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Does a Universal Pension Reduce Elderly Poverty in China?

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Abstract

This paper studies the impact of the universal pension programme on elderly poverty in both rural and urban China. Using the three rounds of panel data based on the Health and Retirement Longitudinal Study (CHARLS) in 2011-2015, we examine whether the universal pension programme reduced elderly poverty, comprehensively defined to cover both unidimensional and multidimensional poverty indices of the households and individuals. To utilise the longitudinal nature of the data, we apply the robust Fixed-Effects (FE) Model with Propensity Score Matching (PSM) and the FE Quantile Model with PSM taking into account the unobservable individual characteristics, such as entrepreneurship or risk preference. Our results show that the universal pension programme reduced poverty in monetary and non-monetary terms in both rural and urban areas. While rural people tend to continue to work in the labour market after the receipt of the pension, urban people work less due to the negative income effect of the programme. The panel quantile regression results suggest that the programme decreased the inequality in both monetary and non-monetary dimensions. Our results provide strong evidence to underscore the success of the Chinese universal pension programme in reducing poverty and inequality in both rural and urban areas.

Keywords: Poverty, Inequality, Multidimensional Poverty Index (MPI), Pension, Impact evaluation, China

JEL Classification: C23, I32, I38, H75

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Does a Universal Pension Reduce Elderly Poverty in China?

1. Introduction

The objective of the present study is to examine whether a universal pension programme reduced elderly poverty in China. While evidence from cross-country studies (outside China) suggests that pensions play a crucial role in poverty alleviation and old-age support systems in developing countries (Barrientos et al., 2003), little is known about whether this conclusion would apply to China. Despite the spectacular economic growth of China during the last few decades, 14.9% of the population was still below the international poverty line at US$1.90 (2011 PPP) a day in 2008, while the county further reduced the poverty rate based on the same poverty line dramatically to 0.1% in 2019.[1] Another serious problem faced by the country is the acceleration of population ageing. As a consequence of longer life expectancy and lower fertility rate, more than 176 million people were over 65 by the end of 2019, comprising 12.6% of all population.[2] In contrast to well-developed welfare systems in Europe, a pension had been regarded as a "privilege" only for workers of governments and State-Owned Enterprises (SOEs) - due to the low and unequal coverage - before the universal pension reform was implemented in 2009. The earlier pension system mostly neglected the large population in rural areas (particularly those working in the agricultural sector) and treated pensioners in different occupations differently.

Given the dual problems - the acceleration of ageing and the low welfare of the elderly -, the Chinese government started a series of pension reforms in 2009 to cover all population into the universal pension protection system in a phased manner. As stated in the State Council's announcement, the eligible rural workers over 60 became entitled to an annual pension of at least 660 yuan in 2009 (about US$97 in the 2009 exchange rate[3]). This basic flat-rate pension amount was adjusted every year with different increment rates applied in different provinces. Due to the large population size in China, the government was not able to implement the policy universally at once. Starting with the 10% of all prefecture-level cities, the pension reform was planned to roll out to cover all of the country and achieve universal coverage by 2020.

The main research questions the present study aims to address are: (i) Did participation in the new pension scheme reduce elderly poverty - proxied by unidimensional or multidimensional poverty of the household to which a program participant belongs, or the individual income, the labour market participation status and working hours?; and (ii) Were the poverty-reducing or welfare-improving effects of the universal pension programme different across different distributional points in the outcome variables? While the previous studies showed poverty-alleviating effects of pension programmes in other countries (e.g., Vietnam- Long and Pfau, 2009; India - Unnikrishnan and Imai, 2020), to our knowledge, there has not been any work to evaluate the poverty-reducing effect of the pension system in China except a few focusing only on rural areas (e.g., Zhang et al., 2020; Huang and Zhang, 2021). The current study aims to fill the gap by estimating the impact of the universal pension programme on both single-dimensional and multi-dimensional poverty using the nationally-representative large panel data covering both urban and rural areas.

When analysing poverty using household survey data, the results are sensitive to the choice of poverty indicators (e.g., the choice of poverty thresholds or units (Imai and You, 2014)). In the present study, we proxy elderly poverty by using several variables to reflect this. First, in our analysis, poverty is estimated at both individual and household levels. To avoid the problem of collinearity, pension income is subtracted from total individual income to capture poverty at the individual level. At the household level, the poverty incidence (based on both national and international poverty lines), per capita expenditure and the Multidimensional Poverty Index (MPI) are adopted as poverty indicators. Besides poverty, the labour market is another area of concern, likely to be affected by the introduction of a universal pension. Here we use a binary variable on the working status and individual's weekly working hours to investigate the effect of a universal pension on labour market decisions.

To address the unobservable characteristics for obtaining robust estimates of the effect of a universal pension programme on elderly poverty, this study employs the panel data constructed by using the China Health and Retirement Longitudinal Survey (CHARLS) in 2011, 2013 and 2015.[4] The identification strategy is based on the phased rollouts of the reform and the eligible ageing residents' characteristics. We use the eligibility status to identify the treated group, while we also use the actual treatment status as a robustness check. Propensity score matching (PSM) allows us to construct comparable pairs of individuals with similar characteristics for treatment and control groups. However, PSM applied to cross-sectional data suffers from a limitation that matching is based only on observable individual characteristics. In order to overcome this limitation and take into account the time-invariant unobservable characteristics, we apply the Fixed Effect (FE)-PSM to the panel of 2011, 2013 and 2015. As poverty-reducing effects are likely to differ depending on the level of consumption or income or the probability/degree of poverty - single- or multi-dimensional -, we also estimate the FE quantile model to address the heterogeneous impact of the universal pension programme. This will provide an important insight into the programme's impact on inequality.

The contribution of our paper to the literature is summarised as follows. First, using the large nationally-representative panel data, poverty and inequality indicators are calculated to demonstrate recent poverty and urban-rural inequality trends from 2011 to 2015 in China. The past empirical works have analysed poverty trends in China, but few examined the urban-rural disparity among the middle and older populations (Du et al., 2005; Brown and Park, 2002; Imai and You, 2014). The second contribution is identifying the causal effect of the universal pension programme on elderly poverty by using the quasi-experimental methods based on the panel data, such as the FE-PSM model and the FE-PSM quantile model. Although several studies examined the relationship between poverty and social welfare in developing countries (Barrientos et al., 2003; de Carvalho Filho, 2008; Long and Pfau, 2009), there have been only a few studies on China and they focused only on rural areas. Our contribution focuses on poverty among the elderly – comprehensively defined to cover both monetary and non-monetary aspects and covering both rural and urban areas. Also, this is the first study to estimate the differential impacts of the universal pension programme at different distributional points in the outcome variables to provide an implication for the change in inequality caused by the universal pension programme.

The rest of this paper is organized as follows. In Section 2, we introduce some institutional background and review the relevant literature. Section 3 discusses our empirical strategies. Section 4 presents the main results and Section 5 concludes.

2. Literature review

The relationship between pension and poverty reduction is widely researched worldwide. Most studies confirm the role of pensions in alleviating elderly poverty (Case and Deaton, 1998; Duflo, 2003; Barrientos, 2003). For instance, Barrientos (2003) finds that non-contributory pensions have a measurable impact on poverty reduction in Brazil and South Africa. Unnikrishnan and Imai (2020) show that India's pension programme helps improve beneficiaries' consumption expenditure, food and non-food expenditure and assets. Viet Nguyen (2021) finds that social pensions in Vietnam have a significant effect on household income, but effects on working, saving, and healthcare services are limited among the elderly.

The accelerating ageing in China has caused poverty problems among the older population (Lloyd-Sherlock, 2000). The low fertility rate as a consequence of the One-Child Policy introduced in the 1970s - together with higher longevity due to the improvement in health and nutrition – increased the overall dependency of the elderly on younger generations over time.

Chen and Fang (2021) identify the causal impact of the family planning policies in 1970 on elderly parents. They found that the affected generation has a lower fertility rate. If fewer children live close by, they are more likely to report depression symptoms. Thus, it places more pressure on the poverty problem among the old population, especially on those living in rural areas (Qiao et al., 2006; Cai et al., 2012). A number of policy measures taken by the Chinese government reduced poverty over the past decades where social assistance programmes play a crucial role in poverty alleviation (Chen and Ravallion, 2004).

China had not developed a universal pension as a key component of the modern welfare system before the New Rural Social Pension Program (NRSP) was introduced in 2009. The previous pension programme was only available for urban workers of governments or SOEs. NRSP started to provide the numerous rural workers with a flat-rate basic pension and a contribution-based personal account pension. It was compulsory for the local governments to provide this programme but individuals can choose to participate or not. The basic part is financed by central and local governments, while personal pensions depend on how much they have contributed. Beginning with NRSP, China's central government implemented a series of policies to reform the Chinese pension system. In 2011, the Urban Resident Pension Pilot programme (URPP), which shared the same mechanism as NRSP, was introduced for urban workers who were out of government or SOEs. These two similar pension programmes were unified in 2014 into the Urban and Rural Basic Pension System (URBPS).

