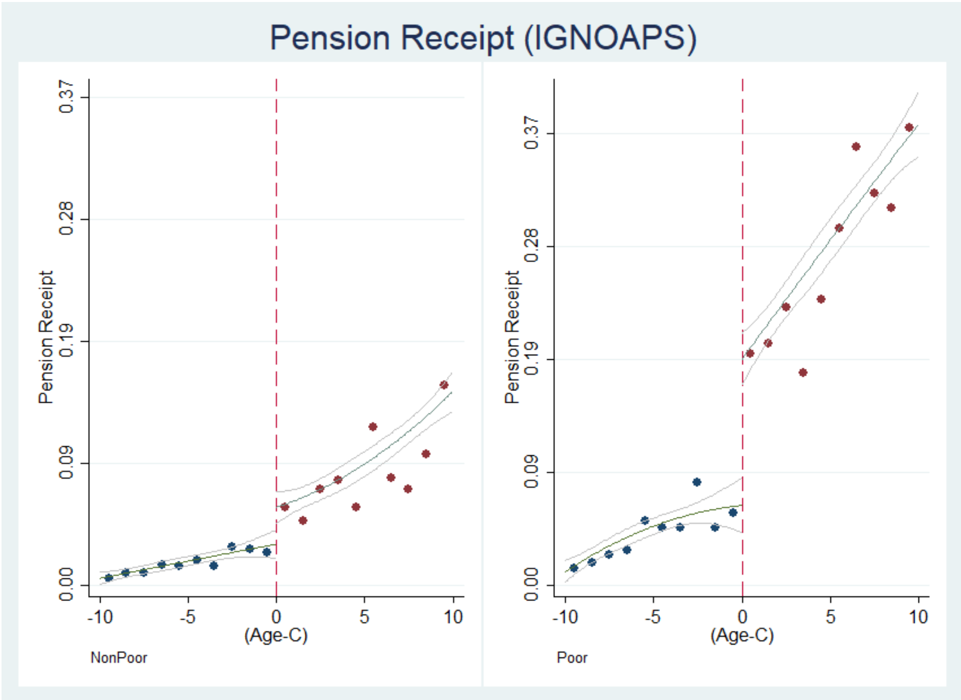
1.8 Conclusion

While past studies have established strong ties between pension earnings and labor supply of individuals, recent studies have explored how this association translates into benefits for household members co-residing with pension beneficiaries. Developing nations have continued to implement social pensions to protect the increasing aging population. I investigate the role of these pensions in poor households with multiple generations living together using the 2011 expansion of a non-contributory targeted program, with eligibility for pension defined by their age and poverty status. Exploiting the state-age eligibility variations in a regression discontinuity design and the state-year eligibility variations in a difference-in-differences framework, I find a decrease in the labor supply of men and women. Children living with grandmothers also indicate having better nutritional status. The regression discontinuity design acts like a randomized experiment, as a consequence of the inability of program participants to control the assignment variable near the age cutoff. The fuzzy regression discontinuity estimates suggest an immediate response to the pension program. On the other hand, the difference-in-differences estimation exploits the panel nature of the dataset, and differences out changes due to factors other than the 2011 expansion of the pension policy.

The primary question is if the targeted pension has reduced poverty among poor elderly. If it has, then does this translate into additional benefits for the household with an improvement in the health of the old and the young? This paper suggests that gender plays a crucial role in determining the effects of this pension program. Female beneficiaries enjoy an increased power within the household because of pension income. This increased power to women trickles down to improve the health of children cohabiting with elderly women. Understanding the effects of social pensions provided to poor elderly is important for considering a continuation of such policies across developing nations.

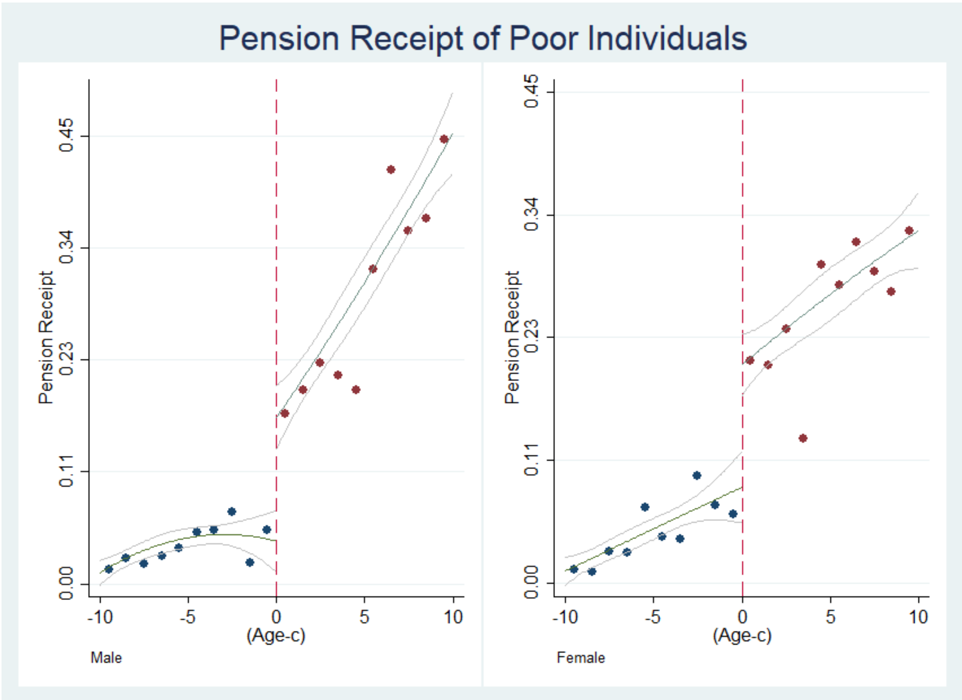
1.9 Figures and Tables

1.9.1 Figures



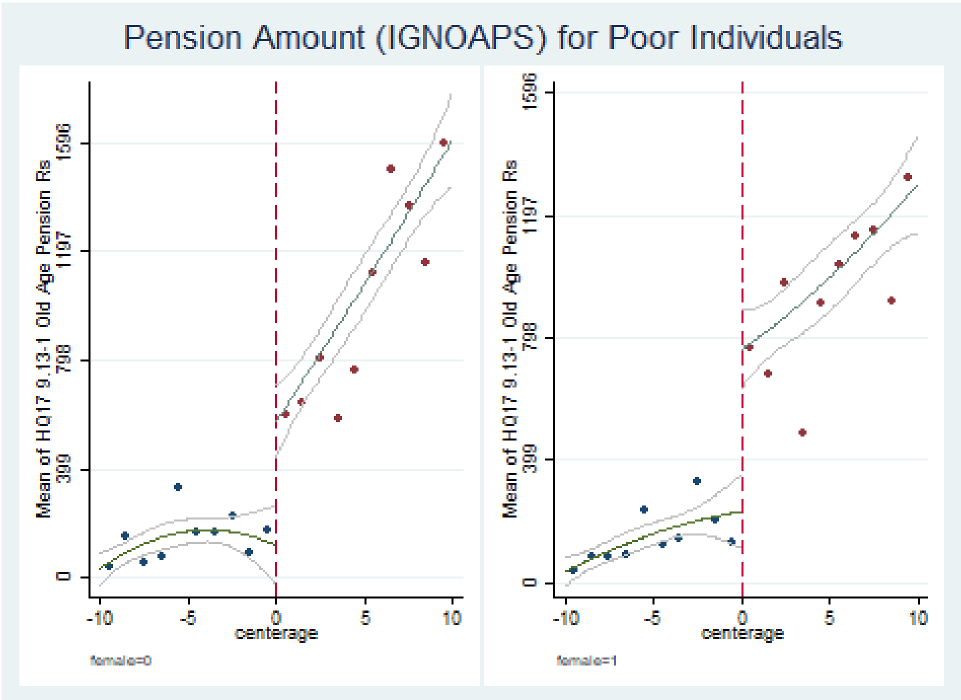
Notes: Source: IHDS 2012. x axis denotes age centered at the cutoff, (Age - C), where C is the state cutoff; y-axis plots probability of receiving pension. Poor defined as individuals who belong to a HH with ration card "BPL" or "Antyodaya". Non-Poor defined as individuals who belong to HH with ration card "APL". Sample is individuals with age 10 years of the cutoff.

Figure 1.1: Discontinuity in probability of receiving pension at cutoff



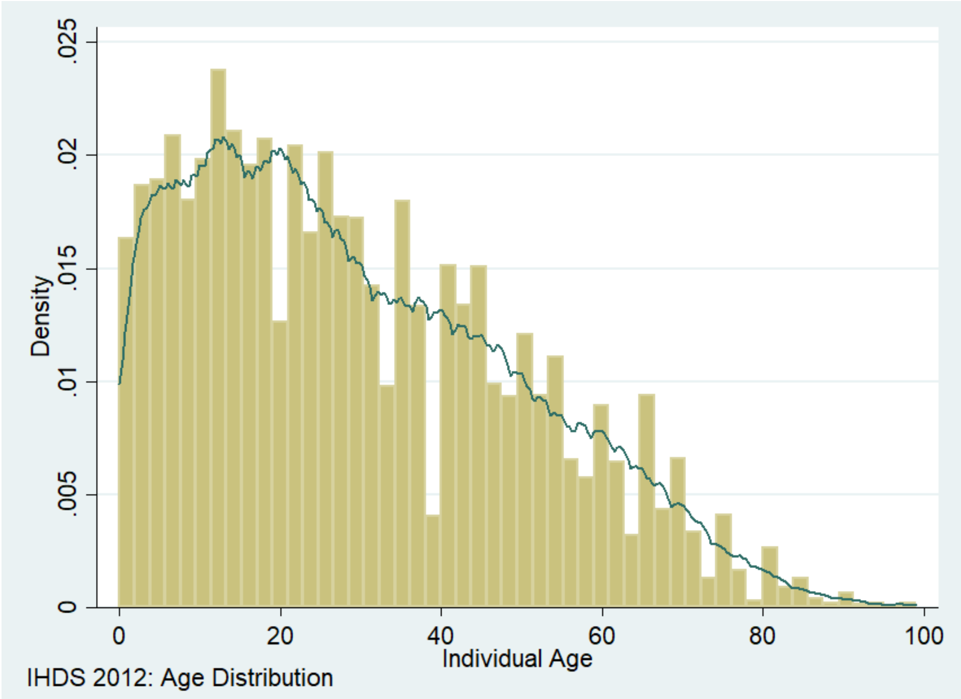
Notes: Source: IHDS 2012. x axis denotes age centered at the cutoff, (Age - C), where C is the state cutoff; y-axis plots probability of receiving pension. Poor defined as individuals who belong to a HH with ration card "BPL" or "Antyodaya". Non-Poor defined as individuals who belong to HH with ration card "APL". Sample is individuals with age 10 years of the cutoff.

Figure 1.2: Discontinuity in probability of receiving pension at cutoff by gender



Notes: Source: IHDS 2012. The x axis denotes age centered at the cutoff, (Age - C), where C is the state cutoff; y-axis plots pension amounts from IGNOAPS. Poor defined as individuals who belong to a HH with ration card "BPL" or "Antyodaya". Non-Poor defined as individuals who belong to HH with ration card "APL". Sample is individuals with age 10 years of the cutoff.

Figure 1.3: Discontinuity in pension amount received by poor individuals



Notes: Source: IHDS 2012. This figure plots the age distribution of individuals in 2012.

