Noncontributory Pensions and Mental Health: Evidence from Rural China

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Abstract

The extent to which wealth and public policy can shape mental health outcomes has been studied previously, but how noncontributory pensions can, either temporarily or permanently, alleviate mental illness remains unclear. This paper exploits the staggered introduction of the New Rural Pension Scheme between 2009 and 2012 in a difference-in-differences framework. Using CHARLS data from 2011-2018, we reveal an effect of approximately 60% on pension take-up, a 900 yuan increase in yearly pension income and crowding out of transfers from children and grandchildren. We find positive effects on in mental health and a reduction in depressive symptoms, while private intrafamily transfers are crowded out.

Keywords: mental health, China, pensions, income shock

JEL classification: I12, I18, J14, J22, J26

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1 Introduction

Mental health adversities constitute a major global disease burden. They account for welfare losses of up to 4 percent of GDP (OECD, 2020). Within countries, elderly and groups of low socioeconomic status disproportionately suffer from mental health issues (Lund et al., 2010; Ridley et al., 2020). Among the poor in particular, a low income can be both the cause and the result of bad mental health because of the endogenous dependence on adverse characteristics. While there has been an increasing interest in income transfers and their effects on physical and mental health, results on this topic are mostly limited to small-scale experiments, with relatively few results from nationally representative settings (Baird et al., 2013, 2011; Balboni et al., 2022; Egger et al., 2022; Haushofer and Shapiro, 2016).

In this paper, we obtain first nationally representative estimates on the mental health effects of the Chinese New Rural Pension Scheme (NRPS) from a stacked Difference-in-Differences setting with multiple time periods. The NRPS is a rural pension expansion with a noncontributory component which for the first time gave all Chinese elderly aged 60 and above who choose to participate access to a windfall cash receipt. The cash receipt was initially set at 55 yuan (approximately 8 USD without adjusting for purchasing power) and does not impose any work limits. The rollout of the NRPS was staggered in four yearly rounds between 2009 and 2012, on a county-by-county basis. Participation in the pension is voluntary and after contributing for up to 15 years to an *individual* account, pension receipt from a *basic* account is available from the age of 60 onwards. People who at rollout were already older than 60 could claim pension benefits without ever contributing. We exploit this feature in our identification.

Noncontributory pensions have been implemented in several other low- and middle-income countries. Prominent examples that have been evaluated include the National Old Age Pension in India (Kaushal, 2014), the Old Age Pension Program in South Africa (Duflo, 2003; Jensen, 2004). Several Latin American countries have also implemented similar programs, such as the Adultos Mayores Program in Mexico (Galiani et al., 2016), the 'Pension 65' pension in Peru (Bando et al., 2020), and the Pensiones Alimentarias Program in Paraguay (Bando et al., 2022). In Sub-Saharan Africa, the Ekiti State Pension in Nigeria (Alzua et al., 2023) is comparable. Although intuitively similar to these in its basic design, the NRPS is much larger than these as it constitutes one of the largest pension expansions in the world with more than 480 million participants and a cumulative fund balance of more than 250 billion yuan. Moreover, the NRPS does not condition on any characteristics other than age and local household registration, whereas in other countries the transfers are in most cases conditional on household-specific factors, such as having children to take care of. In this sense, the NRPS is particular in its kind deserving its own attention, as it is in its institutional design more closely comparable to unconditional basic incomes in developing countries (Banerjee et al., 2020, 2019; Hanna and Olken, 2018).

Our identification strategy relies on a difference-in-difference design which exploits the staggered introduction of the NRPS across Chinese counties, between 2009 and 2012. We combine the temporal variation in NRPS availability within counties with the temporal variation in NRPS age-eligibility within individuals (i.e becoming age-eligible by reaching the age of 60 years) to obtain an estimate for our treatment effect. For one, the temporal variation in NRPS availability within counties allows for the comparison of individuals before and after their county became eligible with a counterfactual group that is already treated at baseline (because the first NRPS rollout precedes the first year of data collection). For another, the temporal variation in age-eligibility within individuals allows us to compare individuals before and after they become age-eligible with younger comparison cohorts.

The validity of using younger cohorts (who did not yet reach the age-threshold) as untreated comparison units should not be taken for granted, given that these individuals may anticipate that the cash transfer can affect them in the future and they may change their lifestyle behaviors in ways that could affect their mental health. Similar to Galiani et al. (2016), we conjecture such an anticipatory effect on mental health to be unlikely, given that in the presence of liquidity constraints any adaptations to lifestyle are difficult prior to an actual transfer. We provide evidence that supports our use of individuals below the cutoff as untreated counterfactuals by showing that, with respect to our outcome, individuals who never reach the age-cutoff are unaffected by their county becoming eligible for the NRPS. We implement a Two-Way Fixed Effect (TWFE) specification and compare the results with other estimators that are robust to treatment effects that are heterogeneous in time and across treatment units.

Our data come from the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative longitudinal retirement survey fielded in 2011, 2013, 2015, 2018 and 2020-2023. CHARLS collects data on demographics, employment, retirement, pensions, financial transfers, physical and mental health as well as biomarker information of the Chinese elderly population. At every survey wave, refresher samples were added to replace lost individuals. This data contains detailed information on pension receipt and mental health, and a community questionnaire contains NRPS implementation across resident communities, the lowest level of administrative divisions in China. We merge this data to the administrative rollout of the NRPS provided by the China's State Council Leading Group Office of Poverty Alleviation and Development, which contains rollout year and eligibility status for all counties in both rural and urban government subdivisions. At the baseline of the CHARLS study in 2011 (which was conducted before the later NRPS rollout in the fall of 2011), 27 percent of the included counties were already covered by the NRPS. In the fall of 2011 and though the end of 2012, the remaining 73 percent of the included counties obtained access to the NRPS, as the program was expanded nationwide by this date. The staggered rollout showing eligibility at the individual level is illustrated in Figure 1.

We find robust evidence that the NRPS increases pension receipt and income. On average, NRPS eligibility increases pension takeup by 60 percentage points, pension income increases by about 900 Yuan per year. We also find (negative) effects on the CESD scale and cognition, suggesting a reduction in experiencing depressive symptoms and worsening of cognition. On average, eligibility is associated with a reduction on the CESD score by about 0.053 of a standard deviation, or about 0.084 SD (=0.053/0.63) among the compliers. This translates into a 3 percentage point reduction in the share of depressed people. For cognition, we estimate an effect of 0.04 SD, or about 0.06 (=0.04/0.63) among the compliers. This translates into a 2 percentage points *increase* in the share of people with severe cognitive impairment.

Most previous studies on the NRPS and other noncontributory pensions in the developing world rely on short-term results using either (repeated) cross-section data or a short panel. In this paper, we use four waves of CHARLS allowing to study longer-term effects of a non-contributory pension, which is important to assess when mental health improvements only improve gradually after experiencing a permanent income shock. Additionally, our paper adds causal interpretation to previously found (often negative) associations linking poverty and mental health (Das et al., 2007; Hanandita and Tampubolon, 2014; Tampubolon and Hanandita, 2014).

The remainder of this paper will proceed as follows. Section 2 discusses the institutional background of NRPS and reviews the literature on the policy reform. Section 3 describes the data and the main variables used, and Section 4 presents the methodology. Sections 5 and 6 present results and extensions, and Section 7 concludes.

2 The New Rural Pension Scheme (NRPS)

2.1 Institutional Framework

The New Rural Pension Scheme (NRPS), also referred to as the New Rural Social Endowment Insurance or New Agricultural Insurance, was rolled out between 2009 and 2012 on a county-by-county basis. The pension was introduced with the objective of providing all rural elderly with social security. Before its introduction in 2009, less than 5% of rural elderly above the age of 60 had access to any formal pension (Cheng et al., 2018a).

According to official policy documents, on September 1, 2009, the Chinese State Council issued the "Guiding Options on Launching the Pilot of New Rural Social Endowment Insurance", which included 10% of counties across mainland China. By December 2009, 320 counties (about 10%) launched the pilot. In July 2010, this program was expanded to 518 additional counties (reaching about 23%) which included all of Tibet and several counties in Yunnan, Sichuan, Qinghai and Gansu provinces. Border counties in Xinjiang province close to the national border expanded the program on a priority basis. In July 2011, the focus was on ethnic minority areas, poor provinces and other border regions, increasing coverage to 1076 additional counties (reaching about 60%). By September 2012, full coverage in all county-level administrations was achieved and by the end of March 2013, 486 million residents were already insured (out of which 133 were elderly receiving the pension).[1]

The NRPS was not the first attempt of the government to expand pension coverage to rural areas of the country. Before economic reforms in the 1970s, old-age security of rural elderly was ensured by local communes (Wang, 2006). Under the Five Guarantees (*Wubao*) scheme, Chinese elderly were guaranteed basic necessities such as food and clothing, but were left to manage themselves after the reforms had abolished the communes.[2] As a consequence, the 'old' rural pension scheme was initiated in 1992 to expand pension coverage to the rural population. However, issues associated with embezzlement of funds and the Asian financial crisis hindered its expansion, as a result of which the scheme only reached 80 million participants at its peak in 1997 (Shi, 2006). In 2018, less than 4% of rural elderly reported to be enrolled in this pension according to the data used in this

[1] More details on the rollout can be found at http://www.gov.cn/zhengce/xxgk/index.htm, http://www.gov.cn/zhengce/content/2009-09/04/content_7280.htm, http://www.gov.cn/zhengce/content/2011-06/13/content_7241.htm, and http://www.gov.cn/zhengce/content/2014-02/26/content_8656.htm

[2] In the subsequent years, rural policy attempts were initiated by the Ministry of Civil Affairs. However, these were often shaped to the political context, and disagreements about the need for rural old-age security among officials led to a failure of developing a functioning rural coverage system (Shi, 2006; Wang, 2006).

paper.[3]

The NRPS is structured into a *basic* account and an *individual* account. The basic account is a non-contributory, defined-benefit plan without work limits and provides enrollees with a fixed pension benefit independent of prior earnings. It is entirely subsidized by the central government for central and western provinces, but in the more affluent eastern provinces local and central governments each share 50% of the expenses. The individual account is a defined-contribution plan which provides additional benefits on top of the basic account, based on an annual contribution amount chosen among a discrete choice set (initially either 100, 200, 300, 400 and 500 yuan, where a minimum of 30 yuan on every 100 yuan was subsidized by the local governments). Most participants choose the minimum permissible amount (Huang and Zhang, 2021).[4] Local governments could, at their own expense, increase the contribution subsidy standards (initially 30 yuan per year) (whereby these standards would be determined democratically by the villagers' committee), as well as the amount of the basic pension (initially 55 yuan per month), but in our data there is little actual heterogeneity in the reported amount of pension receipt (Appendix Figure A.2b). The individual account can be inherited by other insured household members after death, but the basic account cannot.[5]

Participation in NRPS occurs on a voluntary basis. Residents with rural household registration ('hukou') who are older than 16 and are not in school are eligible to participate. In order to receive benefits, one must contribute for the equivalent of 15 years to the individual account and must not be receiving any other pension. After reaching the age of 60, recipients are each month compensated with 1/139 of the total accumulated funds, in addition to the fixed monthly basic pension benefit. Importantly, individuals who were already of retirement age at the relevant roll-out could immediately start receiving the basic pension, without ever contributing.[6] Despite this institutional design, there is no discontinuity in the probability to retire at age 60 among rural

[3]There is no such question in the 2011 wave. In the community questionnaire of 2011, 17% of the 300 village community heads (the 150 urban communities were not asked this question) responded to 'have' the old rural pension scheme, but availability also does not imply takeup. According to their responses, as a share of the population in these village communities only 7% received the old pension. The policy documents that we discussed earlier also state that the old pension scheme in areas where it had been available shall be incorporated into the new pension scheme.