The earlier studies on the Chinese pension system were mainly qualitative or descriptive. Many of them focus on the former pension system (e.g., Feldstein, 1999; Wang, 2006). Regarding the studies on the universal pension reform since 2009, earlier studies focus on aspects other than poverty reduction. Feng et al. (2011), for instance, reveal a significant offset effect of pension wealth on household savings. Cai et al. (2012) thoroughly reviewed the welfare of the rural elderly and explored the evolution of pension systems in rural China. The authors argued that more attention should be paid to rural areas where the dual problems of accelerating ageing and poverty are more pronounced than in urban areas. However, in more recent years, a few studies have examined the poverty or welfare impacts of NRSP in rural areas. For instance, using the CHARLS data in 2015, Zhang et al. (2020) apply the fuzzy regression discontinuity design to the local average treatment effect of NRSP by utilising the fact that people became eligible at the age of 60 and find that NRSP significantly increased the expected food expenditure amongst the elderly or decreased the vulnerability defined as the probability of experiencing food poverty in the future. On the other hand, using the CHARLS and CFPS datasets in 2010-2013, Huang and Zhang (2021) make use of the phased introduction of NRSP at the county level and apply the difference-in-difference method to identify the effect on the eligible group after the introduction of the programme. The authors find that the pension scheme raises household income and food expenditure, while improving health and lowering mortality. Using the Chinese Household Income Project survey data for 1988, 1995, 2002 and 2013, Li et al. (2020) investigate the role of public pensions in income inequality among households with elderly members and conclude that pension income was the largest source of income inequality for elderly households since 2002. However, it should be noted that the authors did not take into account the endogeneity associated with participation in the pension scheme (e.g., different probabilities of a household or an individual accessing the pension programme) and it is not clear whether it actually increased overall inequality. To estimate the health impacts of NRSP, Cheng et al. (2018) apply the fixed-effects instrumental variable (FE-IV) model to the 2008/09 and 2011/12 waves of Chinese Longitudinal Healthy Longevity Survey data where the instrument is the programme implementation duration at the county level. The authors have found, consistent with the findings by Huang and Zhang (2021), that pension income improved objective measures of physical health and cognitive function of the rural elderly. To our knowledge, however, there has not been any study to evaluate the impact of the universal pension programmes in both urban and rural areas. Our study contributes to this literature by utilising the longitudinal nature of the CHARLS data in 2011-2015 - the period during which the nation experienced a dramatic poverty reduction - and estimating the impact of the pension programme on the elderly poverty in both rural and urban areas. So this is the first comprehensive study to examine the heterogeneous impact of the universal pension programme in *both rural and urban areas* of China to fill the gap in the literature.

3. Data and Methodology

Data

To analyse the effect of the new universal pension programme on poverty among the ageing population, we construct the panel data based on the three waves of the China Health and Retirement Longitudinal Study (CHARLS) in 2011, 2013 and 2015.[5] The survey is nationally representative of the Chinese residents aged 45 and above and collects rich data on household and individual characteristics, including demographics, family structures, household assets, individual health status, income and expenditures. Households and individuals in the survey are followed up every two years to enable us to construct the panel data.

The 2011 baseline survey was conducted in 28 provinces, 150 counties/districts, 450 villages/urban communities, across the country. All samples were drawn in four stages: county-level sampling, neighbourhood-level sampling, household-level sampling and respondent-level sampling.[6] At the first stage, all county-level units (except Tibet) were stratified by region, rural or urban and GDP per capita. After sorting, the population of each county was listed, along with the cumulative population. The 150 counties/districts were selected by a defined interval.[7] In the second stage of neighbourhood-level sampling, CHARLS selected 3 Primary Sampling Units (PSUs) within each county-level unit, using ‘Probabilities Proportional to Size sampling’. Next, CHARLS conducted household-level sampling based on maps with the support of local informants. If each PSU sampling frame was accurate and enumerated, 80 households were randomly sampled in the geographical frame. CHARLS then interviewed all age-eligible sample households in each PSU who were available and willing to participate in the survey[8]. In the final stage of Respondent-level sampling, CHARLS used a short filter survey to identify whether the household had a member meeting our age eligibility requirements (i.e., 45 or older)[9]. The selected qualified person becomes a main respondent and CHARLS also interviewed his or her spouse. It should be noted that CHARLS did not collect the data for the individuals younger than 45, but this will not cause any problem in our analysis of poverty impacts because the eligible individuals are matched by PSM (where virtually no individuals under 45 will be matched to the eligible individuals).

Figure 1 provides sample distribution among provinces. In this administrative map of China, deeper colour indicates that more samples were collected in that province. Among all 34 provinces, there are six provinces (Shandong, Henan, Sichuan, Yunnan, Hebei and Anhui) that take up more than 5% of the whole sample. This reflects the survey design reflecting both the population density and the proportion of rural residents. In the eastern region, Shandong, Henan, Hebei and Anhui are the four main agricultural provinces with a high population density. According to the 2010 census, both Shandong and Henan had over 90 million residents registered, taking up over 7% of the national population. Hebei and Anhui had 71 million and 59 million residents respectively, each counting for around 5% of the national population (NBS, 2010). In the south-east region, Sichuan and Yunnan, mountainous lands prevent their urbanization process. They were with 80 million (Sichuan) and 45 million (Yunnan) residents, mostly in rural areas. The sample distributions in other provinces are also consistent with the entire population distribution.

[Figure 1 inserted around here]

The sample in the 2011 wave covers 17,708 individuals. The sample size changed to 18,567 in 2013 and further increased to 21,061 in 2015. For the main analysis, only observations for the individuals aged between 45 and 75 are kept as the people in this age group were most likely to be affected by the universal pension programme in which the individuals not comparable to the recipients are dropped by applying PSM. The individuals below 45 were not surveyed, but this would not influence the results as those people are unlikely to be matched with the treated individuals. To eliminate the effect of the very rich on the results, individuals with per capita expenditure above 1,000,000 yuan were capped at 1,000,000. After all these adjustments, 21,858 individuals remain in the dataset. To maximize the coverage of the individuals, we have constructed the unbalanced panel data where 53% are observed three times, 23% twice, and the rest (24%) only once.

In order to consider regional differences across different pension areas properly, we employ the household registration (*HuKou*) to identify whether the individual belongs to the urban or rural area. For instance, there are 3,918 individuals from urban areas among all 17,251 individuals in the first wave of data, taking up 23% of the total population. This proportion does not change much in the next two waves.

Variables

As described above, NRSP was implemented first in 10 % of all prefecture countries and gradually rolled out nationwide later. In principle, all workers above 60 years old can receive an unconditional pension if their *HuKou* is included as part of the NRSP-available areas in the transition periods (2011-15). URPP in the urban area was implemented in the same way. We define the eligibility status by using an indicator variable that takes 1 if (i) the individual is over 60 years old and (ii) the universal pension programme is available in his/her *Hukou* place and 0 otherwise. This would measure the “Intention to Treat (IIT)” of the universal pension programme. As a robustness check, we also define the treated group based on whether an individual actually received the pension by utilising the questionnaire on the enrolment status.

We adopt several poverty indicators to estimate poverty at both individual and household levels as the results are sensitive to the choice of the poverty threshold or proxies for poverty. At the individual level, we adopt the individual income, the labour market participation status or working hours as the main outcome variable. At the household level, the poverty incidence (under both national and international poverty lines), per capita expenditure and the Multidimensional Poverty Index (MPI) are adopted as poverty measures. In 2003, China raised the national poverty line to 2,300 yuan per person per year to reflect the rise in the average living standard. This was yet much lower than the international poverty line of US$1.25 (at 2011 PPP) per day (equivalent to 2,875 yuan per year in 2011). This study mainly uses the national poverty line as a primary poverty threshold, while also adopting the international poverty line.

However, the monetary indicators are not adequate to understand the complexity of poverty. This is because the access to pension programme would mitigate not only monetary poverty - which is more or less expected -, but also non-monetary poverty, such as ill-health (e.g. chronic illness) or deteriorated living standards (e.g. poor sanitation). Our focus on both monetary poverty and the MPI is justified because (i) the MPI embodies human beings’ capabilities in multiple dimensions, which are unlikely to be captured by the monetary poverty (Alkire and Foster, 2011) and (ii) subjective well-being (e.g., happiness or life satisfaction) is correlated with not only income or consumption but ill health or education (Kahneman and Krueger, 2006). Based on Alkire and Santos’s (2014) method and the data available in our study context, we develop the MPI by keeping the same three dimensions (education, health, living standards) as in Alkire and Santos but using different variables in each dimension. The composition of our MPI is detailed in Table 1.