Figure 1.4: IHDS (2012): Age distribution

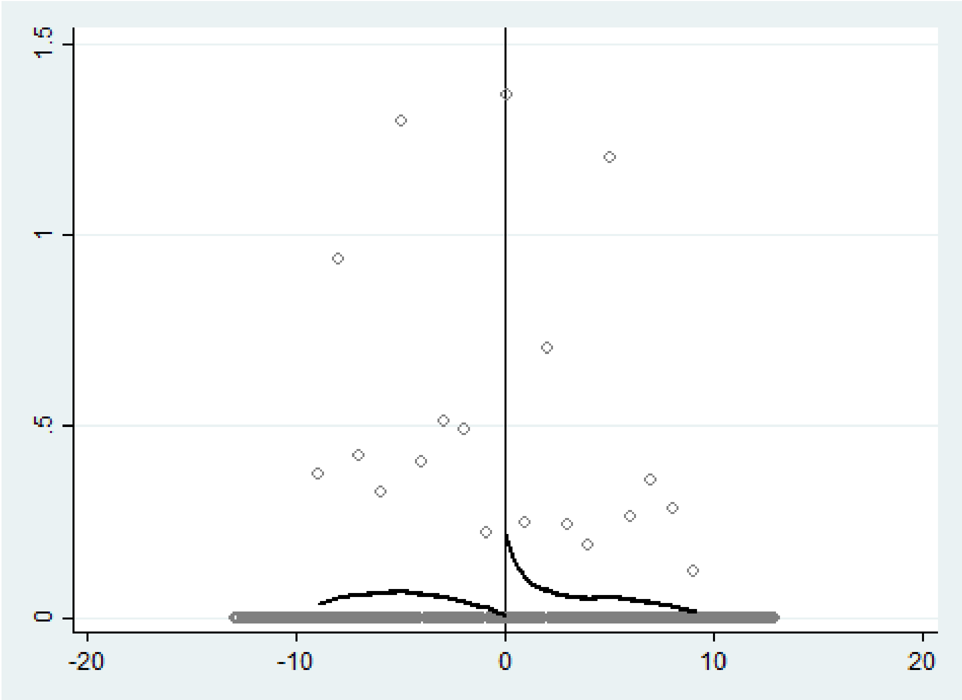
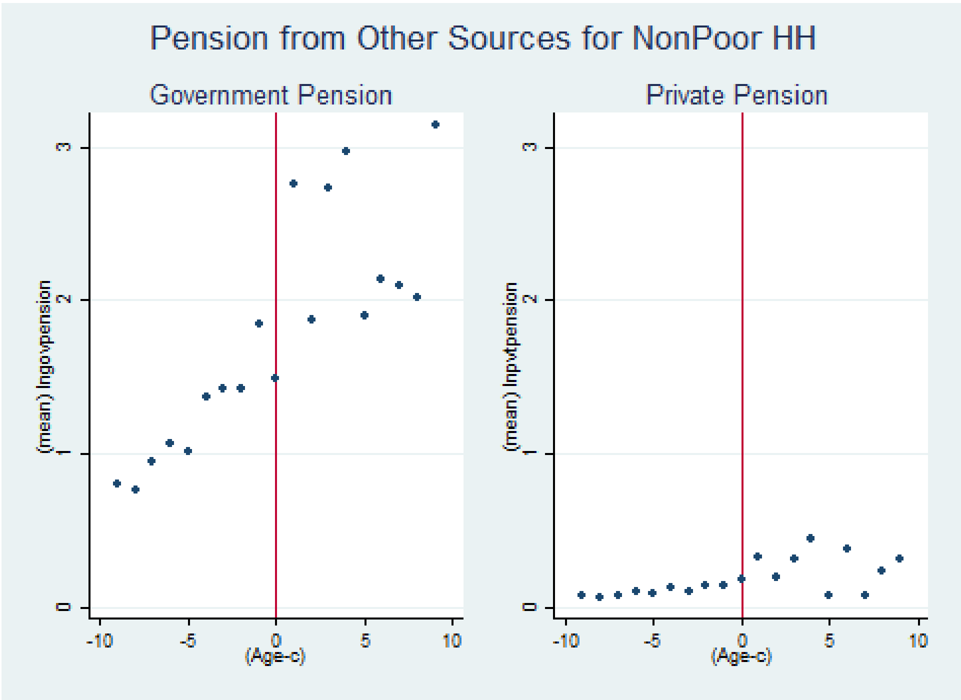


Figure 1.5: McCrary test for manipulation of running variable

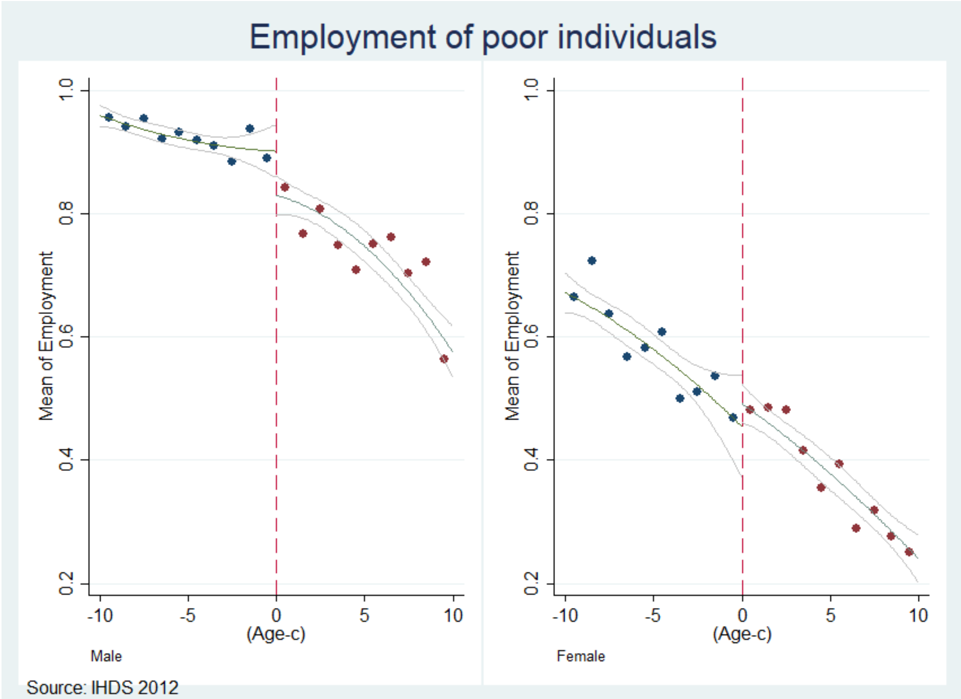
Notes: This figure plots pension amounts from other sources (government and private). x-axis is the age centered by state cutoffs, (Age-C) and the y axis reports the pension amount for poor households.Sample is individuals with age 10 years of the cutoff.

Figure 1.6: Government and private pension for poor households



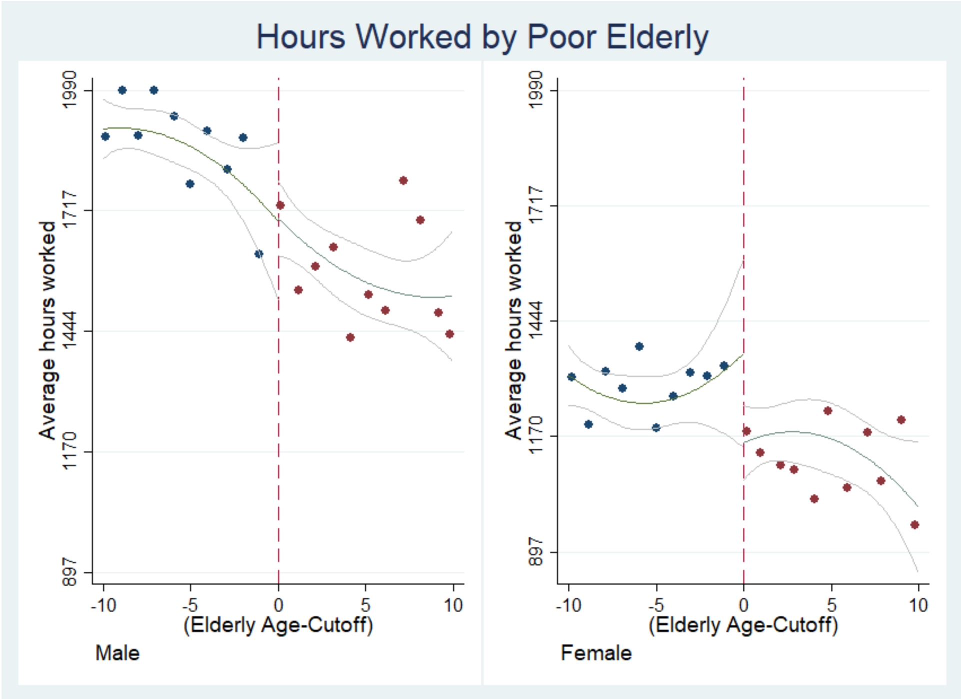
*Notes:*This figure plots pension amounts from other sources (government and private) x-axis is the age centered by state cutoffs, (Age-C) and the y axis reports the pension amount for nonpoor households.Sample is individuals with age 10 years of the cutoff.

Figure 1.7: Government and private pensions for non-poor households



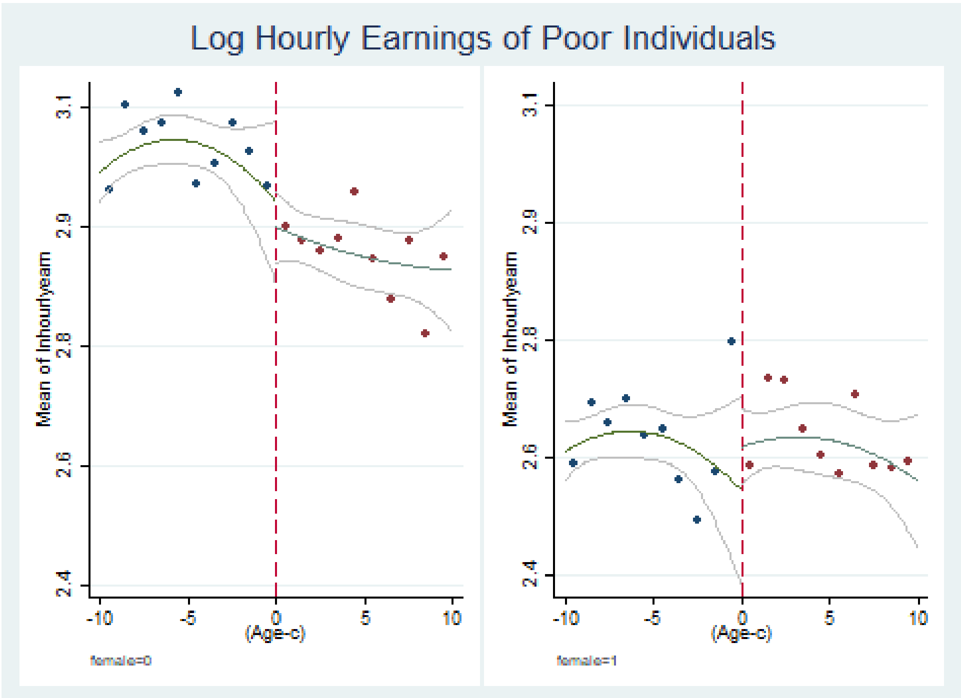
Notes: Source: IHDS 2012. x axis denotes age centered at the state cutoff (Age-C). y-axis is a binary indicator for employment. Sample is individuals with age 10 years of the cutoff.

Figure 1.8: Employment of older individuals



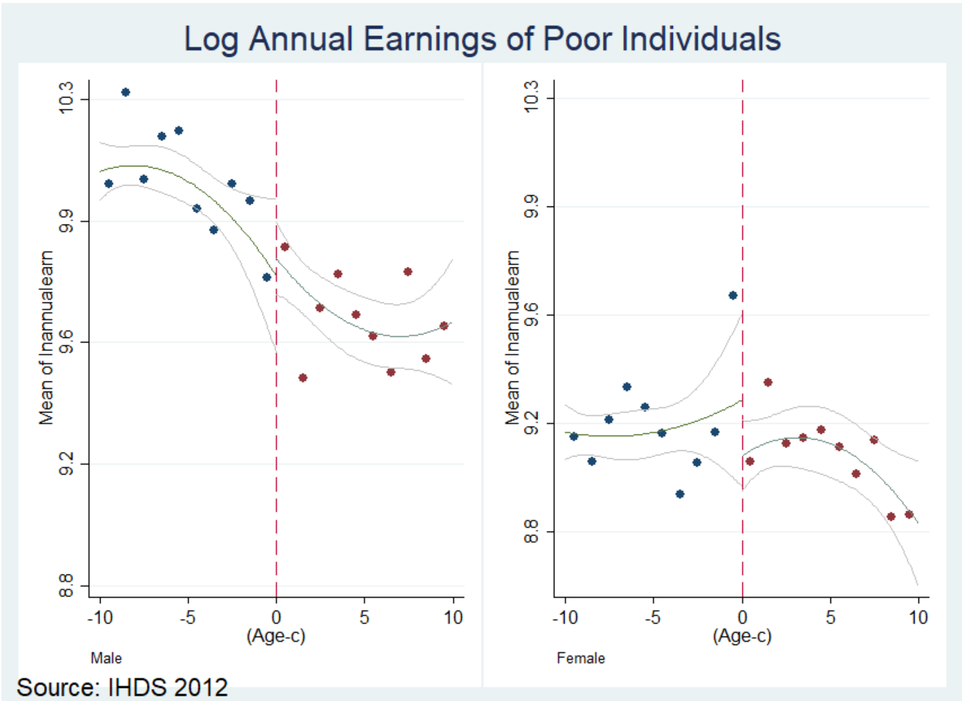
Notes: This figure shows the discontinuity in number of hours worked of elderly males and females in poor households.

Figure 1.9: Annual number of hours worked



*Notes:*Source: IHDS 2012. This figure shows the discontinuity in log hourly earnings of elderly males and females in poor households. Sample of individuals age 10 years from the threshold.

Figure 1.10: Log hourly earnings



Notes: This figure shows the discontinuity in log annual earnings of elderly males and females in poor households.

Figure 1.11: Log annual earnings

1.9.2 Tables

Table 1.1: Summary statistics

Variable	Mean	Std. Dev.	N
Pension from IGNOAPS			
Pension receipt	0.15	0.35	12309
Annual pension amount	3639.33	2502.23	1818
Labor Supply of Elderly			
Employment	0.66	0.47	12030
Annual earnings	11765.71	30089.61	12030
Hours worked per year	878.01	985.08	12030
Health of Elderly			
Underweight	0.27	0.44	7462
Overweight	0.17	0.37	7462
Days ill in last month	1.55	4.28	12309
Health of Children			
Underweight	0.33	0.47	1337
Stunting	0.38	0.48	1250
Wasting	0.17	0.37	1289

Summary statistics for poor individuals 10 years from the cutoff. Labor supply includes work in business, farming and non-farm work. Annual pension amount is conditional on receiving pension. Elderly underweight=1 if BMI<18.5 and overweight=1 if BMI>=25. Child underweight=1 if weight for age (WAZ) <-2; Wasting=1 if weight for height (WHZ)<-2 and Stunting=1 if height for age (HAZ)<-2. WAZ and WHZ are restricted between -6 and 5, and HAZ between -6 and 6 (as per WHO guidelines).

