Pensions and Depression: Gender-Disaggregated Evidence From the Elderly Poor in India*

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Abstract

We leverage the expansion of the National Social Assistance Program (NSAP) in India in 2006 to estimate the impact of access to public pensions on three measures of depression for the elderly in below poverty line households, using a regression discontinuity design based on age-eligibility cutoffs. We focus on India given that it is the largest lower-middle-income country in terms of population, has limited welfare safety nets, and relatively large proportions of disadvantaged people with mental health vulnerabilities. We find that becoming eligible for public pensions reduces the likelihood that the elderly poor are depressed. In particular, the intent-to-treat estimate is a 10.1 percentage point decline in the broadest measure of depression. Our gender-specific analyses reveal heterogeneous impacts across demographic groups. More specifically, widowed populations, the majority of whom are elderly poor women, gain the most. Our investigation into the underlying mechanisms reveals that pension eligibility improves mental health through decreased labor market participation, increased healthcare utilization, improved lifestyle choices, enhanced life satisfaction and greater control over resources. Our results offer insights for shaping effective social assistance policies aimed at raising the welfare of the most at-risk populations in resource-constrained contexts.

Keywords: Pension eligibility, depression, mental health, elderly populations, gender, poor, widowed, India

JEL Codes: H55, I12, I18, I38, J14

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1. Introduction

Rapid aging of the world's population caused by decreases in fertility rates coupled with longer life expectancies has prompted important new strands of research focused on interventions aimed at promoting the physical and mental health of the elderly. Changes in population characteristics resulting from demographic transitions present several challenges for policy and social welfare as they exert pressure on resources and increase demand for services. Although there is growing attention on the physical health of the elderly, an aspect that is still relatively largely neglected is their mental well-being. This is especially true in low and lower-middle-income countries (Banerjee et al. 2023), despite the fact that the increase in the proportion of elderly people in the developing world outpaces that in the industrialized world (Kaushal, 2014), and in spite of the increasing recognition that mental health is a global challenge. An estimated 970 million people around the world lived with a mental disorder in 2019, with more than 80% of all people with mental disorders living in low and middle-income countries (WHO 2022). Yet, mental health systems in developing contexts remain marked by major imbalances in resources, services and governance, and literature on the mental health of the elderly in these contexts remains limited.[1] Our study aims to rectify some of this deficiency by providing new evidence on the mental well-being of the elderly in India.

In addition to the relative paucity of work on mental health of the elderly, there is evidence that the relationship between poverty and mental health illnesses such as depression and anxiety are bi-directional and causal in nature (Ridley et al. 2020). Consistent with this, recent studies evaluating the provision of pension programs have found ameliorative effects on depressive symptoms (Galiani et al. 2016, Cheng et al. 2018, Chen et al. 2019, Bando et al. 2020, Bando et al. 2022, Pak 2021). However, the evidence is mixed as Banerjee et al. (2023)

[1] The Mental Health Atlas 2020 reports that 4.6% of the total general health research output was on mental health in 2019, with the percentage of country-level mental health research output being three times greater in high-income countries than in low-income countries.

analyzes the impact of a public pension program in India on the mental health indicators of the elderly to find no impacts. Using a large nationally representative dataset from India that focuses on elderly people living in below poverty line (BPL) households and a regression discontinuity (RD) design, our study brings new evidence to this debate by asking three questions.[2] First, does access to pensions improve the mental health of the elderly poor? Second, does the income security that pension eligibility affords have gender-differentiated mental health effects in this population? And third, what are the specific pathways through which pensions influence the mental health indicators of the elderly poor?

To answer these questions, we leverage the expansion of the National Social Assistance Program (NSAP) in India in 2006 to estimate the impact of access to NSAP on three measures of depression for the elderly poor using an RD design based on age-eligibility cutoffs. More specifically, public pension eligibility involves two criteria including the respondent's birth year and the household's economic status. A respondent is considered eligible if they were born in or before 1946 (thus, 60 years old in 2006), and belong to a below poverty line household. Our analysis involves conditioning on years of exposure which is estimated as the difference between a respondent's age in years and 60, for respondents in BPL households. This technique results in a person who was 60 years old in 2006 having 0 years of exposure, that is, consistent with other studies in this area, we normalize the running variable to zero relative to the pensionable age cutoff. As in a standard sharp RD design, we estimate effects at the age threshold by comparing people who just became eligible to those who are not. The

[2] The Government of India uses an income-based measure to identify economically disadvantaged households which can subsequently be targeted for assistance. This measure differs across states and union territories in India, and across rural and urban areas. Lack of household surveys beyond 2011/12 make accurate predictions of poverty in the country uncertain. Edochie et al. (2022) notes that with a pass-through and survey-to-survey methodology, and using the international $1.90 poverty line for extreme poverty, this measure was about 10.4 % in 2017 in India, with a confidence interval of 8.1% to 11.3%. For purposes of our study, we use the below poverty line household indicator provided in the data and adjust it to 2006 levels using appropriate price indices.

identifying assumption is that the assignment to treatment is as good as random in the close vicinity of the pension eligibility age cutoff.

Our main source of data is the Longitudinal Aging Study in India (LASI), a comprehensive survey on India's elderly population from 2017-2019. The focus on India is especially appropriate as it is the largest lower-middle-income country in terms of population (Sharma and Popli (2023) notes that 18% of the world's population resides in India) with a significant share of elderly poor who report that they feel depressed sometimes, often, most or all of the time. Our estimates indicate that close to 50% of 75-79 years old poor elderly individuals report feeling depressed by this measure. Concomitantly, the country has an almost thirty year history of schemes that provide non-contributory pensions to at-risk groups including widows, the elderly, and people with disabilities. LASI, which is an individual-level dataset, provides scope to understand the impacts of economic conditions on the mental health of the elderly poor, while providing the richness of information required to document channels linking our variables of interest.

We use three measures of depression based on the commonly used CES-D scale (Radloff 1977). Two of these measures gauge the intensity to which an individual subjectively reports being depressed in the week before the survey (broader measure: Respondent reports feeling depressed sometimes (1-2 days), often (3-4 days) or most (5-7 days) of the time, and narrower, more severe measure: The respondent reports feeling depressed often or most of the time). The third measure for depression is objectively evaluated by CESD-10. This variable is assigned a value of 0 if the respondent's sum of answers to 10 questions ranges from 0 to 3, and assigned a value of 1 if the score ranges from 4 to 10. Using both subjective and objective measures of depression is a unique feature of our study.

We find that becoming eligible for NSAP reduces the likelihood that the elderly poor report being depressed. In particular, the intent-to-treat RD estimate for the full sample is a

10.1 percentage point decline in the broader subjective measure of depression, a 6.7 percentage point decline in the narrower more severe subjective measure of depression, and a 4.4 percentage point decrease in the objective CESD-10 based measure, at the age cutoff. Our gender-disaggregated analyses indicate that pensions have a beneficial impact on both poor elderly men and women, albeit with varying degrees of effectiveness. Notably, we observe a larger benefit for men in terms of a reduction in the broader measure of depression. Meanwhile, significant improvements in the CESD-10 indicator are observed uniquely for elderly women. These results withstand a series of robustness checks pertaining to additional controls for childhood experiences, alternative estimation procedures, optimal bandwidths, tests of manipulation of the running variable, imperfect compliance, and a careful account of all leading correlates of the pension-depression association.

We then evaluate impacts for widowed populations (51.4% of the eligible sample is widowed, and among these, 75.7% are widowed women – widowed women thus comprise the bulk of the eligible individuals in our study), and document significant ameliorative effects of pension eligibility on mental health of widowed poor elderly women. Similar beneficial impacts are also evident in the sample of urban elderly women. The results in the full sample and for widowed women suggest that by providing financial security, pension eligibility improves the mental well-being of the primary earner. This may also be true for urban elderly women who have a relatively higher likelihood to be or to have been in formal employment (as compared to rural elderly women).[3] Pronounced beneficial effects for widowed women suggest that beyond financial security, having control over resources is important.

We then carry out an in-depth analysis of the mechanisms by which pension eligibility influences mental health, with a special focus on gender and widowhood status. In this, we

[3] We are unable to estimate effects in rural areas with the full set of covariates that includes state fixed-effects. In models excluding state fixed-effects (not reported in the paper), magnitudes of beneficial impacts are up to 80% lower in rural settings as compared to urban ones.

draw from a broad literature that relates pensions with factors such as labor supply (Kaushal 2014, Juarez and Pfuze 2015, Cheng et al. 2018, Dutronc-Postel and Tondini 2023, Bando et al. 2022, Viet Nguyen 2021), healthcare usage and behaviors (Schwarzer and Querino 2002, Lloyd-Sherlock 2006, Aguila et al. 2015, Nikolov and Hossain 2023), as well as overall well-being and perceived social status. Our findings highlight the intricate ways in which financial stability through pension eligibility shapes mental health landscapes, offering insights into the diverse pathways through which income security impacts mental health.

Our analyses reveal consistent negative effects on labor supply, at both the intensive (hours worked) and extensive (work status) margins, with important gender and widowhood status variations. Pension eligibility leads to a marked decrease in employment and work hours, particularly among widowed individuals. Specifically, differences by gender in working for pay appears to be an explanatory factor for the heterogeneity in impacts.

Turning next to healthcare access, utilization, and the adoption of preventive measures, we find that pension income marginally boosts healthcare visits for men and significantly improves drug coverage under health insurance for all those who are pension eligible. This suggests that pensions may alleviate the financial burden of healthcare, leading also to a reduction in out-of-pocket expenditures, especially for women and widowed individuals. Furthermore, while no significant changes are observed in physical activity or smoking habits among the pension eligible, there is a decreased prevalence of obesity and diabetes, suggesting that pensions may indirectly contribute to healthier lifestyles. Pension-eligible women and the widowed show higher engagement in preventive healthcare practices.

Studies show that well-being may be improved because pensions allow elders to devote more time to pleasant activities, to share income with children, to reduce childcare constraints and economic dependence, while also providing economic autonomy and more self-determination (Duflo 2003, Ardington et al. 2009, Knabe et al. 2010, Gertler et al. 2012,

Krueger and Muller 2012). Our findings reveal that access to public pensions enhances social engagement among poor elderly women, particularly increasing their participation in social groups and personal care activities, although it does not significantly affect religious attendance or grandchild care, except for widowed individuals.

Our analysis also delves into how pension income affects subjective well-being, optimism, and perceived social status. Pension eligibility boosts life satisfaction mostly for men and widowed individuals. Sleep quality improves across the board for the eligible elderly poor, and widowed individuals report a substantial rise in perceived social status. We find suggestive evidence that financial autonomy and control over pension income may be important as in comparison to widowed individuals co-residing with children, widowed women living alone experience the largest gains.

Our focus on income security in old-age speaks to the literature that considers the effects of income and cash transfers on adults' welfare. Frijters et al. (2004) argues that while there seems to be a consensus that unemployment negatively affects life satisfaction, the relationship between the latter and income remains less clear. Using data for East Germany following reunification, they find that around 35-40 percent of the increase in life satisfaction in East Germany was attributable to the large increase in real household income. Other studies have used quasi-experimental designs to identify the causal impacts of income on mental health.[4] Gardner and Oswald (2007) uses medium-sized lottery wins, Friedman and Thomas (2009) examines the impact of a financial crisis, and Sullivan and Wachter (2009) analyzes the possible effects of job displacement, to trace pathways between money and mental well-being.

Turning to the effect of pension incomes in India, Kaushal (2014), Unnikrishnan and Imai (2020), and Unnikrishnan (2022), are the only three studies, to the best of our knowledge,

[4] The use of quasi-experiments becomes necessary because the empirical challenge is to correct for the bias that results from reverse causality due to both contemporary and/or life-cycle factors (Chen et al. 2018).

that evaluate the impact of the National Old Age Pension Scheme. The focus in these studies however, is on household welfare and labor supply; these papers document that pensions increase consumer expenditure and assets, while reducing labor supply. Exploiting an exogenous poverty cutoff to determine eligibility to a non-contributory pension plan in Peru, Bando et al. (2020) also finds that households with a pension recipient increased their consumption and reduced the proportion of older adults who were working, thus raising subjective welfare. Bando et al. (2022) repeats the analysis for Paraguay to find similar effects. Other studies that consider effects of pensions on labor market indicators include Juarez and Pfutze (2015) for Mexico and Dutronc-Postel and Tondini (2023) for South Africa.

Considering work on pension enrollment and mental health, Finkelstein et al. (2012) and Baicker et al. (2013) find lower self-reported depression in low-income adults who had access to Medicaid Health insurance in the United States. Similarly, Salinas-Rodriguez et al. (2014) finds that after a year of exposure to the non-contributory social pension program *70 y mas* in rural areas of Mexico, older adults reported a significant reduction of depressive symptoms and an increase in empowerment (with older adults participating more in household decisions related to expenses).[5] The New Rural Pension Scheme in China has received considerable attention in this area. Cheng et al. (2018) and Chen et al. (2019) consider this scheme and document effects on self-reported depressive symptoms. Using a fixed-effects instrumental variables framework, Cheng et al. (2018) finds beneficial effects on depression among both rural men and women. Alternatively, Zhang et al. (2018), which focuses on urban China, does not find any significant effects of attaining retirement age on an index for mental

[5] Other studies have considered the ways in which pensions affect welfare. Case and Deaton (1998), in their study of the redistributive effects of the South-Africa's old-age pension, finds that there are positive effects on food expenditures. Case and Menendez (2007) finds that a pension recipient in the household lowered food insecurity. Posel et al. (2006) shows that pension income for old women allowed working-age women to migrate and to find work away from the household. Abel (2019) finds that pensions increase the reservation wage, and thus reduce household labor supply. Miglino et al. (2023) finds that in Chile, receiving a pension reduces the likelihood of death by 2.7 percentage points four years post-enrollment. This positive outcome is linked to increased food consumption and more frequent health center visits by pension beneficiaries.

health problems. Taking advantage of geographic variation in program implementation, Chen et al. (2019) finds positive effects in the aggregate; the analysis is not differentiated by gender. The beneficial effect of pensions on mental health of the elderly resonates with findings in Zhang et al. (2022), where elderly women in particular are found to be positively affected. Pak (2021) examines the impact of expanding social pension on health in South Korea, and finds that the 2014 social pension reform led to an average decrease in depressive symptoms by 8.1-9.0%.