(Table 1 to be inserted around here)

The MPI ranges between 0 and 1 where the higher index indicates the more impoverished situation of the household. Each of the three aspects contributes one-third to the index with a different number of sub-dimensions. In the category of education, if no one completed primary school in the household, it is considered ‘deprived’ (taking 0) or ‘not deprived’ (1) otherwise. Even though the pension programme targets the elderly, the income effect at the household level could relax the budget constraint and would help children complete primary school. Within the health category, two binary variables on disability and chronic illness are used. If there is any disabled household member, the binary variable on “Disabled” takes the value 1 and 0 otherwise. If any household member has more than three chronic illnesses, the binary variable on “Chronic illness” takes 1 and 0 otherwise. Both binary variables are given the same weight (1/6) and the two variables together compose the health dimension, taking up 1/3 of the entire MPI. The income effect of the pension income at the individual or household level would prevent household members from suffering from illness or old-age disability. Apart from the short-run income effect, the pension would provide the household with some security or insurance that would buffer any future shortfall in non-pension income. This would have a positive effect on mental health, which would indirectly influence the probability of suffering from illness, even if the amount of pension income is relatively small. For the category of the living standards, we employ five binary variables on the basic facilities of the house, i.e., electricity, running water, separate toilet, solid floor and necessary home appliances. The household is regarded as ‘deprived’ in each of these five dimensions if they do not have it. Each of the five sub-indicators is given the weight of 1/15, adding up to 1/3 for the dimension of living standards. Here we would expect the income effect or the insurance effect which would positively influence the living standard, such as improvement in the household assets.

Apart from monetary or non-monetary poverty discussed above, the labour market outcome of the individual could be affected by access to a universal pension program. There are many studies discussing the relationship between pension and labour outside China (see the studies on South Africa, e.g., Posel et al., 2006; Bertrand et al., 2003) but none for China. As the most important source of individual income, the role of labour income is non-negligible in poverty reduction. Here we employ a binary variable of working status as well as an individual's weekly working hours to investigate the effect of the universal pension on labour market decisions.

In the main econometric analyses, we choose covariates based on the empirical literature reviewed in the last section as well as the data availability. We include gender, education level, marriage status and self-rated health as covariates at the individual level, which are considered to be important determinants of income or poverty. Meanwhile, household size and structure (proportion of aged members) are employed to capture household characteristics, which would influence the intra-household resource allocations as well as the probability of having the household members eligible for the pension program. Table 2 lists all variables described above and their summary statistics in all three waves from 2011 to 2015.

(Table 2 to be inserted around here)

The first three rows list the critical identifiers in this quasi-experimental context. Individuals' age in 2011 is used to determine the qualification to receive the NRSP pension. If they are over 60 years old and living in the policy area, they are eligible for the new programmes. As participation in NRSP is on a voluntary basis, individuals may be eligible but choose not to join. Our definition of the NRSP participation based on the eligibility criteria thus capture the "intention to treat (ITT)" effect, although the case where eligible individuals did not participate is relatively rare in practice. If the NRSP works well, it is supposed to reduce poverty and labour market participation among the ageing population. Therefore, we expect individual income and per capita expenditure to increase, but the probability of falling below the poverty line (using domestic and international standards) and the probability and duration of working in the labour market to decrease.

An Empirical Framework

Before estimating the causal effect of pension reforms on the ageing population, we first use a class of the Foster-Greer-Thorbecke Indices (FGT) (Foster et al., 2010) and the Sen Poverty index (Sen, 1976) to measure the overall poverty and inequality trends in China from 2011 to 2015. We present the results based on the headcount ratio (the proportion of the population living below the poverty line), the poverty gap (the poverty depth measure defined as the average distance to the poverty line as a proportion of the poverty line) and the squared gap (the poverty severity measure where poverty gap is squared to capture inequality as well as poverty) (Bisogno, Chong, 2001). The Sen- Shorrocks-Thon poverty index places a greater weight on poorer people and is derived from equity considerations without necessarily using interpersonally comparable cardinal utility functions (Sen, 1976).

After we describe the overall change of poverty and inequality, we will estimate the main econometric model. We first apply PSM to construct a counterfactual distribution of the individuals without receiving NRSP. The Propensity Score (PS), the probability of an individual eligible for NRSP, is estimated by the Probit model (Equation (1)) which will be applied to each round of the panel data.

$$P_{it}(D_{it} = 1 \mid X_{it}) = \emptyset(\alpha X_{it}), \qquad t \in \{1, 2, 3\} \tag{1}$$

where P_{it} denotes the probability of individual i being eligible to the NRSP in wave t, $D_{it} = 1$ if individual i is eligible to receive NRSP at wave t and 0 otherwise, $\emptyset$ represents the cumulative distribution function of the standard normal distribution, α is the vector of parameter estimates and X_{it} denotes a vector of covariates for the individual i for the wave t. Covariates for matching and scoring should affect both participation and outcome variables (Jalan and Ravallion, 2003). Here we include gender, an age dummy variable showing whether the individual is equal to or above 60 years old, education, marital status and self-reported health in all three waves. To ensure the matching validity, the balancing property should be checked. If it is satisfied, each participant is matched to non-participants based on the propensity score, using the kernel density matching algorithm.[10] The incomparable samples outside the region of common support are dropped during the matching process.

After PSM and dropping all the observations outside the common support region, we apply the FE model to wipe out the effect of unobservable time-invariant characteristics of the individual (e.g., entrepreneurship and risk preference) which would affect outcome variables, such as MPI. As not all individual characteristics can be included, the unobserved difference would cause bias in the main equation for the outcome variable. The FE model is applied only for the individuals matched after PSM to address the within-individual variation in the balanced panel dataset as in Equation (2).

$$y_{it} = \alpha_0 + \alpha_1 D_{it} + \alpha_2 C_{it} + \dot{a}_i + u_{it} \tag{2}$$

where y_{it} is the outcome variables defined in the last subsection, D_{it} is the individual i's eligibility (or enrolment) at the time t, C_{it} is a vector of control variables including education, marital and health status, $\dot{a}_i$ is the individual fixed effect and u_{it} is the error term. It should be noted that, as all samples are collected among the middle-aged and above, the education level and gender hardly or never change over time. Thus, gender and education variables are only included in the matching process and dropped in the FE estimation.

As described above, we estimate the policy effect on both individual and household levels. However, the CHARLS data is collected on a household basis in a way that a sampling distribution of households reflects the distribution of the entire households in each geographical unit (e.g., village, province, nation). That means error terms are not independent but correlated within the household. Conventional error terms will lead to biased confidence intervals and t-statistics (Cameron and Miller, 2015). Meanwhile, possible outliers may exist in the data and affect the distribution of observations. To relax the basic assumptions on the independence and the normality of error term distributions, the variance-covariance matrix is adjusted by using a robust and clustered estimate where the standard errors are clustered at the household level in all the cases.

As an extension, we estimate the FE-PSM quantile model to (i) examine the heterogeneous impacts of the universal pension programme at different percentile points in the distribution of the outcome variable, y_{it} and (ii) to carry out the robustness check for the (robust) FE-PSM model addressing the heteroscedasticity in a different way by estimating the model at different quantiles with location-specific fixed effects. While there is a growing body of literature on quantile regression using panel data (e.g., Canay, 2011), it is not technically straightforward to estimate the panel quantile model. We follow Machado and Silva (2019) who proposed "the quantiles-via-moments estimator" based on the location-scale model for the panel quantile estimation. Suppose the vector X_{it}' consists of D_{it}, C_{it} and constant terms in Equation (2). The location-scale model can be written as:

$$y_{it} = \alpha_i + X_{it}'\beta + (\delta_i + X_{it}'\gamma)u_{it} \qquad (3)$$

$\eta(\tau)_i = \alpha_i + \delta_i Q_u(\tau)$

$\beta(\tau) = \beta + \gamma Q_u(\tau)$

where τ stands for τ-th quantile, X'_{it} and u_{it} are assumed to be independent, $Pr((\delta_i + X'_{it}\gamma) > 0) = 1$ (Machado and Silva, 2019, p. 147).[11]

4. Main results

Poverty trends

Table 3 shows the results of various poverty measurements in 2011, 2013 and 2015. Overall, all these aggregate figures indicate a reduction in poverty from 2011 to 2015 consistent with the national estimates based on the international poverty line discussed earlier. The first two rows compare the poverty headcount ratios by both domestic and international standards. In the pooled sample, the national poverty headcount decreased from 17% in 2011 to 8% in 2013 and further down to 6% in 2015. These figures are higher than those based on the official data[12] (9.12%, 6.06% and 4.06% in 2011, 2013 and 2015, respectively). It is reasonable as CHARLS data were collected among those over 45 with a higher representation in the rural area where people earn less than those in urban areas. This can be further verified by the headcount ratios for urban and rural subgroups. In 2011, the year when NRSP started, the domestic poverty headcount ratio was 5.4% in the urban sample, while over 20% in the rural sample. After four years of implementation, the poverty headcount ratio decreased to 2.3% in the urban subsample and 7.3% in rural ones. Using the international poverty line based on US$1.25 per day (2005 PPP), the above trend still holds with the absolute levels higher. Although poverty and inequality situations were getting better from 2011 to 2015, the large urban-rural disparity persisted for all poverty indicators.

(Table 3 to be inserted around here)

PSM

In the matching process, the inclusion of too many covariates often leads to violations of the common support assumption. We have thus chosen gender, education, marital status and health as covariates. The final models used for estimating the PS for all waves, i.e., 2011, 2013 and 2015, are presented in Table 4.