Table 1.2: RD based estimates of probability of receiving pension and pension amounts in poor households

	Pension Receipt			Annual Pension Amount		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Female	Male	All	Female	Male
Linear	0.091***	0.098***	0.081***	342.748***	417.259***	253.120***
	[0.016]	[0.020]	[0.016]	[56.086]	[73.997]	[60.575]
Quadratic	0.102***	0.093***	0.111***	416.572***	411.919***	418.264***
	[0.021]	[0.031]	[0.025]	[67.415]	[102.652]	[84.620]
Observations	12275	6427	5848	12275	6427	5848

The table reports the probability of receiving pension from IGNOAPS and the average pension amounts for individuals between 50 and 70 in poor households. Bandwidth is restricted to 5 years above and below the centered age (age-cutoff by states). Controls used include religion, caste and education of head of the household, number of children and number of people in the household. State fixed effects are also included. Standard errors are clustered at the state level.* p<0.10, ** p<0.05, *** p<0.01

Table 1.3: Covariate Balance Test

	(1)	(2)	(3)	(4)
	HigherSecondary	UpperCaste	Hindu	Family Size
Linear	-0.008*	-0.028	-0.035***	-0.331**
	[0.005]	[0.020]	[0.011]	[0.142]
Joint F-test		10.79		
p-value (Prob> χ^2)		0.0290		
Quadratic	-0.010	-0.030	-0.031	-0.200
	[0.008]	[0.035]	[0.021]	[0.255]
Joint F-test		20.79		
p-value (Prob> χ^2)		0.3057		
Observations		6436		
Linear	-0.016	-0.032	0.021*	0.258*
	[0.011]	[0.020]	[0.012]	[0.143]
Joint F-test		14.28		
p-value (Prob> χ^2)		0.0290		
Quadratic	-0.019	-0.019	0.013	0.094
	[0.019]	[0.036]	[0.020]	[0.250]
Joint F-test		1.30		
p-value (Prob> χ^2)		0.8608		
Observations		5856		

Table presents covariate balance tests for eligible women (top panel) and eligible men (bottom panel) RD specifications within the bandwidth of 10 years from the cutoff age for poor individuals and households. *p<0.10, ** p<0.05, *** p<0.01

Table 1.4: HH Pension Amount(Log) from Non-IGNOAPS Sources

	Government	Private
	(1)	(2)
	Poor Households	
Eligible	0.158	0.090
	[0.142]	[0.076]
Observations	4306	4317
Adjusted R^2	0.033	0.001
	Non-Poor Households	
Eligible	0.353	0.205***
	[0.255]	[0.043]
Observations	5797	5947
Adjusted R^2	0.107	0.011

Notes: Table presents the pension amounts from other government and private sources received by households with an eligible individual. Eligible is a dummy; Eligible=1 if Age above state cutoff. * p¡0.10, ** p¡0.05, *** p¡0.01

Table 1.5: Effect of Pension on Poor Elderly Employment

	Employment		Hours Worked		Log Annual Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Female	Male
			Reduced form			
Linear	0.019	-0.038**	-73.882	-67.846	-0.145**	-0.096
	[0.027]	[0.017]	[69.867]	[70.227]	[0.069]	[0.085]
Quadratic	0.037	-0.066**	-239.508**	43.783	-0.222**	0.107
	[0.037]	[0.028]	[102.240]	[92.903]	[0.099]	[0.079]
Observations	6365	5631	1968	3259	1967	3252
			Instrument pension receipt by eligibility			
Linear	0.216	-0.436**	-622.267	-661.281	-1.230*	-1.005
	[0.253]	[0.217]	[630.954]	[683.191]	[0.732]	[0.797]
Quadratic	0.386	-0.613**	-1366.274*	412.112	-1.274*	0.996
	[0.377]	[0.298]	[809.106]	[925.336]	[0.771]	[0.859]
Observations	6365	5631	1968	3259	1967	3252

Table reports employment and earnings of elderly males and females. Earnings are reported in logs. Hours worked and annual earnings are conditional on being employed. Bandwidth used is 10 years above or below the cutoff age. Controls include education, caste, religion and family compostiion. State fixed effects are also included. Standard errors are clustered at the state level.

Table 1.6: Sum of annual earnings and pension

	Earnings+Pension		Share of Household Earnings+Pension	
	(1)	(2)	(3)	(4)
	Female	Male	Female	Male
Linear	1081.846	-6227.404**	0.053***	0.011
	[797.033]	[2922.577]	[0.017]	[0.014]
Quadratic	371.347	-684.073	0.050*	0.046
	[972.164]	[5750.822]	[0.028]	[0.033]
Observations	6427	5848	5559	5141

This table presents change in sum of annual earnings and pensions of individuals 10 years from the cutoff in poor households. Columns 1 and 2 represent the sum of annual earnings and pension. Columns 3 and 4 denote the share of the sum of individual earnings and pensions to sum of household earnings and pensions for eligible individuals (Individual earnings+Pension/ (Household Earnings+Pension)). Controls include education, caste, religion of individual, family size, and state fixed effects. Standard errors are clustered at the state. * p<0.10, ** p¡<.05, *** p<¡0.01

Table 1.7: Health of elderly individuals in poor households

	Underweight		Overweight		Days ill in last month	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Female	Male
	Panel A: Reduced form					
Linear	-0.031	0.054	0.022	-0.019	0.304	-0.164
	[0.027]	[0.043]	[0.025]	[0.032]	[0.179]	[0.247]
Quadratic	-0.027	0.064	0.008	-0.049	0.612	-0.593
	[0.040]	[0.077]	[0.038]	[0.047]	[0.399]	[0.494]
Observations	4119	3327	4119	3327	6427	5848
	Panel B: Instrument pension receipt by eligibility					
Linear	-0.318	0.616	0.226	-0.213	3.107	-2.031
	[0.288]	[0.498]	[0.253]	[0.333]	[1.941]	[3.116]
Quadratic	-0.263	0.537	0.074	-0.406	6.559	-5.363
	[0.398]	[0.645]	[0.359]	[0.378]	[5.489]	[4.614]
Observations	4119	3327	4119	3327	6427	5848

This table reports health of elderly individuals 10 years from the cutoff. Controls included are religion and caste, education level of individual and state fixed effects. Standard errors are clustered at the state level. Panel A reports the OLS coefficients for eligible:1(Age>=C_s) where C is the cutoff age. Panel B reports the 2SLS estimates using eligibility as an instrument for pension receipt. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 1.8: Summary statistics for poor children (0-5)

Variable	**Mean**	**Std. Dev.**	**N**
Children living with grandmother			
Underweight	0.33	0.47	1337
Underweight boys	0.326	0.469	703
Underweight girls	0.334	0.472	634
Stunting	0.386	0.487	1250
Stunting boys	0.405	0.491	642
Stunting girls	0.365	0.482	608
Wasting	0.173	0.378	1289
Wasting boys	0.175	0.38	674
Wasting girls	0.171	0.377	615
Children living with grandfather			
Underweight	0.324	0.468	1152
Underweight boys	0.308	0.462	598
Underweight girls	0.341	0.475	554
Stunting	0.404	0.491	1083
Stunting boys	0.399	0.49	551
Stunting girls	0.408	0.492	532
Wasting	0.159	0.366	1109
Wasting boys	0.18	0.385	572
Wasting girls	0.136	0.343	537

Table 1.9: Anthropometric measures status of boys and girls living with grandparents (0 to 5 yrs)

	Underweight		Wasting		Stunting	
	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
Panel A: Children age 0-5 living with grandmothers						
Eligible	-0.047	-0.141	-0.035	-0.074	-0.025	-0.045
	[0.085]	[0.092]	[0.070]	[0.075]	[0.094]	[0.114]
Pension Receipt	-0.808	-0.668	-0.702	-0.509	-0.417	-0.253
	[1.575]	[0.481]	[1.819]	[0.614]	[1.461]	[0.607]
Observations	1337	1330	1289	1280	1250	1242
Panel B: Children age 0-5 living with grandfathers						
Eligible	-0.068	-0.071	-0.032	-0.020	-0.078	-0.051
	[0.072]	[0.077]	[0.050]	[0.052]	[0.059]	[0.065]
Pension Receipt	-4.263	-2.549	-0.810	-0.366	-1.602	-0.978
	[23.764]	[8.740]	[1.712]	[0.975]	[3.085]	[1.969]
Observations	1152	1152	1109	1109	1083	1083

This table reports the change in nutritional status of children living with their grandparents. Children age between 0 to 5 years and grandparents bandwidth is 5 years above and below the cutoff age by states. Controls include education, caste, religion of the oldest individual. Child age and state fixed effects are also included. Standard errors are clustered at the state level. Definition for health measures of children- underweight=1 if weight for age (WAZ) <-2; wasting=1 if weight for height (WHZ)<-2 and stunting=1 if height for age (HAZ)<-2. WAZ and WHZ are restricted between -6 and 5, and HAZ between -6 and 6 (as per WHO guidelines). *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 1.10: Summary of Household Characteristics

	2004			2011		
Variable	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
Education(%)	2.233	4.637	7545	2.986	5.685	8593
Food(%)	48.797	16.543	7545	40.192	13.262	8593
Medical(%)	9.927	14.141	7545	10.594	13.278	8593
Rent(%)	0.499	3.045	7545	0.953	4.812	8593
Clothing(%)	5.92	5.057	7545	5.316	5.599	8593
Services(%)	4.156	9.102	7545	4.666	8.006	8593
Others(%)	25.645	12.702	7545	34.389	11.621	8593
Tobacco(%)	2.823	4.111	7545	0.903	0.988	8593
Household characteristics						
Number of children	1.506	1.67	7555	1.337	1.411	8593
Number of persons	5.608	2.932	7555	5.114	2.482	8593
HH Annual Pension	1873.375	1550.799	523	4328.538	3139.71	1996
Total HH Consumption	3445.436	3028.586	7555	8036.021	7771.813	8593

Table 1.11: Household Pension Amount using state eligibility and 2011 poor definition

	Annual Pension Amt		Pension Receipt	
	Poor	NonPoor	Poor	NonPoor
Eligible*After	1125.204***	496.721**	0.172***	0.060***
	[200.892]	[208.246]	[0.036]	[0.021]
Eligible	-202.526	-258.577	-0.006	-0.024
	[220.533]	[198.969]	[0.048]	[0.034]
After2011	219.466***	171.360*	0.053**	0.024**
	[60.113]	[96.565]	[0.019]	[0.011]
Observations	16148	28062	16148	28062
Adjusted R^2	0.225	0.082	0.244	0.083

This table presents change in household pension amount and pension receipt after the 2011 expansion of the policy. Controls include household fixed effects and oldest individuals age fixed effects.

Table 1.12: Change in income and pension in HH with oldest eligible male/female

	All households		Households with children	
	(1)	(2)	(3)	(4)
	Income	Consumption	Income	Consumption
EligibleFemale*After	-0.095	0.072	0.761	0.169**
	[0.361]	[0.075]	[0.519]	[0.073]
EligibleFemale	0.464	-0.024	0.012	-0.074
	[0.454]	[0.049]	[0.584]	[0.054]
After2011	0.080	0.742***	-0.253	0.694***
	[0.336]	[0.062]	[0.333]	[0.053]
Observations	11321	11333	7304	7308
EligibleMale*After	-0.616*	0.044	0.195	0.100
	[0.341]	[0.060]	[0.322]	[0.067]
EligibleMale	1.183***	0.130**	0.881**	0.055
	[0.373]	[0.060]	[0.391]	[0.049]
After2011	0.594**	0.772***	0.171	0.708***
	[0.239]	[0.042]	[0.263]	[0.056]
Observations	10894	10903	6705	6709

This table presents change in income and consumption (in logs) after the 2011 expansion of the policy. Households and age fixed effects are included. Standard errors are clustered at the state level. * 0.10 ** 0.05 *** 0.01

Table 1.13: Consumption expenditure in poor households with children

	(1)	(2)	(3)
	Food	Education	Medical
EligibleFemale*After	0.163*	0.431	0.185
	[0.079]	[0.269]	[0.178]
EligibleFemale	-0.024	-0.314	-0.167
	[0.050]	[0.205]	[0.250]
After2011	0.461***	1.227***	0.750***
	[0.061]	[0.178]	[0.168]
Observations	7308	7308	7308
EligibleMale*After	0.066	0.087	0.192
	[0.101]	[0.251]	[0.297]
EligibleMale	0.132*	-0.034	-0.171
	[0.074]	[0.157]	[0.318]
After2011	0.476***	1.151***	1.028***
	[0.085]	[0.163]	[0.195]
Observations	6709	6709	6709

This table reports change in household consumption (in log) with eligible females and males after the 2011 expansion of the policy. Household and age fixed effects included. Standard errors clustered at the state level. *0.10 ** 0.05 *** 0.01

Table 1.14: Summary statistics for poor 0-5 yr old boys and girls living with grandparents

	Before			After		
Variable	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
Underweight Boys	0.385	0.487	1548	0.322	0.467	1989
Underweight Girls	0.377	0.485	1347	0.312	0.463	1876
Stunting Boys	0.493	0.5	1406	0.401	0.49	1873
Stunting Girls	0.479	0.5	1243	0.372	0.483	1807
Wasting Boys	0.158	0.365	1475	0.168	0.374	1917
Wasting Girls	0.15	0.357	1273	0.158	0.365	1802

Source: IHDS (2004 and 2011). This table provides summary statistics for children age 0 to 5 years living with their grandparents. 2004 indicates the year before the policy expansion and 2011 is the year after the policy expansion.