[4]See Appendix Figure A.2a for the self-reported contribution amount among participants in 2011.

[5]For a seperate review on the structure of the New Rural Pension Scheme (NRPS), refer to Chen et al. (2021b), Cheng et al. (2018a), and Huang and Zhang (2021).

[6]Although initial regulation of NRPS required that the children of individuals who were already 60 or older at each roll-out would contribute on their behalf, this requirement was dropped already in the early years of implementation (Huang and Zhang, 2021). Upon communication with the authors, this insititutional detail had already changed in anticipation of the 18th party congress (which took place in 2012), by which the Jintao administration wanted to achieve universal coverage before handing over the power to the successor.

residents, as Appendix Figure A.3 illustrates.

The amount of the monthly basic pension for rural residents was initially set at 55 yuan (approximately 8 USD) at the first rollout, but this was later increased to 78 yuan by 2013 and to 90 yuan by 2018 (Cheng et al., 2018a; Giles et al., 2021). While the initial amount appears very low, we note that it is close to the Chinese poverty threshold at the time (Cheng et al., 2018a). In many parts of rural China, wages and household expenditures are low, and the basic benefit can make a significant difference to the quality of life among residents. According to the data used in this paper, among the rural population aged 60 and above the pension amount in 2011 coincided with about 20% of total household income excluding intrahousehold transfers (a similar figure is presented in Fang and Feng (2020)). About 80% of the same subpopulation reported to primarily rely on transfers from children for old-age support, and the basic monthly pension of 55 yuan is equivalent to about 30% of all transfers received in one month. Therefore, although relatively small compared to noncontributory pensions in other developing countries, the NRPS amount can still be impactful, especially for those living at the lower end of the income distribution.

A final point is worth mentioning. The NRPS would later in 2014 be merged with the Urban Resident Pension (URP) into the unified Urban and Rural Resident Pension (URRP). The URP was a pension with contribution and payout sums equivalent to the NRPS for residents with urban (as opposed to rural) household registration. It also expanded nationwide by 2012, but it was only initiated after June 2011. From the merging of the two systems onwards, the subsidy standard increased (from 30) to 60 yuan per person per year, and contribution choices changed to a set of 12 grades between 100 and 2000 yuan annually. We only use the NRPS rollout because we do not have access to the URP rollout.

2.2 Overview on NRPS effects

Previous research has investigated the effects of the NRPS on various outcomes. Among these, Chen and Park (2023) use the first two waves of CHARLS in a regression discontinuity design to find that the NRPS increased outpatient care and outpatient expenditures. If behavioral adaptations to noncontributory pension receipt are immediate after pension takeup, a regression discontinuity design is a suitable approach. Shan and Park (2023) on the other hand use a difference-in-difference design comparing late- to always treated-by-county (area-eligible) individuals to find that the rollout reduced transfers from adult sons while transfers from adult daughters were unaffected.

Among research on health, most studies focus on physical health and only few investigate mental health outcomes. These include Cheng et al. (2018a) and Cheng et al. (2018b), who use CHARLS data and implement fixed effect models with instrumental variable correction. They find that the NRPS had positive impacts on health and cognitive function. Nikolov and Adelman (2018) and Nikolov and Hossain (2023) use the 2011 and 2013 waves of CHARLS to study short-term effects of the NRPS on physical health and cognition in a Difference-in-Differences design using observations below the age-eligibility threshold as controls for those above the threshold. In both studies, they use standardized indices that are constructed from several health indicators available in CHARLS, and they find improvements in physical health and worsened cognition. Chen et al. (2019) use the 2012 China Family Panel Studies (CFPS) and exploit the duration of NRPS rollout in a county as an instrument for own enrollment in the program. The exclusion restriction requires that rollout duration can only be correlated with mental health through its impact on pension enrollment. They find that enrollment reduces the total CESD score by 6 points and the rates of depressive symptoms by 18 percentage points.

Our paper complements Huang and Zhang (2021), who use county-level administrative records of implementation dates of the NRPS to study its effects on labor supply, intrahousehold transfers and mortality. To our knowledge, this is the only paper that has used administrative records of NRPS rollout. Using official government rollout data, they are able to map actual NRPS rollout timing to the counties in their data, using a pooled sample from two sources with two time-period each, the 2011 and 2013 waves of CHARLS and the 2010 and 2012 waves of CFPS. They find overall positive effects of NRPS on health, but do not elaborate on mental health outcomes. Using both of these datasets to study mental health is difficult, since CHARLS and CFPS use two different scales for depression (CFPS uses an 8-item scale while CHARLS uses a 10-item scale). We examine the effects of noncontributory pensions on mental health through its impact on the CESD-10 scale, which is a shortened alternative of the CESD-20 scale (nevertheless, the CESD-10 scale has been shown to be a high quality alternative with a strong predictive accuracy (Andresen et al., 1994)). In addition, most previous studies on the NRPS use either cross-sectional data or rely on short-term evaluations based on one or two survey waves. Because we use four waves of CHARLS collected in an interval of up to 7 years, we are able to study longer-term effects of the NRPS program.

2.3 Contemporaneous rollout of the New Cooperative Medical Scheme

In the years prior to the NRPS rollout, the New Cooperative Medical Scheme covering rural residents was also rolled out (Gruber et al., 2023). This scheme, which was initiated in 2003 and gradually rolled out to a national coverage by 2008, was endogenous to county characteristics (average GDP among early-adopting counties was *higher* than late-adopting counties). The program focuses on inpatient care, generosity varies by region, and initially 200-500 Yuan of hospital expenses could be reimbursed. While we acknowledge that the contemporaneous rollout of the NCMS could affect the results from the NRPS that we estimate, we note that at baseline of our data in 2011 more than 95% of respondents already report to be covered by some type of health insurance.

3 Data

3.1 The China Health and Retirement Longitudinal Study (CHARLS)

Our data come from the China Health and Retirement Longitudinal Study (CHARLS). CHARLS is the first Chinese nationally representative survey of the elderly population aged 45 and above, and collects information on demographics, employment, retirement, pensions, family transfers, physical and mental health, as well as biomarker information for approximately 20,000 individuals in 10,000 households. CHARLS is designed along the same lines of the Health and Retirement Study in the United States (HRS), and follows individuals in mostly biennial intervals.[7] Currently, the waves from 2011, 2013, 2015, 2018, and 2020-23 are publicly available.

CHARLS stratifies by region, urban/rural districts and GDP per capita. In total, 150 counties from all Chinese provinces except Tibet were randomly selected using probability-proportional-to-size (PPS) sampling (Chen et al., 2021a; Zhao et al., 2014, 2020, 2013). From each county, three primary sampling units (PSUs), or 'communities', consisting of urban neighborhoods (shequ) or villages (cun) were chosen using probabilities proportional to their population. Within each community, households from randomly selected housing units were interviewed if they had at least one member aged 45 or older. Within each household, CHARLS interviewed a main respondent and their spouse, if available. At baseline, this resulted in a sample of 17,708 individuals, living in

[7] Other equivalent sister surveys are the Aging and Retirement in Europe (SHARE), the English Longitudinal Survey of Aging (ELSA), the Japanese Study of Aging and Retirement (JSTAR), and the Longitudinal Aging Survey of India (LASI). To obtain the CHARLS data, researchers need to request access from https://charls.charlsdata.com.

10,257 households, located in 450 resident communities (villages and urban neighborhoods) from 150 counties or urban districts. Respondents who were not present at the first wave were still contacted in the follow-up waves. The dropout rate is approximately 15%, which is comparable to that of retirement surveys in other countries.[8]

3.2 NRPS rollout

The NRPS was introduced at the county-level between 2009 and 2012, but our main dataset (CHARLS) does not contain official government data on the implementation dates of the NRPS at the county level. The only available information on the NRPS rollout in the data is at the community-level, which is reported by the village head and may be subject to misreporting (community heads might report that they are providing the NRPS when in fact they are not, or the opposite may be the case). Because of this, we decided to merge our data to the official rollout in Huang and Zhang (2021), using the individual identifiers that are available in the data.[9]

From this rollout, we note that 26.7 percent of counties were covered by NRPS before the 2011 rollout, and all were covered by the end of 2012, since the program was expanded nationwide by this date. An overview of how the NRPS rollout relates to the CHARLS survey was previously presented in Figure 1.

3.3 Main outcomes

CESD-10 score Our main outcome of interest is the 10-item CESD scale for mental health, which contains a set of 10 questions on the intensity of negative emotions experienced in the week prior to interview. Possible response options are "rarely or none of the time (1 day or less)", "some or a little of the time (1-2 days)", "occasionally or a moderate amount of time (3-4 days)", "most or all of the time (5-7 days)". The CESD-10 scale is a high-quality alternative to its longer 20-item version (CESD-20) originally developed by Radloff (1977), both of which are clinically validated measures for depression in individuals because of their strong internal consistency (Andresen et al., 1994; Radloff, 1991; Roberts, 1980). The total CESD-10 score constitutes a summary measure

[8]In the second, third and fourth waves, respectively, 86%, 82% and 77% of the original participants who responded to the first wave were present.

[9]Since NRPS rollout, the administration of the NRPS has moved from the Ministry of Civil Affairs of China (MCA) to the Ministry of Human Resources and Social Security of China (MOHRSS). However, neither office replied to our formal requests for this documentation. We obtained replication data with rollout information from their online appendix: https://www-aeaweb-org.proxy-ub.rug.nl/articles?id=10.1257/app.20170789

of mental health ranging from 0 to 30, where a high score is interpreted as a high perception of negative feelings and a low score as better mental health. A cutoff of 10 on this score is used to identify symptoms that are consistent with major depressive disorder.[10]

One issue that arises from using the CESD score as a measure of depression is that not all respondents answer all questions of the interview. As is more generally the case with the scale (Andresen et al., 1994; Bono et al., 2007), approximately 15% of respondents skip at least one question when answering the questionnaire. While some studies deal with this issue by using a complete case approach (excluding responses when any is missing), it has been shown that it is safe to impute missing responses with the individual weighted average for up to one missing answer (Andresen et al., 1994). To recover more observations, we however impute up to 4 missing answers because our results remain robust to this imputation. For the ease of economic interpretation, we standardize the resulting CESD score using its values across all time periods and all ages in the sample.

Cognition Defining dementia in populations is not trivial since people with dementia often cannot respond to surveys and live in nursing homes. Because we dropped people who enter nursing homes at any point in time and few people in China live in nursing homes, we can only detect milder cases of cognitive impairment. Using a cutoff for severe cognitive impairment on a total score composed of the sum to individual test responses is not straightforward. While the HRS data contain a subset of respondents who are specifically screened for dementia (and on which measures can be validated), there is not a comparable group in the CHARLS data.