(Table 4 to be inserted around here)

After constructing the PS model, we use a Kernel density matching algorithm to pair treated individuals with their counterfactual ones. There are two key assumptions to make PSM valid. The first is the Conditional Independent Assumption (CIA), which means that outcomes are independent of programme participation and conditional on a set of observable characteristics (Becerril and Abdulai, 2010). The second assumption requires that the ATT is only defined within the region of common support (Heckman et al., 1997). After the Kernel density matching, we build the counterfactual group to pair treatment with control units. We repeated the same procedure separately for 2011, 2013 and 2015 waves.

Figure 1 shows common support regions. In all three figures, the proportion of matched controls is similar to that of the treated unit. To make PSM valid and meet the requirement of the second assumption, individuals outside the region of common support are dropped. In 2011, 9,567 of the total of 15,671 individuals are dropped, taking up 61.05% of the first wave. This is expected as the sample includes individuals 45 years or older while those 60 years or older are eligible for NRSP. In 2013, 9,284 of 16,312 samples are dropped, taking up 56.92%. In 2015, 9,815 of the total 17,926 samples are dropped, taking up 54.75%. A balanced panel dataset is constructed for the individuals within the region of common support in all three waves. Removing the individuals present only once or twice in the panel, there are 11,533 individuals in the reconstructed panel.

(Figure 1 to be inserted around here)

After matching and dropping all individuals out of common support areas, Figure 2 plots the distribution of the propensity score in the treatment and matched control group. It can be observed that the treatment and control units have a similar distribution in all three years, indicating that the overlap assumption is well satisfied. Our results have confirmed that the above two assumptions hold, which would validate the PSM procedure. The results of the balance test are reported in Appendix 1.

(Figure 2 to be inserted around here)

FE Model with PS Weighting

To wipe out the effect of time-invariant unobservable characteristics that would affect outcome variables, we utilise the panel data structure and estimate the treatment effect on the outcome variables using a FE model. The results for rural areas are presented in Table 5 and those for urban areas in Table 6 based on the eligibility status. The results based on the actual treatment (enrolment) are reported in Tables A5 and A6 in Appendix 2. As all samples are collected among the middle-aged and above, their education level and gender hardly changed over time. Thus, gender and education variables are omitted and dropped in the FE estimations.

(Tables 5 and 6 to be inserted around here)

The first row in Table 5 indicates the effect of NRSP eligibility on several outcome indicators for rural areas. While the individual income *without* pension or the household income is not affected by the access to NRSP, the individual income increased by 189% (the first three columns in Table 5). We find in the fourth column that per capita household expenditure increased by 11.1%. This implies that, although the pension is received by the recipient, the average household expenditure per person significantly increased. These results imply that the welfare - proxied by monetary measures - at the individual or household level improved significantly as a result of participation in NRSP.

However, while NRSP increased the individual income and the per capita household expenditure significantly, it had no significant effect on monetary poverty indices - defined as whether per capita household income is below the national poverty line of 2,300 (or 2,875) yuan per person per year. This would imply that, while the income (at the individual level) increased significantly as a result of participation in NRSP, we do not observe significant estimates on the probability of a household falling into consumption poverty (the fifth and sixth columns of Table 5). However, the panel quantile model shows that consumption poverty reduced significantly as a result of participation in NRSP (Table 7). Overall, while we do not have the disaggregated income data on all the household members, the results imply that other younger household members were dependent on the pension income. On the contrary, MPI, our proxy for non-monetary poverty, decreased by 6.2% if the household had a member eligible for the universal pension programme (the seventh column). We have disaggregated this into the three sub-components of MPI, education, health and living standards (the eighth to tenth columns). We find that pension income improved education poverty by increasing the schooling years of younger members of the household, suggesting that the pension income relaxed the budget constraint of the households and helped them spend more on education.

Poverty is defined in terms of disability and chronic illness reduced significantly, which is consistent with earlier findings (Cheng et al., 2018; Huang and Zhang, 2021). Poverty defined in terms of the living standard did not reduce significantly, as it is more about the asset deprivation which cannot change in the short run. Finally, whether or not the individual is eligible for the pension hardly changed the labour market outcomes, in terms of whether the individual worked in the labour market or the hours of working per week. So we do not observe the evidence that those who accessed the pension scheme significantly reduced their labour supply. However, the variable on self-evaluation of health status, one of the control variables, significantly increases the labour supply. Given the positive effect of pension on health status (Cheng et al., 2018), we cannot deny the possibility that the universal pension programme will have a *positive* effect on the labour market outcomes over time.

Table 6 indicates the results on the effect of the universal pension programme on poverty and well-being indicators in urban areas. Overall, we have confirmed the poverty-reducing effects of the universal pension programme, though the relative effects are smaller in urban areas than in rural areas, reflecting the initially high standards of monetary and non-monetary well-being in urban areas. The first and second columns indicated that the individual income with the pension income increased by 74%, but that without the pension income is not significantly influenced. Household income or expenditure was not significantly influenced (the third and fourth columns). As in rural cases, we do not observe statistically significant effects on income poverty indices (the fifth and sixth columns) - though significant effects are observed in the results of the quantile regression (Table 8), while MPI is significantly reduced in urban areas, but to a lesser degree than in rural areas. A similar pattern of the results is found for urban areas on sub-components of MPI. That is, poverty in education and poverty in health reduced significantly, while poverty in living standards (in terms of assets) was not significantly influenced by the household access to the universal pension. On the effects of the universal pension programme on the labour market outcomes, whilst the probability of the participant in the universal pension scheme working in the labour market is found to be not influenced by the pension income, hours of working per week are reduced significantly by nearly 3 hours at the 5 per cent significance level in urban areas. This result is in sharp contrast with the corresponding result for rural areas. While people in rural areas continued to work for roughly the same number of hours after they started to receive a pension, people in urban areas worked less, possibly due to the overall higher level of income in urban areas. Theoretically speaking, the transfer could have a negative income effect to reduce the incentive to work in the labour market, while the degree of reducing the labour supply is lower if the individual or the household's relative valuation of leisure to wage income, which tends to be lower among poorer households who are close to the subsistence level and have a higher incentive to keep or raise the income than to enjoy the leisure. It is surmised from our result on the negative and significant effect of the universal pension programme found for only urban areas, that the negative income effect is stronger for urban residents than for rural residents given that the former's income level is higher.

FE Quantile Model with PS Weighting

In order to examine the heterogeneous impacts of the universal pension programme, we have estimated the panel quantile model with PS weighting as an extension. The results for rural areas are presented in Table 7 and those for urban areas in Table 8. We mainly highlight the variables which show a statistically significant estimate.[13]

The second column of Table 7 indicates that the log of individual income (with the pension income) of rural residents increased significantly as a result of accessing the universal pension programme, but the percentage increase is much larger for poorer individuals (at the 10^{th} percentile of the individual income) where the increase rate is 274% than for the 'average' individual at the median (at the 50th percentile, with the increase rate 253%) or for the 'rich' households (at the 90th percentile, with the increase rate 224%) given that the individual income is defined in logarithm.[14] That is, in a relative sense, inequality between poorer and richer individuals is found to decrease as a result of the introduction of the universal pension programme. A similar pattern is found for the household expenditure (the fourth column) where the percentage increase as a result of the access to the universal pension programme changes from 24.1% at the 10th percentile (i.e., for the poor households) to 21.1% at the median and 17.9% at the 90th percentile (i.e., for the rich households). So the universal pension programme reduced inequality of household expenditure. This is in sharp contact with Li et al. (2020) who found that the public pension contributed to the widening of inequality between 2002 and 2013 at the national level. The difference could be due to the fact that we focus on a different period (2011-2015) using a different dataset as poverty reduced dramatically between 2013 and 2015 as noted earlier. More importantly, while Li et al. used the repeated cross-sectional data without controlling for the sample selection bias of the pension access, we use the panel data and control for the sample selection bias through PSM.

A broadly consistent result is found for poverty indices. For the income poverty index based on the upper poverty line in the sixth column (the lower poverty line in the fifth column), the absolute value of the estimated (negative) coefficient of the access to the universal pension programme decreases from a 7.7% (6.6%, though statistically non-significant) reduction for the poorest households at the 90th percentile (i.e. with the highest probabilities of being poverty) to 5.4% (4.2%) for the median households and 4.7% (3.4%) for the richest households at the 10th percentile.[15] Hence, poverty reduced in rural areas but at a larger degree for the poorest households. That is, not only did poverty decrease on average but also the severity of poverty decreased, which can be shown without using the inequality-sensitive poverty measures, such as a poverty gap measure. Multi-dimensional poverty also reduced significantly for not only the aggregate MPI but also sub-dimensions in MPI, including MPI in the living standards, while the magnitude of reduction is larger for the poorer households (the seventh to tenth columns). That is, the universal pension reduced inequality in multi-dimensional welfare. As found in Table 5, we do not observe any statistically significant estimates for the labour market outcomes in Table 7. This is consistent with statistically non-significant results for the individual income *without* the pension income across different percentiles (the first column of Table 7). That is, rural residents did not reduce their labour supply after participating in the universal pension programme *regardless of* their income level.