In sum, while there is literature that assesses the effects of pensions on the mental health of the elderly, it is mostly restricted to high- or upper-middle-income countries. Viet Nguyen (2021) considers the impact of pensions in lower-middle-income Vietnam to document effects on self-reported health and life-satisfaction, but few effects on labor supply or healthcare utilization. This study does not focus on individuals in poor households. To our knowledge, there are no other studies that evaluate the benefits of public pensions on the vulnerable poor in a developing/lower-middle-income country context, where social support schemes of this nature are likely to be especially meaningful given dearth of resources for economic assistance. We are also not aware of studies that consider heterogeneity of impacts on poor widowed populations, the majority of whom are likely to be elderly women.

Our study contributes to the literature by providing new evidence from a rigorous RD design that highlights that while providing income security may be sufficient to improve mental health markers in old-age on average, the extent of these benefits varies across different demographic groups. Our comprehensive analyses provide scope to broaden our knowledge of the effectiveness of common social assistance options, underscoring the importance of gender disparities and widowhood status in structuring support systems. Our research thus has important policy implications for programs that aid some of the most disadvantaged people in developing countries.

2. The National Social Assistance Program (NSAP)

Initiated in 1995 by the Government of India, the National Social Assistance Program (NSAP) is a centrally sponsored scheme designed to provide non-contributory social pensions to the elderly, widows, and persons with disabilities.[6] A key component of this initiative is the National Old Age Pension Program (NOAPS), which is specifically crafted to serve as a safety net for the most vulnerable elderly segments of society, with a particular focus on those living below the poverty line. At initiation, NOAPS allocated a monthly payment of Rs. 75 (US $8 in 2006 purchasing power parity) to each beneficiary aged 65 and above. State and Union Territory (UT) governments followed these thresholds initially. However, acknowledging the inadequacies of the central guidelines and the significant erosion of the real value of old-age pensions due to inflation, several states took the initiative to bolster the programs using their own resources. This was achieved by increasing pension amounts, expanding coverage, and/or supplementing the central scheme with own state-specific program pensions (Dreze and Khera 2017).

The NSAP has undergone numerous revisions and expansions over the years including a decrease in the age threshold for participants, an increase in the transfer amount, and an extension of coverage to below poverty line (BPL) households (Unnikrishnan and Imai 2020). More specifically, as noted in Kaushal (2014), following the 2006-2007 budget speech by the then finance minister, the central government increased the social pension monthly contribution from Rs. 75 to Rs. 200 (about US $22 in 2006 purchasing power parity) and expanded coverage to all elderly in households below the federal poverty line. As part of a broader social protection initiative, the federal government encouraged state governments to provide additional matching funds which resulted in the monthly total pension of the elderly

[6] These individuals need not belong to BPL households. Originally, the NSAP consisted of three main programs: NOAPS, the National Family Benefit Scheme (NFBS), and the National Maternity Benefit Scheme (NMBS). Over time, it has evolved to incorporate the Indira Gandhi National Widow Pension Scheme (IGNWPS) and the Indira Gandhi National Disability Pension Scheme (IGNDPS).

poor ranging from US $22-$108 in 2006 purchasing power parity, across states (there were variations in these amounts by gender lines as well, following state-specific regulations). These amendments to eligibility rules doubled the number of beneficiaries from about 8.7 million to almost 16 million, equaling roughly one in five elderly people (Pal and Palacios 2008).[7]

In November 2007, NOAPS was renamed as the Indira Gandhi Old Age Pension Scheme (IGNOAPS). In 2011, the finance minister announced a proposal under the ongoing IGNOAPS to reduce the eligibility age for BPL beneficiaries from 65 to 60 years with additional benefits to those 80 years and above.[8] The pension program aims to assist elderly individuals in meeting essential needs and in decreasing dependence on family.[9] The objectives include enriching various aspects of the lives of the elderly as well as improving household welfare (Kaushal 2014, Unnikrishnan and Imai 2020, Unnikrishnan 2022).

3. Data

Our main source of data to empirically evaluate the impact of pension eligibility on mental health is the Longitudinal Aging Study in India (LASI) Wave 1 from 2017-2019. LASI, a large and comprehensive nationally representative survey, focuses on the economic, social, and health aspects of India's elderly population, and is comparable to other international health surveys on aging. Designed with a multistage, stratified area probability cluster approach based on the 2011 Indian Census, the survey considers individuals aged 45 and above, as well as their spouses regardless of age. The sample is representative of India's 29 states and 6 UTs, and

[7] Detailed information can be found at the NSAP website https://nsap.nic.in/circular.do?method=aboutus. (Accessed January 12, 2024).

[8] We use 60 years and above in 2006 as the age eligibility threshold since our data indicate that this is the cutoff at which share of public pensions received by individuals in below poverty line households rises significantly above 0% (discussed below in Figure 1). 60 years is also the average retirement age in India. We would have followed Bertanha (2020) to implement a multiple threshold RD design that conditions on NSAP policies in 2006 and 2011 if we had larger sample sizes of elderly people in BPL households, and if our sample had revealed multiple points in the running variable when the likelihood of pension receipt rose above 0%.

[9] Dutta et al. (2010) evaluates India's social pension schemes focusing on coverage, targeting, and compliance. Their analysis, based on national and state-specific surveys, indicate that these schemes largely reach their target: the impoverished households, with no noticeable diversion of funds. Pudussery and Chopra (2014) echo these findings but also highlight issues including inadequate pension amounts, inefficient distribution mechanisms, high collection costs, and inconsistent payment schedules; but these are for a few cases only.

provides information for over 70,000 adults in about 42,000 households, shedding light on various facets of life such as household economics, demographics, health metrics, employment, and health care utilization. LASI Wave 1 from 2017-2019 was funded by the Ministry of Health and Family Welfare, Government of India, the National Institute on Aging, and the United Nations Population Fund, India. LASI was intended to have additional rounds every 2-3 years, although only the 2017-2019 round is currently publicly available as far as we are aware.

3.1 Measures of mental health and pension eligibility

Our main measures of mental health are constructed from the respondents' answers to a 10-question version of the CES-D.[10] Respondents were asked to indicate how often they experienced feelings pertaining to depression, loneliness, difficulty concentrating, amongst others. They could give one of the possible options to characterize the frequency of the specific depression symptom being considered. For instance, when asked how often they felt depressed over the week prior to the interview, they indicated the frequency by choosing from four options – "rarely or never (less than one day)", "sometimes (1-2 days)", "often (3-4 days)", or "most of the time (5-7 days)." In our baseline specifications, we code a first outcome variable "Depression1" as one if the respondent reports feeling depressed sometimes, often or most of the time, and as zero otherwise. A second outcome variable, "Depression2" takes a value of one if the respondent reports feeling depressed often or most of the time, and a value of zero otherwise. These are our subjective measures of depression. We use a third outcome for depression measured by CESD-10. In the survey, this variable is assigned a value of zero if the sum of the respondent's answers to 10 questions (after adjusting the scales for each question so that the answers are dichotomous) ranges from 0 to 3, and assigned a value of one if the score ranges from 4 to 10. This is our more objective measure of depression.

[10] The CES-D was originally developed by Radloff (1977), and remains one of the most common screening tests for evaluating an individual's depression quotient.

LASI collects information on public pensions. In the household interview, respondents were asked to provide information for each household member on any public pension received in the past 12 months. Public pensions include central government pensions, state government pensions, NOAP, Widow's pension, Annapurna scheme, or any other state or government scheme or program. The data are not detailed enough for us to separate out which part of public pensions received by an elderly individual is from the NOAP alone; however, for aged individuals in poor households, the bulk of the public pension received is likely to be under social welfare schemes like NOAP which specifically targets this group.[11] Based on this information, an indicator variable is created for individuals who receive a public pension.

Figure 1 depicts the share of elderly respondents in below poverty line households receiving a public pension by age cohorts in our data. This share is close to zero until age 60 years, beyond which it rises significantly to above 40% until about the 65-69 years age group. The share continues to increase beyond 70 years until 75-79 years but at a less steep rate. Significantly, even at its peak, the share of individuals receiving a public pension in below poverty line households does not exceed 50%. This indicates that a relatively large proportion of economically disadvantaged elderly people in India are receiving no public financial support even though they are eligible.

Figure 2 shows the proportion of elderly in below poverty line households who report feeling depressed sometimes, often or most or all of the time. This proportion is about 38% in the youngest age cohort of 45-49 years, but rises to close to 45% for the cohort that is a decade older. The rate then holds relatively steady until depicting a rise in the early seventies age group before peaking at 50% in the 75-79 age cohort. The share then declines somewhat for the oldest individuals in our study. This figure underlines that even the share of those feeling depressed

[11]As noted above, Figure 1 which is discussed below shows that for the elderly above 60 years, there is a measurable increase in public pension receipt. If the source of this was not primarily NOAP which is intended for older individuals, such a sharp jump should not be evident at this age threshold.

in middle-age among economically disadvantaged adults in India is significant, and this rate mostly increases with age such that one out of every two people who are 75-79 years old reports feeling depressed sometimes, often or most or all of the time.

Figure 3 depicts counterparts of Figure 1 and Figure 2 disaggregated by gender. Panel A of Figure 3 notes that the average share of elderly women receiving a public pension is somewhat higher than the share of elderly men in below poverty line households, with the gap widest among those in the 60-64 years age group. In Panel B of Figure 3, we show the percentage of respondents in our data who reported feeling depressed, by age groups and gender. We find that, in general, for most age categories, depression rates are higher for elderly women relative to elderly men in poor households. Relatively higher rates of depression among women echoes findings in Banerjee et al. (2023). Further, depression rates increase with age, peaking slightly above 50% for elderly women in the 65-69 years age group (this is when the gender gap is the largest) and at about the same proportion for elderly men in the 75-79 years age group. These rates decline thereafter for our oldest individuals, but still remain relatively high at about 45% for elderly men in their eighties and about 47% for elderly women in their eighties.

3.2 Summary statistics

Table 1 presents the summary statistics for three different samples: (a) eligible individuals, that is those who were aged 60 years or older in 2006 in BPL households, whose statistics are presented in columns (1) to (3), (b) ineligible individuals in columns (4) to (6), and (c), the full sample of all individuals in the data, in columns (7) to (9). Focusing first on the mental health measures, estimates in Table 1 reveal that the mean of the depression indicators are relatively higher in the eligible sample of the elderly poor as compared to the ineligible and full samples. For instance, the mean for the broader measure that includes those who report feeling depressed sometimes, often, most or all of the time in the week leading up

to the interview is 47.8% in the eligible sample of elderly poor as compared to 39.6% in the full sample. The mean for the narrower more severe indicator of depression is 20.8% in the eligible sample while it is 13.3% in the full data. Moreover, 36.2% on average, with a relatively wide dispersion, had a CESD-10 outcome variable coded as one in the sample of the elderly poor. The corresponding estimates in the ineligible and complete samples are 26.3% and 26.5%, respectively.

Considering other variables next, the mean age in the eligible sample is about 78.2 years, with a standard deviation of 6.0 years, while the full sample has a mean age of about 58.0 years, with a standard deviation of 10.9 years. The elderly poor have extremely low levels of education with about 80.0% never having attended school and 15.3% completing primary school. Proportions of those completing middle, secondary or tertiary education are essentially zero. Although no and low educational attainment is true for the ineligible and full samples as well, the magnitudes for the eligible elderly poor are measurably lower. Marital status also varied significantly between these groups; almost half of the eligible sample was widowed.

Other variables of interest include those measuring life satisfaction (indicator for somewhat or very or completely satisfied with life), self-rated health (indicator for good, very good or in excellent health), loneliness (indicator for sometimes, often or most or all of the time lonely), and an indicator for an individual who reports difficulties in carrying out the activities of daily life. Regarding these important predictors of quality of life, estimates in Table 1 reveal that a relatively lower percentage of the eligible disadvantaged elderly report feeling satisfied with life, they are relatively more lonely, and are in relatively less good health, as compared to others. Approximately 36.9% of the elderly poor report encountering difficulties in carrying out activities of daily life. The corresponding proportion in the full data is less than half at 14.4%. We condition on these important correlates when we evaluate the effect of pension eligibility on mental health measures of the elderly poor. In subsequent analyses, we

explicitly document how these quality of life measures as well as indicators of labor supply and healthcare utilization shed light on the means by which attaining pensionable age affects mental health.