We therefore restrict ourselves to three measures that are consistently available across waves: immediate and delayed word recall (a summary score of the number of words the respondent can recall correctly from a 10-word list after an immediate (delayed) time spent answering other survey questions, ranging from 0 to 20), serial 7s (number of correct subtractions from 100, ranging from 0 to 5), and the correct naming of current date, week, month and year (ranging from 0 to 4). We weight the score obtained from each measure using the highest possible score in that measure and standardize the sum of the weighted scores. As in Hudomiet et al. (2022) We classify observations with a negative standardized score as having severe cognitive impairment. We obtain a prevalence of dementia (severe cognitive impairment) of 10.1%, which is similar to that obtained in Hudomiet et al. (2022), which was validated using the "ADAMS" sample and additional cognitive measures

[10]Interpretation of individual scores or group averages should not be made when using the CESD scale. Scores should be interpreted as the level of symptoms that accompany depression instead of rates of illness (Radloff, 1977).

which are not available to us. The distributions of the two scales are visualized in Figure 3.

3.4 Additional Outcomes

Takeup We are not able to directly measure NRPS take-up consistently, because the question wording on the NRPS changed substantially across waves. Instead we observe whether the respondent received any public pension in a given year, excluding payouts due to disability. In 2011, 14% of rural residents indicated receiving a public pension, and this share increased to 49% by the fourth wave. We construct two takeup variables: one variable indicating whether an individual him or herself is receiving a pension and another variable indicating whether anyone in the household is receiving a pension (either respondent or spouse, if available).

Pension amount The amount received is the total amount received from public pensions, excluding payouts due to disability. The total public pension amount is provided in yearly terms, since the yearly amounts are calculated using the number of months of actual pension receipt. We construct also this variable based on individual-level receipt and on household-level receipt (average total household receipt per household respondent).

3.5 Sample selection

Our population of interest consists of rural elderly who may experience different mental health developments in response to receiving a permanent income shock. We therefore restrict the sample to individuals who were at least 45 of age when they first entered the panel (i.e. first responded to the survey). Additionally, we use only individuals who ever report having a rural household registration ("hukou"), because such certification is required for the receipt of NRPS. Furthermore, we follow Cheng et al. (2018a) and exclude 0.5% respondents who were institutionalized in any of the waves, because we focus on people with milder mental health issues, as institutionalized respondents are often unable to respond to surveys.

After considering missing values in responses, our entire sample without missing observations in our main outcomes consists of 45,879 individual-year observations collected across four waves of CHARLS, from 13,983 respondents in 9,052 households, 149 of 150 counties and 430 of 450 resident communities (ignoring observations missing due to death). We do not use the 2020-23 wave that was released in November 2023 because this was fielded during Covid-19 which in itself is likely to have affected people's mental health in more complicated ways.

3.6 Summary Statistics

Ideally, we would be able to show average county characteristics prior to the start of the NRPS (i.e. in 2008) to identify any selection on observables which could be correlated with the rollout year, but the CHARLS data only starts in 2011. In Table 1, we provide summary statistics for respondents of the 2011 wave, separated by the eligibility status of their county in the same year. In our DiD analyses, we exclude individuals who are treated already when they enter the survey (60+ and living in an eligible county), but we present summary statistics for the whole sample which includes these (since we want to compare already eligible individuals with those who are not yet eligible)

Most background characteristics do not differ between groups, but eligibility status and pension income does. Neither group is more likely to be retired, but the proportion of married people differs slightly between groups. Overall, it appears that the sample of early eligible counties is fairly similar to the population in later eligible counties. (In Appendix Table A.1, we stratify the same 2011 sample on the respective rollout year of the NRPS. Although there is some evidence that individuals differed across groups, the means are in a similar range. We also provide summary statistics of the 2011 sample based on age-eligibility groups in Appendix Table A.2.)

We provide summary statistics, separately for each wave, from the full sample in Table 2. Across time, individuals are more likely to receive a pension, and by 2018 the mean household has about one member (main respondent or partner) that is currently receiving a pension.

4 Empirical Setup

In our data, individuals are first observed in 2011 but the rollout of the NRPS already started in 2009. Additionally, because all counties are already eligible by the end of 2012, we do not have an *external* control group consisting the same type of people (i.e. elderly Chinese with rural hukou), of the same age group in control localities, as for instance in Galiani et al. (2016).[11] Therefore,

[11] Although we considered using people with urban hukou as a control group in this setting, we deviated from this choice for two reasons. First, this group may differ in terms of unobservables. For instance, people with urban hukou may have different family backgrounds which we cannot sufficiently control for. Second, around the same time that the NRPS was rolled out, the urban pension scheme (to which the NRPS was later unified in 2014) was also rolled out for residents with urban hukou.

we cannot implement the canonical difference-in-difference estimator where individuals in treated counties are compared to an untreated counterfactual group. We illustrate the setup of treatment statuses in Appendix Figure A.4, by first eligible year for area- and area-age-eligibility in the sample.

We consider individuals younger than 60 as our internal control (comparison) group. These individuals are not yet eligible to receive the pension, regardless of whether they live in an eligible area. Because individuals who are younger than 60 may anticipate that the new pension policy will affect them in the future, mental health may improve even in absence of an income effect (which would invoke a violation of the limited treatment anticipation assumption). This would bias our point estimate towards zero. We show that such anticipation is unlikely, given that for this group the time-trends of mental health are unchanged after the rollout.

4.1 Parallel Trends

We start evaluating the credibility of our common trends assumption by plotting the age profiles of our main outcome variables, CESD and cognition for 2011 when not all counties were yet eligible for NRPS. If, before reaching the age-cutoff, always-area-eligible and later-eligible individuals were to exhibit different age profiles of mental health, this would cast doubt about our common trends assumption. This is because the two groups may differ in (un)observed characteristics. Figure 4 plots CESD and cognition across ages, separately for individuals who were area-eligible and for those who were not area-eligible for the NRPS in 2011. We aggregate cohorts above the age of 80 with equal weight into one group because few observations fall in this category and there is a large variance. The CESD score increases with age almost linearly between ages 45-60, which confirms the documented positive relationship between age and depressive symptoms. The trends of the two groups do not seem to differ prior to treatment for ages younger than 60.

Next, in Figure 5 we plot the crude time trends of the outcomes for the group of individuals that are never age-eligible (i.e. D1). From the plot it appears that, among never age-eligible people, the time trends in mental health are unaffected by a later NRPS rollout in late 2011 and 2012. We conclude from this that we can safely use the younger cohorts as comparison cohorts in our specification.

4.2 NRPS eligibility

Throughout the remainder of this paper, we clearly distinguish between the following binary indicators:

- **area-eligibility ($nrps_{ct}$):** whether NRPS was implemented in county c in year t. In 2011, not all counties are area-eligible, but in 2012 all rural residents with a local hukou are. People younger than 60 can also be area-eligible.
- **age-eligibility ($age60_{it}$):** whether an individual reached the age-eligibility threshold. An individual may be not age-eligible in one year, but then becomes age-eligible after reaching the age of 60. $age60_{it}$ refers to "$age_{it} >= 60$".
- **area-age-eligibility ($nrps_{ct} \cdot age60_{it}$):** whether an individual is 60 and older **and** is living in an area where the NRPS has already been implemented. Only people older than 60 can be area-age-eligible. This is our treatment variable of interest. Figure 2 illustrates area-age-eligibility by age-cohort.

We additionally stratify individuals from our sample into three distinct groups $d = \{D1, D2, D3\}$. The first group consists of never (across time) age-eligible individuals (those who never reach age 60) **(D1)**, the second group is always age-eligible (always 60+) **(D2)**, and the third group contains the remaining individuals who turn 60 during the time interval we consider.

We proceed as follows. To provide empirical support for the use of our internal comparison (control) group, we show that the outcome trends throughout the years of policy implementation are not affected for the group that is never age-eligible between 2011 and 2018, regardless of whether any of these were already area-eligible at the beginning of 2011 or not. Next, we run individual-level regressions on groups D1 and D2 using the late rollout as our treatment indicator ($\mathbb{E}[Y_{ict}|nrps_{late}, X_{i,0}, D_i = \{1,2\}]$) and compare our results with earlier findings on the NRPS. We then run a Two-Way-Fixed Effect (TWFE) regression at the individual level, but using individual area-age eligibility as our treatment indicator. Essentially, in this specification we are comparing individuals before and after they become age-eligible for pension receipt, provided that they live in an eligible county, and compare these with younger counterfactuals who are not (yet) age-eligible. We therefore include only groups D1 and D3, since for always age-eligible individuals (D2) we would only identify the same effect as from the county-level regression (i.e. Equation 1 below).

Since our TWFE estimator may be biased due to heterogeneous treatment effects in our staggered treatment setting (Goodman-Bacon, 2021), we also implement the Callaway and Sant'Anna (2021) estimator in our latter approach. We cannot implement Callaway and Sant'Anna (2021) in the former approach because of the comparison of earlier to always area-eligible individuals.

4.3 County-level eligibility

We begin with the following simple specification:

$$Y_{ict} = \beta_0 + \beta_1 * nrps_{ct} + \delta_c + \delta_t + X_{ict} + \epsilon_{ict} \tag{1}$$

where β_0 is the intercept, β_1 captures the effect of becoming area-eligible, and δ_c and δ_t denote county and time fixed effects. Controls included in X_{ict} are age and its square, marriage status (married or partnered versus separated, divorced, widowed or never married)) gender and education level (university or vocational school versus primary education). We run this regression for never and always age-eligible groups D1 and D2. Y_{ict} are our main outcomes: public pension receipt, income and mental health. A similar specification with minor differences is commonly used in the NRPS literature (e.g.Huang and Zhang (2021); Shan and Park (2023)).

The treatment parameter β_1, which compares later-treated units to always-treated comparison units, is a consistent estimator in the absence of pretrends if area-eligibility, $nrps_{ct}$, shifts the outcome in levels but does not change its time trend. However, with respect to a permanent income shock, such an assumption is hard to justify. A permanent income shock may also permanently change lifestyle behaviors, such as having more money to spend on better food or a substitution of work for leisure, whereby positive health behaviors improve as individuals adapt to a higher income. We therefore extend the analysis below.

4.4 Individual-level Eligibility

We estimate a Two-way Fixed Effect (TWFE) specification using both the treatment group D3 (which reaches the age-cutoff during our time interval) and internal control (comparison) group D1 (which never reaches the age-cutoff). Individuals from D2 are only becoming eligible through county-eligibility, therefore for this group we would estimate the same effect as from Equation 1. Individuals who at time t are younger than 60 and/or live in a NRPS non-eligible county serve as comparison units.

We estimate the following specification:

$$y_{ict} = \theta_i + \theta_1(nrps_{ct} \cdot age60_{it}) + \delta X_{it} + \alpha_{p,t} + \alpha_u + \epsilon_{ict} \tag{2}$$

where $nrps_{ct}$ and $age60_{it}$ are the binary indicators defined previously. θ_i is the intercept, X_{it} includes gender, education level (university or vocational school versus primary education), marriage status (married or partnered versus separated, divorced, widowed or never married). $\alpha_{p,t}$ are province-time fixed effects. α_u are unobserved factors that differ between units, which we remove using within transformations. A unit refers to either county (and cohort) (α_c) or individual (α_i). ϵ_{ict} is the idiosyncratic error that is not capured by the model. Standard errors are clustered at the county level, the level at which the NRPS was rolled out.

The coefficient of our DID estimator, θ_1, provides the intention-to-treat (ITT) effect of area-age-eligibility on the outcome variable. Treatment hence refers to being older than 60 and living in a NRPS-eligible county.