Table 1.15: Health measures of poor children (0-5 years) with eligible female in HH

	(1) Underweight	(2) Wasting	(3) Stunting
Panel A: Children under 5 living with grandmother			
EligibleFemale*After	-0.181	-0.145**	-0.131
	[0.120]	[0.069]	[0.111]
EligibleFemale	0.189*	0.219**	0.064
	[0.092]	[0.090]	[0.102]
after2011	-0.081	0.072**	-0.100
	[0.094]	[0.033]	[0.108]
Observations	5206	4987	4875
Adjusted R^2	0.236	0.112	0.261
Panel B: Children under 5 living with grandfather			
EligibleMale*after	-0.142	0.029	-0.156
	[0.108]	[0.093]	[0.112]
EligibleMale	0.109	0.137	0.055
	[0.112]	[0.122]	[0.133]
After2011	-0.018	0.036	-0.078
	[0.136]	[0.054]	[0.080]
Observations	4834	4637	4526
Adjusted R^2	0.203	0.145	0.231

Notes: Table reports health measures of children under 5 years living with their grandparents age 50 to 79 years. Controls include age fixed effects (child and grandmother), household fixed effects. Definition for health measures of children- underweight=1 if weight for age (WAZ) <-2; wasting=1 if weight for height (WHZ)<-2 and stunting=1 if height for age (HAZ)<-2. WAZ and WHZ are restricted between -6 and 5, and HAZ between -6 and 6 (as per WHO guidelines). * 0.10 ** 0.05 *** 0.01

Table 1.16: Health measures of children (0-5 years) with grandparents in poor households

	Girls			Boys		
	(1)	(2)	(3)	(4)	(5)	(6)
	Underweight	Wasting	Stunting	Underweight	Wasting	Stunting
Panel A: Children age 0 to 5 living with grandmother						
EligibleFemale*After	-0.271	-0.129	-0.112	0.019	-0.153	-0.098
	[0.231]	[0.167]	[0.245]	[0.306]	[0.155]	[0.163]
EligibleFemale	0.250	0.245	0.097	0.053	0.229	0.113
	[0.172]	[0.212]	[0.167]	[0.325]	[0.202]	[0.235]
After2011	-0.173	0.066	-0.063	-0.079	0.086	-0.092
	[0.164]	[0.116]	[0.153]	[0.228]	[0.160]	[0.203]
Observations	2467	2352	2323	2738	2635	2540
Adjusted R^2	0.239	0.116	0.266	0.232	0.113	0.323
Panel B: Children age 0 to 5 living with grandfather						
EligibleMale*After	-0.085	0.082	0.078	0.071	-0.114	0.056
	[0.181]	[0.224]	[0.339]	[0.188]	[0.139]	[0.243]
EligibleMale	-0.048	0.013	-0.036	0.083	0.221	-0.123
	[0.154]	[0.219]	[0.339]	[0.223]	[0.213]	[0.230]
After2011	-0.181	-0.049	-0.254	-0.123	0.141	-0.168
	[0.225]	[0.169]	[0.309]	[0.225]	[0.118]	[0.256]
Observations	2301	2203	2184	2532	2434	2330
Adjusted R^2	0.205	0.237	0.218	0.209	0.166	0.301

Notes: The table reports health measures of children age 0 to 5 years living with their grandparents age 50 to 79 years. Controls include age fixed effects (child and oldest male and female in household). Standard errors are clustered at the state level. Definition for health measures of children- underweight=1 if weight for age (WAZ) <-2; wasting=1 if weight for height (WHZ)<-2 and stunting=1 if height for age (HAZ)<-2. WAZ and WHZ are restricted between -6 and 5, and HAZ between -6 and 6 (as per WHO guidelines). Significance at * 0.10 ** 0.05 *** 0.01

1.9.3 Robustness Check

Table 1.17: Donut Regression: Probability of Receiving Pension and Pension Amount

	Pension recipient		Pension Amount	
	Poor	NonPoor	Poor	NonPoor
Eligible	0.152***	0.018	617.545***	113.747**
	[0.024]	[0.012]	[101.923]	[53.085]
Observations	3065	5180	3065	5180

Notes: The table reports the pension amounts for poor and non-poor households using a donut regression; dropping individuals at 55, 60 and 65. The reported results are for the linear specification, controlling for education, gender, religion and caste of the individual. Standard errors in brackets. * p¡0.10, ** p¡0.05, *** p¡0.01

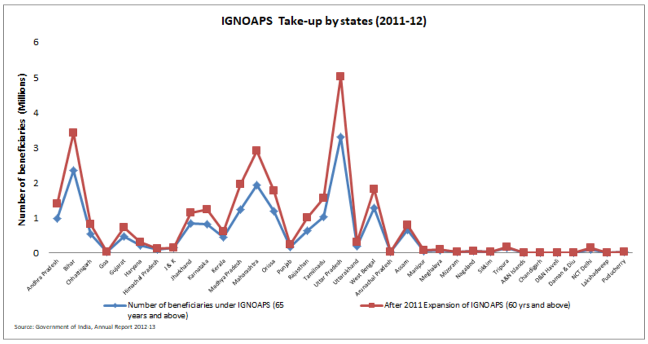
Table 1.18: Health measures (Age in Months)

	Diabetes	Hypertension	Weight	BMI
Eligible	0.059	0.016	-0.894	-0.623
	[0.067]	[0.059]	[1.511]	[0.602]
Observations	12881	13280	12934	12934
Adjusted R^2	0.029	0.039	0.213	0.091

This table represents change in heatlh measures using DLHS 4. Controls used include religion, caste and education. State fixed effects are included. Standard errors are clustered at the state.

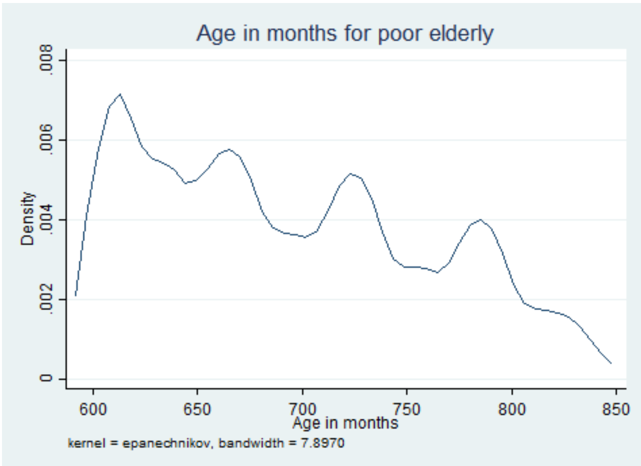
1.10 Appendix A

1.10.1 Figures



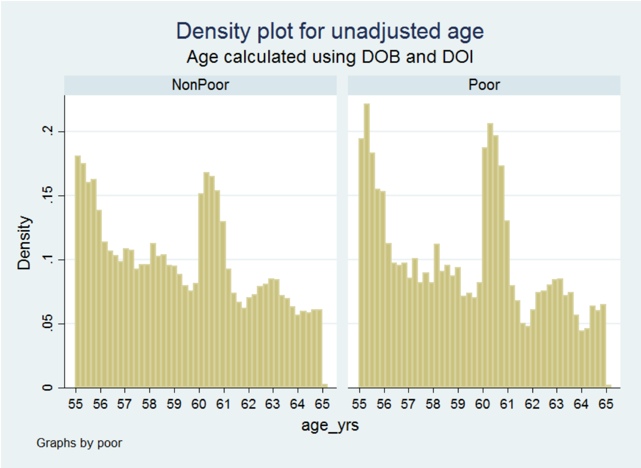
Notes: Source: Ministry of Rural Development Annual Report (2012-13) This figure denotes the increase in number of IGNOAPS beneficiaries across states after the 2011 expansion of the policy.

Figure A.1: State take-up of IGNOAPS (2012-13)



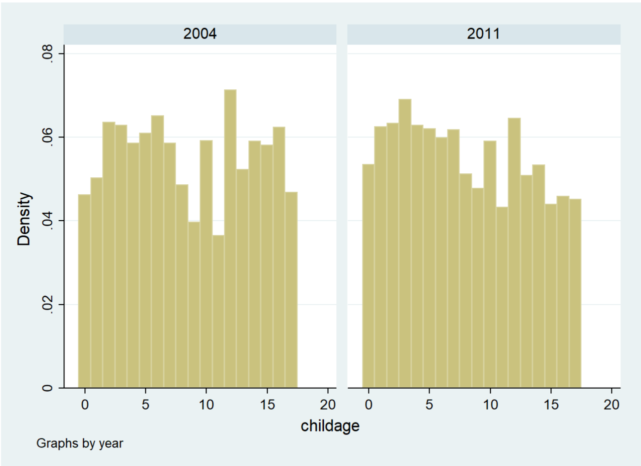
*Notes:*Source: DLHS 2012. This figure shows the distribution of the age of elderly in months calculated using the reported date of birth and date of interview.

Figure A.2: DLHS: Age (in months) distribution



Notes:DLHS This figure provides the age distribution of individuals in poor and nonpoor households, where age is calculated using the reported date of birth and date of interview.

Figure A.3: DLHS: Age distribution of individuals in poor and non-poor households



Notes: This figure provides the age distribution of children in poor households in the years 2004 and 2011.

Figure A.4: Age distribution of children in 2004 and 2011

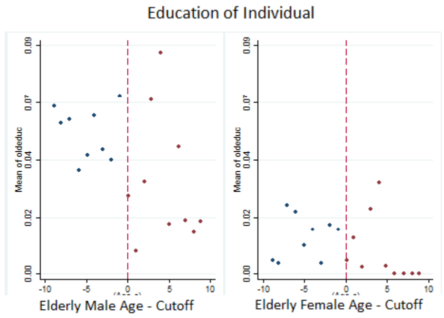


Figure A.5: Education of elderly men and women

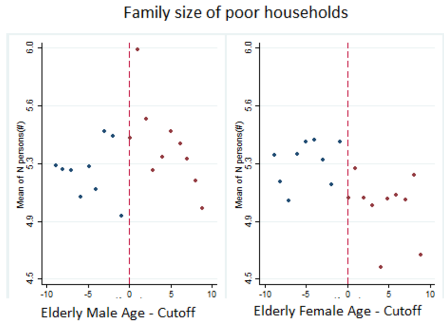


Figure A.6: Family size of poor households

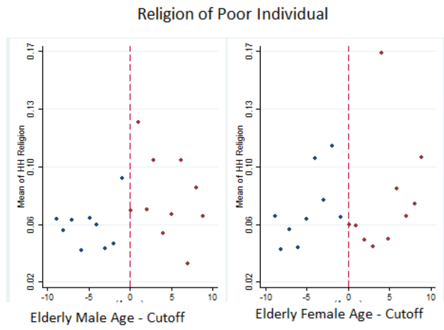


Figure A.7: Religion of elderly men and women

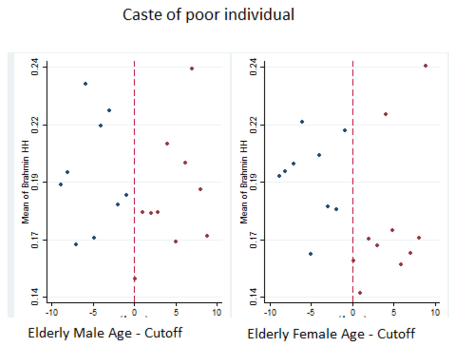


Figure A.8: Caste of elderly men and women

1.10.2 Tables

Table A.1: Probability of Receiving Pension and Pension Amount in Households

	Pension recipient		IGNOAPS Amount	
	Linear	Quadratic	Linear	Quadratic
	(1)	(2)	(3)	(4)
Eligible	0.053***	0.109**	178.499**	390.232**
	[0.018]	[0.039]	[64.041]	[157.418]
Observations	8057	8057	8057	8057

This table presents the probability of receiving pension and pension amounts for the bottom 50 percent of the sample. They are defined as the poorest half using wealth index created from consumer durables. This result holds for individuals who are 5 years from the threshold. Controls include caste, religion, education of the individual, family composition of the household and state fixed effects. * p¡0.10, ** p¡0.05, *** p¡0.01

Table A.2: Household income and consumption

	Income		Consumption	
	(1)	(2)	(3)	(4)
	Female	Male	Female	Male
Linear	-0.04	-0.02	-0.03	-0.05*
	[0.04]	[0.05]	[0.02]	[0.02]
Quadratic	0.05	0.16*	0.01	-0.04
	[0.07]	[0.08]	[0.05]	[0.04]
Observations	6427	5848	6427	5848

This table presents change in log household income and consumption with an eligible female and male in poor households. Controls include education, caste, religion of the individual, family size and state fixed effects. Standard errors are clustered at the state level. *p<0.10, ** p<0.05, *** p<0.01