For urban residents, individual income without pension income significantly increased in urban areas across different percentiles (the first column of Table 8). This is more clearly observed for richer individuals (at the 10^{th} percentile) with a larger coefficient estimate than for poorer individuals (at the 90^{th} percentile). No significant estimates are found for the individual income without the pension income (the second column). This is consistent with the result that working hours reduced significantly across different percentiles (the last columns). Here, as expected, those who worked longer in the labour market reduced more working hours after the introduction of the universal pension programme. The probability of working in the labour market is not significantly influenced.

Household expenditure increased significantly to a different degree across different percentiles (e.g., by 12% at the 10^{th} percentile (the poorest), by 10% at the median and by 8.6% at the 75^{th} percentile). So as in rural cases, the universal pension programme reduced inequality to some extent. Income poverty is found to reduce only at the median, not at different percentiles. Consistent with the FE-PSM results in Table 6, the aggregate MPI decreased across different percentiles, but it is significant from the 10^{th} percentile to the median with the degree of reduction higher at the upper percentiles, suggesting some reduction in inequality in multidimensional welfare. Statistically significant estimates are found for all the sub-dimensions in MPI in education, health and living standards across different distributional points. We find that multi-dimensional wellbeing in sub-dimensions improved as a result of participation in the universal pension programme across different percentiles and its inequality was also reduced.

5. Conclusion

Evidence from cross-country studies found that pensions play a key role in reducing poverty among the ageing population in both rural and urban areas. Despite the rapid economic growth in the last several decades, China's old-age support system was not well developed until the universal pension reform in 2009. This study has examined the effect of China's universal pension programme on poverty in both monetary and non-monetary terms based on the Multidimensional Poverty Indices (MPI). More specifically, we have assessed the effects of the programme on per capita income, per capita consumption expenditure, and poverty headcount using domestic and international standards and the Multi-Dimensional Poverty Index (MPI). Besides, a pension provides the elderly an extra income, which could affect their labour market decision. Then we further investigate the effect of the new universal pension on the work decision and weekly working hours.

In this study, we have used the three waves of the household survey data CHARLS, namely, 2011, 2013 and 2015. The general trends of poverty and urban-rural inequality are demonstrated by a class of FGT indices and the Sen poverty index. Overall, all these macroeconomic figures indicate a reduction in poverty from 2011 to 2015. Although the huge urban-rural difference still exists severely in all three waves from 2011 to 2015, the inequality level decreased during the period.

With the help of the Propensity Score Matching (PSM) method, we reconstructed the sample as a treatment and control group by matching them based on the household characteristics. In the reconstructed balanced sample, the robust FE method is applied to eliminate the effects of time-invariant heterogeneity where the standard errors are clustered at the household level. As an extension, we have estimated the panel FE quantile model to examine the heterogeneous impact of the universal pension program.

Our econometric results show that, when a rural worker is eligible to receive NRSP, the programme positively affects the individual income (without the pension income) and the household consumption expenditure. Household consumption poverty was also significantly reduced (only in the panel quantile regression). We have found that the aggregate MPI as well as its sub-dimensions in education and health at the household level reduced significantly. It is notable that the pension income had a statistically-significant indirect effect of increasing the schooling years of children in the households to assist them to help them prevent dropouts or adopting a higher level of education. We do not observe any effect on the labour market outcomes of the individual after he or she accesses the universal pension programme, suggesting that those who started to receive a pension continued to work in the labour market to increase his or her income. The panel quantile regression results have suggested that NRSP reduced the inequality in both monetary and non-monetary wellbeing measures. For instance, we have found that NRSP reduced the inequality among the individual income with the pension due to the progressive nature of the pension system where everyone is entitled to the same amount of the pension regardless of the income level or the past contribution (during the period of our study). We have also found that NRSP reduced the inequality in household consumption expenditure. The panel quantile regression results suggest that MPI reduced to a greater degree among poorer households, that is, the inequality in non-monetary well-being also declined as a result of NRSP. The results suggest that rural participants in NRSP did not change their labour supply and kept their income. Hence, the pension income was used to raise their income and living standards in rural areas.

We have also confirmed that the universal pension reduced monetary and non-monetary poverty in urban areas to a lesser extent than in rural areas, reflecting the initial low levels of poverty and higher levels of income and consumption in urban areas. Individual income (with pension) increased, household consumption poverty reduced significantly (only in the panel quantile regression results), and MPI reduced significantly. The urban participants in the universal pension programme reduced on average weekly working hours by 2.8 hours, that is, the negative income effect of the pension due to the disincentive effect is observed only in urban areas. It is notable that the inequality in the individual income, household consumption expenditure and multi-dimensional well-being proxied by MPI decreased in urban areas. The overall smaller 'poverty-reducing' or 'well-being improving' effects of the universal pension programmes in urban areas than in 'rural areas' suggested that the rural-urban disparity also declined as a result of the introduction of the universal pension programme.

In sum, our empirical results based on the national panel data in 2011-2015 serve as strong evidence to underscore the success of the universal pension reform in 2009 introduced by the Chines government since the programme reduced both monetary and non-monetary measures in rural and urban areas. Notably, the universal pension programme reduced inequality among rural residents or urban residents to some extent. Given that the proportion of elderly in China keeps rising, the universal pension programme continues to play an essential role in the welfare of the elderly. The programme served as a milestone in unifying the long-divided welfare system for workers in the public and private sectors. What we have not examined, however, were the fiscal implications and the sustainability of the universal pension programme as the proportion of the elderly is expected to rise in the future. The future study should examine the cost-effectiveness of the universal pension programme as well as their poverty and inequality reducing potentials under different scenarios of growth performances and changes in the demographic structure using more recent data.

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Table 1: Revised MPI Framework

Dimensions	Indicator	Poverty Threshold	Weight
Education	Years of Schooling	Deprived if no household member has completed primary school	1/3
Health	Disabled	Deprived if any household member is disabled.	1/6
	Chronic Illness	Deprived if any household member has more than 3 chronic illnesses.	1/6
Living Standard	Electricity	Deprived if the household has no electricity.	1/15
	Water	Deprived if the household has no running water.	1/15
	Sanitation	Deprived if the household has no separate toilet.	1/15
	Flooring	Deprived if the household has a dirt, sand or dung floor.	1/15
	Asset Ownership	Deprived if the household does not own more than one of: radio, TV, telephone, motorcycle, washing machine, refrigerator or Internet.	1/15

Source: Author's adaption from Alkire, Santos (2014) and CHARLS data.

Table 2: Variable Definition and Summary statistics

Variable	Definition	Obs	Mean	S.D.	Min	Max
age (i)	Integer: age	34599	59.074	7.142	45	75
d (i)	dummy: =1 if age>=60	34599	0.456	0.498	0	1
Eligibility (i)	An indicator variable: =1 if eligible to receive the universal pension	34599	0.366	0.482	0	1
Enrolment (i)	An indicator variable: =1 if actually enrolled in the universal pension programme	34465	0.474	0.499	0	1
Poverty Indicators						
lincp (i)	Log Individual Income without pension	34599	2.740	4.189	0	15.16178
lindi_inc (i)	Log Individual Income (with pension)	34599	4.643	4.395	0	15.16178
linc (hh)	Log Household income (with pension)	24957	7.937	2.275	0	14.07706
lexp (hh)	Log per capita Household Expenditure	25718	8.789	0.911	0	13.18693
p01e (hh)	An indicator variable =1 if per capita Expenditure < National Poverty Line 2,300	25718	0.113	0.316	0	1
p02e (hh)	An indicator variable=1 if per capita Expenditure < International Poverty Line 2,875	25718	0.169	0.375	0	1
mpi (hh)	Multidimensional Poverty Index	34372	0.146	0.165	0	0.933333
mpi_edu (hh)	Educational Component of MPI	34467	0.133	0.340	0	1
mpi_health (hh)	Health Component of MPI	34447	0.117	0.232	0	1
mpi_living (hh)	Living-Standard Component of MPI	34391	0.187	0.182	0	1
Labor Supply Indicators						
working (i)	dummy: =1 if working	34,289	0.736	0.441	0	1
wwhour (i)	Integer: Weekly working hours	34,599	30.083	28.844	0	98
Control Variables						
male (i)	dummy: =1 if male	34599	0.477	0.499	0	1
edu (i)	dummy: =1 if receiving NRSP	34599	0.117	0.322	0	1
married (i)	dummy: =1 if married	34599	0.845	0.362	0	1
health_rate (i)	dummy:=1 if Selfrated above average	34599	0.733	0.442	0	1

hhsize (hh)	Integer: Household size	34599	3.518	1.692	1	16
aged_prop (hh)	Aged member proportion	34599	0.177	0.235	0	1

Note: (i) indicates the variable is on individual level, (hh) indicates it is on household level;
Source: Author's elaboration from CHARLS data

Table 3: Poverty Measurements in 2011, 2013 and 2015

	Full Sample			Urban			Rural		
	2011	2013	2015	2011	2013	2015	2011	2013	2015
Headcount Ratio(2,300)	0.171	0.08	0.06	0.054	0.025	0.023	0.203	0.098	0.07
Headcount Ratio(2,875)	0.248	0.122	0.1	0.087	0.044	0.034	0.292	0.147	0.12
Poverty Gap Ratio	0.061	0.027	0.02	0.017	0.007	0.008	0.073	0.026	0.02
Squared Gap Ratio	0.031	0.013	0.01	0.008	0.003	0.004	0.037	0.016	0.01
Sen Poverty Index	0.115	0.052	0.04	0.033	0.013	0.016	0.136	0.064	0.05

Source: Authors' elaboration based on CHARLS.