De Chaisemartin and d'Haultfoeuille (2020) and Goodman-Bacon (2021) show that the TWFE estimator can be severely biased in cases with staggered treatment adoption when the effect of the treatment varies by covariate values due to covariate-specific trends. In our case, earlier treated units serving as control (comparison) units for later-treated units can be problematic. We therefore implement the Callaway and Sant'Anna (2021) DID estimator, which compares earlier treated units only to later- and never treated units, but not to earlier treated units. Regarding the choice of comparison units, we have two options. We can either include or drop not-yet treated individuals (in group D3) from the comparison group. Each option has its own advantages. If we include not-yet treated individuals, we may estimate a biased treatment effect due to anticipatory effects (although we have shown such effects are unlikely, we cannot disregard this possibility). If we exclude not-yet treated individuals, we may exclude cohorts that are relatively similar to the earlier treated cohorts. Although the choice does not change our results substantially, we decide to exclude not yet treated individuals due to the aforementioned concerns.

We are interested in the following (causal) effect:

$$ATT(g(t)) = \mathbb{E}[Y_t(g) - Y_t(0)|G_g = 1, \mathbf{x}] \text{ for } t > g$$

where $g \in \{2013, 2015, 2018\}$ is the first area-age-eligibility year and $t \in \{2011, 2013, 2015, 2018\}$ denotes time. $Y_t(g)$ is the outcome of group g at time t (conditional on being first treated at time g) and $Y_t(0)$ is the counterfactual outcome. The first possible "pre-post" difference that can be calculated in our case is for 2011 and 2013, hence there is no difference that can be computed for the always area-age-eligible ($g = 2011$) group. These are people who in 2011 are already area-age-eligible and therefore do not have an untreated pre-period. Naturally, there are more such eligible individuals in the $nrps_{late} = 0$ group than in the $nrps_{late} = 1$ group.

We estimate the following expectation (using sample equivalents):

$$ATT^{nev}(g(t)) = \mathbb{E}[Y_t(g) - Y_{g-1}|\mathbf{x}, G_g = 1] - \mathbb{E}[Y_t - Y_{g-1}|\mathbf{x}, C = 1] \text{ for } t > g \tag{3}$$

where $C = 1$ refers to belonging to the comparison group (which is the never treated group). We implement the default Sant'Anna and Zhao (2020) doubly robust estimator based on stabilized inverse probability weighting. Cohort fixed effect are nested within individual fixed effects. The process of ageing is linearly capured though time fixed effects. Although the ageing process can matter nonlinearly for mental health, we believe this is not a severe issue in our context because we have four time periods. Because there is little heterogeneity in the amount of the pension receipt and we do not know which local governments implemented a basic pension above the national standard, we assume the treatment dose is homogenous across counties and individuals and do not use a Callaway et al. (2024) treatment design.

An improvement to our setup would be to distinguish people who became first area-age-eligible at time t or during a gap between waves. We can distinugish such groups based on age, but cannot compute our treatment effect due to time-gaps in the data (our data is biennial; we define time in waves, because defining time in years results in missing periods and the estimator cannot be applied)

4.5 Eligibility and Identification Issues

The NRPS was rolled out in four rounds between 2009 and 2012, each time during the later summer months of the year. At every roll-out, the central government selected the counties in which the NRPS was made available. The first roll-out of NRPS was evenly distributed across the country. At the second and third rounds, the government tried to prioritize less affluent regions in the west of

China by giving them earlier access to NRPS (Huang and Zhang, 2021). The rollout was described in more detail in section 2.

One case of concern to our identification arises if poorer counties are chosen first to become eligible for NRPS and this could explain the mental health outcome. We deem this concern to not apply in our case for two reasons. First, even if the government first prioritized eligibility in poorer counties of the country, eligibility is still exogenous from the perspective of individuals and households, who are also generally not able to migrate to a different county for due to the restrictive Hukou system (Pozen, 2013). Selective migration could be an issue but we note that 97% of people in our sample who were 60 or older lived in the same province in which they were born. Second, Huang and Zhang (2021) do not find differing pre-trends across counties with different rollout years in per-capita income levels, rural population shares, government revenues and expenditures, savings and beds in hospitals.

Finally, contributions into the individual account (i.e not the basic account) by the individual or their children was a prerequisite for NRPS eligiblity in the initial stage of implementation after the first policy rollout (Huang and Zhang, 2021). However, because this requirement slowed takeup in the population and hindered the general rollout in the country, it was dropped. The exact year in which this was dropped is not known to us, although it was around the time of the first survey of CHARLS.[12] Therefore, we cannot exploit this detail of the institutional setting.

5 Results

5.1 Main Results

We first report the results from equation 1 using county-level eligibility in Table 3. In this table, we only control for county and cohort fixed effects, but in Appendix Table A.3 the same regressions with individual fixed effects are reported. Columns 1 and 2 show the effect of area- (county-) eligiblity on pension receipt for never and always age-eligible groups, respectively. Columns 3-4 show results for pension income, 5-6 for CESD and 7-8 for cognition.

[12]There were political considerations behind the implementation of the NRPS, as the government aimed to achieve universal coverage by the end of 2012, when the 18th party congress took place and the General Secretary Hu Jintao handed over power to his successor. Therefore, officials in the Ministry of Human Resources and Social Security decided to drop this requirement soon after the initiation of the NRPS pilot to promote participation. The same was confirmed by field surveys according to the authors of Huang and Zhang (2021).

The NRPS rollout increases pension receipt and pension income for D2 (always age-eligible), but not for D1 (never age-eligible). On average, pension receipt increases by 56 percentage points and pension income increases by 3.5 %. There is no effect on mental health (neither CESD nor cognition) for any of the two groups. Although the coefficients are negative, they are small in magnitude and standard errors are large.

Essentially, these regressions can be compared to Huang and Zhang (2021) (hereinafter referred to as HZ) who used the first two waves of CHARLS (in addition to the CFPS data). Our coefficient on pension receipt is larger (0.56) compared to the coefficient in their regression when only the CHARLS data is included (Appendix Table B6 in Huang and Zhang (2021)). To ensure the results are nevertheless reliable, we also present a comparison of the results in HZ with our results using rural individuals from the first two waves of the data in Appendix Tables A.4 A.5 A.6 A.7.

We now proceed to show results from equation 2 in Table 4, using individual-level area-age-eligibility, where the same individuals are compared before and after they turn 60. Panel-level IV results are included in Appendix Table A.8, where we instrument pension receipt and pension income by area-age-eligibility.)

County and cohort fixed effects are included in the first column, the second column includes individual fixed effects (aging is captured linearly through time fixed effects). Columns 3 and 4 report results from Callaway & Sant'Anna (2021) (column 3 reports the aggregated simple ATT and column 4 is a weighted average of the 'pre-post' difference obtained from the corresponding event study. On average and holding other factors constant, eligibility increases the probability of individual public pension receipt by 60 percentage points. This is a larger effect than the one estimated using county-level eligibility among the age-eligible population, suggesting that becoming age-eligible in an already eligible county increases the probability of pension receipt. Pension income also increases by about 900 yuan per year. Overall, these results suggest that the NRPS was effective in distributing the pension to rural residents.

Mental Health is also impacted by eligibility. The estimated coefficients on CESD are negative, indicating that eligibility reduced the intensity of negative emotions accompanying depression. However, the results indicate also worsened cognition (a lower cognition score indicates worse cognition). On average, eligibility is associated with a reduction in the CESD score by about 0.05 of a standard deviation, or about 0.083 SD (=0.05/0.6) among the compliers. This translates into a 4 percent reduction evaluated at the mean CESD score, or a 3 percentage point reduction in the share of depressed people. For cognition, we estimate an similar effect of 0.04 SD, or about 0.07 (=0.04/0.6) among the compliers. This translates into a 2 percentage points *increase* in the share of people with severe cognitive impairment.

Overall, the estimated coefficients in the TWFE specification and Callaway & Sant'Anna are similar. Both the weighted ATT and the average for the post-periods from columns 3 and 4 slightly larger in magnitude than the TWFE estimate, but their confidence intervals overlap. (We decomposed the TWFE treatment effect using a Bacon Decomposition in Appendix Figure A.5 (Goodman-Bacon et al., 2019)).

5.2 Effects on other outcomes

One important task in understanding the estimated treatment effects we obtained above is to assess the effects on other outcomes (as well as potential mediators). In other words, the effects on mental health that we found could arise because the NRPS affected other factors which in turn influence mental health. For example, one may assess whether individuals are more likely to retire, smoke more or drink more after being affected by the cash transfer. Prior research has highlighted such associations. Another important question is whether the income transfer may crowd out private transfers from family members, which are an important source of income for the Chinese elderly.

We thus again run Equation 2, but for other outcomes. Results are presented in Table 5. Becoming area-age-eligible does not decrease the probability of working (or increase the probability of retiring) (Panel B1). Food consumption or unhealthy health behaviors also seem unaffected. However, the likelihood of visiting a doctor in the prior month is reduced by about 3 percentage points, out of pocket expenditure is not affected. This could be because after the permanent income shock, individuals reallocate time to take care of their own health and visit a doctor less frequently.

What seems consistent with earlier research on the NRPS, is that the cash transfer reduces the likelihood of receiving a transfer from children or grandchildren, which at the extensive margin translates into a reduction of about 50% in the amount received. Hence, consistent with earlier evidence (e.g. Shan and Park (2023)), the NRPS appears to have crowded out intrahousehold transfers.

5.3 Event Studies

Event studies on our main outcome variables are visualized in Figure 6. While there is no evidence for pretrends for public pension receipt and pension income, this is less clear for mental health. Although pre-treatment coefficients are not significantly different from zero, we cannot safely ignore the possibility of an underlying trend that we did not capture in our model. Although our pretrends test indicated there are no existing pretrends (P-value 0.77), we caution to make any sensible conclusions because this is based on a limited number (2) of pretreatment periods for which we can estimate a coefficient. Although there appears to exist an effect of noncontributory pensions on mental health, we caution to make any decisive statements in this regard.

6 Extensions

6.1 Spillovers: Main effects using eligibility at the household level

There may be spillovers in the mental health effect from the NRPS. For example, an permanent income shock to one's spouse may affect own healthy lifestyle behaviors or mental health. We thus estimate the regression using variable definitions at the household level. We modify Equation 2 using household-level age-eligibility, rather than own age-eligibility:

$$y_{ict} = \theta_0 + \theta_1(nrps_{ct} \cdot age60_{ht}) + \delta X_{it} + \alpha_{p,t} + \alpha_u + \epsilon_{ict}$$

Results are presented in Appendix Table A.9. The coefficients on pension receipt and income are similar to those estimated previously, but we do not find any effects on CESD or cognition.

7 Discussion and Conclusion

Our findings provide first estimates on the effect of the NRPS using a staggered treatement design. We find that the NRPS rollout increased pension takeup and income, but the results on mental health warrant caution. Our estimates suggest a reduction in depressive symptoms and worsened cognition, but we cannot completely rule out the possibility of existing pretrends.

Our findings can be compared to earlier research highlighting a beneficial effect of pension income on mental health (Chen et al., 2019; Galiani et al., 2016). In studies using a cross-sectional research setting, unobserved heterogeneity may be explaining the mental health outcome which is not easily captured. If unobserved characteristics of NRPS participants explain both their enrollment outcome and mental health, the effect of NRPS in this setting cannot be interpreted causally. Additionally, addressing the findings of Galiani et al. (2016), we may be finding comparatively small effects of the income shock on mental health because the NRPS amount is relatively small. While the Adultos Mayores Program in Mexico provided enrollees with 90 USD every two months, the amount of approximately 25 USD (averaged over all waves) provided to Chinese rural elderly is much smaller. Because we find negative coefficients of NRPS on mental health which remain robust across specification, we suspect that a larger effect may appear if the pension amounts were more sizeable. Furthermore, our age-eligible cohort is younger (60 years) compared to the one in Mexico (70 years). It may be that the effects are larger for older age groups.