Table A.3: 2SLS:Consumption Expenditure for Poor Households (Logs) with children

	Eligible Female								Eligible Male							
	Food		Education		Medical		Tobacco		Food		Education		Medical		Tobacco	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Share	Amount	Share	Amount	Share	Amount	Share	Amount	Share	Amount	Share	Amount	Share	Amount	Share	Amount
Panel A: Reduced form																
Linear	0.314	-0.039	0.585**	0.209	-0.765	-0.053	-0.260	-0.404**	0.143	-0.037	0.748	0.231	-0.127	0.097	-0.114	0.162
	[1.502]	[0.051]	[0.225]	[0.204]	[1.314]	[0.254]	[0.224]	[0.147]	[1.337]	[0.054]	[0.507]	[0.249]	[1.273]	[0.242]	[0.264]	[0.115]
Quadratic	-1.610	-0.071	2.201**	0.748	-2.912	-0.250	0.513	-0.067	1.024	-0.052	0.128	0.190	-2.650	-0.399	-0.114	0.162
	[2.536]	[0.117]	[0.798]	[0.511]	[2.834]	[0.341]	[0.535]	[0.339]	[1.898]	[0.101]	[1.160]	[0.568]	[2.310]	[0.366]	[0.264]	[0.115]
Observations	3633	3633	3633	3633	3633	3633	3633	3633	3261	3261	3261	3261	3261	3261	3261	3261
Panel B: Instrument pension receipt by eligibility																
Linear	3.981	-0.493	7.418***	2.648	-9.711	-0.671	-3.303	-5.121**	1.544	-0.395	8.054	2.489	-1.364	1.047	-1.224	1.741
	[18.205]	[0.723]	[2.691]	[1.928]	[15.969]	[3.061]	[2.760]	[2.098]	[14.023]	[0.554]	[6.659]	[2.934]	[13.357]	[2.490]	[2.866]	[1.149]
Quadratic	-10.018	-0.441	13.696***	4.652*	-18.122	-1.557	3.192	-0.414	7.159	-0.365	0.897	1.326	-18.519	-2.787	1.261	1.942
	[17.171]	[0.771]	[5.247]	[2.797]	[14.924]	[2.001]	[3.390]	[2.044]	[12.782]	[0.656]	[7.997]	[4.066]	[19.020]	[3.096]	[5.327]	[3.637]
Observations	3633	3633	3633	3633	3633	3633	3633	3633	3261	3261	3261	3261	3261	3261	3261	3261

This table reports consumption by gender of elderly individuals. Controls included are religion and caste, education level of individual and state fixed effects. Standard errors are clustered at the state level. Panel A reports the OLS coefficients for eligible:1(Age>=C_s) where C is the cutoff age. Panel B reports the 2SLS estimates using eligibility as an instrument for pension receipt. Columns 1-8 indicate households with eligible females and columns 7-16 report consumption of households with an eligible male. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.4: Earnings and Pension (in Logs)

	(1) Annual Earnings	(2) Annual Pension	(3) Earnings +Pension	(4) Share of Earnings and Pension
EligibleFemale*After	0.390	1.042	1.790	0.074
	[0.857]	[1.380]	[1.106]	[0.065]
EligibleFemale	-0.057	0.799	-0.395	-0.047
	[0.891]	[0.966]	[1.182]	[0.052]
After2011	0.200	1.581**	0.334	-0.014
	[0.741]	[0.721]	[0.724]	[0.049]
Observations	6317	6317	6317	5212
EligibleMale*After	-0.862	1.516	0.148	0.094
	[0.781]	[0.896]	[0.963]	[0.095]
EligibleMale	0.222	0.167	0.465	0.021
	[1.011]	[1.252]	[1.318]	[0.090]
After2011	1.003	0.842*	1.238	-0.098
	[0.820]	[0.481]	[0.810]	[0.070]
Observations	6316	6316	6316	5214

The table presents earnings and pension of individuals in poor households. Column 4 represents (Individual Earnings+Pension)/(Household Earnings+Pension). * 0.10 ** 0.05 *** 0.01

Table A.5: Old Age Pension by States

State	IHDS State Code	2007		2011	
		Age	Pension Amount (Rs)	Age	Pension Amount (Rs)
Jammu and Kashmir	01	65	200	60	200+150
Himachal Pradesh	02	65	200	60	200+130
Punjab	03	65m,60f[19]	200+250	65m, 60f	200+250
Chandigarh	04	65	200	60	500
Haryana	06	65	200+100	60	200+300
Delhi	07	60	200+400	60	200+800
Rajasthan	08	58m,55f	200+200	58m,55f	200+300
Uttar Pradesh	09	65	200+200	60	200+200
Bihar	10	60	200	60	200
Sikkim	11	65	200+200	60	200+200
Arunachal Pradesh	12	60	200	n/a	200
Nagaland	13	65	200	60	200+100
Manipur	14	65m,60f	200+175	60	200
Mizoram	15	65m,60f	200+50	65m,60f	200+50
Tripura	16	65	200+100	65	200+200
Meghalaya	17	65m,60f	200	60	200+50
Assam	18	65m,60f	200+50	65m,60f	200+50
West Bengal	19	65	200+200	60	200+200
Jharkhand	20	65	200+200	60	200+200
Orissa	21	65	200	60	200
Chhattisgarh	22	65	200+75	60	200+100
Madhya Pradesh	23	60	200+75	60	200+75
Gujarat	24	60	200+200	60	200+200
Maharashtra	27	65m,60f	200+175	60	200+400
Andhra Pradesh	28	60	200	65	200
Karnataka	29	60	200+200	60	200+200

[19] m males, f females

Table A.5: Old Age Pension by States

State	IHDS State Code	2007		2011	
		Age	Pension Amount (Rs)	Age	Pension Amount (Rs)
Goa	30	60	200+800	60	200+800
Kerala	32	65	200+35	60	200+50
Tamil Nadu	33	65	200+200	65	200+800
Pondicherry	34	60	200+400	56	200+400

Notes: The following information is collected from various sources. Ministry of Rural development Annual Reports; Answers to Parliament Questions `http://164.100.47.5/qsearch/QResult.aspx`; Also referred to Kaushal (2014), () and Asri et al. (2016) to compare eligibility criteria by states. Due to the unavailability of information on pension in Daman and Diu, Dadra Nagar Haveli and Uttarakhand, these union territories/states have been dropped.

Chapter 2

Housing and Risk Preferences of Older Individuals

2.1 Introduction

Standard models in economics assume risk aversion is inherent and stable over time. But recent literature suggests that risk aversion can change with time, altered by some shock in the environment (e.g. unemployment, serious health shocks, financial wealth fluctuations). Since the risk preference parameter is used as an important input in economic models to explain migration, consumption and savings and technology adoption, it is crucial to understand potential factors that determine risk aversion.

I approach the stability of risk aversion as an empirical question by examining the effect of home equity. Home equity is the primary contributor to households' assets, more so for elderly households that are near retirement or post retirement. In the United States, almost 80 % of the individuals above 50 are homeowners and more than 50% of their wealth is from housing. Given that housing wealth is an important component of asset portfolio for so many aging US households, unexpected shocks to housing value could affect decision making among these individuals.

I estimate the causal relation between housing and risk aversion using the restricted panel dataset of the Health and Retirement Study (HRS) between 1998 and 2006.[1] The advantage of using this dataset is that it provides us a unique way to study risk aversion using hypothetical income gamble questions asked repeatedly to the same individuals. The time period when these questions were asked overlaps with the period before the Great Recession. Years between 1998 and 2006 witnessed a sharp rise in house prices, that may have a significant effect on the preference of individuals, especially those who are close to the retirement age. I build on the existing literature that explains the relation between risk aversion and wealth fluctuations (Brunnermeier and Nagel (2008), Liu (2013) and Paravisini et al. (2016)) to examine the effect of an increase in housing value on risk aversion.

Following existing literature, I define home equity as the difference between property value and mortgage. With increasing housing value, studies have found an increase in share of risky assets (Chetty, 2017). I examine if an increase in housing value can reduce risk aversion among the elderly homeowners. Since housing choice is endogenous, I use the zip code level average house prices to introduce exogenous variation to housing value. Figure 1 denotes the trends in self-reported property value and mortgage debt of the primary residence of individuals with average house prices at the zip code level. I find a positive

[1]The Health and Retirement Study began in 1992 and is a binennial panel survey of Americans above the age of 50 and their spouses. More information on the data are available `http://hrsonline.isr.umich.edu/`

trend in the self-reported home equity and the average house prices at the zip code level, to denote that the zip code level house prices could be an indicator of the change in home equity of households.

Using data from the Health and Retirement Study, I apply the hypothetical income gamble questions as risk aversion, taking values 1 through 6 in increasing order of risk aversion. Average house prices is obtained from the Federal Housing Finance Agency (FHFA). Controlling for unobserved heterogeneity using individual fixed effects, and local housing and labor market conditions using state and year fixed effects, I find that the risk aversion of individuals does not change significantly with changes in house prices between 1998 and 2006. Additionally, I investigate the effect of home equity on risky behavior using data on portfolio allocation of elderly individuals that extends over the period 1992 to 2014. This is one of the first studies to explain the causal relationship between risk preferences and home equity, using hypothetical gamble questions to explain risk aversion.

One might be concerned about the use of income gambles to address risk aversion among the elderly. But a study by Barsky et al. (1997) finds that the hypothetical income gamble questions are significantly correlated with risky behavior like smoking, drinking, holding more risky assets than safe assets and the failure to take up insurance. Since they find that the hypothetical gamble questions determine risky behavior, I use the same to explain risk aversion.

This paper is organized as follows: Section 2 provides a brief summary of the existing literature on risk preferences and housing; section 3 explains the empirical strategy to determine the causal relation between risk aversion and home equity; section 4 provides information on the data and variables. In section 5, I report the results. Section 6 concludes.

2.2 Existing Literature

Most studies in economics assume that risk preference of individuals is stable and is unaltered by economic experiences. However, literature in psychology argues that life experiences can have a significant impact on personal decisions (Weber et al. (1993) and Hertwig et al. (2004)). In the recent past, studies in economics have also contributed to this literature to explain how risk aversion can vary with time and is affected by wealth, age and natural disasters (Hanaoka et al. (2018), Sahm (2007), Brunnermeier and Nagel (2008), Liu (2013), Malmendier and Nagel (2011)).

It has been suggested that a macroeconomic shock such as the Great Depression has had a long lasting effect on the risk attitudes of individuals who witnessed this shock (Malmendier and Nagel (2011)). In addition, studies that examine the effect of natural disasters like the earthquake in Japan also suggest that risk preferences can be altered in the short and the long run (Hanaoka et al. (2018) and Malmendier and Nagel (2011)). Along with the aforementioned factors, wealth fluctuations have also proved to have a significant impact on risk preferences.

Brunnermeier and Nagel (2008) investigate the change in portfolio allocations with wealth fluctuations. They theorize that risk aversion of individuals is time-varying as a result of habits and consumption commitments, and they find that the share of risky assets held by households does not change with wealth fluctuations. While Brunnermeier (2008) uses the share of risky assets of a household to determine changes in risk preference, a study by Sahm (2007) uses hypothetical income gambles to define risk aversion. She finds that about 30% of the variation in risk tolerance is a result of household income and wealth, or changes in employment and health. Both papers suggest that risk aversion need not be constant over time. While there are studies that show risk aversion changing with time, there is limited literature on the relationship between risk aversion and housing value, which is known to be the primary contributor to a household's assets.

Housing value could act as another medium to affect individual decision making about mobility, insurance, labor market participation and portfolio choices (Demyanyk et al. (2017), Campbell and Cocco (2007), Davidoff (2010), Zhao and Burge (2017) and Cocco (2004)). Previous studies that have estimated regressions of portfolio shares on home equity, mortgage and property value have presented mixed findings. On the one hand, Michielsen et al. (2016) find that home equity and mortgage debt have a non-significant impact on household stock holdings using administrative Dutch data. But on the other hand, Heaton and Lucas (2000) Yao and Zhang (2004) explain the positive association between property value and the share of stock holding.

A seminal paper by Cocco (2004) endogenizes housing and examines the joint relation between housing and assets. However, he does not establish any causal link between the two. A recent study by Chetty et al. (2017) builds on the model by Cocco (2004) to determine the causal relationship between portfolio allocation and housing using the Survey of Income and Program Participation (SIPP) panels. In their paper, they instrument for property values and home equity using the current and year of purchase national average house price interacted with state level housing supply elasticity. They show that commitments affect risk preferences by amplifying risk aversion with respect to moderate stake shocks and create a motive to take large payoff gambles. Portfolio allocation is an indicator of an individuals risk taking ability, and they find that an increase in home equity, while keeping property values constant, increases stock holding.

In my paper, I add to the existing literature on risk aversion, portfolio allocation and home equity by examining if an increase in home equity can result in reducing risk aversion among older homeowners using hypothetical income gambles. Additionally, I also study the causal relation between portfolio allocation and home equity among elderly homeowners.

My paper contributes to this existing literature by addressing the stability of risk aversion in response to changes in house prices in two ways. First, I use the hypothetical gambles surveyed in the Health and Retirement Study to define risk aversion and explain changes in risk stability over time with changes in house prices. Second, I focus on individuals above fifty years of age, and their response to change in house prices prior to the Great Recession. Almost 80 % of these individuals are homeowners, and more than 50 % of their wealth comes from housing wealth. As explained by Sahm (2007), a smaller variation in risk tolerance could be attributed to changes in wealth and health of individuals. However, since my focus is on the aging population, I hypothesize that wealth fluctuations could have a more significant impact on these individuals than those who are still in the prime working age.

I examine the effects of exogenous changes in home equity on risk preferences of individuals over 50 years using differences in house prices across markets as an instrument for home equity. I use the zip code specific house price index as plausible exogenous variation in housing wealth. Since I have longitudinal data and can track household mobility using the restricted data from HRS, I can verify that the household resided in the same zip code over multiple waves.

2.3 Empirical Strategy

Individuals are expected to become less risk averse with an increase in wealth. I use an instrumental variable approach to establish the effect of home equity on risk aversion. The primary specification to estimate the effect of home equity for individual i in zip code j at time t is as follows:

$$Y_{ijt} = \alpha_0 + \alpha_1 Home\ Equity_{ijt} + \pi X_{ijt} + \gamma_i + \eta_a + \mu_s + \nu_t + \epsilon_{ijt} \tag{2.1}$$

where, Y_{ijt} can take values of risk aversion or share of assets. Home equity, is defined by self-reported property value less outstanding mortgage debt. The hypothetical income gambles used to measure risk aversion are asked from 1998 to 2006. Hence the analysis for the risk outcomes is between the same period, and is restricted to homeowners. Also, the zip code level data helps me track individuals geographic location over time, and I restrict my sample to nonmovers (people who remain in the same zip code between 1998 and 2006), to identify a the impact of changes in housing value on the preference of individuals who do not sell their primary residence.