Table 4: PS estimation in 2011, 2013 and 2015

	2011	2013	2015
male	-0.0142	0.0583	0.0479
	(0.0329)	(0.0430)	(0.0351)
edu	0.326***	-0.152**	0.00908
	(0.0645)	(0.0761)	(0.0647)
married	0.0865**	0.0729	-0.00859
	(0.0402)	(0.0526)	(0.0440)
health	0.125***	-0.00920	0.0491
	(0.0345)	(0.0461)	(0.0380)
_cons	0.0397	1.279***	1.020***
	(0.0436)	(0.0566)	(0.0477)
N	6104	7028	8111

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

Source: Authors' elaboration based on CHARLS data

Table 5: Full FE Estimation with PS weighting in Rural Areas - Eligibility

	lincp	lindi_inc	linc	lexp	p01e	p02e	mpi	mpi_edu	mpi_health	mpi_living	Working	wwhour
Eligibility	-0.0203	1.891***	0.111	0.111***	-0.0144	-0.0184	-0.0621***	-0.113***	-0.0231***	0.00776	-0.00599	-0.115
	(0.101)	(0.122)	(0.116)	(0.0409)	(0.0177)	(0.0202)	(0.00569)	(0.0132)	(0.00550)	(0.0178)	(0.0115)	(0.770)
married	-0.710***	-0.503***	-0.351*	0.250***	-0.0668***	-0.0964***	0.00962	0.00457	0.00350	-0.0315	0.0266*	-0.578
	(0.153)	(0.154)	(0.187)	(0.0621)	(0.0241)	(0.0262)	(0.00715)	(0.0165)	(0.00703)	(0.0256)	(0.0148)	(1.083)
health	0.525***	0.430***	0.108	-0.00622	-0.00487	0.000399	-0.00499	-0.0113	-0.00186	-1.357***	0.0450***	3.016***
	(0.0894)	(0.0954)	(0.0904)	(0.0283)	(0.0117)	(0.0132)	(0.00391)	(0.00905)	(0.00407)	(0.0137)	(0.00928)	(0.681)
hhsize	0.0510*	0.0748**	0.211***	-0.196***	0.0367***	0.0542***	-0.00596***	-0.0287***	0.0101***	0.00155	0.00569*	0.386*
	(0.0306)	(0.0317)	(0.0421)	(0.0127)	(0.00513)	(0.00594)	(0.00126)	(0.00276)	(0.00165)	(0.00514)	(0.00308)	(0.229)
agedpop	0.286	0.198	-0.0105	0.486***	-0.173***	-0.187***	-0.122***	-0.285***	-0.0525***	-0.0153	-0.0599*	-8.013***
	(0.297)	(0.348)	(0.365)	(0.120)	(0.0456)	(0.0529)	(0.0151)	(0.0352)	(0.0152)	(0.0508)	(0.0348)	(2.213)
_cons	2.530***	3.198***	7.013***	9.120***	0.0785**	0.100***	0.195***	0.316***	0.166***	4.028***	0.720***	30.07***
	(0.203)	(0.208)	(0.253)	(0.0826)	(0.0311)	(0.0342)	(0.00875)	(0.0200)	(0.00972)	(0.0336)	(0.0201)	(1.438)
N	27549	27549	19984	20307	20307	20307	27380	27456	27398	26917	27349	27549

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

Source: Authors' elaboration based on CHARLS data

Table 6: Full FE Estimation with PS weighting in Urban Areas - Eligibility

	lincp	lindi_inc	linc	lexp	p01e	p02e	mpi	mpi_edu	mpi_health	mpi_living	working	wwhour
Eligibility	-0.379	0.741**	0.443	0.0587	-0.00827	-0.0432	-0.0360***	-0.0532**	-0.0285***	-0.00163	-0.0355	-2.872**
	(0.295)	(0.375)	(0.283)	(0.0813)	(0.0254)	(0.0305)	(0.00891)	(0.0207)	(0.00989)	(0.0463)	(0.0277)	(1.406)
married	-0.256	-0.449	0.381	0.147	-0.0416	-0.0599	0.0191	0.0132	-0.00120	0.110	-0.0443	-0.616
	(0.451)	(0.548)	(0.423)	(0.141)	(0.0439)	(0.0551)	(0.0139)	(0.0266)	(0.0182)	(0.0824)	(0.0383)	(2.225)
health	0.904***	1.061***	0.414*	-0.0382	0.0217	0.0227	-0.0167**	-0.0188	-0.00579	-1.291***	0.0170	2.462*
	(0.257)	(0.318)	(0.251)	(0.0619)	(0.0163)	(0.0206)	(0.00738)	(0.0145)	(0.00832)	(0.0356)	(0.0240)	(1.343)
hhsize	-0.0284	0.344***	0.0248	-0.168***	0.0150*	0.0395***	0.00200	-0.00320	0.0108***	-0.0149	0.00562	0.773
	(0.106)	(0.119)	(0.0853)	(0.0294)	(0.00857)	(0.0128)	(0.00288)	(0.00647)	(0.00353)	(0.0161)	(0.00921)	(0.540)
agedpop	-0.709	-1.599	-0.806	0.520**	-0.0331	0.0420	-0.0150	-0.0463	-0.00230	-0.0284	-0.144*	-1.970
	(0.830)	(1.012)	(0.950)	(0.227)	(0.0623)	(0.0867)	(0.0233)	(0.0464)	(0.0269)	(0.130)	(0.0767)	(3.806)
_cons	3.067***	5.529***	8.239***	9.522***	0.0189	-0.0192	0.104***	0.0880**	0.109***	3.886***	0.511***	16.19***
	(0.584)	(0.692)	(0.552)	(0.183)	(0.0574)	(0.0753)	(0.0174)	(0.0365)	(0.0209)	(0.107)	(0.0540)	(3.225)
N	6333	6333	4559	4902	4902	4902	6281	6297	6282	6161	6248	6333

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

Source: Authors' elaboration based on CHARLS data.

Table 7: Quantile Estimation in Rural Areas - Eligibility

	lincp	lindi_inc	linc	lexp	p01e	p02e	mpi	mpi_edu	mpi_health	mpi_living	working	wwhour
P10	0.0777	2.738***	0.0989	0.241***	-0.0340***	-0.0465***	-0.0766	-0.148***	-0.0575***	-0.0272***	-0.0198	-0.310
	(0.0947)	(0.401)	(0.0902)	(0.0338)	(0.0121)	(0.0133)	(0.0489)	(0.0200)	(0.00533)	(0.00558)	(0.0976)	(0.986)
P25	0.0909	2.647***	0.0924	0.232***	-0.0362**	-0.0487***	-0.0889**	-0.164***	-0.0633***	-0.0364***	-0.0206	-0.725
	(0.0710)	(0.312)	(0.0706)	(0.0272)	(0.0141)	(0.0122)	(0.0399)	(0.0172)	(0.00500)	(0.00413)	(0.0604)	(0.706)
P50	0.102	2.529***	0.0761	0.211***	-0.0417*	-0.0543***	-0.104***	-0.190***	-0.0741***	-0.0471***	-0.0220	-1.475
	(0.0775)	(0.209)	(0.0859)	(0.0203)	(0.0248)	(0.0101)	(0.0295)	(0.0135)	(0.00498)	(0.00334)	(0.0867)	(0.918)
P75	0.132	2.345***	0.0651	0.189***	-0.0596	-0.0730***	-0.147***	-0.270***	-0.132***	-0.0646***	-0.0229	-2.313
	(0.171)	(0.159)	(0.132)	(0.0298)	(0.0704)	(0.0150)	(0.0145)	(0.0177)	(0.0113)	(0.00499)	(0.142)	(1.750)
P90	0.144	2.244***	0.0607	0.179***	-0.0659	-0.0771***	-0.157***	-0.310***	-0.172***	-0.0716***	-0.0234	-2.693
	(0.215)	(0.220)	(0.152)	(0.0371)	(0.0864)	(0.0176)	(0.0191)	(0.0253)	(0.0179)	(0.00623)	(0.172)	(2.168)