Our estimates can also be compared to those of experimental unconditional cash transfers to adolescents and children in several African countries. These have shown to improve outcomes on several health dimensions among adolescents, including psychological well-being, stress and depression (Baird et al., 2010, 2013, 2011; Blattman et al., 2014; Gertler, 2004; Haushofer and Shapiro, 2016). However, single-time transfers were not transformative and effects were mostly short-lived (Baird et al., 2019; Balboni et al., 2022; Blattman et al., 2020; Egger et al., 2022), as a result of which permanent transfers in the form of universal basic incomes in developing countries are instead considered as an effective anti-poverty tool (Banerjee et al., 2020, 2019; Hanna and Olken, 2018).

The results from this paper invite future research to reassess findings on noncontributory pensions in other contexts. Although studied on other mental health scales, the direction of our effect is similar to prior research. Using an exogenous eligibility threshold of rural adults older than 70 in treatment localities, Galiani et al. (2016) find that the bimonthly cash transfer of USD 90 reduced the Geriatric Depression scale in Mexico by 9.11% (on our scale the estimated reduction is 4%). Bando et al. (2020) use a sharp regression discontinuity approach based on an exogenous poverty cutoff in Peru on elderly 65 and older to find that the bimonthly transfer of USD 78 reduced the score by 8.68%, and Bando et al. (2022) find using an RCT design in Paraguay on elderly 65 and older an effect of the monthly transfer of USD 92 of 6.85%. The transfer in Paraguay is larger than the one in Mexico and Peru, and much larger than the NRPS transfer, which could explain the difference in magnitude.

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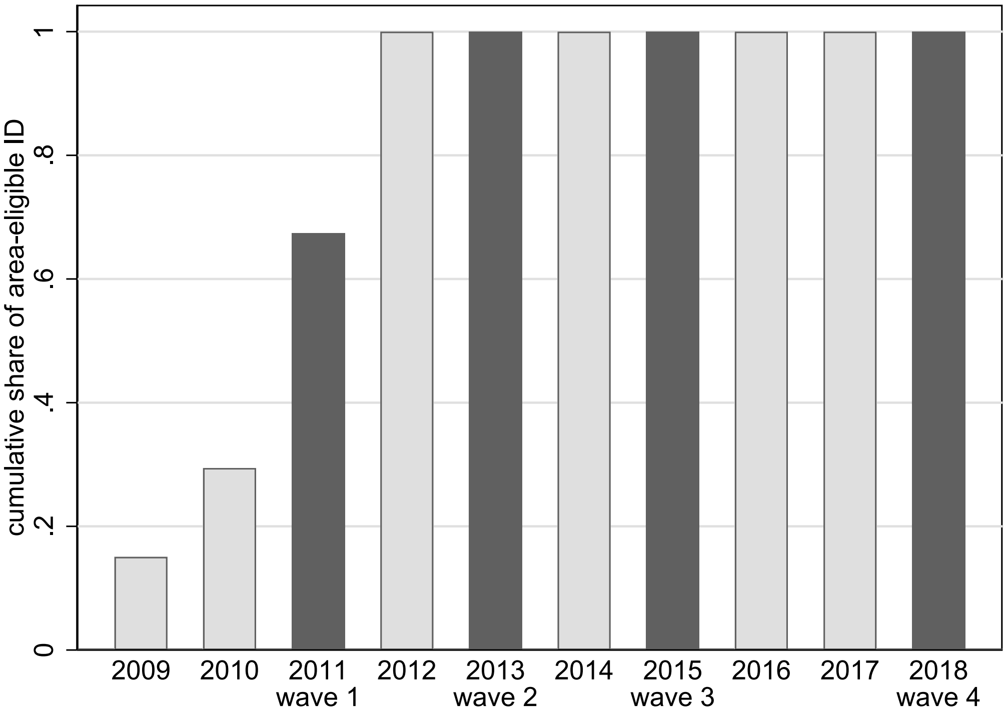
Figures and Tables

Figure 1: NRPS Rollout



Notes: The figure illustrates the staggered rollout of the New Rural Pension Scheme (NRPS) and the CHARLS data used in the paper. In our data, waves are available in 2011, 2013, 2015 and 2018. We do not use the 2020-2023 wave. The NRPS rollouts occurred on a county-to-county basis in 2009 (14%), 2010 (13%), 2011 (38%), and 2012 (35%). The rollout in 2011 occurred between July and September, while the survey collection of the 2011 wave ran primarily in the summer months from June 2011 but until March 2012. Appendix Figure A.1 illustrates the same rollout by county, separated by Chinese regions that differ in geographic location and stage of economic development.

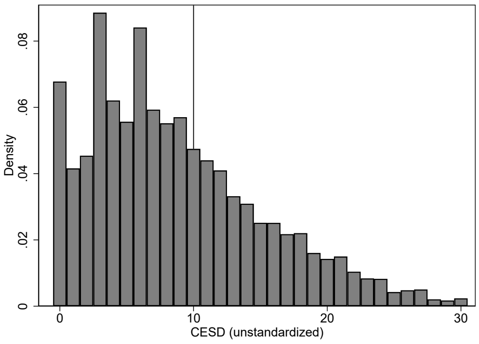
Figure 2: NRPS receipt eligibility by age

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Rollout Steps		*1*	*2*	*3*	*4*						
Birthyear	**Age**										
1943	65	66	67	68	69	70	71	72	73	74	75
1944	64	65	66	67	68	69	70	71	72	73	74
1945	63	64	65	66	67	68	69	70	71	72	73
1946	62	63	64	65	66	67	68	69	70	71	72
1947	61	62	63	64	65	66	67	68	69	70	71
1948	60	61	62	63	64	65	66	67	68	69	70
1949	59	60	61	62	63	64	65	66	67	68	69
1950	58	59	60	61	62	63	64	65	66	67	68
1951	57	58	59	60	61	62	63	64	65	66	67
1952	56	57	58	59	60	61	62	63	64	65	66
1953	55	56	57	58	59	60	61	62	63	64	65
1954	54	55	56	57	58	59	60	61	62	63	64
1955	53	54	55	56	57	58	59	60	61	62	63
1956	52	53	54	55	56	57	58	59	60	61	62
1957	51	52	53	54	55	56	57	58	59	60	61
1958	50	51	52	53	54	55	56	57	58	59	60

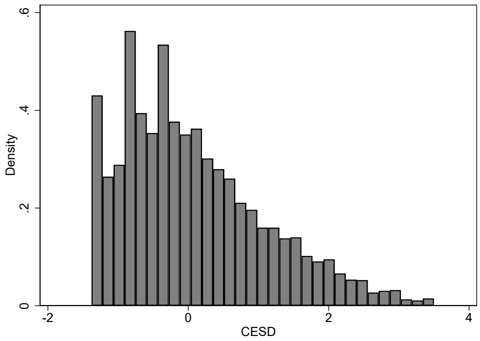
survey years (fall)
treated (summer)
treated only if area eligible

Notes: The plot illustrates the timing at which each individual becomes eligible for the receipt of the NRPS. After passing the age-eligiblity threshold of 60 years, Chinese elderly with local household registration became eligible for receipt of the NRPS cash transfer, if living in an eligible county in a particular year. Rows indicate year of birth, columns indicate survey or rollout year. We use survey information from the waves 2011, 2013, 2015 and 2018. From 2009 onwards up until 2012, being 60 years of age is not sufficient for NRPS receipt, since living in an eligible county is also necessary. Therefore, before 2012 not all green areas are dark. From 2012 onwards, only age determines eligiblity for NPRS receipt, since all counties had already rolled out the NRPS by this date.

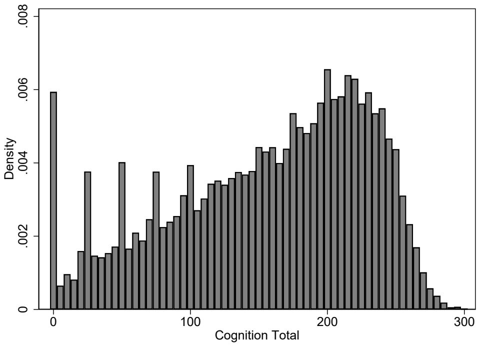
Figure 3: Distribution of CESD



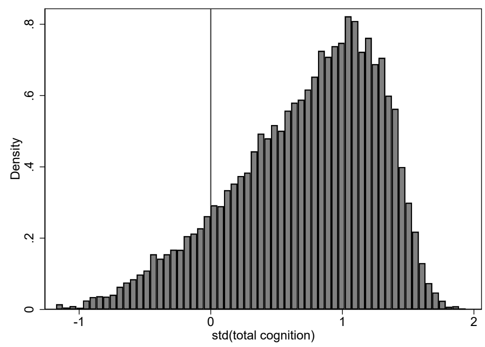
(a) CESD-10



(b) standardized CESD-10



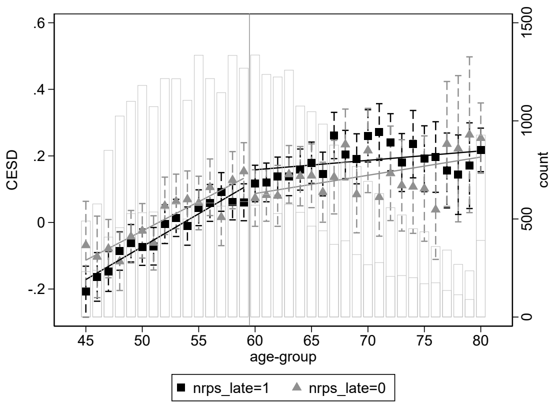
(c) cognition total



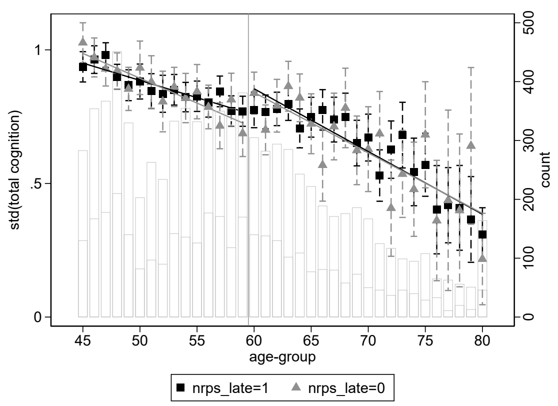
(d) standardized cognition

Notes: Data come from the China Health and Retirement Longitudinal Study (CHARLS). A higher CESD score indicates a higher intensity of depressive symptoms. A total score of 10 is used as a threshold for depression on the 10-item scale. We standardize this score as well as the cognition score, and use these in the remainder of the paper.