Turning to household level variables, all samples are predominantly Hindu, and the proportion of scheduled castes and scheduled tribes, as well as the proportion of other backward classes, are higher in the eligible sample as compared to the remaining groups. These samples are also mainly rural. Indicators for socio-economic status that are considered in our analyses include household size, an indicator for access to electricity, and whether the house has a "pucca" (firm) structure. The elderly poor live in households that are somewhat larger in size, are less likely to have access to electricity, and have relatively lower likelihoods of having a pucca house, as compared to individuals in the full data and in the ineligible sample. Overall, and not surprisingly, the statistics in Table 1 underline that the elderly in below poverty line households are a more vulnerable demographic group as compared to ineligible individuals and the full sample of individuals.

4. Estimation strategy

The eligibility criteria under the NSAP scheme allows the application of a RD design as in Aslim et al. (2023) which studies life satisfaction after retirement in China. Public pension eligibility involves two criteria: the respondent's birth year and the household's economic status. A respondent is considered eligible if they were born in or before 1946 (thus, 60 years old in 2006) and belong to a household that is at or below the poverty line. Our analysis involves conditioning on years of exposure where years of exposure are estimated as the difference between a respondent's age in years and 60, for respondents in BPL households. This technique results in a person who was 60 years old in 2006 having 0 years of exposure, that is, we normalize the running variable to zero relative to the pensionable age cutoff, as in Aslim et al. (2023). As in a standard RD design, we estimate effects at the age threshold by

comparing people who just became eligible to those who just fall short. The validity of our causal estimates hinges on the identifying assumption in RD designs that the assignment to treatment is as good as random in the close vicinity of the eligibility age cutoff.

4.1 First-stage

Figure 4 shows the discontinuity in the likelihood of receiving a public pension and age relative to 60 years, for elderly men and women in BPL households. The discontinuity is estimated using a default uniform kernel and a fourth order polynomial fit to approximate the population conditional mean functions for control and treated individuals. The figure facilitates a visual inspection of the relationship between the running variable and the probability that an eligible individual receives a public pension. We see that there is a noticeable increase in the likelihood of eligible respondents receiving a pension beyond the normalized-zero threshold. Figure 4 thus provides graphical evidence for the first-stage: There is a sharp increase in the likelihood of receiving public pensions for both men and women in BPL households once the age of eligibility is attained.

Further regression-based inference on the relationship between eligibility and pension receipt around the age threshold shows an approximate 24 percentage point increase in the probability of receiving a pension at the cutoff, aligning with the graphical depiction in Figure 4. This estimate of the discontinuity at the age cutoff remains robust to the inclusion of controls and state fixed-effects, which we discuss in detail below.

4.2 Pensions and mental health

Following the evidence above, we use an RD design as our empirical methodology to evaluate intent-to-treat (ITT) effects of becoming eligible on measures of mental health. In particular, we estimate the following specification:

$$y_{ist} = \gamma_0 + \gamma_1 \mathbf{1}(a_{ist} \geq c) + \gamma_2 (a_{ist} - c) + \gamma_3 X'_{ist} + \lambda_s + \epsilon_{ist} \quad (1)$$

where y_{ist} is the outcome of interest pertaining to mental health for individual i living in state s in year t.[12] As discussed above, we use three measures of mental health: "Depression1," "Depression2" and "CESD-10." Age of the individual is a_{ist}, c is the pensionable age cutoff (60 years), and $\mathbf{1}(a_{ist} \geq c)$ is an indicator variable determining treatment (an individual is treated if $a_{ist} \geq c$ and not treated if $a_{ist} < c$). In this sharp RD design, age is the running variable which determines treatment, and γ_1 is the parameter of interest which is the ITT effect of pension eligibility on the outcome of interest. We interpret $(a_{ist} - c)$ as $yrsofexposure_{ist}$, that is, an individual's years of exposure since becoming pension eligible for all living in BPL households.[13]

We include a vector of individual and household level controls (X'_{ist}) that contain correlates of mental health including binary variables for life satisfaction, loneliness, and being in good health. Other individual controls include gender, four indicator variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (Scheduled Caste/Scheduled Tribe (SCST) and Other Backward Class (OBC), as well as whether the respondent encounters any difficulty in carrying out activities of daily life. The household controls include a dummy for rural residence, a continuous variable for the number of people living in the household (household size), binary indicators for whether the household has concrete/firm dwelling/structure, and access to electricity. State fixed-effects, λ_s, control for state-level time-invariant unobservables that may influence the outcome and eligibility status simultaneously, while ϵ_{ist} is the standard error term.[14] We report coefficients from weighted regressions and

[12] We include time subscripts as individuals were interviewed from 2017 through 2019. However, about 93% of the sample was interviewed in the first two years. We do not have a need to leverage time for our RD design.
[13] The LASI includes an indicator for whether the household qualifies as a BPL household when surveyed.
[14] The data do not allow us to identify more disaggregated regions of residence like districts or villages.

cluster standard errors at the age level in order to control for correlation in pension eligibility and the outcome of interest for individuals of the same age.

5. Results

5.1 Impacts on mental health measures

We present our main results in Table 2. As seen in Panel A, conditional on individual and household controls and state fixed-effects, the RD estimate is consistently negative and significant in all columns when we consider the depression-related outcomes. Specifically, the estimate in column (2) indicates that access to public pensions significantly reduces the probability of feeling depressed sometimes, often, most or all of the time (broader measure of depression) by 10.1 percentage points at the critical age threshold (about a 21% decrease relative to its mean). For other measures of depression (depression2 and CESD-10), the reductions are 6.7 and 4.4 percentage points in columns (3) and (4), respectively (representing about a 32% and 12% decrease relative to their means).[15]

The results presented in Panels B and C of Table 2 indicate that pension eligibility improves mental health measures in the gender-disaggregated samples, with important differences. More specifically, access to pensions reduces the likelihood of the broader measure of depression by 13.8 and 5.5 percentage points (approximately a 29% and 12% decrease respectively, relative to their means) at the age cutoff in column (2), for elderly men and women, respectively. Although the impacts on the other two depression measures for elderly men are not significant, the effects on the CESD-10 outcome for elderly women stands out. It is negative and statistically significant at the 1 percent level, indicating a notable reduction of 8.6 percentage points in the likelihood of depression with access to pensions beyond the age

[15] In results not reported and following Viet Nguyen (2021), we obtain Q-values, which are adjusted *p*-values from approaches in Simes (1986) and Benjamini and Yekutieli (2001) using methods developed in Newson (2011), in order to ensure that multiple hypotheses testing does not affect these outcomes. These Q-values are similar to the original *p*-values, and all our coefficients maintain their levels of statistical significance.

threshold. This represents a 23% decrease compared to its average, underlining significant mental health benefits of pension eligibility for poor elderly women.

To investigate potential heterogeneous effects of pension eligibility among the elderly in BPL households, we report results for distinct sub-samples in Table 3. The coefficients highlight a statistically significant impact of eligibility on mental health as measured by the first two measures of depression (Panel A, columns (1) and (2)) for widowed respondents, who, as we note above, comprise more than half of our eligible sample. Estimates are of relatively larger magnitude for widowed women in Panel B (more than three-fourth of those who are eligible); on average, pension eligibility significantly decreases the likelihood of both Depression1 and Depression2 (columns (1) and (2) of Panel B). In particular, widowed women experience a 21 percentage point decline in the more severe Depression2 measure when they reach pensionable age. The magnitude of this effect as well as its comparison with the effect for widowed respondents in general in Panel A suggests that autonomy over pension income, which is more likely for women who are widowed as compared to their married counterparts, is especially important in influencing mental health outcomes.[16] When examining urban, urban women, and urban married women samples in Panels C, D, and E, there are again significant ameliorative effects of access to pensions on mental health for most measures of depression.[17]

We compare the magnitude of these effects to other studies that consider the impact of pensions on mental health. Cheng et al. (2018) evaluates China's New Rural Pension Scheme (NRPS) on a self-reported depression index for men and women using a fixed-effects IV methodology. The study finds that NRPS take-up reduced the depression index by 20% relative to its mean. Our estimate of pension eligibility reduces the broader measure of depression by

[16] Lack of information on control over resources within the household limits a more careful exploration of this issue. However, in section 7.5, we examine underlying proxies for financial autonomy that may be explanatory.
[17] We interpret the results in Panel E of Table 3 more cautiously given the reduced sample size. Further, we are unable to estimate effects in rural areas with models that include state fixed-effects due to insufficient variation in that sample. The same is true when we consider widows in urban areas.

about 21% relative to its mean, which is in the same ballpark. In terms of differences by gender, Cheng et al. (2018) finds that both elderly men and women benefit in terms of reduced measures for the depression index. Our analyses across various outcomes also reveal that pensions positively affects both elderly men and women. However, the impact exhibits variability: We observe a notably larger benefit for men in terms of a reduction in the broader measure of depression – approximately 29% relative to the mean. Meanwhile, significant improvements in the CESD-10 indicator are observed exclusively for elderly women. Chen et al. (2019) considers pensions and mental health in the aggregate using variations in geographic rollout to identify effects and finds that depressive symptoms are up to 17.5 percentage points lower among NRPS pensioners in China. The corresponding rate in our study is lower at 10.1 percentage points, perhaps because only 50% of those elderly in BPL households who are eligible actually report having a public pension (enrollment in the NRPS for those aged 60 and higher is greater at about 65%). Pak (2021) finds that the 2014 social pension reform in South Korea led to an average decrease in depression symptoms by 8.1 to 9.0%.

6. Robustness checks

6.1 Additional controls for childhood experiences and other covariate checks

We begin by checking the robustness of our findings by controlling for factors related to the respondent's early life, in light of the literature indicating that childhood conditions can influence outcomes in the future (Ahmed et al. 2023, Irshad et al. 2022). We control for the respondent's financial status while growing up, their health status as a child, and the socioeconomic status of their parents, as indicated by their educational attainment. As seen in Table A1, conditioning on these variables does not alter the size or statistical significance of our main estimates.

We then use these early-life variables along with factors related to education, location, religion, caste, and widowhood status to investigate whether there are discontinuities in

densities around the eligible age cutoff point. We run regressions with these covariates as outcomes of interest and present the results in Table A2. We find no significant effects for most covariates except for religion and SCST caste status, which are controlled for in all models.[18]

6.2 Manipulation of the eligibility criteria

We use a RD design with age as the running variable. The key assumption for local random assignment is that individuals have limited power to influence the assignment variable and there is no manipulation at the age cutoff. That is, elderly individuals in BPL households should not be able to deliberately misreport their age to qualify for public pensions.

Manipulation of the eligibility criteria is improbable in our case as it would be difficult for elderly individuals to misrepresent both age and income status. Indeed, many of the elderly likely have no official birth certificate to verify age, which may be one reason why even the peak share of public pension receipt in Figure 1 is markedly low at only 50%. More specifically, the NSAP in India has established eligibility criteria for applicants and necessary verification documents include proof of age attested by a medical officer, an income certificate, and a BPL card bearing the applicant's name. In rural regions, potential beneficiaries are identified from the BPL list curated by States/UTs, in line with the guidelines set by the Ministry of Rural Development from the BPL Census 2002. For urban locations, they are identified using the BPL list associated with the poverty alleviation initiative of the Ministry of Urban Housing and Poverty Alleviation. Gram Panchayats play a key role in the beneficiary identification process across all programs.[19] This structured approach is likely to impede strategic alterations of the eligibility criteria by program administrators as well as potential beneficiaries. Furthermore, to enhance accountability, NSAP has annual verification and audit processes with national level monitors equipped with scheme checklists during their on-field evaluations. These monitors

[18] Frölich and Huber (2019) document that controlling for covariates can reduce bias and diminish variance in RD designs, especially when the distributions of the covariates exhibit discontinuities at the cutoff.
[19] More details can be obtained from the NSAP's official site.

are also encouraged to interact with government officials and beneficiaries to garner feedback on how effectively schemes are being executed.

Dreze and Khera (2017) note that recent studies reveal little corruption within pension programs. An in-depth review of pension lists from 10 diverse states in 2013 showed that 98% of the 3,789 listed individuals were alive and actively receiving their pensions. Echoing this, Dutta et al. (2010) posit that India's social pensions might be less prone to corruption than other safety nets. The study references the Public Evaluation of Entitlement Programs (PEEP) survey, carried out between May and June 2013 across ten Indian states. This survey found pension schemes have limited corruption, indicating that they are relatively better managed than many other development programs. Despite a few discrepancies, the overarching conclusion was that most pension recipients were the intended beneficiaries, and significant leakages in the NSAP were rare.

With these pieces of evidence, we believe that treatment in our case is essentially random at the pensionable age cutoff, and hence, significant discontinuous shifts in our mental health outcomes at the relevant age threshold may be causally linked to pension eligibility.[20] We provide formal evidence for this below.

6.3 Formal test of manipulation of the running variable

While it is unlikely that manipulation of the running variable is an issue for us, we explicitly investigate that possibility by implementing formal tests to ensure the validity of the RD design. These include conditional density tests that are used to detect strategic sorting or intentional manipulation around the threshold. The null hypothesis is that there is no manipulation (that is, the density function is continuous at the age cutoff) and that there are no overly influential observations near the cutoff.

[20] Further, sorting is unusual in programs that assign treatment based on age (Huh and Reif 2021, Altindag et al. 2022, Aslim et al. 2023).