Using the above specification, it is possible that individuals with low risk aversion would choose to have lower mortgage debt and hence have higher home equity. To deal with the endogeneity of housing choice, I introduce exogenous variation in home equity using the annual zip code level house prices from the Federal Housing Finance Agency (FHFA) as an instrument for home equity. Another concern that is addressed by using the average house prices by zip code, is measurement error coming from the self reported property values. Individuals may not know the exact value of their property at all times, and misreporting of data could bias the results.[2] Hence, using zip code average house prices helps in explaining changes in risk aversion with housing.

The use of current year fixed effects corrects for confounding effects coming from fluctuations in factors like interest rates that could affect house prices and risk taking ability. Inclusion of state fixed effects accounts for biases as a result of differences across housing markets, and aggregate shocks across housing markets. Finally, I also add age fixed effects to compare individuals within an age group in a given year in a particular state facing fluctuations in house prices at the zip code level. The inclusion of individual fixed effects corrects for time invariant individual characteristics (for example, individuals selecting to live in a particular neighborhood). X_{ijt} is a series of individual characteristics that include marital status, health, if an individual is employed and number of children.

[2] In general, zip code average price is a good predictor of self reported property value

While the aforementioned analysis is primarily restricted to homeowners, an alternative approach to examine the effect of housing wealth is to use a difference-in-differences setup to identify heterogeneity between homeowners and renters using a more precise movement in housing prices across zip codes over the years. The zip code specific house price indices proxy for changes in housing wealth experienced by homeowners. Homeowners and renters residing in the same zip code would witness similar shocks in house prices. Using the interaction between growth of zip code specific HPI and homeowners gives the effect of housing wealth for homeowners relative to renters.

$$Y_{ijt} = \beta_0 + \beta_1 ln(HPI)_{jt} + \beta_2 Home\ owners_{ijt} + \beta_3 Home\ owner_{ijt} X ln(HPI)_{jt} + \pi X_{ijt} + \gamma_i + \eta_a + \mu_s + \nu_t + \epsilon_{ijt} \tag{2.2}$$

where Y_{ijt} can take values of risk aversion or share of assets for homeowners. The main coefficient of interest is β_3, which compares homeowners and renters in the same zip code to see if the effect of homeownership on risk preference is affected by the magnitude of housing price changes in a given zip code where homeowners and renters face similar market conditions otherwise.

2.4 Data

The primary data used is from the Health and Retirement Study (HRS). HRS is a biennial panel for Americans above 50 years and their spouse, sponsored by the National Institute on Aging. The publicly available dataset provides information on the age, marital status, demographics, financial investments, savings, health, insurance and other related data across years 1992 to 2014. I use the RAND version which is derived from all waves of the HRS. [3]

The data consists of five different cohorts, namely,the original HRS cohort (OHRS born between 1931 and 1941), the Assets and Health Dynamic cohort (AHEAD born before 1924), the Children of Depression cohort (CD born between 1924 and 1930), the War Baby cohort (WB born between 1942 and 1947) and the Early Baby Boomer cohort (EBB born between 1948 and 1953). In 1992, all self-reporting respondents were asked the income gamble question, but skipped in 1994 and 1996. In 2004, only the Early baby boomer cohort(1948-1953) is asked the question, which results in a smaller sample in 2004. Cohorts entered the survey at different times, so the results are not likely to be driven by one particular cohort.

The hypothetical gamble questions I use to define risk aversion were first asked in the year 1992, where individuals had to choose between a hypothetical new job and the current one. The question was not asked in the following years of 1994 and 1996. Following is the hypothetical income gamble question asked in 1992:

"Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job,

1. With a 50-50 chance it will double your (family) income and a 50-50 chance that it will cut your (family) income by a third. Would you take

[3] The RAND data are available to download from the HRS website (`http://hrsonline.isr.umich.edu/data/index.html`).

the new job?"

2. If yes, then: "Suppose the chances were 50-50 that it would double your (family) income, and 50-50 that it would cut it in half. Would you still take the new job?"

3. If no, then: "Suppose the chances were 50-50 that it would double your (family) income and 50-50 that it would cut it by 20 percent. Would you then take the new job?"

In the year 1998, the income gambles were re-framed where people were given the option to choose from two hypothetical new jobs. In these questions the respondent is asked to choose between pairs of jobs where one guarantees current family income and the other offers a chance to increase income but also carries the risk of loss of income. If the Respondent says he/she would take the risk, the same scenario but with riskier odds is presented. If Respondent says he/she would not take the risk, the same scenario with less risky odds is asked. The pair of jobs presented are both new jobs, given that Respondent will need to move and find a new job. The options are as follows:

1. Respondent would take a job with even chances of doubling income or cutting it by 75 %.

2. Respondent would take a job with even chances of doubling income or cutting it in half.

3. Respondent would take a job with even chances of doubling income or cutting it by a third.

4. Respondent would take a job with even chances of doubling income or cutting it 20%.
5. Between categories 3 and 4 above: Respondent would take a job with even chances of doubling income or cutting it by 10 %.
6. Respondent would take or stay in the job that guaranteed current income given any of the above alternatives.

Since the gamble question in 1992 varies from the rest of the years, I use the risk data from 1998 to 2006, dropping 1992 to maintain uniformity.

Respondents wealth and income data is self reported. Using the property values and mortgage amounts reported by the individuals, I define home equity as the difference between property value and mortgage (Chetty et al. (2017)). As mentioned earlier, since housing choice is endogenous, I introduce exogenous variation in house prices by using the average house price at the zip code.[4] I merge the publicly available RAND Version P dataset of HRS with the restricted geographic information. Further, I merge the zip code level house prices to the aforementioned merged data. The final dataset now gives me risk preferences and portfolio allocation of individuals age 50 and above, along with data on housing by geographic locations.

The summary statistics in Table 1 reports characteristics of all homeowners above 50 years. There are 10,711 individuals in the sample of non-moving homeowners who respond to the hypothetical income gamble questions. 76 % of these individuals are married and the average age is about 58 years. I find

[4] Data on zip code house price indices can be found in the following website http://www.fhfa.gov/papers/wp1601.aspx

that almost 60 % of their investments are in safe assets defined as savings or checking accounts, treasury bills and bonds. About 15 % of their assets are as stockholdings and the remaining 25 % are in the form of IRA and KEOGH accounts. HRS does not provide the further division of types of assets among the retirement accounts. The full sample of homeowners with data on share of assets (Table 2) is of 155,520 individuals, of whom about 63 % of them own safe assets and about 15 % of them risky assets.

2.5 Results

2.5.1 Risk Aversion

Using the hypothetical income gamble questions to examine changes in risk aversion, their two-year variation is observed in Figure 2. Since individuals who are most risk averse and least risk averse cannot move to a higher or lower category respectively, Figure 2 includes individuals without the two extreme categories (Figure A.1. presents the change in risk aversion for the full sample). The bar at 0 shows no change in risk aversion compared to the previous time period, and a bell shaped distribution of changing risk aversion is observed for all years.[5]. Following this change in risk aversion, Figure 3 denotes the proportion of individuals in each risk category over time. While almost 50 % of individuals are most risk averse, one can see a change in the trend over time for the more risk averse categories. Given that risk aversion is a categorical variable

[5] In the year 2004, income gamble questions were restricted to the Early Baby Boomers (EBB) and hence are a much smaller sample. No change in risk aversion is observed in this smaller sample

with an increasing value of risk aversion (1 is least risk averse; while 6 is most risk averse), I measure risk in two ways - one is to use the categorical variable, and second is to define a binary variable such that 1 denotes individuals who are most risk averse (categories 5 and 6) and 0 who are less risk averse (categories 1 through 4).

I start with an OLS estimation to find a positive relation between home equity and risk aversion, i.e. an increase in home equity makes individuals more risk averse (as seen in Table 4). However, this effect might not be causal since there could be other unobserved factors that could affect risk preference and home equity (for eg. individuals who are more risk averse could choose to lower their mortgage faster). To account for endogeneity coming from omitted variables, I use the zip code house price index as an instrument for the self reported home equity. Column 4 (of Table 4) indicates that individuals become less risk averse as home equity increases, although the effect is not significant. On re-defining the risk measure as a binary outcome, I find that there is a reduction in risk aversion by 20 percentage points on using the zip code HPI as an instrument for home equity.

Table 5 reports the difference-in-differences estimation to examine the heterogeneous effect of zip code housing price change between homeowners and renters. I find that the risk aversion reduces for homeowners compared to renters as the house price changes between 1998 and 2006, although not significantly.

2.5.2 Portfolio Allocation

The hypothetical income gamble question indicates the risk preference of the respondent. An alternate measure of risk is to study risky behavior by examining the portfolio allocation of individuals above 50 years. The OLS estimates in Table 6 (columns 2,4,6) explain the relation between home equity and the share of assets as safe assets, risky assets and retirement accounts. Consistent with the findings of Cocco (2004) and Chetty et al. (2017), I find that an increase in home equity is positively associated with stock holdings. I also find a negative association between safe assets and home equity. This relation, however, cannot be explained as a causal relation since housing choice is endogenous. Individuals could choose to own a larger property based on their future income expectations, thereby facing lower background risk. Such omitted factors could induce individuals to hold a larger share of risky, than safe assets. This endogeneity of housing choice could bias the effect of home equity on portfolio allocation upward. To account for the endogeneity of home equity, I use the average zip code house prices in the current year as an instrument for home equity.

I examine the effect of home equity on asset holdings of homeowners who do not move between zip codes. In Table 6, after controlling for state, year, individual and age fixed effects, I find that the OLS and IV results are consistent. Increase in home equity increases the share in risky assets and retirement accounts, but decreases the share in safe assets. However, the results are not statistically significant. Intuitively, this indicates that a rise in home equity can reduce risk aversion among individuals above 50 years.

Using the difference-in-differences approach (Table 7), I find that the magnitude of the growth of house prices affects the portfolio choice of homeowners more than the renters. With an increase in home equity, I find no significant changes in the risk aversion or portfolio allocation of these elderly.

While the analysis using hypothetical income gambles is restricted to the period between 1998 and 2006, HRS respondents are asked about their wealth and assets across all waves (1992 to 2014). To explain risky behavior of individuals in the period before the 2008 financial crisis, I restrict the analysis using portfolio allocation between 1998 and 2006, making them comparable to the risk aversion of individuals (Table A.1). With an increase in home equity, I find that the results are similar to that across the full sample.

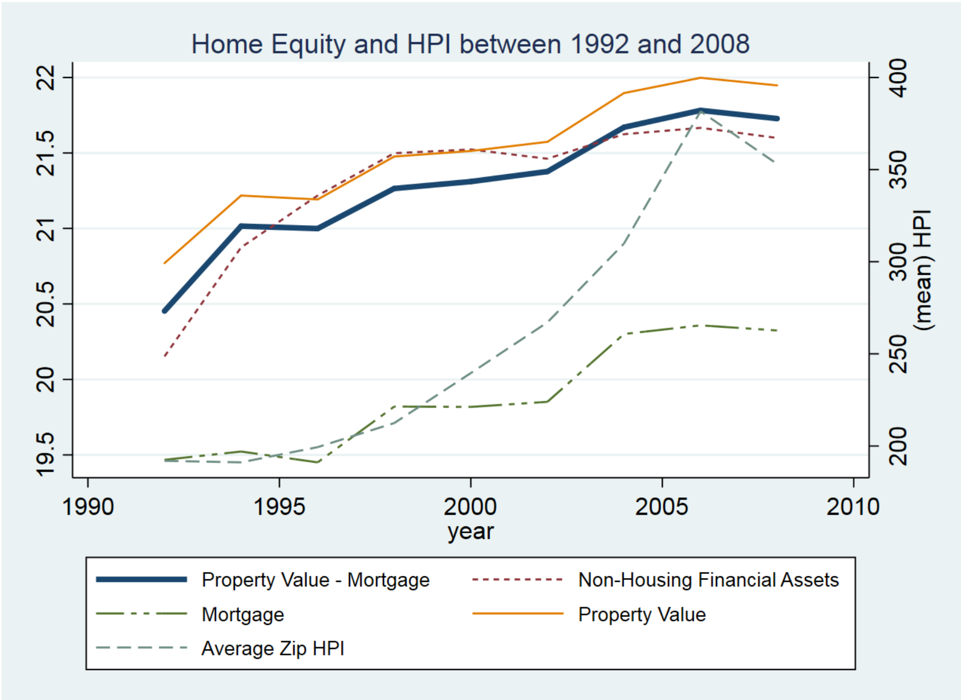
2.6 Discussion

Rise preference is a key determinant of an individuals' decision making. The stability of risk preference has been questioned in the recent past, and evidence suggests that risk aversion can be altered by some shock in the environment. In this paper, I use the HRS data from 1998 to 2006 to investigate the effect of home equity on risk aversion of individuals above 50 years. This paper benefits from the increase in house prices before the 2008 financial crisis. The fluctuations in house prices within this period provides an exogenous variation to home equity, and provides the setting to study its effect on risk aversion.

I find no evidence of home equity having a significant effect on risk aversion. As an alternate measure of risk, I examine the effect of home equity on portfolio allocation. Although the results indicate that an increase in home equity reduces risk aversion, they are not statistically significant, and could be an interesting question to explore in the future.