Figure 4: Mental Health by age-group



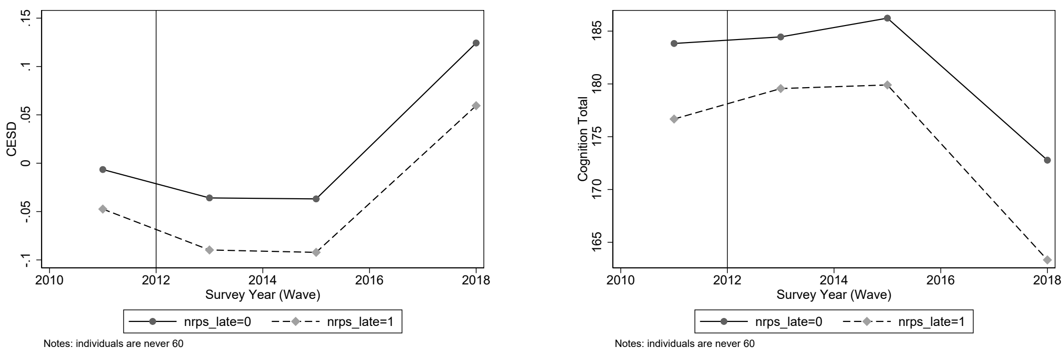
(a) CESD



(b) Cognition

Notes: Figure plots CESD and Cognition by age-cohort and NRPS eligibility status at the first survey wave in 2011. Data come from the China Health and Retirement Longitudinal Study (CHARLS) waves 1-4. Cohorts above the age of 80 are aggregated to the same age group because few observations fall into this category.

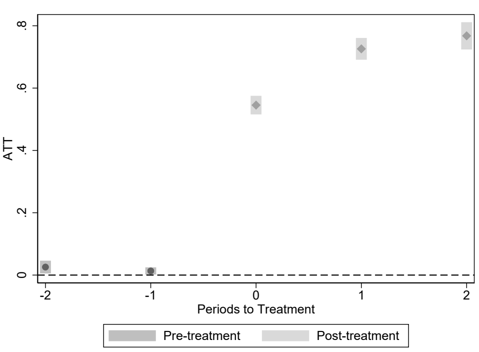
Figure 5: Outcome trends by $nrps_{late}$ status, never age-eligible group



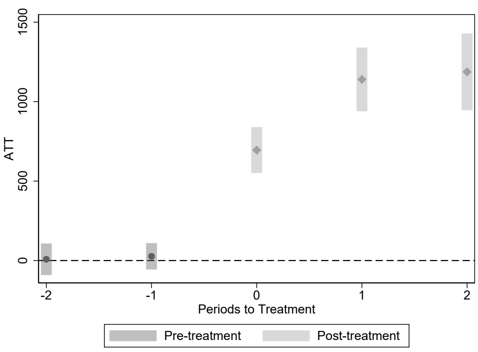
(a) CESD (b) Cognition

Notes: The figure contains diagnostic plots which are used to assess the parallel-trends assumption for the group that is never age-eligibile for the NRPS between 2011 and 2018. Outcome trends are provided for two groups, based on area-eligibility in 2011.

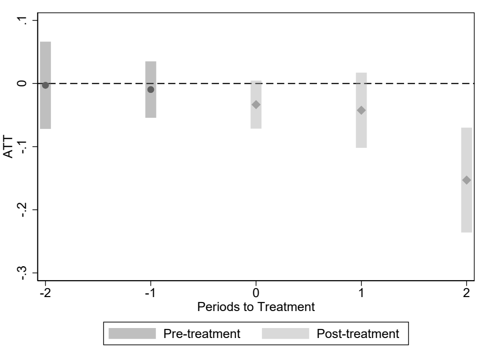
Figure 6: Event Studies



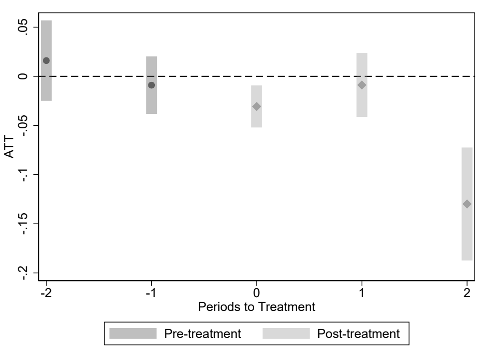
(a) Pension Receipt



(b) Pension Income



(c) CESD



(d) Cognition

Table 1: Summary Statistics in 2011, by $nrps_{c,2011}$ ($nrps\_late$) status

	nrps_late=0	nrps_late=1	Total	Test
	3,289 (30.4%)	7,527 (69.6%)	10,816 (100.0%)	
CESD (unstandardized)	8.81 (6.63)	8.98 (6.35)	8.92 (6.44)	0.214
CESD	0.09 (1.04)	0.11 (1.00)	0.10 (1.01)	0.214
Cognition Total	162.71 (67.87)	158.93 (68.46)	160.08 (68.30)	0.008
Cognition	0.74 (0.54)	0.70 (0.56)	0.71 (0.55)	0.002
age at interview	58.03 (8.73)	58.24 (8.96)	58.17 (8.89)	0.264
education level				
0.educ: up to primary	3,075 (93.5%)	7,076 (94.0%)	10,151 (93.9%)	0.305
1.educ: vocational or university	214 (6.5%)	451 (6.0%)	665 (6.1%)	
ever died (by time t)	0.00	0.00	0.00	.
male	0.47	0.47	0.47	0.514
married or partnered	0.90	0.88	0.88	0.004
retired	0.26	0.27	0.26	0.810
rural hukou	0.98	0.98	0.98	0.071
receive public pension	0.31	0.07	0.14	<0.001
age started receiving public pension	65.62	64.24	65.15	<0.001
anyone in HH receives public pension	0.37	0.10	0.18	<0.001
anyone in HH receives any pension	0.40	0.14	0.22	<0.001
# of HH members with (any) pension	0.60	0.18	0.31	<0.001
income from public pension	274.35 (996.93)	162.43 (1172.00)	196.46 (1122.79)	<0.001
HH income from public pension per capita	293.35 (966.64)	189.56 (1196.34)	221.12 (1132.40)	<0.001
amount of transfers from children/grandchildren	1719.33 (7342.08)	1570.01 (7111.98)	1615.40 (7182.69)	0.322
number of people living in this household	3.69 (1.81)	3.74 (1.88)	3.73 (1.86)	0.181
# of living children	2.76 (1.42)	2.73 (1.38)	2.74 (1.39)	0.381
child coresiding or in same city/county	0.91 (0.29)	0.92 (0.28)	0.92 (0.28)	0.189

Table 2: Summary Statistics by wave: full sample

	2011 wave 10,816 (23.6%)	2013 wave 11,695 (25.5%)	2015 wave 11,645 (25.4%)	2018 wave 11,723 (25.6%)	Total 45,879 (100.0%)
CESD (unstandardized)	8.92 (6.44)	8.31 (5.97)	8.45 (6.55)	9.27 (6.76)	8.73 (6.44)
CESD	0.10 (1.01)	0.01 (0.94)	0.03 (1.03)	0.16 (1.06)	0.07 (1.01)
Cognition Total	160.08 (68.30)	160.41 (70.87)	162.68 (69.24)	141.31 (77.42)	156.03 (72.13)
Cognition	0.71 (0.55)	0.73 (0.55)	0.72 (0.54)	0.71 (0.57)	0.72 (0.55)
age at interview	58.17 (8.89)	59.25 (9.02)	59.71 (8.82)	62.52 (8.56)	59.93 (8.97)
education level					
0.educ: up to primary	10,151 (93.9%)	10,938 (93.5%)	10,856 (93.2%)	10,911 (93.1%)	42,856 (93.4%)
1.educ: vocational or university	665 (6.1%)	757 (6.5%)	789 (6.8%)	812 (6.9%)	3,023 (6.6%)
ever died (by time t)	0.00	0.00	0.00	0.03	0.01
male	0.47	0.48	0.49	0.48	0.48
married or partnered	0.88	0.88	0.88	0.86	0.88
retired	0.26	0.25	0.26	0.28	0.27
rural hukou	0.98	0.97	0.97	0.96	0.97
receive public pension	0.14	0.37	0.35	0.49	0.34
age started receiving public pension	65.15	65.53	63.99	62.52	63.99
anyone in HH receives public pension	0.18	0.43	0.42	0.56	0.40
anyone in HH receives any pension	0.22	0.46	0.44	0.60	0.43
# of HH members with (any) pension	0.31	0.72	0.66	0.96	0.67
income from public pension	196.46 (1122.79)	472.21 (1846.79)	644.55 (2426.10)	1177.07 (3461.61)	626.92 (2408.45)
HH income from public pension per capita	221.12 (1132.40)	455.46 (1425.83)	608.32 (1991.03)	1156.10 (3032.12)	613.98 (2062.60)
amount of transfers from children/grandchildren	1615.40 (7182.69)	3206.02 (8235.95)	5619.19 (13065.76)	4901.69 (11409.46)	3884.68 (10450.48)
number of people living in this household	3.73 (1.86)	3.76 (1.87)	3.13 (1.38)	2.83 (1.52)	3.36 (1.71)
# of living children	2.74 (1.39)	2.77 (1.40)	2.77 (1.35)	2.73 (1.29)	2.75 (1.36)
child coresiding or in same city/county	0.92 (0.28)	0.89 (0.32)	0.86 (0.34)	0.53 (0.50)	0.80 (0.40)
nrps_ct	0.30	1.00	1.00	1.00	0.84
age60_it	0.40	0.46	0.48	0.60	0.49
age60_ht	0.51	0.56	0.58	0.69	0.58
nrps_ctXage60_it	0.12	0.46	0.48	0.60	0.42
nrps_ctXage60_ht	0.15	0.56	0.58	0.69	0.50
nrps_late	0.70	0.68	0.69	0.69	0.69

Table 3: Regression using county-level rollout

	(1) receive pension	(2) receive pension	(3) pension income	(4) pension income	(5) CESD	(6) CESD	(7) Cognition	(8) Cognition
nrps_ct	0.00582	0.564***	6.326	306.1***	-0.0234	-0.0104	0.00166	-0.0145
	(0.00657)	(0.0457)	(8.068)	(38.68)	(0.0547)	(0.0572)	(0.0256)	(0.0303)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
rabyear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16691	16188	16540	15619	16691	16188	13947	11320
r2	0.082	0.334	0.050	0.345	0.145	0.130	0.148	0.194
N_clust	147	147	147	147	147	147	146	145
sample	never 60	always 60+	never 60	always 60+	never 60	always 60+	never 60	always 60+
controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Regression using area-age-eligibility

	(1)	(2)	(3)	(4)
Panel A1: receive public pension				
nrps_ctXage60_it	0.611***	0.625***	0.624***	0.631***
	(0.0180)	(0.0182)	(0.0228)	(0.0238)
N	39769	39769	38142	38142
ymean	0.279	0.279	1	1
Panel A2: income from public pension				
nrps_ctXage60_it	757.1***	768.3***	781.2***	834.9***
	(54.20)	(52.53)	(56.41)	(60.82)
N	39769	39769	38142	38142
ymean	530.3	530.3	1	1
Panel B1: CESD				
nrps_ctXage60_it	-0.0668***	-0.0688***	-0.0579**	-0.0607**
	(0.0171)	(0.0169)	(0.0228)	(0.0245)
N	39769	39769	38142	38142
ymean	0.0644	0.0644	1	1
Panel B2: Cognition				
nrps_ctXage60_it	-0.0298***	-0.0458***	-0.0528***	-0.0730***
	(0.00904)	(0.00875)	(0.00948)	(0.0105)
N	30906	29416	27223	27223
ymean	0.846	0.857		
Cohort FE	Yes	(nested)	(nested)	(nested)
County FE	Yes	(nested)	(nested)	(nested)
ID FE	No	Yes	Yes	Yes
Province-time FE	Yes	Yes	Yes	Yes
N_clust	149	149	149	149
controls	Yes	Yes	Yes	Yes
model	TWFE	TWFE	CS ATT	Event Post_avg

SE clustered at the county level $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: Table reports results from Equation 2. Standard errors are clustered at the county level. Controls included are gender, education and marriage status (married and partnered).