Guided by the recommendations of McCrary (2008), Lee and Lemieux (2010), Cattaneo et al. (2020), and Bugni and Canay (2021), we apply continuity tests on the full sample. To align with the estimation approach, we use a data-driven bandwidth selection, applying local polynomial density estimation techniques (Cattaneo et al. 2020). The *p*-values from this test cannot reject the null hypothesis of no manipulation(the *p*-values are 0.581, 0.759 and 0.216, for Depression1, Depression2, and the CESD-10 measure, respectively). Analyses of the Cattaneo et al. (2020) density tests in Figure 5 (with the point estimates and 95% confidence intervals) reinforces this conclusion. Given these results, along with the details in Section 6.2 on eligibility criteria, we conclude that manipulation is unlikely in our case.

6.4 Alternative bandwidths

We conduct further robustness checks using alternative bandwidths in Table A3, recognizing that selecting the optimal bandwidth allows us to balance accuracy and bias, thus providing additional confidence in our main estimates (Calonico et al. 2014).[21] In order to accomplish this, we re-estimate our RD regressions using distinct bandwidths: A common mean square error (MSE) optimal bandwidth selector for the RD treatment effect estimator in Panel A, and two different MSE optimal bandwidth selectors, one for below and one for above the cutoff in Panel B. In Panel C, we report results using a second-order polynomial function. Results for the combined sample are shown in columns (1), (4), and (7) for our three measures of depression, respectively. The remaining columns present gender-disaggregated results, correspondingly. Overall, the results in Table A3 align with those from Table 2.

6.5 Fuzzy regression discontinuity design

We estimate effects using Fuzzy RD techniques as another test of our main results. As is well known, Fuzzy RD addresses partial policy compliance to estimate local average

[21] Calonico et al. (2014) identifies the optimal bandwidth based on minimizing mean square error, conditional on covariates, data, and applications. The method facilitates bandwidth selection for local polynomial regression.

treatment effects (LATE) among compliers. This becomes relevant when there is a mismatch between the intended treatment and the one actually received by some target groups because of incomplete participation, or when variables other than the predetermined cutoff influence the likelihood of entering a program.[22] Contrasting with the sharp RD design used in our main methodology, Fuzzy RD allows for subtle shifts in the treatment assignment probability at the predetermined threshold.

Estimating the effect of public pensions on mental health among the elderly in BPL households in a Fuzzy RD framework essentially follows an instrumental variables (IV) methodology where the IV assumptions of monotonicity and the exclusion restriction apply. Monotonicity here requires that there are no individuals 60 years of age who are less likely to take up a pension (defiers). The existence of defiers in this context is difficult to justify since anyone who reaches the threshold age of 60 years is eligible to receive a pension, and this is difficult to manipulate. The exclusion restriction requires that age affects mental health only through its impact on pensions. This may be violated if there were other policy changes at the 60 year threshold; however, as we discuss in Section 6.7 below, although there were other policies that also occurred around the time of the NSAP, none of them directly targeted elderly people of 60 years and above in BPL households. There are also several other reasons for why our results are not affected as outlined in Section 6.7.

The results from the Fuzzy RD method using default bandwidths and standard errors clustered at the age level are reported in Table A4. The estimate in column (1) for the first-stage indicates that pension eligibility is positively associated with the likelihood that the elderly poor receive a public pension in the full sample. The second stage results are broadly

[22] Dutta et al. (2010) outlines five possible non-compliance issues in Indian pensions schemes: (1) duplicate records causing overpayments or unauthorized payouts; (2) absentees (missing enrolled pensioners) leading to fraud; (3) underpayment of rightful pensioners; (4) bribes demanded upon or post-enrollment; and (5) ineligible individuals enrolled in the scheme. The more recent Dreze and Khera (2017) study underlines that all of these cases are likely minimal. Nonetheless, we undertake this alternate RD method to ascertain robustness.

consistent with those in Table 2 across two of the three depression measures we consider (in comparison with results in Table 2, we lose significance for Depression2), albeit larger in magnitude.

6.6 Changes in the pension-eligible age cutoff

Figure 1 shows that 60 years is the age at which the share of public pensions received by individuals in below poverty line households rises significantly above 0%. However, given the discussion in Section 2 that notes that the pension eligible age cutoff was reduced from 65 years to 60 years in 2011, it is possible that someone aged 60 years in 2006 would not have been eligible to receive a public pension. This implies that our estimate of the impact of becoming pension eligible on mental health may be an underestimate. In order to address this, we re-estimate our main results in Table 2 excluding individuals who may have been exposed to the previous age cutoff. This re-estimation reveals that the results in Table 2 remain essentially the same.[23]

6.7 Concurrent national policy changes

Klonner and Oldiges (2022) notes that the implementation of other policies and welfare programs during 2006 and 2007, such as the National Rural Employment Guarantee Act (NREGA) and the Backward Regions Grant Fund (BRGF), complicates evaluations of individual programs initiated in this time period. The RD framework is most apt for causal inference in this context as it compares individuals at the margin (just ineligible versus those who are just eligible) who are otherwise comparable. Further, given sample sizes and only broad knowledge of where individuals live (we do not have district information in these data, only state of residence) we are unable to include state-specific linear trends or district-by-year

[23] There are 959 elderly in BPL households who fall in this category. This is only 1.3% of our sample. Hence, excluding them does not significantly change our main results. These results are available on request.

fixed-effects. We do, however, include state fixed-effects together with multiple individual-level controls to alleviate concerns and to underline the validity of our results.

Further, it is unlikely that alternate programs contaminate any of our results. Focusing on NREGA, this was enacted in 2005, and offers every rural household in India the right to 100 days of work annually at a statutory minimum wage set by state governments. Eligibility criteria mandate that beneficiaries must be at least 18 years old and prepared to perform unskilled labor. Although the program is accessible to elderly individuals under specific conditions, it predominantly offers labor-intensive public works. Consequently, while some elderly residents may be eligible and have a chance of being selected into the program (Bernal et al. 2024), the physically demanding nature of the work likely limits full-scale participation by those of advanced ages.

The BRGF is an Indian government initiative launched in 2007 to mitigate regional development imbalances. It aimed to bridge infrastructural and developmental gaps through targeted funding and capacity building at the local governance level. The BRGF's effects on individual mental health are likely to be indirect and long-term, relying on the gradual improvement of local infrastructure and governance. We therefore argue that the different eligibility and targeting criteria for these alternate programs reduce the likelihood that our elderly poor-specific results are influenced by them. Employment of the RD framework that relies on differences between comparable individuals at the margin further increases our confidence that the impact of confounding effects is minimal.

7. Mechanisms

The aim of this section is to understand different pathways by which pension eligibility affects depression among elderly men, women, and widows. We begin by investigating the labor supply channel, followed by empirically examining shifts in healthcare utilization,

objective health metrics, and preventive health practices. We then assess impacts on overall well-being, perceived social standing and financial autonomy.

7.1 Labor supply

Pension eligibility can influence mental health through its impact on labor supply encompassing two key mechanisms: The income effect, which reduces the financial need for older individuals to engage in employment, and the substitution effect, which can shift the balance in favor of leisure over labor.[24] Pensions offer a crucial layer of financial stability in later life, potentially mitigating stress and anxiety associated with economic precariousness, especially for very poor households. This provision of economic security may allow elders to afford retirement, and may lead to reductions in labor supply, thereby having important implications for depression.[25]

Although a few papers have examined the impact of pensions on labor supply, the effects are mixed, and the existing analyses are mostly restricted to upper middle income countries (Juarez and Pfutze 2015, Cheng et al. 2018, Bando et al. 2020, Bando et al. 2022, Dutronc-Postel and Tondini 2023). Viet Nguyen (2021) finds that in Vietnam (the only other lower-middle-income context), old-age pensions did not significantly affect employment status. Turning to the only two studies on India, Kaushal (2014) analyzed the impact of NOAPS on the labor supply of the elderly to find that public pensions modestly reduced the employment rates of elderly or near-elderly men with limited education. Unnikrishnan and Imai (2020)

[24] For the average individual, it is possible that the income effect channel is ambiguous in that those who become pension-eligible lose relative earnings over time, particularly if pensions are not indexed to the cost of living. However, the eligible in our sample are those in BPL households. Given their extreme indigence prior to becoming pension eligible, this is unlikely to be a significant factor for them.

[25] A "time-composition" effect emerges (Galiani et al. 2016), where the opportunity to allocate more time to leisure activities and pursuits of personal enjoyment contributes positively to overall happiness. Consequently, elderly people who place a significant value on the time-composition effect may choose to decrease their labor supply in response to the financial security afforded by pension eligibility. Further, the reduced need to engage in work may also mitigate the negative impact of strenuous jobs on health outcomes (Giuntella and Mazzonna 2015, Cheng et al. 2018).

documents a fall in household labor supply. Neither of these studies evaluate subsequent effects on mental health.

Our analysis begins with an examination of labor market outcomes including both intensive (hours worked) and extensive margin (employment status) responses. As seen in Table 4, the RD estimates are consistently negative for the labor supply indicators, with varying impacts by gender and widowed status. In Panel A, we focus on two aspects of the respondent's work life. The first, in columns (1) through (4), examines their employment status, while the second, in columns (5) through (8), considers work for pay. We find that pension eligibility significantly decreases the probability of all respondents being employed and working for pay by 8.1 and 6.2 percentage points, respectively. Notably, the effect on employment status as measured by "currently works" is more pronounced among widowed individuals. Further, women in particular are less likely to work for pay with pension eligibility.

Focusing on hours worked in Panel B, we find that pension eligibility significantly reduces weekly hours dedicated to the primary job in columns (1) through (4), with an exception for women. The estimates are mostly negative and significant for the full sample and for male, but measured with error for women and widows when we evaluate total weekly working hours (encompassing both the primary job and any supplementary employment). As a robustness check, Panel C focuses on the results for two additional labor market evaluators: A binary variable "works a second job," indicating whether an individual is engaged in more than one job; and "participates in the labor force," another binary variable that denotes whether an individual is either employed or unemployed but actively seeking work. Consistent with previous results on labor supply, these results also exhibit important differences for poor widowed populations, the majority of whom are elderly women, who are found to experience large beneficial effects of pension eligibility.

Overall, these results indicate that pension eligibility has important heterogeneous effects on labor-force participation (with magnitudes that are in the general ballpark of previous studies). This is evident through reduced employment likelihood, fewer working hours, and decreased participation in the labor force or holding a second job. The impact is larger in certain sub-samples including widowed populations. Specifically, the extensive margin responses where poor eligible elders reduce engagement in terms of "currently works" and "participates in the labor force" appear to be key factors. These results are consistent with a comparison of pension schemes in more developed contexts that shows that increasing social security and cash transfers is associated with an increase in the rate of retirement of older adults from formal employment (Gruber and Wise 1998, Galiani et al. 2016).

The results in Table 4 are further supported by additional evidence on leisure and time allocation presented in Table A5. Panel A shows that pension eligibility increases the probability of elderly women's involvement in social groups and regular interactions by 1.8 percentage points. This aligns with the literature indicating that decreased labor market participation may boost social engagement (which is beneficial for mental health), corroborating results in Cheng et al. (2018). There are mostly no significant effects on attendance at religious functions in columns (5) through (8). In Panel B, pension eligibility appears to reduce childcare provision for grandchildren in the total sample and for elderly men. The exception is widowed respondents (primarily widowed women) who are 10.4 percentage points more likely to engage in such caregiving activities. Further, elderly women experience a 2.4 percentage point increase in providing personal care to family or non-family members, underlying that with pension eligibility elderly women in particular may reduce labor market engagement in order to provide additional (often unpaid) care work.

Building on our analyses of labor market impacts in Table 4, we document a significant drop in both individual and household income from earnings in columns (1) through (2) of

Table A6. We find a corresponding decrease in household total expenditure in column (4), possibly a result of altered spending habits and strategic financial adjustments in response to changed income levels.[26] Following Cheng et al. (2018), we test whether pensions crowd-out intra-family transfers by considering impacts on the net value of financial transfers. Our findings indicate an increase in net value of financial transfers for poor eligible households, suggesting that, if anything, pension eligibility triggers additional financial transfers.

Taken together, our findings in this section suggest that pension eligibility significantly affects time allocation, labor supply, social engagement and personal care. These multifaceted impacts highlight pensions' role in providing stability and fostering social connections, underscoring the importance of these factors in improving the mental health of the elderly poor.

7.2 Healthcare utilization, health behaviors, and preventive measures

We next analyze the link between pension eligibility and mental health though the lens of healthcare access, utilization, and status. The complex nature of healthcare access and utilization in India, particularly among the elderly, is important to consider. The elderly's preference for private health centers, along with significant disparities in healthcare utilization (Sahoo et al. 2021), indicates that pension eligibility could enhance health investments (Lei et al. 2015, Cheng et al. 2018), utilization of healthcare services, and adoption of preventive health measures.[27] Our empirical investigation in this realm is supported by the literature that

[26] Reassuringly, we find no changes in weekly consumption levels; our data, however, lacks detailed information to check for changes in respondents' diets. Unnikrishnan (2022) analyzes how NOAPS influences the allocation of food budget shares among pension-receiving households. Findings reveal that access to pensions for women positively impacts the proportion of the budget dedicated to purchasing vegetables, fruits, nuts, and protein-rich foods. Bernal et al. (2024) finds that pensions improve anemia and nutrition-related mortality indicators in Peru, driven by improvements in diet quality and increased spending on food and healthcare.