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

Source: Authors' elaboration based on CHARLS data

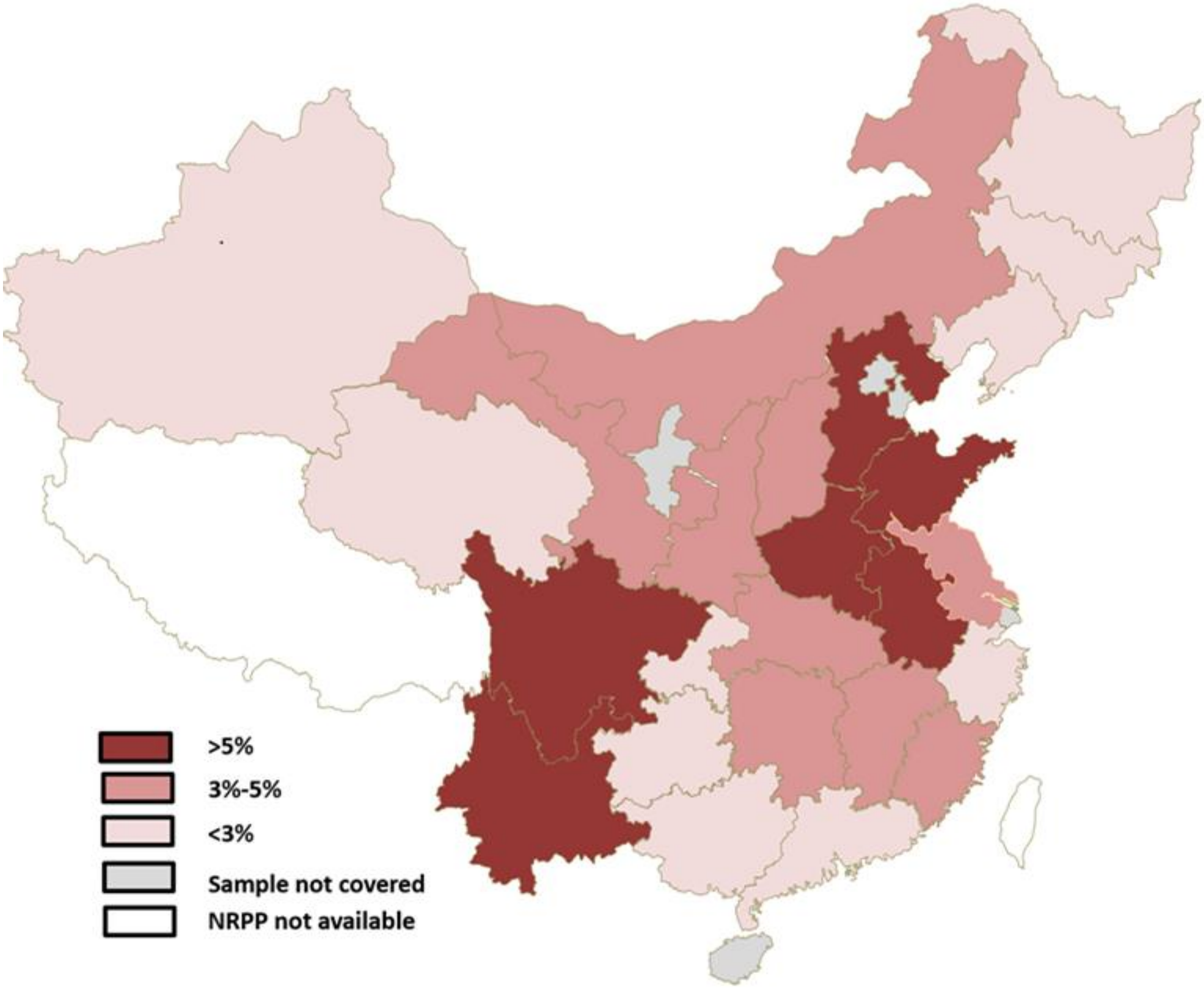
Table 8: Quantile Estimation in Urban Areas - Eligibility

	lincp	lindi_inc	linc	lexp	p01e	p02e	mpi	mpi_edu	mpi_health	mpi_living	working	wwhour
P10	-0.600*	0.474	0.324	0.120*	-0.0180	-0.0354	-0.0369***	-0.0480***	-0.0320**	-0.0305***	-0.0526	-2.504**
	(0.320)	(1.008)	(1.325)	(0.0668)	(0.0145)	(0.0262)	(0.0115)	(0.0152)	(0.0154)	(0.0113)	(0.117)	(1.256)
P25	-0.585**	0.465	0.321	0.114**	-0.0190	-0.0369	-0.0417***	-0.0538***	-0.0355**	-0.0337***	-0.0473	-2.741***
	(0.244)	(0.823)	(1.052)	(0.0534)	(0.0130)	(0.0226)	(0.0115)	(0.0147)	(0.0144)	(0.00839)	(0.0838)	(0.968)
P50	-0.560***	0.437	0.315	0.1000***	-0.0218*	-0.0397**	-0.0520**	-0.0701***	-0.0475***	-0.0368***	-0.0387	-3.092***
	(0.166)	(0.340)	(0.435)	(0.0334)	(0.0114)	(0.0167)	(0.0250)	(0.0206)	(0.0165)	(0.00745)	(0.0342)	(0.717)
P75	-0.537***	0.426	0.310	0.0860**	-0.0268	-0.0469**	-0.0655	-0.0944**	-0.0667**	-0.0433***	-0.0345	-3.581***
	(0.205)	(0.332)	(0.256)	(0.0414)	(0.0189)	(0.0192)	(0.0475)	(0.0375)	(0.0304)	(0.0122)	(0.0244)	(0.986)
P90	-0.522*	0.418	0.308	0.0796	-0.0293	-0.0496*	-0.0717	-0.113**	-0.0796*	-0.0461***	-0.0293	-3.803***
	(0.269)	(0.426)	(0.353)	(0.0528)	(0.0249)	(0.0255)	(0.0581)	(0.0522)	(0.0418)	(0.0156)	(0.045)	(1.258)

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

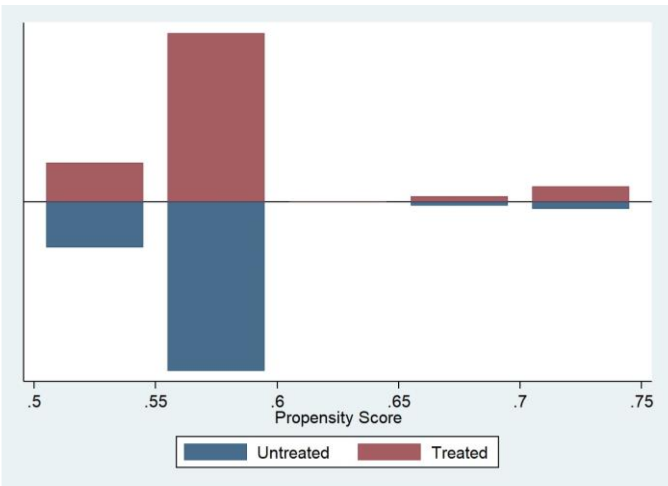
Source: Authors' elaboration based on CHARLS data.

Figure 1: Province Distribution in Constructed Dataset

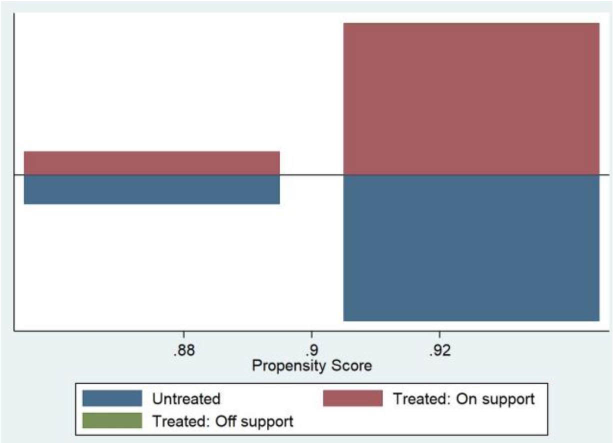


Source: Author's elaboration from CHARLS, 2011

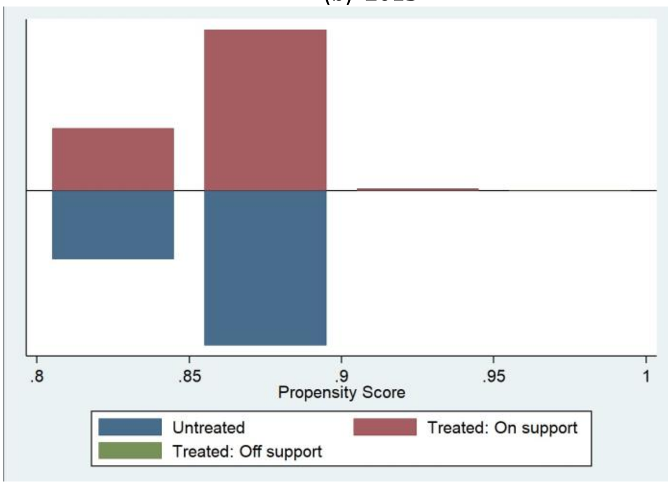
Figure 2: Regions in common support in 2011, 2013 and 2015