Table 5: Regression using area-age-eligibility, other outcomes

	(1)	(2)	(3)	(4)
Panel A1: CESD (unstandardized)				
nrps_ctXage60_it	-0.424***	-0.437***	-0.368**	-0.386**
	(0.108)	(0.107)	(0.145)	(0.156)
N	39769	39769	38142	38142
ymean	8.668	8.668	1	1
Panel A2: CESD (log)				
nrps_ctXage60_it	-0.0545***	-0.0602***	-0.0516***	-0.0581***
	(0.0137)	(0.0134)	(0.0177)	(0.0191)
N	39769	39769	38142	38142
ymean	1.992	1.992	1	1
Panel A3: depressed (cesd10a4 >= 10)				
nrps_ctXage60_it	-0.0343***	-0.0388***	-0.0400***	-0.0418***
	(0.00827)	(0.00867)	(0.0111)	(0.0119)
N	39769	39769	38142	38142
ymean	0.380	0.380	1	1
Panel A4: has cognitive impairment				
nrps_ctXage60_it	0.0137**	0.0236***	0.0321***	0.0457***
	(0.00668)	(0.00600)	(0.00689)	(0.00771)
N	30906	29416	27223	27223
ymean	0.114	0.1000	1	1
Panel B1: currently working				
nrps_ctXage60_it	-0.0174**	-0.0239***	-0.0460***	-0.0539***
	(0.00814)	(0.00818)	(0.0116)	(0.0123)
N	39584	39523	37814	37814
ymean	0.741	0.742	1	1
Panel B2: HH food cons., past year				
nrps_ctXage60_it	-0.0441	-0.0390	-0.0675	-0.0788
	(0.0379)	(0.0399)	(0.0506)	(0.0537)
N	34651	33830	31509	31509
ymean	9.076	9.080	1	1
Panel C1: ever drank any alcohol last year				
nrps_ctXage60_it	-0.00130	-0.00170	0.00232	0.00467
	(0.00593)	(0.00611)	(0.00828)	(0.00876)
N	39749	39747	38120	38120
ymean	0.344	0.344	1	1
Panel C2: currently smoking				
nrps_ctXage60_it	-0.00823	-0.00552	-0.00687	-0.00950
	(0.00508)	(0.00407)	(0.00589)	(0.00629)
N	37722	37516	35178	35178
ymean	0.280	0.278	1	1
Panel C3: in good or very good health				
nrps_ctXage60_it	0.0112	0.0126*	0.0132	0.0117
	(0.00738)	(0.00703)	(0.00893)	(0.00947)
N	39749	39745	38114	38114
ymean	0.229	0.229	1	1
Panel C4: doctor visit/outpatient last month				
nrps_ctXage60_it	-0.0182***	-0.0208***	-0.0281***	-0.0304***
	(0.00687)	(0.00692)	(0.00833)	(0.00871)
N	39735	39733	38087	38087
ymean	0.188	0.188	1	1
Panel C5: doctor visit out-of-pocket expenditure last month				
nrps_ctXage60_it	8.672	14.62	15.84	8.254
	(24.06)	(25.18)	(26.59)	(28.86)
N	39260	39207	37396	37396
ymean	151.7	151.8	1	1
Panel D1: any transfer from children/grandchildren				
nrps_ctXage60_it	-0.0780***	-0.0802***	-0.0895***	-0.102***
	(0.0111)	(0.0109)	(0.0136)	(0.0143)
N	38535	38338	36538	36538
ymean	0.665	0.665	1	1
Panel D2: amount of transfers (log)				
nrps_ctXage60_it	-0.497***	-0.536***	-0.564***	-0.653***
	(0.0869)	(0.0829)	(0.103)	(0.108)
N	38501	38295	36479	36479
ymean	5.152	5.159	1	1
Cohort FE	Yes	(nested)	(nested)	(nested)
County FE	Yes	(nested)	(nested)	(nested)
ID FE	No	Yes	Yes	Yes
Province-time FE	Yes	Yes	Yes	Yes
N_clust	149	149	149	149
controls	Yes	Yes	Yes	Yes
model	TWFE	TWFE	CS ATT	Event Post_avg

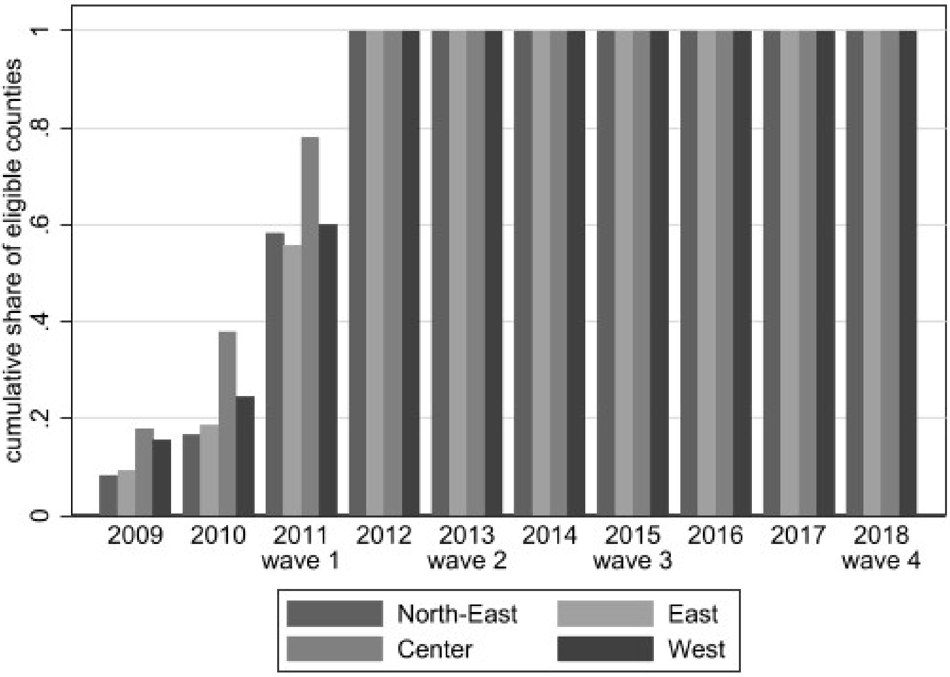
Standard errors clustered at the county level in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Table reports results from Equation 2. Standard errors are clustered at the county level. Controls included are gender, education and marriage status (married and partnered).

A Appendix

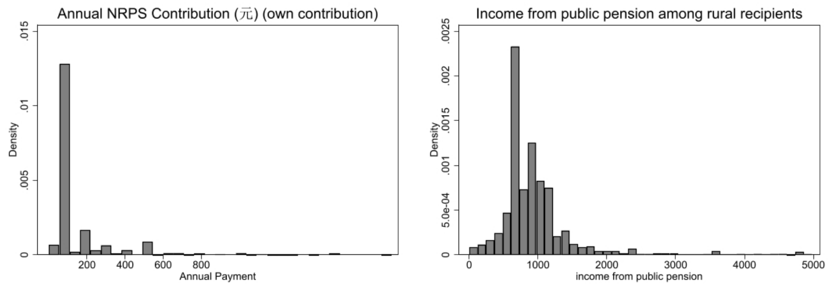
Figures

Figure A.1: NRPS rollout by region



Notes: The figure illustrates the staggered rollout of the New Rural Pension Scheme (NRPS) and the CHARLS data used in the paper. In our data, waves are available in 2011, 2013, 2015 and 2018. We do not use the 2020-2023 wave. The NRPS rollouts occurred on a county-to-county basis in 2009 (14%), 2010 (13%), 2011 (38%), and 2012 (35%). The rollout in 2011 occurred between July and September, while the survey collection of the 2011 wave ran primarily in the summer months from June 2011 but until March 2012. Regions are separated by as North-East (Jilin, Liaoning, Heilongjiang), East (Shanghai, Beijing, Tianjin, Shandong, Guangdong, Jiangsu, Zhejiang, Fujian), Center (Inner Mongolia, Anhui, Jiangxi, Hebei, Henan, Hubei, Hunan), and West (Yunnan, Sichuan, Shanxi, Guangxi, Xinjiang, Gansu, Guizhou, Chongqing, Shaanxi, Qinghai)

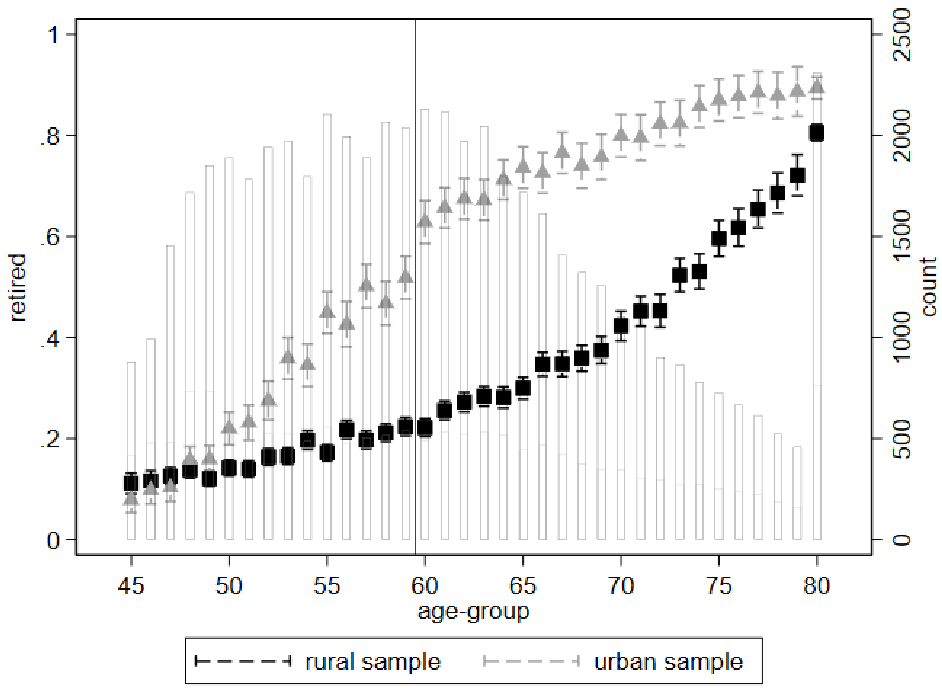
Figure A.2: Variation in NRPS contribution and public pension receipt



(a) Contribution amount among participants in 2011

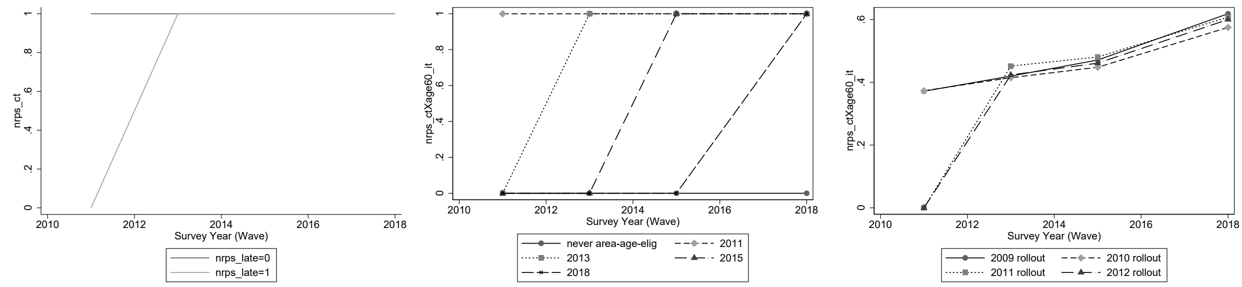
(b) Income from public pension

Figure A.3: Retirement probability by age-group



Notes: The figure plots the mean of the variable with 95% confidence interval, separate for each age group.