[27] Sahoo et al. (2021) notes that despite improvements in public healthcare use from 2004 to 2018, a large segment of the elderly population remains unaware of or does not use available geriatric welfare services. This issue is particularly acute for older women and widows who are more susceptible to health challenges and access barriers.

connect pensions with improved healthcare access, health-related behaviors, and objective health markers.[28]

In Panel A of Table 5, we begin by focusing on healthcare utilization, using a binary variable that takes a value of one if respondents accessed services like consultations or home visits in the past year. The results suggest that there is no significant impact across subsamples except for men, where pension eligibility increased healthcare visits by 2.5 percentage points. In columns (5) through (8), we evaluate insurance covered drug expenses, observing a 3.8 to 7.3 percentage point rise in coverage across the sub-groups considered. This suggests that pension eligibility may be positively associated with enhancement of insurance benefits to pay for drug expenses. Panel B shifts attention to out-of-pocket expenditures related to hospitalization and comprehensive (total) expenses, including outpatient services and medications over the previous year. We see mostly negative impacts across subsamples, with a more pronounced effect for widowed individuals.[29] These patterns imply that pension eligibility may correlate with improved access to affordable health insurance and preventive care (a hypothesis we test below), thereby potentially decreasing the need for costly emergency or specialized treatments that typically require significant out-of-pocket spending.[30]

In Table A7, we further explore gender-specific behaviors among pension recipients, considering how regular exercise, smoking habits, and dietary choices are potential modifiers

[28] Aguila et al. (2015) documents that income supplementation leads to health benefits for Mexico's impoverished elderly, enabling them to allocate more funds for healthcare and to reduce their reliance on relatives for medical costs. Duflo (2003) and Case (2004) both document significant health improvements in South Africa resulting from its program, highlighting enhanced nutritional status and reduced stress levels. Cheng et al. (2018) notes that increased pension income reduces financial barriers to medical care in China. Lloyd-Sherlock (2006) and Schwarzer and Querino (2002) highlight how pensions in Brazil increased access to healthcare and medications. Nikolov and Hossain (2023) reveals that while pensions improve health behaviors, they also lessen social engagement and mental sharpness. Pak (2021) and Viet Nguyen (2021) find that social pensions in South Korea and Vietnam, respectively, improve elderly's mental well-being and life satisfaction without significantly raising physical health or healthcare utilization.

[29] In India, where only 15% of the population has health insurance covered, high out-of-pocket expenditures are a common burden (Sahoo et al. 2021).

[30] The impact of pension income on out-of-pocket expenditures can vary largely across different local contexts. Aguila et al. (2015), for instance, finds that treated elderly individuals were more likely to cover their own medical expenses while reducing financial reliance on their relatives for these costs in Mexico.

of mental health impacts (Saneei et al. 2016, Sarris et al. 2014).[31] We do not find significant effects on the frequency of physical activity or whether the individual currently smokes. However, we observe that women and the widowed elderly poor have a notably lower prevalence of obesity. A reduced prevalence of diabetes is apparent across all groups except for the widowed. We then examine preventive healthcare practices. Pension eligible elderly women are more inclined to have had a mammogram (breast x-ray) within the last two years, and widowed groups are 1.3 percentage points more likely to have received a flu shot in the same period. We find weak evidence that elderly women have had a cholesterol test.

7.3 Life satisfaction, optimism, and welfare

We assess impacts on subjective well-being, optimism, and relative social status (Koivumaa-Honkanen et al. 2004, Collins and Goldman 2008). In Panel A of Table 6, we examine the effects of pension eligibility on life satisfaction and optimism, and note apparent gender differences. Pension eligibility is linked to a significantly higher likelihood of life satisfaction among men, while the impact on women is measured with noise. The effect is positive also for widowed populations, the majority of whom are women, thus signaling that autonomy is perhaps important in these domains. Further, pension eligibility improves feeling hopeful about the future, but primarily for women and widowed groups.

Panel B shifts the focus to sleep quality, where the pension eligible are less likely to experience difficulties sleeping. When assessing subjective social status through the Cantril Ladder, we find that only widowed groups report a noticeable increase in perceived social status by 8.3 percentage points as a result of becoming pension eligible.[32] Overall, and mostly

[31] We note that depression can influence the uptake of health-promoting behaviors and affect the occurrence of other diseases. As discussed in Aslim et al. (2023), our goal here is not to draw causal connections between these health aspects, but rather to shed light on various mechanisms that may be at play across the different subgroups we consider with a view to explaining our primary results.

[32] The survey asked participants to evaluate their societal position by showing them an illustration of a ladder consisting of 10 steps. They are then prompted as follows: "*Think of this ladder as representing where people stand in our society. At the top of the ladder are the people who are the best off - those who have the most money, most education and best jobs. At the bottom are the people who are the worst off - who have the least money, least education, and the worst jobs or no jobs. The higher up you are on this ladder, the closer you are to the people at*

consistent with the literature, these results underline that pension eligibility brings non-pecuniary benefits in terms of life satisfaction and subjective well-being.

7.4 Mediation

We next investigate the importance of the mechanisms through which pensions may alleviate depressive symptoms by gradually augmenting the baseline regression with identified mediators. This approach provides a nuanced examination of how these mechanisms differently affect subgroups, shedding light on the relative importance of each channel. The idea is that if pensions indirectly improve mental health via specific pathways, then including measures for these mediators should attenuate the coefficient of interest (Pak, 2021).

In Table 7, we consider these results when the outcome of interest is "Depression1." We observe that the coefficient in the complete sample is largely attenuated when we consider the full set of mediators (column 5), indicating that these variables collectively explain about 33% of the pension's impact on our broadest measure of depression. For male respondents, as we gradually augment the baseline regression, the RD estimates decrease, though they remain negative and highly significant. We find suggestive evidence that for elderly men, improvements in life satisfaction, optimism, and welfare, serve as key mechanisms, accounting for about 25% of the pension's effect on depression.

For women, the estimates reduce in magnitude and lose significance when we control for healthcare utilization and life satisfaction (columns 3 and 4), and this insignificance persists in column (5) with the inclusion of all mediators. Healthcare and life satisfaction are thus important determinants for this group. In the case of widowed respondents, the introduction of variables related to labor supply and leisure, healthcare utilization, and life satisfaction individually leads to reductions in the original estimate by about 28%, 30%, and 29%,

the very top and the lower you are, the closer you are to the people at the very bottom of your society. Please indicate the number given on the rung on the ladder where you would place yourself." The scoring system ranges from 1 to 10, with 1 representing the lowest rung on the ladder and 10 representing the highest. Our variable is coded as one if the respondent's answer falls within the 8-10 range on the ladder.

respectively. When all mediators are considered together in this sub-group (column 10), the effect, though still negative, is insignificant.

The analyses in this section underscore a more pronounced attenuation effect among women and widows across the three mediator categories, with healthcare utilization and wellbeing emerging as particularly influential.

7.5 Financial autonomy and pension impacts for widows

One of our main findings is that the impact of pensions is stronger for widows than for most other demographic groups, implying that widows may experience unique gains, potentially due to independent control over pension income in the absence of a spouse or children. Such financial control could improve their well-being, as it allows them financial autonomy to allocate funds towards goals that they see fit including health, nutrition, and self-care. Our data lacks indicators of financial autonomy or control over pension income, limiting our ability to confirm these mechanisms directly. To address this, we examine proxies for financial autonomy such as living alone, children's co-residence, and reliance on external financial support.

First, we focus on widowed individuals in single-person households, where it is likely that they exert independent financial control without influence from other household members. In results available upon request, we find that the impact of pension income is larger for such individuals as compared to the full sample. Estimates are also relatively higher for elderly widows living alone, suggesting that financial autonomy may enhance the positive impact of pensions. However, these are small samples and so we are wary of generalizing results.

Second, we examine whether the main effects remain when individuals co-reside with children. For the full sample, the intent-to-treat effect for pension eligibility on mental health remains negative and significant but drops to 7.5%. When we restrict the sample to widowed individuals with co-residing children, the estimate is still negative but loses statistical

significance, suggesting that control over pension income may indeed play a key role in shaping mental health outcomes. This pattern implies that the presence of adult children may dilute the beneficial effects of pensions on well-being of co-residing elderly.

Third, we investigate the effect of pension eligibility on the likelihood of receiving financial support from children, grandchildren, parents, or other sources for elderly widows who live alone. We create a binary variable coded as one if individuals received such support. Our findings show that pension-eligible widows who live alone are less likely to receive external financial support, indicating that the financial autonomy provided by pensions may alleviate economic hardship while enhancing self-sufficiency, thus potentially contributing to mental well-being. We note, however, that when examining the net value of financial transfers across the full sample above, we do not find evidence that pensions crowd out intra-family transfers. This nuanced response limited to widows living alone highlights potential benefits of targeted pension policies for this vulnerable demographic.

8. Conclusion

We use a nationally representative comprehensive dataset on elderly individuals' health and socioeconomic status to empirically analyze the relationship between pension eligibility and mental health in below poverty line households of India. We document important age-gender gradients in the income security-depression relationship. More specifically, we find that becoming eligible for public pensions reduces the likelihood that the elderly report being depressed. In particular, the ITT regression discontinuity coefficient estimates a 10.1 percentage point decline in the likelihood that an elderly poor person reports feeling depressed sometimes, often, most or all of the time. Our examination of three depression-related outcomes, coupled with gender and marital status-disaggregated analyses indicates that pensions have a beneficial impact on both elderly men and women, though the magnitude of the effect varies. We specifically note a more pronounced benefit for men in reducing

(subjective) depression levels. On the other hand, we find that the CESD-10 indicator (a relatively objective measure of depressive symptoms), shows marked improvements exclusively for elderly women. These gender-specific differences underline the importance of considering several measures of depression in tandem as opposed to relying on a single measure alone.

We next consider impacts for widowed populations and find significant ameliorative effects of pension eligibility on the mental health of widowed elderly women in BPL households. Beneficial impacts of attaining financial security are also evident for urban elderly women. We reconcile these aggregate and sub-sample-specific results by noting that through provision of income stability and financial autonomy, pension eligibility improves the mental well-being of the primary earner. We use information on labor market participation, healthcare access and usage, life satisfaction and social status to analyze mechanisms, and to provide additional insights into channels that may be explanatory.

Our findings have important policy implications for at-risk populations in developed and developing countries. Concerted efforts have put the elderly's mental health status on public policy agendas, yet much remains to be done. The World Mental Health Report 2022 (WHO 2022) indicates that around half of the world's population today lives in countries where there is just one psychiatrist to serve 200,000 or more people, and that countries, on average, devote less than 2% of their health care budgets to mental health. While the median number of mental health workers is 13 per 100,000 people, there is significant variation between income groups from below 2 workers per 100,000 people in low-income countries to over 60 in high-income countries (WHO 2022). As the proportion of the population aged 60 and over rises while social security coverage remains absent or relatively low in many less developed contexts, there is an urgent need to broaden safety nets, as well as to improve their efficacy in protecting the elderly poor. We evaluate one such system in a large developing country and

demonstrate differential benefits by gender and widowhood status. While improvements in income security may not be the only remedial course of action for ameliorating the mental health of the elderly poor, we find that such policies do improve well-being. For those who remain susceptible, gender-sensitive initiatives may yield larger gains.