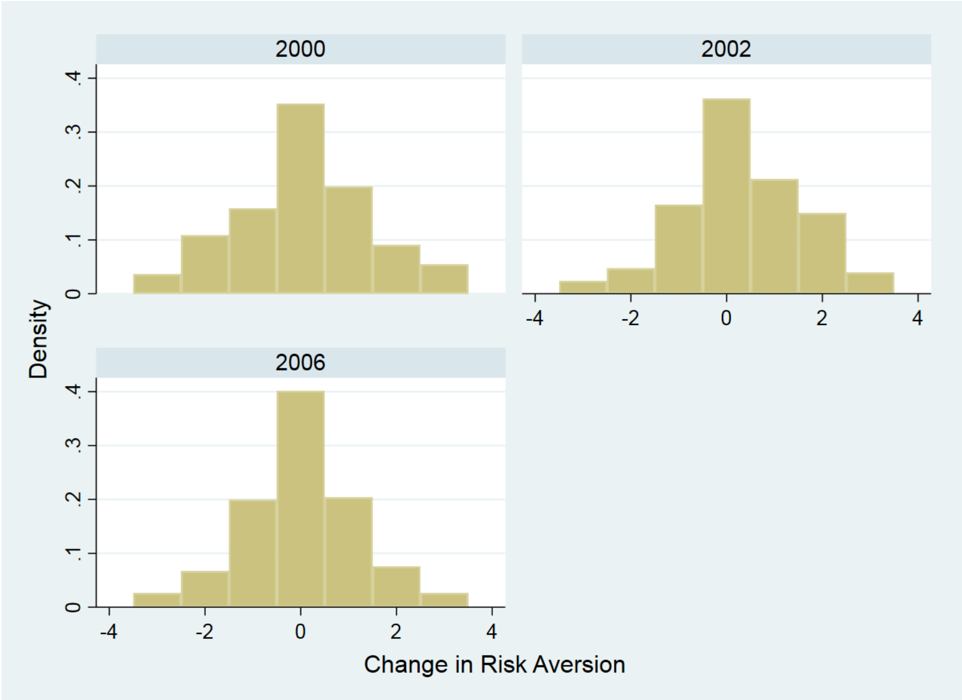
2.7 Figures and Tables

2.7.1 Figures



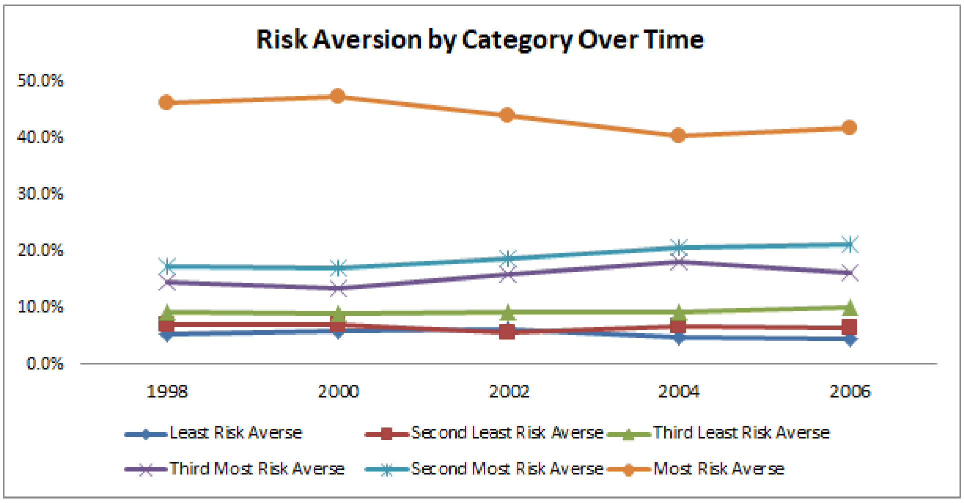
Notes: This figure shows the changes in self reported property values and housing price index between 1992 and 2008.

Figure 2.1: Housing wealth between 1992 and 2008



Notes: The figure above presents the change in risk aversion among individuals above 50 years, dropping individuals in the most risk averse and least risk averse categories. Δ RA= $RA_t - RA_{t-2}$

Figure 2.2: Variation in risk: Two year lags



Notes: This figure shows the proportion of individuals above 50 in each category of risk aversion, ranging from least to the most risk averse between 1998 and 2006.

Figure 2.3: Risk Aversion Over Time

2.7.2 Tables

Table 2.1: Summary Statistics, Health and Retirement Study (HRS) Data Sample, 1998 - 2006

Variable	Mean	Std. Dev.	Min.	Max.	N
Individual Characteristics					
Married	0.767	0.423	0	1	15870
Age in Years	58.094	5.898	50	90	15875
College Educated	0.438	0.496	0	1	15874
Children (#)	3.063	1.985	0	20	15765
White	0.806	0.395	0	1	15871
Black	0.151	0.359	0	1	15871
Protestant	0.632	0.482	0	1	15845
Catholic	0.276	0.447	0	1	15845
Employed	0.629	0.483	0	1	15874
Sick	0.22	0.415	0	1	15872
Female	0.558	0.497	0	1	15875
Household Earnings (x100K)	0.411	0.768	0	65.7	15875
Home Equtiy (x100 K)	1.186	1.866	0	96.680	15875
Property Value (x 100K)	1.524	2.104	0	100	15875
Mortgage (x100K)	0.338	0.633	0	13	15875
Share of Assets					
Safe Assets	0.6	0.387	0	1	14113
Risky assets	0.145	0.263	0	1	14113
Retirement	0.254	0.333	0	1	14113

Notes: Summary statistics for homeowners above 50 who do not move between zip codes and respond to the hypothetical income gamble questions (between 1998 and 2006).

Table 2.2: Share of Assets for Homeowners above 50 between 1992 and 2014

Variable	Mean	Std. Dev.	Min.	Max.	N
Safe Assets	0.631	0.391	0	1	155,520
Risky Assets	0.145	0.269	0	1	155,520
IRA and KEOGH	0.224	0.327	0	1	155,520

Notes: Share of assets for homeowners above 50 between 1992 and 2014.

Table 2.3: Risk Aversion of Homeowners over time

Risk Aversion	1998	2000	2002	2004	2006	Total
Least Risk Averse	134	37	173	69	148	561
Second least Risk Averse	173	45	159	94	219	690
Third Least Risk Averse	230	57	266	132	332	1,017
Third Most Risk averse	356	85	455	260	538	1,694
Second Most risk Averse	428	107	537	292	708	2,072
Most Risk Averse	1,147	299	1,262	574	1,395	4,677
Total	2,468	630	2,852	1,421	3,340	10,711

Notes: The table presents number of individuals by risk aversion category by years.

Table 2.4: Effect of home equity on risk aversion for non moving homeowners

Dep. variable	Log Home Equity	Categorical Risk			Binary Risk		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			OLS	IV		OLS	IV
Log (HPI)	0.786***	-0.151			-0.093		
	[0.089]	[0.416]			[0.135]		
Log (Home Equity)			0.283***	-0.193		0.068**	-0.119
			[0.106]	[0.530]		[0.033]	[0.172]
Observations	6754	6754	6754	6754	6754	6754	6754

This table reports the effect of home equity on risk aversion of individuals above 50. Log(home equity) is instrumented with log (zip code housing price index). Risk is a categorical variable in increasing order of risk aversion (1- least risk averse, 2- second least risk averse, 6 is most risk averse etc.). Binary risk is defined as 1 if most risk averse. Age, year, state and individual fixed effects are included. Control for marital status, employed, health of individual, number of children and state unemployment rate. Standard errors are clustered at the zip code.

Table 2.5: Effect of home equity on risk aversion for homeowners and renters

Dep. Variable	Categorical	Binary	Categorical	Binary
	(1)	(2)	(3)	(4)
Homeowner	0.776	0.258	0.669	0.148
	[0.886]	[0.260]	[0.881]	[0.264]
Log (HPI)	0.087	-0.008	0.030	-0.014
	[0.160]	[0.047]	[0.162]	[0.049]
HomeownerXLog(HPI)	-0.139	-0.046	-0.118	-0.026
	[0.158]	[0.047]	[0.157]	[0.047]
State-Year FE	No	No	Yes	Yes
Observations	11741	11741	11741	11741

This table reports the heterogeneous effect of home equity on risk aversion of individuals above 50. Log(HPI) is the logarithmic value of the HPI. Risk is a categorical variable in increasing order of risk aversion (1- least risk averse, 2- second least risk averse, 6 is most risk averse etc.). Binary risk is defined as 1 if most risk averse. Age, year, state and individual fixed effects are included. Control for marital status, employed, health of individual, number of children and state unemployment rate. Standard errors are clustered at the zip code .

Table 2.6: Effect of home equity on portfolio allocation for homeowners who do not move

Dep. variable	Log(Home equity)	Safe assets		Risky assets		Retirement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		OLS	IV	OLS	IV	OLS	IV
Log (HPI)	0.463***						
	[0.026]						
Log (Home Equity)		-0.028***	-0.039	0.011**	0.023	0.017**	0.016
		[0.008]	[0.057]	[0.006]	[0.040]	[0.007]	[0.049]
Observations	78205	78205	78205	78205	78205	78205	78205

This table reports the effect of housing on risk aversion of individuals above 50. Log (self reported home equity) is instrumented with Log(xip code HPI). Safe assets include bonds, savings, checking accounts. Risky assets include stockholdings and reitrement accounts are IRA and Keogh. Age, year, state and individual fixed effects are included. Control for marital status, employed, health of individual, number of children and state unemployment rate. Standard errors are clustered at the zip code.

Table 2.7: Effect of home equity on portfolio allocation for homeowners and renters

	Safe (1)	Risky (2)	Retirement (3)	Safe (4)	Risky (5)	Retirement (6)
Homeowner	0.017	0.029	-0.046	0.024	0.019	-0.043
	[0.044]	[0.034]	[0.035]	[0.045]	[0.034]	[0.035]
Log (HPI)	-0.002	0.005	-0.004	-0.005	0.006	-0.002
	[0.008]	[0.006]	[0.007]	[0.008]	[0.006]	[0.007]
HomeownerX Log(HPI)	-0.010	-0.003	0.014**	-0.012	-0.002	0.013**
	[0.008]	[0.006]	[0.006]	[0.008]	[0.006]	[0.006]
State-Year FE	No	No	No	Yes	Yes	Yes
Observations	125635	125635	125635	125635	125635	125635

This table reports the heterogeneous effect of housing on portfolio allocation of individuals above 50. Log(HPI) is the logarithmic value of the HPI. Safe assets include bonds, savings, checking accounts. Risky assets are stockholdings. Retirement accounts include IRA and Keogh. Age, year, state and individual fixed effects are included. Control for marital status, employed, health of individual, number of children and state unemployment rate. Standard errors are clustered at the zip code.

2.8 Appendix B

Table B.1: Effect of home equity on portfolio allocation for homeowners who do not move before 2008

Dep Variable		Safe assets		Risky assets		IRA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		OLS	IV	OLS	IV	OLS	IV
Log (HPI)	0.516***						
	[0.041]						
Log (Home Equity)		-0.026**	0.003	0.019**	0.045	0.007	-0.048
		[0.010]	[0.073]	[0.008]	[0.054]	[0.009]	[0.063]
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47777	47777	47777	47777	47777	47777	47777

This table reports the effect of housing on portfolio allocation of non-moving homeowners above 50 before the 2008 financial crisis. Log(home equity) is instrumented with the logarithmic value of the HPI. Safe assets include bonds, savings, checking accounts. Risky assets are stockholdings. Retirement accounts include IRA and Keogh. Age, year, state and individual fixed effects are included. Control for marital status, employed, health of individual, number of children and state unemployment rate. Standard errors are clustered at the zip code.

Table B.2: Effect of home equity on portfolio allocation for homeowners who do not move after 2008

Dep. Variable		Safe assets		Risky assets		IRA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FS	OLS	IV	OLS	IV	OLS	IV
Log (HPI)	0.273***						
	[0.049]						
Log (Home Equity)		-0.014	-0.413**	0.013	0.064	0.001	0.349*
		[0.015]	[0.195]	[0.010]	[0.128]	[0.013]	[0.188]
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21711	21711	21711	21711	21711	21711	21711

This table reports the heterogeneous effect of housing on portfolio allocation of individuals above 50 before the 2008 financial crisis. Log(HPI) is the logarithmic value of the HPI. Safe assets include bonds, savings, checking accounts. Risky assets are stockholdings. Retirement accounts include IRA and Keogh. Age, year, state and individual fixed effects are included. Control for marital status, employed, health of individual, number of children and state unemployment rate. Standard errors are clustered at the zip code.

Table B.3: Effect of home equity on portfolio allocation for homeowners and renters before 2008

	(1) Safe	(2) Risky	(3) IRA	(4) Safe	(5) Risky	(6) IRA
Homeowner	0.091	0.008	-0.099**	0.106*	-0.003	-0.102**
	[0.058]	[0.045]	[0.045]	[0.058]	[0.045]	[0.045]
Log (HPI)	0.022**	-0.001	-0.020**	0.012	0.002	-0.014
	[0.011]	[0.008]	[0.009]	[0.011]	[0.009]	[0.009]
HomeownerXLog(HPI)	-0.021**	0.001	0.021***	-0.024**	0.003	0.021***
	[0.011]	[0.008]	[0.008]	[0.011]	[0.008]	[0.008]
State-Year FE	No	No	No	Yes	Yes	Yes
Observations	80084	80084	80084	80084	80084	80084

This table reports the heterogeneous effect of housing on portfolio allocation of individuals above 50 before the 2008 financial crisis. Log(HPI) is the logarithmic value of the HPI. Safe assets include bonds, savings, checking accounts. Risky assets are stockholdings. Retirement accounts include IRA and Keogh. Age, year, state and individual fixed effects are included. Control for marital status, employed, health of individual, number of children and state unemployment rate. Standard errors are clustered at the zip code.