Figure A.4: Visual representation of eligibility by treatment groups

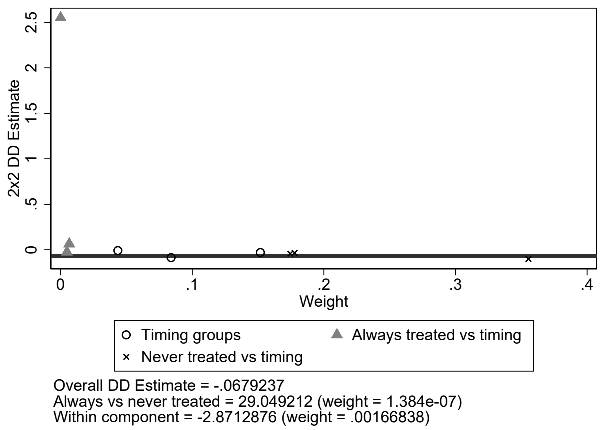


(a) area-eligibility

(b) area-age-eligibility

(c) area-age-eligibility by rollout year

Figure A.5: Bacon Decomposition of TWFE estimate



Notes: The overall DD estimate differs slightly from Table 4 because we manually demeaned province-year fixed effects, which cannot directly be included in -bacondecomp-.

Tables

Table A.1: Summary Statistics in 2011, stratified on NRPS rollout year

	2009 rollout 1,689 (15.6%)	2010 rollout 1,600 (14.8%)	2011 rollout 4,477 (41.4%)	2012 rollout 3,050 (28.2%)	Test
age at interview	58.09 (8.78)	57.96 (8.67)	58.50 (9.05)	57.85 (8.82)	0.011
education level					
0.educ: up to primary	1,585 (93.8%)	1,490 (93.1%)	4,218 (94.2%)	2,858 (93.7%)	0.457
1.educ: vocational or university	104 (6.2%)	110 (6.9%)	259 (5.8%)	192 (6.3%)	
male	0.47 (0.50)	0.47 (0.50)	0.46 (0.50)	0.47 (0.50)	0.785
married or partnered	0.89 (0.31)	0.90 (0.29)	0.88 (0.32)	0.88 (0.33)	0.021
rural hukou	0.98 (0.14)	0.98 (0.12)	0.98 (0.15)	0.98 (0.15)	0.271
lives in rural or urban	0.71 (0.46)	0.78 (0.41)	0.77 (0.42)	0.69 (0.46)	<0.001
has public health insurance	0.94 (0.24)	0.94 (0.24)	0.95 (0.23)	0.94 (0.23)	0.785
amount of transfers from children/grandchildren	1763.22 (6281.33)	1673.03 (8317.33)	1407.93 (6032.37)	1807.38 (8443.21)	0.082
number of people living in this household	3.64 (1.82)	3.75 (1.80)	3.65 (1.87)	3.88 (1.90)	<0.001
# of living children	2.68 (1.41)	2.84 (1.42)	2.71 (1.37)	2.76 (1.40)	0.006
child coresiding or in same city/county	0.90 (0.31)	0.92 (0.27)	0.91 (0.29)	0.93 (0.26)	<0.001

Table A.2: Summary Statistics in 2011, by age-groups

	never 60 3,360 (31.1%)	always 60+ 4,347 (40.2%)	turning 60 later 3,109 (28.7%)
CESD (unstandardized)	8.04 (6.15)	9.67 (6.51)	8.84 (6.51)
CESD	-0.04 (0.97)	0.22 (1.03)	0.09 (1.02)
Cognition Total	178.85 (61.62)	144.00 (70.68)	162.29 (66.32)
Cognition	0.84 (0.51)	0.60 (0.57)	0.72 (0.55)
age at interview	48.50 (2.54)	67.07 (5.90)	56.18 (1.97)
education level			
0.educ: up to primary	2,989 (89.0%)	4,272 (98.3%)	2,890 (93.0%)
1.educ: vocational or university	371 (11.0%)	75 (1.7%)	219 (7.0%)
ever died (by time t)	0.00	0.00	0.00
male	0.44	0.49	0.47
married or partnered	0.95	0.80	0.93
retired	0.16	0.38	0.21
rural hukou	0.98	0.97	0.98
receive public pension	0.01	0.32	0.04
age started receiving public pension	49.51	66.29	55.32
anyone in HH receives public pension	0.03	0.36	0.10
anyone in HH receives any pension	0.05	0.41	0.13
# of HH members with (any) pension	0.05	0.63	0.15
income from public pension	25.31 (424.87)	392.67 (1549.51)	107.09 (860.69)
HH income from public pension per capita	26.43 (327.79)	423.04 (1570.83)	149.21 (890.22)
amount of transfers from children/grandchildren	927.34 (3774.36)	2196.60 (8326.78)	1551.03 (8148.86)
number of people living in this household	3.92 (1.63)	3.44 (1.98)	3.91 (1.89)
# of living children	2.13 (0.90)	3.45 (1.58)	2.41 (1.09)
child coresiding or in same city/county	0.91 (0.28)	0.93 (0.25)	0.90 (0.30)
nrps_ct	0.30	0.30	0.31

Regression using county-level rollout

Table A.3: Regression using county-level rollout, with Individual FE

	(1) receive pension	(2) receive pension	(3) pension income	(4) pension income	(5) CESD	(6) CESD	(7) Cognition	(8) Cognition
nrps_ct	0.00357	0.565***	0.514	286.0***	-0.0100	-0.0363	-0.0187	-0.0358
	(0.00749)	(0.0455)	(7.504)	(36.65)	(0.0478)	(0.0581)	(0.0252)	(0.0274)
ID FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16691	16188	16518	15516	16691	16188	13428	10393
r2	0.472	0.554	0.477	0.638	0.658	0.648	0.673	0.710
N_clust	147	147	147	147	147	147	146	145
sample	never 60	always 60+	never 60	always 60+	never 60	always 60+	never 60	always 60+
controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Comparison of dataset to Huang & Zhang (2021)

We run the same specification as HZ on both their data, and our data (the CHARLS data harmonized by the Gateway (g2aging)). We also only use the first two waves of CHARLS, 2011 and 2013. Appendix Table A.4 is the same as Table B6 in their paper, reproduced using the same dataset that is available on their online appendix. Appendix Table A.5 shows summary statistics. Appendix Table A.6 replicates the same table using our dataset from g2aging. Appendix Table A.7 shows summary statistics using our dataset from g2aging. Since we use the harmonized version of the data, results may slightly differ due to different ways of constructing household income.

We obtain coefficients of a similar magnitude in our dataset when using the same outcome variables, suggesting that our results are consistent with the results in HZ.

Table A.4: Table B6 (online Appendix) in Huang & Zhang (2021): CHARLS data

	(1)	(2)
	HH rec. pension	Log HH income
nrps_ct	0.429***	0.206
	(0.0460)	(0.133)
Observations	11960	11624

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: Summary Statistics in Huang & Zhang (2021): CHARLS data: rural elderly 60+

	(1)	
	mean	sd
nrps_ct	0.68	0.47
=1,men;=0,women	0.48	0.50
age in decimal	68.72	7.04
educ	1.46	0.74
rural	1.00	0.00
survey year	2012.07	1.00
HH rec. pension	0.48	0.50
Log HH income	9.73	1.40
Observations	11962	

Table A.6: Table B6 from in Huang & Zhang (2021): using waves 1 & 2 of CHARLS g2aging version

	(1) HH rec. pension	(2) Log HH income	(3) HH rec. pension (g2)	(4) Log HH income (g2)	(5) CESD
nrps_ct	0.417***	0.210	0.575***	0.0470	-0.111
	(0.0482)	(0.133)	(0.0429)	(0.115)	(0.0603)
Observations	11164	10848	11272	10413	10107

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Columns 1 and 2 estimate Equation 1 on g2aging data waves 1 and 2, using the outcome variables merged from HZ. Columns 3 and 4 estimate the same model on comparable outcome variables from our g2aging data.

Table A.7: Summary Statistics in Huang & Zhang (2021): using waves 1 & 2 of CHARLS g2aging version: rural elderly 60+

	(1) mean	 sd
nrps_ct	0.68	0.47
=1,men;=0,women	0.48	0.50
age at interview	68.23	6.96
educ	1.45	0.72
rural	1.00	0.00
survey year	2012.08	1.00
HH rec. pension (g2)	0.63	0.48
HH rec. pension	0.48	0.50
Log HH income (g2)	8.58	1.61
Log HH income	9.73	1.39
Observations	11890	

Table A.8: TWFE regression with FE, IV results

	(1) CESD	(2) CESD	(3) std(total cognition)	(4) std(total cognition)
receive public pension	-0.0653**	-0.0737**	-0.0737***	-0.0793***
	(0.0323)	(0.0289)	(0.0173)	(0.0158)
F	209.13	20.05	241.33	13.55
income from public pension (log)	-0.0111**	-0.0126**	-0.0125***	-0.0135***
	(0.00549)	(0.00496)	(0.00292)	(0.00268)
F	207.74	20.03	242.44	13.59
N	36115	34438	29666	27182
Cohort FE	Yes	(nested)	Yes	(nested)
County FE	Yes	(nested)	Yes	(nested)
ID FE	No	Yes	No	Yes
Province-time FE	Yes	Yes	Yes	Yes

Notes: Outcome variables are the standardized total CESD score. Each variable is instrumented by area-age-eligility

Table A.9: Regression Table: Household-level area-age-eligibility

	(1)	(2)	(3)	(4)
Panel A1: anyone in HH receives public pension				
nrps_ctXage60_ht	0.357***	0.448***	0.526***	0.565***
	(0.0212)	(0.0244)	(0.0184)	(0.0213)
N	38588	37024	33269	33269
Panel A2: HH income from public pension per capita				
nrps_ctXage60_ht	372.1***	485.1***	568.9***	642.0***
	(0.123)	(0.145)	(0.112)	(0.135)
Panel B1: CESD				
nrps_ctXage60_ht	-0.0495	-0.0589*	-0.0158	-0.0233
	(0.0371)	(0.0345)	(0.0350)	(0.0418)
N	36481	34806	31070	31070
Panel B2: Cognition				
nrps_ctXage60_ht	-0.0191	-0.0328	-0.0280	-0.0571
	(0.0229)	(0.0198)	(0.0318)	(0.0466)
N	29989	27495	24090	24090
Cohort FE	Yes	(nested)	(nested)	(nested)
County FE	Yes	(nested)	(nested)	(nested)
ID FE	No	Yes	Yes	Yes
Province-time FE	Yes	Yes	Yes	Yes
N	38478	36919	35933	35933
r2	0.498	0.692		
N_clust	150	150	150	150
controls	Yes	Yes	Yes	Yes
model	TWFE	TWFE	CS ATT	Event Post_avg

Standard errors clustered at the county level in parentheses

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

Notes: Table reports results from Equation 2. Standard errors are clustered at the county level. Controls included are gender, education and marriage status (married and partnered).
Outcome variables are the standardized total CESD score in Panel A, pension receipt in Panel B, and pension income in Panel C. Household-level variables are used