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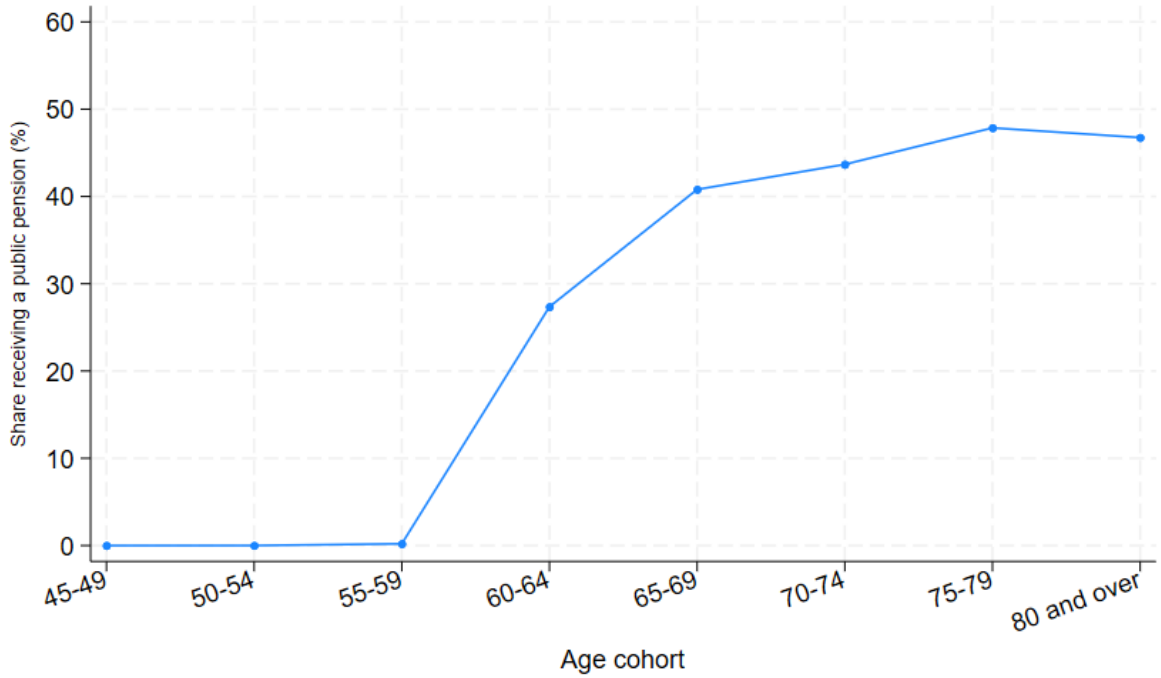
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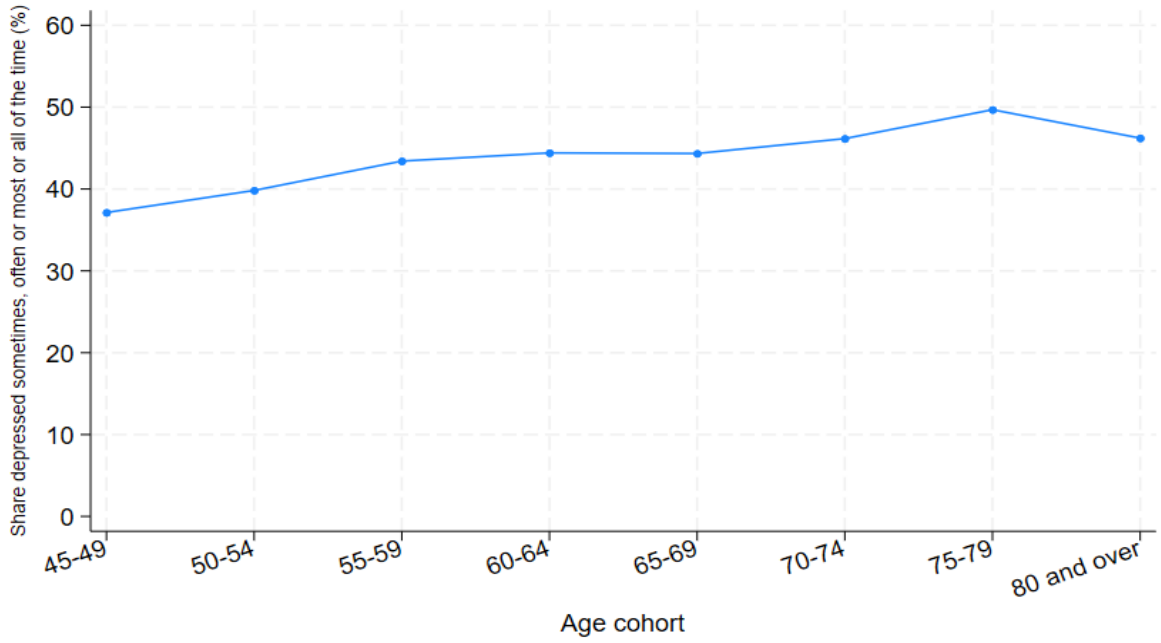
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Figure 1: Share of individuals in BPL households receiving a public pension, by age cohorts



Notes: Authors' calculations using LASI data wave 1.

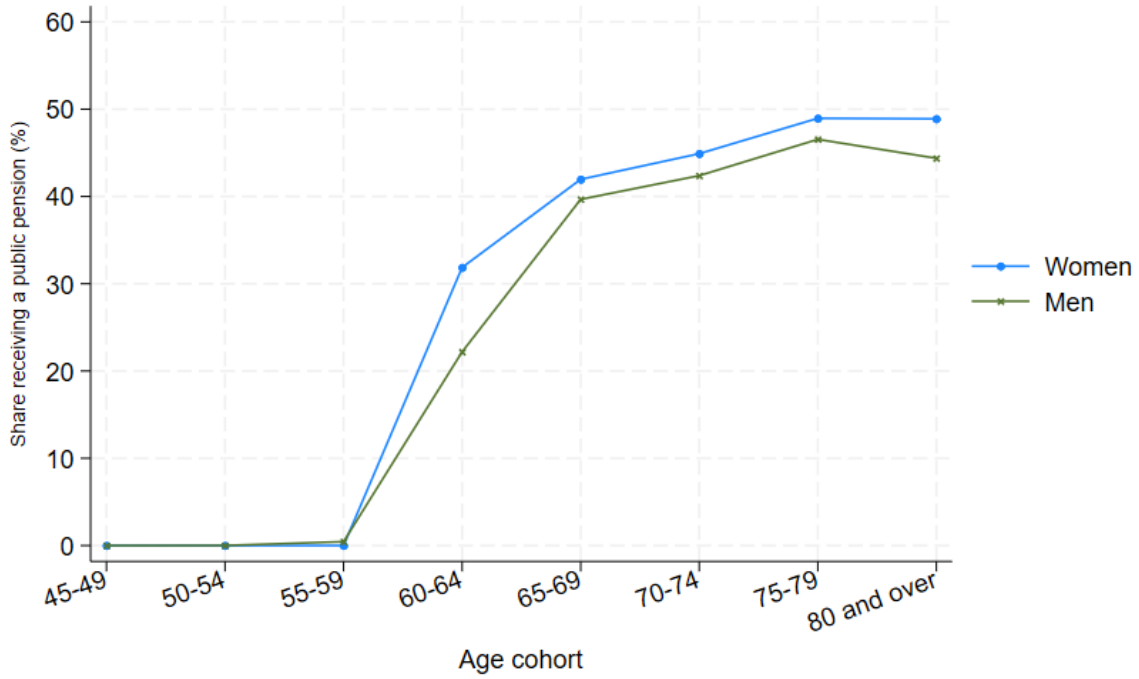
Figure 2: Share of individuals in BPL households who report feeling depressed sometimes, often or most or all of the time, by age cohorts



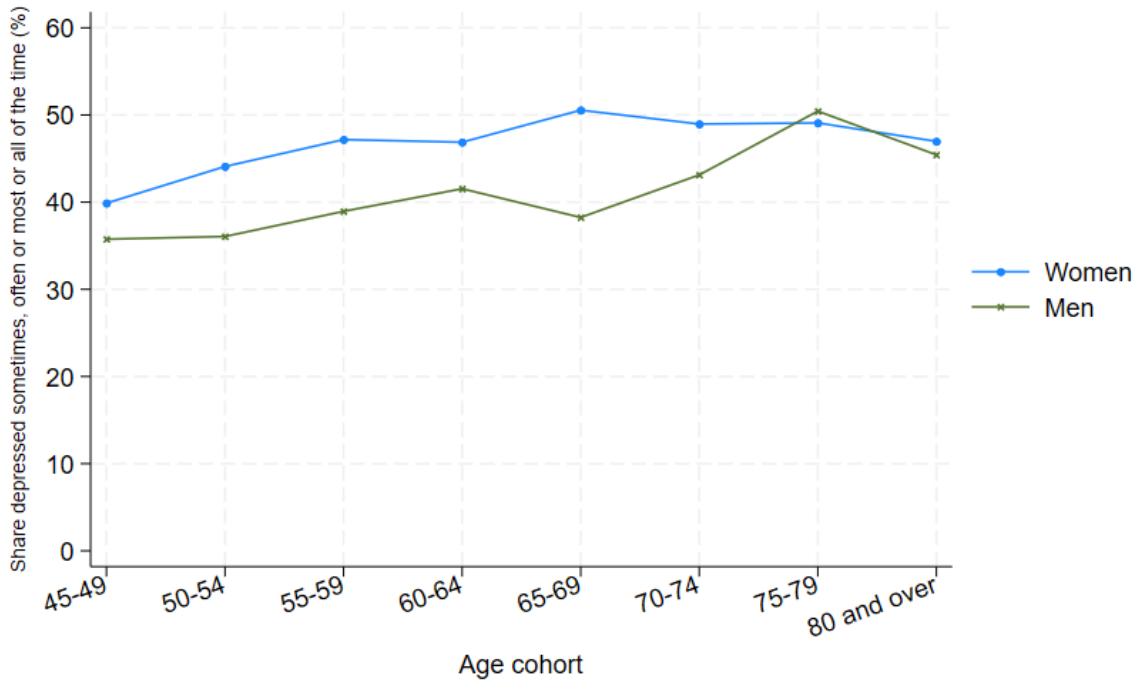
Notes: Authors' calculations using LASI data wave 1.

Figure 3: Share of individuals in BPL households receiving public pensions and share of individuals in BPL households who report feeling depressed sometimes, often or most or all of the time, by age groups and gender

Panel A – Receive public pensions

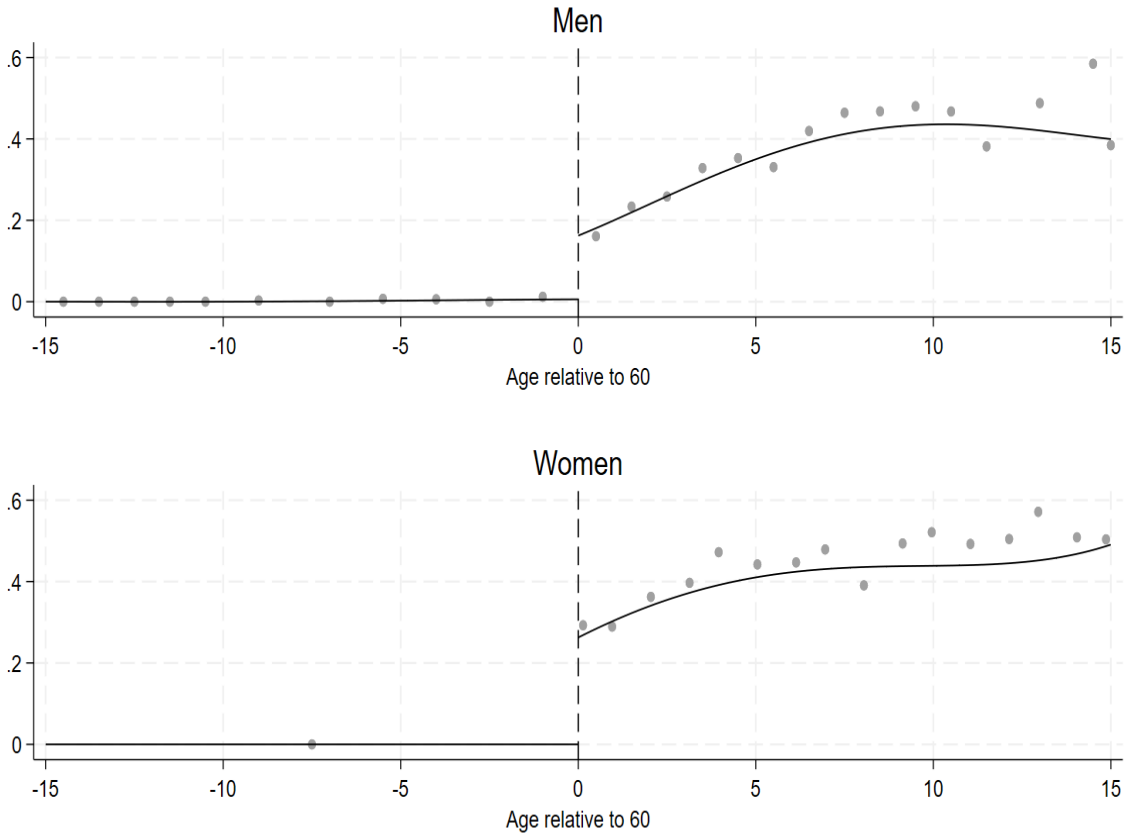


Panel B – Feel depressed sometimes, often or most or all of the time



Notes: Authors' calculations using LASI data wave 1.

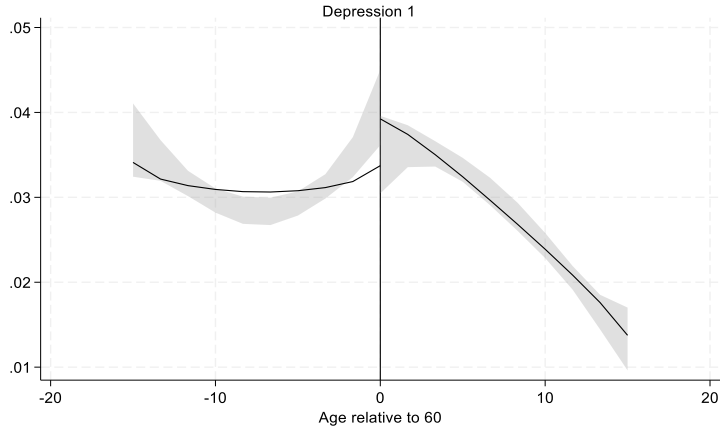
Figure 4: Eligibility and likelihood of reporting receipt of public pensions, by gender



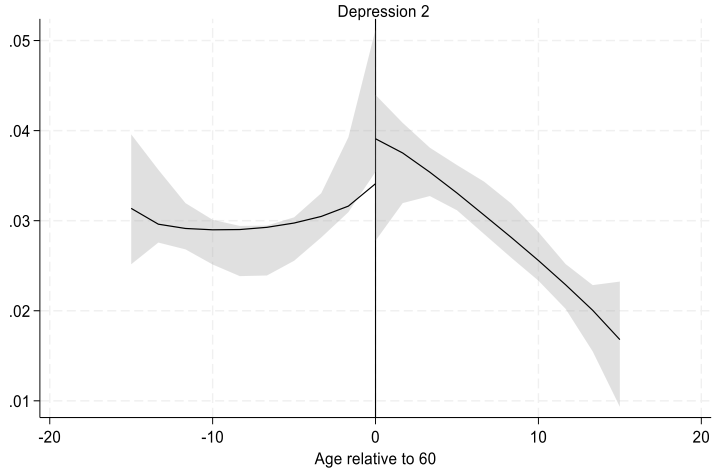
Notes: The figure shows a sharp increase in the likelihood of reporting a public pension at the age cutoff of 60 years, for men and women. The discontinuity is estimated using a default uniform kernel and a fourth order polynomial fit to approximate the population conditional mean functions for control and treated units.