Table B.4: Effect of home equity on risk aversion for all homeowners

	Categorical Risk				Binary Risk
	(1)	(2)	(3)	(4)	(5)
Log (HPI)	0.344***				
	[0.032]				
Log (Home Equity)		0.141*	-0.122	0.030	-0.133
		[0.072]	[0.304]	[0.024]	[0.100]
Observations	12765	12765	12765	12765	12765

This table reports the effect of housing on risk aversion on individuals above 50. Log(home equity) is instrumented with log (zip code housing price index). Risk is a categorical variable in increasing order of risk aversion (1- least risk averse, 2- second least risk averse, etc.). Age, year and household fixed effects are included. Also include state specific time trends. Also control for marital status, employment, health of individual and number of children. Standard errors are clustered by the zip code

Table B.5: Effect of home equity on risk aversion for all homeowners (movers and non movers)

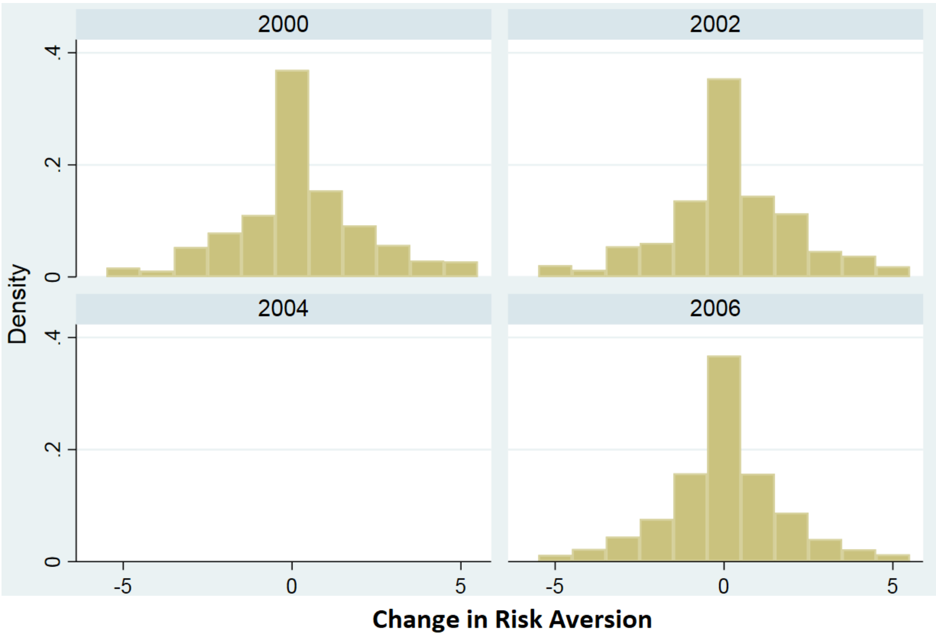
	Categorical Risk				Binary Risk		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log (HPI)	0.319***	-0.129			-0.090**		
	[0.035]	[0.127]			[0.043]		
Log (Home Equity)			0.153	-0.404		0.018	-0.282**
			[0.107]	[0.404]		[0.033]	[0.136]
State-Year FE	No	No	No	No	No	No	No
Observations	8940	8940	8940	8940	8940	8940	8940
Log (HPI)	0.136***	-0.251*			-0.095**		
	[0.036]	[0.139]			[0.046]		
Log (Home Equity)			0.170	-1.847		0.041	-0.697*
			[0.112]	[1.152]		[0.035]	[0.384]
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8940	8940	8940	8940	8940	8940	8940

Table reports change in risk aversion using the instrument log hpi for home equity. Risk aversion is defined as a categorical and binary variable. Age, year and individual fixed effects are included. Controls include marital status, employment and health, and number of children. Standard errors are clustered at the zip code.

Table B.6: Effect of home equity on portfolio allocation for all homeowners (movers and nonmovers)

		Safe assets		Risky assets		IRA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log (HPI)	0.188***						
	[0.012]						
Log (Home Equity)		-0.035***	-0.015	0.012***	0.038	0.024***	-0.023
		[0.005]	[0.037]	[0.003]	[0.028]	[0.004]	[0.034]
State-Year FE	No	No	No	No	No	No	No
Observations	124873	124873	124873	124873	124873	124873	124873
Log (HPI)	0.081***						
	[0.013]						
Log (Home Equity)		-0.038***	-0.092	0.012***	0.096	0.026***	-0.004
		[0.005]	[0.090]	[0.003]	[0.072]	[0.004]	[0.089]
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124873	124873	124873	124873	124873	124873	124873

This table reports the effect of housing on portfolio allocation of all homeowners above 50. Log(home equity) is instrumented with the logarithmic value of the HPI. Safe assets include bonds, savings, checking accounts. Risky assets are stockholdings. Retirement accounts include IRA and Keogh. Age, year, state and individual fixed effects are included. Control for marital status, employed, health of individual, number of children and state unemployment rate. Standard errors are clustered at the zip code.



Notes: The figure above presents the change in risk aversion among individuals above 50 years. Δ RA= $RA_t - RA_{t-2}$

Figure B.1: Variation in risk: Two year lags

Bibliography

Moneer Alam. Ageing, socio-economic disparities and health outcomes: Some evidence from rural india. *Indian Journal of Human Development*, 3(1):47–76, 2009.

Kate Ambler. Bargaining with grandma: The impact of the south african pension on household decision-making. *Journal of Human Resources*, 51(4): 900–932, 2016.

Viola Asri, Katharina Michaelowa, Sourabh B Paul, and Sitakanta Panda. Does transparency improve public program targeting?–evidence from india's old-age social pension reforms. 2016.

Robert B Barsky, F Thomas Juster, Miles S Kimball, and Matthew D Shapiro. Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics*, 112(2):537–579, 1997.

Marianne Bertrand, Sendhil Mullainathan, and Douglas Miller. Public policy and extended families: Evidence from pensions in south africa. *the world bank economic review*, 17(1):27–50, 2003.

Markus K Brunnermeier and Stefan Nagel. Do wealth fluctuations generate time-varying risk aversion? micro-evidence on individuals. *American Economic Review*, 98(3):713–36, 2008.

John Y Campbell and Joao F Cocco. How do house prices affect consumption?

evidence from micro data. *Journal of monetary Economics*, 54(3):591–621, 2007.

Christopher Carpenter and Carlos Dobkin. The effect of alcohol consumption on mortality: regression discontinuity evidence from the minimum drinking age. *American Economic Journal: Applied Economics*, 1(1):164–182, 2009.

Anne Case and Angus Deaton. Large cash transfers to the elderly in south africa. *The Economic Journal*, 108(450):1330–1361, 1998.

Lingguo Cheng, Hong Liu, Ye Zhang, and Zhong Zhao. The health implications of social pensions: Evidence from china's new rural pension scheme. *Journal of Comparative Economics*, 2016.

Raj Chetty, László Sándor, and Adam Szeidl. The effect of housing on portfolio choice. *The Journal of Finance*, 72(3):1171–1212, 2017.

Joao F Cocco. Portfolio choice in the presence of housing. *The Review of Financial Studies*, 18(2):535–567, 2004.

Thomas Davidoff. Home equity commitment and long-term care insurance demand. *Journal of Public Economics*, 94(1):44–49, 2010.

Irineu Evangelista de Carvalho Filho. Old-age benefits and retirement decisions of rural elderly in brazil. *Journal of Development Economics*, 86(1):129–146, 2008.

Yuliya Demyanyk, Dmytro Hryshko, María José Luengo-Prado, and Bent E Sørensen. Moving to a job: The role of home equity, debt, and access to credit. *American Economic Journal: Macroeconomics*, 9(2):149–81, 2017.

2012-13 District Level Household Survey (DLHS4). District level household survey (dlhs4), 2012-13. 2013. URL `http://www.iipsindia.ac.in/default.aspx`.

Esther Duflo. Grandmothers and granddaughters: old-age pensions and intra-household allocation in south africa. *The World Bank Economic Review*, 17 (1):1–25, 2003.

Puja Dutta, Stephen Howes, and Rinku Murgai. Small but effective: Indias targeted unconditional cash transfers. 2010.

Romain Duval. The retirement effects of old-age pension and early retirement schemes in oecd countries. 2003.

Eric V Edmonds. Child labor and schooling responses to anticipated income in south africa. *Journal of development Economics*, 81(2):386–414, 2006.

Eric V Edmonds, Kristin Mammen, and Douglas L Miller. Rearranging the family? income support and elderly living arrangements in a low-income country. *Journal of Human resources*, 40(1):186–207, 2005.

Christopher Garroway. How much do small old age pensions and widowspensions help the poor in india? 2013.

Andrew Gelman and Guido Imbens. Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics*, (just-accepted), 2017.

Aashish Gupta. Old-age pension scheme in jharkhand and chhattisgarh. *Economic & Political Weekly*, 48(34):55, 2013.

Chie Hanaoka, Hitoshi Shigeoka, and Yasutora Watanabe. Do risk preferences change? evidence from the great east japan earthquake. *American Economic Journal: Applied Economics*, 10(2):298–330, April 2018. doi: 10.1257/app.20170048. URL `http://www.aeaweb.org/articles?id=10.1257/app.20170048`.

John Heaton and Deborah Lucas. Portfolio choice in the presence of background risk. *The Economic Journal*, 110(460):1–26, 2000.

Ralph Hertwig, Greg Barron, Elke U Weber, and Ido Erev. Decisions from experience and the effect of rare events in risky choice. *Psychological science*, 15(8):534–539, 2004.

Mark Hoekstra. The effect of attending the flagship state university on earnings: A discontinuity-based approach. *The Review of Economics and Statistics*, 91 (4):717–724, 2009.

Guido W Imbens and Thomas Lemieux. Regression discontinuity designs: A guide to practice. *Journal of econometrics*, 142(2):615–635, 2008.

2005 India Human Development Survey (IHDS). India human development survey (ihds), 2005. 2005. URL `http://doi.org/10.3886/ICPSR22626.v8`.

2011-12 India Human Development Survey (IHDS). India human development survey (ihds), 2011-12. 2012. URL `http://doi.org/10.3886/ICPSR36151.v2`.

Laura Juárez and Tobias Pfutze. The effects of a noncontributory pension program on labor force participation: The case of 70 y más in mexico. *Economic Development and Cultural Change*, 63(4):685–713, 2015.

Neeraj Kaushal. How Public Pension affects Elderly Labor Supply and Well-being: Evidence from India. *World Development*, 56(C):214–225, 2014.

David S Lee and Thomas Lemieuxa. Regression discontinuity designs in economics. *Journal of economic literature*, 48(2):281–355, 2010.

Elaine M Liu. Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in china. *Review of Economics and Statistics*, 95(4):1386–1403, 2013.

Pushkar Maitra and Ranjan Ray. The effect of transfers on household expenditure patterns and poverty in south africa. *Journal of development Economics*, 71(1):23–49, 2003.

Ulrike Malmendier and Stefan Nagel. Depression babies: do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics*, 126(1): 373–416, 2011.

Thomas Michielsen, Remco Mocking, and Sander Veldhuizen. Home ownership and household portfolio choice. 2016.

Manxiu Ning, Jinquan Gong, Xuhui Zheng, and Jun Zhuang. Does new rural pension scheme decrease elderly labor supply? evidence from charls. *China Economic Review*, 41:315–330, 2016.

Sarmistha Pal and Robert Palacios. Understanding poverty among the elderly in india: Implications for social pension policy. *Journal of Development Studies*, 47(7):1017–1037, 2011.

Sarmistha Pal, Robert Palacios, et al. Old age poverty in the indian states: What the household data can say? *Pension Reform Primer working paper series*, 2006.

Daniel Paravisini, Veronica Rappoport, and Enrichetta Ravina. Risk aversion and wealth: Evidence from person-to-person lending portfolios. *Management Science*, 63(2):279–297, 2016.

Dorrit Posel, James A Fairburn, and Frances Lund. Labour migration and households: A reconsideration of the effects of the social pension on labour supply in south africa. *Economic modelling*, 23(5):836–853, 2006.

Irudaya Rajan. Population ageing, health and social security in india. *Centre for Development Studies, Discussion Paper*, (3), 2007.

D Rajasekhar, Santosh Kesavan, and R Manjula. Contributory pension schemes for the poor: Issues and ways forward. 2016.

F Ram, SK Mohanty, and Usha Ram. Understanding the distribution of bpl cards: all-india and selected states. *Economic and Political Weekly*, pages 66–71, 2009.

Claudia R Sahm. Risk tolerance and asset allocation. 2007.

Alessandro Tondini, Cally Ardington, and Ingrid Woolard. Public pensions and elderly informal employment: Evidence from a change in retirement age in south africa. 2017.

Vidhya Unnikrishnan. How well targeted are social assistance programs in india-a case study of indira gandhi old age national pension scheme.

Elke U Weber, Ulf Böckenholt, Denis J Hilton, and Brian Wallace. Determinants of diagnostic hypothesis generation: Effects of information, base rates, and experience. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 19(5):1151, 1993.

Rui Yao and Harold H Zhang. Optimal consumption and portfolio choices with risky housing and borrowing constraints. *The Review of Financial Studies*, 18(1):197–239, 2004.

Lingxiao Zhao and Gregory Burge. Housing wealth, property taxes, and labor supply among the elderly. *Journal of Labor Economics*, 35(1):227–263, 2017.