Figure 5: Tests of manipulation

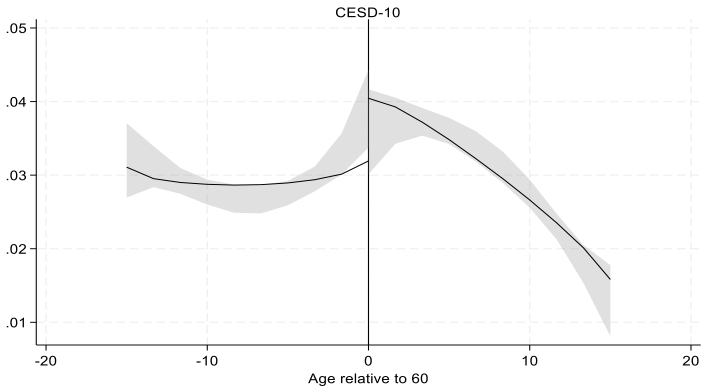
(a)



(b)



(c)



Notes: Manipulation testing plots using local polynomial density estimations from Cattaneo et al. (2020). Panels (a), (b) and (c) report results for our three outcomes - Depression1, Depression2, and CESD-10, respectively.

Table 1: Summary statistics

	Eligible individual			Ineligible individuals			Full sample		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mental health indicators									
Depression1	0.478	0.500	1686	0.394	0.489	69825	0.396	0.489	71511
Depression2	0.208	0.406	1686	0.131	0.338	69825	0.133	0.340	71511
CESD-10	0.362	0.481	1798	0.263	0.440	71608	0.265	0.441	73406
Individual level variables									
Age in years	78.200	6.010	1798	57.400	10.500	71608	58.000	10.900	73406
Male	0.472	0.499	1798	0.506	0.500	71608	0.505	0.500	73406
Never attended school	0.800	0.400	1798	0.512	0.500	71608	0.519	0.500	73406
Less than primary school	0.153	0.360	1798	0.217	0.412	71608	0.215	0.411	73406
Middle school	0.022	0.146	1798	0.077	0.266	71608	0.075	0.264	73406
Secondary school	0.024	0.153	1798	0.136	0.343	71608	0.133	0.340	73406
Other tertiary education	0.001	0.034	1798	0.059	0.235	71608	0.057	0.232	73406
Married	0.457	0.498	1798	0.784	0.412	71608	0.776	0.417	73406
Widowed	0.514	0.500	1798	0.185	0.389	71608	0.193	0.395	73406
Satisfied with life	0.763	0.426	1714	0.892	0.310	70968	0.889	0.314	72682
Lonely	0.439	0.496	1686	0.327	0.469	69825	0.330	0.470	71511
Is in good health	0.389	0.488	1710	0.613	0.487	70741	0.608	0.488	72451
Difficulty in carrying out activities of daily life	0.369	0.483	1792	0.138	0.345	71297	0.144	0.351	73089
Currently works	0.199	0.399	1798	0.558	0.497	71586	0.549	0.498	73384
Works for pay	0.145	0.352	1798	0.495	0.500	71581	0.487	0.500	73379
Hours worked weekly in main job	33.300	18.900	343	39.200	19.500	34754	39.200	19.500	35097
Total hours worked weekly (main + second job)	33.700	19.800	339	41.000	20.900	34393	41.000	20.900	34732
Works a second job	0.011	0.105	1798	0.070	0.255	71555	0.068	0.252	73353
Participates in the labor force	0.202	0.402	1786	0.565	0.496	71316	0.556	0.497	73102
Visited any healthcare provider	0.552	0.497	1785	0.572	0.495	70791	0.571	0.495	72576

Drug expense covered by insurance	0.091	0.288	1742	0.140	0.347	69756	0.139	0.346	71498
Log out of pocket expenditure: Hospitalization	0.357	1.730	1798	0.498	2.100	71519	0.495	2.090	73317
Log out of pocket expenditure: Total	4.020	3.840	1798	4.570	4.080	71519	4.560	4.080	73317
Very hopeful about the future	0.086	0.280	1686	0.103	0.304	69821	0.103	0.304	71507
Has trouble sleeping	0.268	0.443	1792	0.172	0.377	71362	0.174	0.379	73154
Has high subjective social status	0.030	0.171	1668	0.070	0.255	69594	0.069	0.253	71262
Participates in social activities in a year	0.015	0.120	1776	0.069	0.254	70561	0.068	0.252	72337
Looks after grandchildren	0.146	0.353	1778	0.138	0.345	70796	0.138	0.345	72574
Attends religious functions weekly	0.051	0.220	1777	0.089	0.285	70559	0.088	0.284	72336
Provides personal care	0.026	0.158	1773	0.036	0.187	70538	0.036	0.186	72311
Log of individual income from earnings	0.825	2.720	1798	3.480	5.010	71606	3.410	4.990	73404
Exercises regularly	0.137	0.344	1784	0.384	0.486	70966	0.378	0.485	72750
Smokes now	0.135	0.342	1787	0.149	0.356	70964	0.149	0.356	72751
Obese (respondent's BMI > 30)	0.023	0.151	1519	0.068	0.251	64579	0.067	0.249	66098
Ever had diabetes	0.078	0.268	1793	0.116	0.320	71409	0.115	0.319	73202
Had preventive mammogram in the last two years	0.000	0.008	948	0.012	0.108	41128	0.012	0.107	42076
Had preventive papsmear in the last two years	0.003	0.057	949	0.012	0.107	41132	0.012	0.106	42081
Had preventive flu shot	0.011	0.104	1774	0.016	0.127	70695	0.016	0.126	72469
Had preventive cholesterol test	0.066	0.248	1794	0.112	0.315	71387	0.111	0.314	73181
Household level variables									
Religion: Hindu	0.868	0.339	1798	0.808	0.394	71602	0.809	0.393	73400
Caste: Scheduled caste or scheduled tribe	0.370	0.483	1792	0.280	0.449	71036	0.283	0.450	72828
Other backward class (OBC)	0.471	0.499	1792	0.445	0.497	71036	0.446	0.497	72828
Rural household	0.849	0.359	1798	0.671	0.470	71608	0.676	0.468	73406
Household size	5.370	3.030	1798	5.060	2.640	71608	5.070	2.650	73406
Electricity	0.792	0.406	1758	0.923	0.266	70262	0.920	0.271	72020
Pucca house	0.303	0.459	1753	0.556	0.497	70132	0.550	0.498	71885
Log of household income from earnings	6.410	5.130	1797	7.630	5.120	71595	7.600	5.130	73392
Net value of financial transfers	531.000	5910.000	1798	2727.000	65212.000	71606	2674.000	64426.000	73404

Log of total expenditure	10.600	1.190	1798	11.600	0.745	71608	11.600	0.776	73406

Notes: Eligible individuals include persons aged 60 years and above in 2006 living in BPL households. Ineligible individuals include persons below 60 years in 2006 living in BPL households and all individuals in non-BPL households. The full sample includes everyone. "Depression1" is an indicator variable that takes a value of one if the respondent reports feeling depressed sometimes, often, most or all of the time in the last week. "Depression2" takes a value of one if the respondent reports feeling depressed often, most or all of the time in the last week. CESD-10 is assigned a value of 1 if the respondent's score ranges from 4 to 10 on the CESD-10 scale. "Satisfied with life" is an indicator for somewhat or very or completely satisfied with life, "Lonely" is an indicator for an individual feeling lonely sometimes, often or most or all of the time, and "Is in good health" is an indicator for good, very good or in excellent health. Please see text for definition of remaining variables. Authors' calculations using LASI data wave 1.

Table 2: Pensions and mental health of the elderly

	Dependent variables:			
	Public pension	Depression1	Depression2	CESD-10
	(1)	(2)	(3)	(4)
Panel A: Full sample				
RD estimate	0.237***	-0.101***	-0.067*	-0.044***
	(0.011)	(0.027)	(0.039)	(0.008)
Observations	11,660	11,664	11,664	11,664
Panel B: Elderly men				
RD estimate		-0.138***	-0.026	0.021
		(0.023)	(0.018)	(0.030)
Observations		4,906	4,906	4,906
Panel C: Elderly women				
RD estimate		-0.055**	-0.081	-0.086***
		(0.023)	(0.058)	(0.011)
Individual and HH controls		Yes	Yes	Yes
State fixed-effects		Yes	Yes	Yes
Observations		6,758	6,758	6,758

Notes: Column (1) reports the first stage results. In column (2), the dependent variable is a dummy variable that takes a value of one if the respondent reports feeling depressed sometimes, often or most of the time. In column (3), the dependent variable takes a value of one if the respondent reports feeling depressed often or most of the time. In column (4), CESD-10 is assigned a value of 1 if the respondent's score ranges from 4 to 10 (based on the sum of 10 questions). The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), variables for life satisfaction, loneliness, and being in good health, as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Pensions and mental health of the elderly - heterogeneous effects

	Dependent variables:		
	Depression1	Depression2	CESD-10
	(1)	(2)	(3)
Panel A: Widowed respondents			
RD estimate	-0.093***	-0.162***	0.031
	(0.009)	(0.034)	(0.072)
Observations	2,666	2,666	2,666
Panel B: Widowed women			
RD estimate	-0.174***	-0.210***	-0.059
	(0.031)	(0.029)	(0.056)
Observations	2,138	2,138	2,138
Panel C: Urban sample			
RD estimate	-0.267***	-0.015	0.011
	(0.042)	(0.045)	(0.016)
Observations	2,009	2,009	2,009
Panel D: Urban women sample			
RD estimate	-0.365***	-0.121**	-0.185***
	(0.076)	(0.054)	(0.027)
Observations	1,198	1,198	1,198
Panel E: Urban married women sample			
RD estimate	-0.726***	-0.239***	-0.328***
	(0.096)	(0.075)	(0.076)
Observations	730	730	730
Individual and HH controls	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes

Notes: In column (1), the dependent variable is a dummy variable that takes a value of one if the respondent reports feeling depressed sometimes, often or most of the time. In column (2), the dependent variable takes a value of one if the respondent reports feeling depressed often or most of the time. In column (3), CESD-10 is assigned a value of 1 if the respondent's score ranges from 4 to 10 (based on the sum of 10 questions). The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Pensions and labor supply of the elderly

	All	Men	Women	Widowed	All	Men	Women	Widowed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A				Dependent variables:				
		Currently works				Works for pay		
RD estimate	-0.081***	-0.090**	-0.079***	-0.183**	-0.062**	-0.012	-0.113***	-0.124
	(0.019)	(0.046)	(0.028)	(0.078)	(0.029)	(0.042)	(0.036)	(0.106)
Observations	11,664	4,906	6,758	2,666	11,662	4,905	6,757	2,666
Panel B				Dependent variables:				
		Hours worked weekly (main job)				Total hours worked weekly (main job and 2nd job)		
RD estimate	-4.945***	-5.652***	-1.799	-4.631***	-4.036***	-3.410***	-2.586	-3.233
	(1.828)	(1.256)	(2.533)	(1.729)	(1.531)	(1.131)	(3.092)	(2.019)
Observations	6,038	3,411	2,627	849	5,933	3,348	2,585	841
Panel C				Dependent variables:				
		Works a second job				Participates in the labor force		
RD estimate	-0.005***	0.014	-0.016	-0.050***	-0.079***	-0.079**	-0.076***	-0.191**
	(0.001)	(0.016)	(0.022)	(0.007)	(0.011)	(0.033)	(0.029)	(0.075)
Observations	11,658	4,902	6,756	2,666	11,605	4,865	6,740	2,657
Individual and HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the RD estimates when considering dependent variables related to labor supply for different sub-samples. In Panel A, columns (1)-(4) present the results for the different sub-samples using the first labor supply metric "currently works" which is assigned a value of one if the individual is presently employed. In columns (5)-(8), the dependent variable is coded as one if the respondent reports that they are currently in paid work. In Panel B, we consider the average weekly working hours in two dimensions: firstly, the average hours dedicated to the primary job, and secondly, the total average weekly hours, including both the primary job and any additional employment. In Panel C, "works a second job" is a binary variable denoting if an individual holds more than one job, and "participates in labor force" is also binary, indicating labor force participation (this includes both employed individuals and those unemployed but actively job-seeking). The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), variables for life satisfaction, loneliness, and being in good health, as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Pensions and healthcare utilization

	All	Men	Women	Widowed	All	Men	Women	Widowed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A	Dependent variables:							
	Visited any healthcare provider				Drug expenses covered by insurance			
RD estimate	-0.004	0.025*	-0.012	-0.083	0.045***	0.048***	0.038***	0.073**
	(0.029)	(0.014)	(0.048)	(0.063)	(0.011)	(0.013)	(0.012)	(0.035)
Observations	11,649	4,900	6,749	2,663	11,409	4,819	6,590	2,598
Panel B	Dependent variables:							
	Out-of-pocket expenditure (in log)							
	Hospitalization				Total			
RD estimate	-0.359***	-0.212	-0.535***	-1.611***	-0.387*	-0.536***	-0.136	-0.974**
	(0.125)	(0.142)	(0.122)	(0.402)	(0.227)	(0.164)	(0.286)	(0.443)
Observations	11,662	4,905	6,757	2,666	11,662	4,905	6,757	2,666
Individual and HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the RD estimates for different sub-samples. In Panel A, columns (1)-(4) show results when we consider a binary dependent variable that takes a value of one if the respondent utilized healthcare services, including consultations or home visits by a healthcare provider, in the previous year. We also consider a dummy variable that equals one if the respondent has drug coverage through their health insurance in columns (5)-(8). In Panel B, we focus on continuous variables for reported out-of-pocket expenditures for hospital stays over the last year in columns (1)-(4), and for hospitalization, outpatient services, and medication or health supplements within the same time frame. The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), variables for life satisfaction, loneliness, and being in good health, as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Pensions and other measures of welfare

	All	Men	Women	Widowed	All	Men	Women	Widowed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A				Dependent variables:				
		Satisfied with one's life				Very hopeful about the future		
RD estimate	0.069***	0.157***	-0.002	0.067***	0.038***	0.040	0.033*	0.055***
	(0.011)	(0.021)	(0.021)	(0.016)	(0.006)	(0.031)	(0.019)	(0.010)
Observations	11,664	4,906	6,758	2,666	11,662	4,906	6,756	2,666
Panel B				Dependent variables:				
		Has trouble sleeping				High subjective social status		
RD estimate	-0.078**	-0.065*	-0.092***	-0.125**	-0.026**	-0.051	-0.007	0.083***
	(0.031)	(0.039)	(0.033)	(0.056)	(0.010)	(0.040)	(0.020)	(0.025)
Observations	11,663	4,906	6,757	2,665	11,593	4,882	6,711	2,641
Individual and HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the RD estimates for different sub-samples. In Panel A, we focus on life satisfaction, using a variable assigned a value of one for respondents who report being somewhat, very, or completely satisfied with their life. Next, we consider optimism about the future, defining a variable to identify individuals who feel very hopeful about the future most or all of the time. In Panel B, we examine sleep quality with a binary variable coded as one if the respondent reports having trouble falling asleep frequently (5 or more nights per week) or occasionally (3-4 nights per week). We then use the Cantril Ladder to gauge subjective social status, assigning a value of one to responses within the 8-10 range on the ladder, indicating higher perceived social status (please see the text for further details). The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), variables for life satisfaction, loneliness, and being in good health, as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Evaluation of the potential transmission channels

	Dependent variable: Depression1									
	Sample: All respondents					**Sample: Men**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RD estimate	-0.101***	-0.097***	-0.087***	-0.084**	-0.068**	-0.138***	-0.127***	-0.133***	-0.123***	-0.104***
	(0.027)	(0.025)	(0.026)	(0.034)	(0.030)	(0.023)	(0.016)	(0.021)	(0.027)	(0.018)
Labor supply and leisure		x			x		x			x
Healthcare utilization			x		x			x		x
Life satisfaction, optimism, welfare				x	x				X	x
Observations	11,664	11,624	11,392	11,591	11,304	4,906	4,886	4,812	4,882	4,779
	Sample: Women					**Sample: Widowed**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RD estimate	-0.055**	-0.052**	-0.029	-0.035	-0.008	-0.093***	-0.067***	-0.065***	-0.066***	-0.015
	(0.023)	(0.022)	(0.021)	(0.028)	(0.027)	(0.009)	(0.023)	(0.008)	(0.013)	(0.026)
Labor supply and leisure		x			x		x			x
Healthcare utilization			x		x			x		x
Life satisfaction, optimism, welfare				x	x				x	x
Observations	6,758	6,738	6,580	6,709	6,525	2,666	2,660	2,595	2,641	2,571
Individual and HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the RD estimates when the regressions are gradually augmented with potential mediators. The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), variables for life satisfaction, loneliness, and being in good health, as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A1: Pensions, depression, childhood conditions

	Dependent variable: Depression1					
	Sample: All respondents					
	(1)	(2)	(3)	(4)	(5)	(6)
RD estimate	-0.101***	-0.105***	-0.097***	-0.101***	-0.100***	-0.108***
	(0.027)	(0.024)	(0.028)	(0.028)	(0.029)	(0.028)
Mother's education		x				x
Father's education			x			x
Childhood poverty				x		x
Childhood health status					x	x
Observations	11,664	11,259	11,333	11,595	11,659	11,085
Individual and HH controls	Yes	Yes	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the RD estimates when the regressions are gradually augmented with the respondent's early-life controls for parent's education, childhood poverty, and their health status as a child. The individual controls include gender, four dummy variables for the level of education (with the omitted category being “never attended school”), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), variables for life satisfaction, loneliness, and being in good health, as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Covariates around the age cutoff

	Sample: All respondents					
	Dependent variables:					
Panel A						
	Parents' education		**Childhood conditions**		**Respondent's education**	
	Mother	Father	Poverty	Health		
	(No school or less than primary)				(No. years)	(< primary)
RD estimate	-0.004	-0.003	-0.014	-0.004	-0.009	0.022
	(0.006)	(0.023)	(0.012)	(0.027)	(0.020)	(0.029)
Observations	11,719	11,799	12,149	12,216	12,260	12,260
Panel B	**Respondent education**	**Widowed**	**Religion**	**Caste**		**Rural**
	(< middle)		hindu	scst	obc	
RD estimate	-0.018	0.044	0.020*	0.049**	-0.059	0.001
	(0.015)	(0.030)	(0.011)	(0.021)	(0.057)	(0.034)
Observations	12,260	12,260	12,258	12,200	12,200	12,260

Notes: This table shows the RD estimates for different covariates, providing changes around the age cutoff. We run separate regressions. Standard errors reported within parentheses are clustered at the age level.

Table A3: Pensions and mental health of the elderly - alternative bandwidths

	Dependent variables:								
	Depression1			Depression2			CESD-10		
	All	Men	Women	All	Men	Women	All	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Using the MSE optimal bandwidth									
RD estimate	-0.069**	-0.139***	-0.036	-0.056	-0.030**	-0.041	-0.044***	0.014	-0.081***
	(0.032)	(0.020)	(0.025)	(0.038)	(0.014)	(0.050)	(0.008)	(0.030)	(0.014)
Observations	11,664	4,906	6,758	11,664	4,906	6,758	11,664	4,906	6,758
Panel B: Using two MSE optimal bandwidth (below and above cutoff)									
RD estimate	-0.058*	-0.122***	-0.032	-0.051	-0.032**	-0.038	-0.035***	0.019	-0.074***
	(0.035)	(0.028)	(0.026)	(0.038)	(0.016)	(0.050)	(0.012)	(0.029)	(0.015)
Observations	11,664	4,906	6,758	11,664	4,906	6,758	11,664	4,906	6,758
Panel C: Polynomial function of order 2									
RD estimate	-0.165***	-0.158***	-0.117***	-0.180***	-0.090***	-0.235***	-0.025**	0.072	-0.098***
	(0.042)	(0.053)	(0.019)	(0.037)	(0.004)	(0.062)	(0.011)	(0.063)	(0.015)
Individual and HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,664	4,906	6,758	11,664	4,906	6,758	11,664	4,906	6,758

Notes: This table shows the RD estimates using alternative bandwidths. In column (1), the dependent variable is a dummy variable that takes a value of one if the respondent reports feeling depressed sometimes, often or most of the time. In column (2), the dependent variable takes a value of one if the respondent reports feeling depressed often or most of the time. In column (3), CESD-10 is assigned a value of 1 if the respondent's score ranges from 4 to 10 (based on the sum of 10 questions). The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Pensions and mental health of the elderly - fuzzy RD design

	Dependent variables:			
	Public pension	Depression1	Depression2	CESD-10
	(1)	(2)	(3)	(4)
RD estimate	0.217***	-0.463**	-0.308	-0.205***
	(0.010)	(0.142)	(0.192)	(0.032)
Individual and household controls	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes
Observations	11660	11,660	11,660	11,660

Notes: The first-stage results are shown in column (1). We present the second-stage results in columns (2)-(4). In column (2), the dependent variable is a dummy variable that takes a value of one if the respondent reports feeling depressed sometimes, often or most of the time. In column (3), the dependent variable takes a value of one if the respondent reports feeling depressed often or most of the time. In column (4), CESD-10 is assigned a value of 1 if the respondent's score ranges from 4 to 10 (based on the sum of 10 questions). The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Pensions and leisure/welfare of the elderly

	All	Men	Women	Widowed	All	Men	Women	Widowed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A	Dependent variables:							
	Participates in social activities				Attends religious functions weekly			
RD estimate	0.016*	0.007	0.018***	0.033	-0.027*	-0.041	-0.008	0.075
	(0.008)	(0.014)	(0.003)	(0.027)	(0.015)	(0.032)	(0.006)	(0.051)
Observations	11,650	4,898	6,752	2,664	11,653	4,900	6,753	2,665
Panel B	Dependent variables:							
	Looks after grandchildren				Provides personal care			
RD estimate	-0.014**	-0.043***	0.014	0.104**	0.003	-0.026	0.024***	-0.027
	(0.007)	(0.010)	(0.017)	(0.048)	(0.010)	(0.020)	(0.008)	(0.022)
Observations	11,655	4,903	6,752	2,663	11,640	4,896	6,744	2,662
Individual and HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the RD estimates for different sub-samples. In Panel A, columns (1)-(4) show the results when we consider a binary dependent variable that takes a value of one based on the frequency of the respondent's interactions with their social groups - ranging from daily or almost daily, to once or twice a week, monthly, every other month, or annually. A value of 0 is assigned if the respondent is not affiliated with any social groups or is inactive in their participation. In columns (5)-(8), we consider another dependent variable related to whether respondents attend religious functions or events on a weekly basis. In Panel B, "looks after grandchildren" is assigned a value of one if the respondent is involved in caring for any grandchildren. The variable "provides personal care" is also coded as one if the respondent offers personal care to either family or non-family members. The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), variables for life satisfaction, loneliness, and being in good health, as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Pensions, income, transfers and expenditure

	Dependent variables:			
	Individual income from earnings (log)	Household income from earnings (log)	Net value of financial transfers	Total expenditure (log)
	(1)	(2)	(3)	(4)
RD estimate	-1.261***	-0.450**	1,651.862***	-0.125***
	(0.386)	(0.208)	(415.757)	(0.014)
Observations	11,664	11,659	11,664	11,664
Individual and HH controls	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes

Notes: This table shows the RD estimates for different sub-samples. In column (1), the dependent variable is the respondent's income from earnings (in log). Column (2) considers the effects on household income from earnings (in log), while column (3) focuses on the household's net value of financial transfers. Lastly, in column (4), the continuous dependent variable relates to the household's yearly total expenditure (in log). The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), variables for life satisfaction, loneliness, and being in good health, as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Pensions, healthcare behaviors, objective health measures

	All	Men	Women	Widowed	All	Men	Women	Widowed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A				Dependent variables:				
			Exercises regularly				Smokes now	
RD estimate	0.006	0.064	-0.043	0.013	-0.002	-0.001	-0.008	-0.082
	(0.013)	(0.081)	(0.059)	(0.039)	(0.023)	(0.030)	(0.028)	(0.094)
Observations	11,658	4,903	6,755	2,663	11,661	4,904	6,757	2,665
			Obese				Ever had diabetes	
RD estimate	-0.012***	0.011*	-0.036***	-0.115***	-0.060***	-0.078***	-0.036***	-0.005
	(0.002)	(0.007)	(0.004)	(0.023)	(0.012)	(0.022)	(0.009)	(0.035)
Observations	10,788	4,548	6,240	2,445	11,660	4,903	6,757	2,665
Panel B				Preventive measures				
			Mammogram				PAP smear	
RD estimate			0.003***				-0.001	
			(0.001)				(0.008)	
Observations			6,748				6,750	
			Flu shot				Cholesterol test	
RD estimate	0.001	0.006	-0.006	0.013***	0.002	0.034	-0.013*	0.026
	(0.003)	(0.006)	(0.004)	(0.002)	(0.014)	(0.027)	(0.008)	(0.037)
Observations	11,592	4,876	6,716	2,648	11,662	4,905	6,757	2,664
Individual and HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In Panel A, we use a first variable that measures the intensity of physical activity, and code an indicator to denote whether an individual engages in vigorous exercise at least weekly (this includes daily, more than once a week, or exactly once a week). "smoking" denotes a binary variable for whether the respondent currently smokes tobacco. The presence of obesity and diabetes are also represented by binary variables, with obesity defined by a BMI of 30 or higher and diabetes identified through self-reporting. In Panel B, "mammogram" and "PAP smear" are coded as indicator variables, with a value of one indicating if the women respondent has undergone mammograms and PAP smear tests, respectively, within the past two years. We evaluate the adoption of preventive measures through two additional indicators: one for receiving an influenza vaccination "flu shot" within the past two years, and another for undergoing a cholesterol blood test within the same time frame. The individual controls include gender, four dummy variables for the level of education (with the omitted category being "never attended school"), marital status, widowhood status, religion, two binary indicators for caste (SC/ST and OBC), variables for life satisfaction, loneliness, and being in good health, as well as whether the respondent encounters any difficulty in daily activities. The household controls include a rural/urban dummy, household size (number of people living in the household), binary indicators for whether the household has concrete dwellings and access to electricity. Standard errors are clustered at the age level. All regressions are weighted. *** p<0.01, ** p<0.05, * p<0.1.