(a) 2011



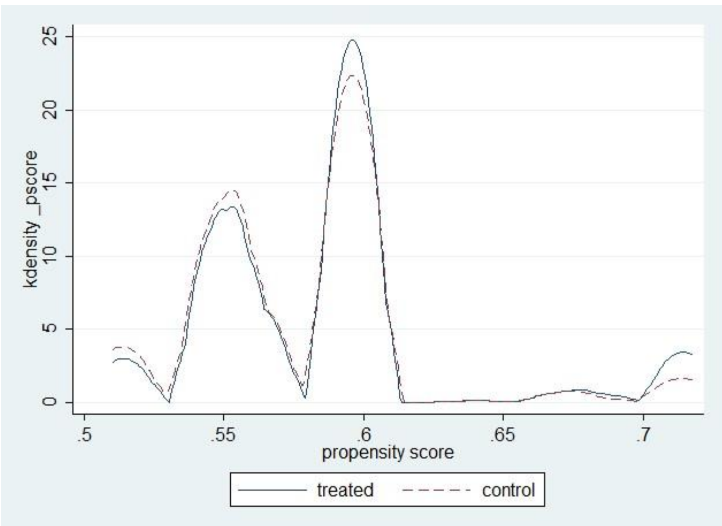
(b) 2013



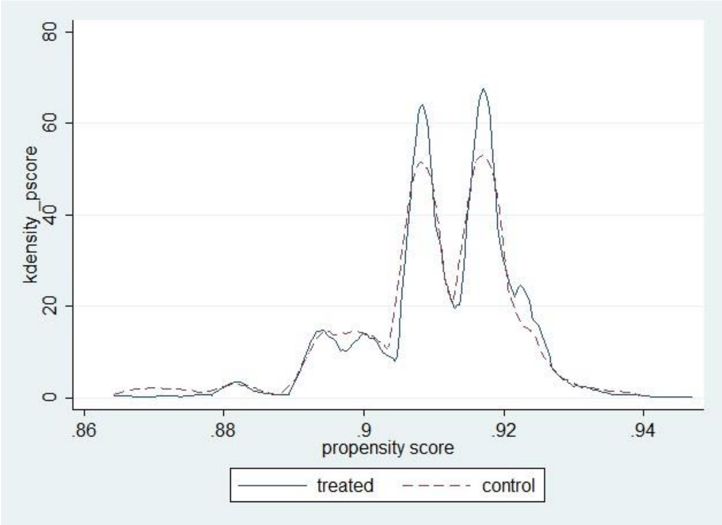
(c) 2015

Source: Authors' elaboration based on CHARLS data

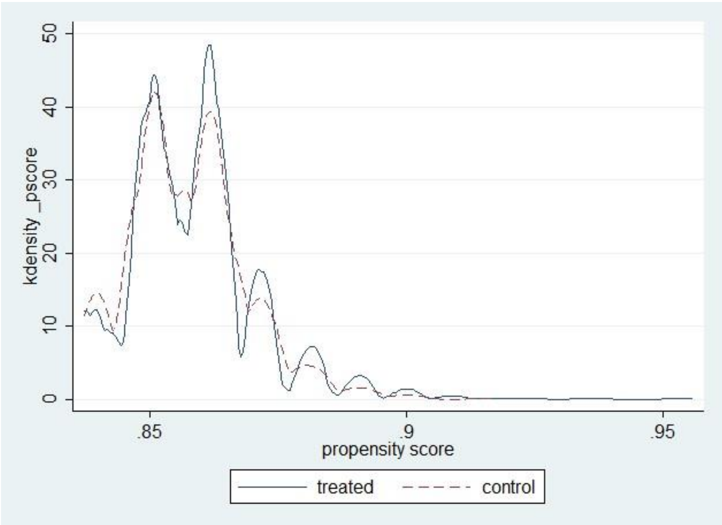
Figure 3: Full Distribution of PS across Treatment and Comparison Groups in 2011, 2013 and 2015



(a) 2011



(b) 2013



(c) 2015

Source: Authors' elaboration based on CHARLS data

Appendix 1: Balancedness Test for PSM

Various standard tests for overall balancing of the treated and untreated samples for 2011, 2013 and 2015 are in Panels A, B and C of Table A1. After matching there should not be any difference between the treatment and control group, which implies a low pseudo-R-square (Caliendo and Kopeinig, 2008). This is approved by the fairly low pseudo-R-square in the first column. The likelihood ratio test on the joint insignificance of the covariates is still rejected in both 2013 and 2015. The reduced mean and median bias in the 4th and 5th columns indicates a reduction in the systematic differences in the distribution of covariates between treatment and control groups. Although there is an only exception in 2013, where mean bias slightly increases from 5 to 5.4, the overall balancedness has improved. The Rubin's B is the absolute standardised difference of the means of the PS. Rubin (2001) suggests that Rubin's B-value after matching should be less than 25. Rubin's R-value should be higher than 0.5 but less than 2 for the treatment and control group to be balanced. In all three waves, the Rubin's B value after matching falls considerably below the recommended value of 25. Meanwhile, the Rubin's R, which is the ratio of the treated to non-treated variances of the PS, was relatively well balanced before the matching and remained so after. These statistics all suggest the overall balancing improvement is taken as a positive.

Table A1: Balance test for each covariate after Matching 2011, 2013 and 2015

	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	Rubin’s B	Rubin’sR	%Var
2011								
Unmatched	0.006	47.890	0.000	5.600	4.000	18.000	1.350	0.000
Matched	0.001	7.240	0.299	2.200	1.900	6.400	1.070	50.000
2013								
Unmatched	0.002	9.120	0.167	5.000	5.600	12.400	0.830	0.000
Matched	0.005	85.560	0.000	5.400	5.500	16.400	1.190	100.000
2015								
Unmatched	0.002	10.330	0.112	3.500	4.000	10.300	1.220	50.000
Matched	0.002	41.120	0.000	3.100	2.000	10.900	1.330	50.000

Source: Authors' elaboration based on CHARLS data

Table A2: Balance test for each covariate after Matching for 2011

	Unmatched	Mean			%reduct	t-test		V(T)/
Variable	Matched	Treated	Control	%bias	|bias|	t	p>t	V(C)
male	U	0.51281	0.50372	1.8		0.7	0.484	.
	M	0.51281	0.51645	-0.7	59.9	-0.31	0.759	.
d	U	1	1	.		.	.	.
	M	1	1	.	.	.	.	.
edu	U	0.09063	0.0537	14.3		5.41	0	.
	M	0.09063	0.08941	0.5	96.7	0.18	0.857	.
married	U	0.80411	0.77891	6.2		2.4	0.016	.
	M	0.80411	0.79808	1.5	76.1	0.64	0.524	.
health	U	0.689	0.64014	10.4		4	0	.
	M	0.689	0.69076	-0.4	96.4	-0.16	0.872	.
Household size	U	3.414	3.4159	-0.1		-0.04	0.969	1.01
	M	3.414	3.4187	-0.2	-145.7	-0.1	0.918	1.02
Proportion of people	U	0.39387	0.39513	-0.6		-0.22	0.826	0.97
	M	0.39387	0.39278	0.5	13.5	0.21	0.834	1.01

* if variance ratio outside [0.98; 1.02] for U and [0.98; 1.02] for M

Source: Authors' elaboration based on CHARLS data

Table A3: Balance test for each covariate after Matching for 2013

	Unmatched	Mean			%reduct	t-test		V(T)/
Variable	Matched	Treated	Control	%bias	|bias|	t	p>t	V(C)
male	U	0.50273	0.4752	5.5		1.31	0.189	.
	M	0.50227	0.47703	5	8.3	2.85	0.004	.
d	U	1	1	.		.	.	.
	M	1	1	.	.	.	.	.
edu	U	0.07372	0.0944	-7.5		-1.87	0.062	.
	M	0.07383	0.07776	-1.4	81	-0.84	0.401	.
married	U	0.8079	0.7824	6.3		1.54	0.124	.

	M	0.8076	0.79289	3.6	42.3	2.08	0.037	.
health	U	0.69327	0.696	-0.6		-0.14	0.888	.
	M	0.69341	0.69539	-0.4	27.5	-0.24	0.808	.
Household size	U	3.5346	3.4256	5.8		1.37	0.172	1.04
	M	3.5198	3.412	5.7	1.1	3.28	0.001	1.02
Proportion of people	U	0.37502	0.38417	-4.4		-1.06	0.29	1.01
	M	0.37548	0.38374	-4	9.8	-2.28	0.022	1.04
1.01								

* if variance ratio outside [0.98; 1.02] for U and [0.98; 1.02] for M

Source: Authors' elaboration based on CHARLS data

Table A4: Balance test for each covariate after Matching for 2015

	Unmatched	Mean			%reduct	t-test		V(T)/
Variable	Matched	Treated	Control	%bias	|bias|	t	p>t	V(C)
male	U	0.49598	0.47263	4.7		1.47	0.142	.
	M	0.4959	0.47689	3.8	18.6	2.24	0.025	.
d	U	1	1	.		.	.	.
	M	1	1	.	.	.	.	.
edu	U	0.0806	0.07732	1.2		0.38	0.704	.
	M	0.08073	0.07833	0.9	26.6	0.52	0.6	.
married	U	0.80675	0.80626	0.1		0.04	0.968	.
	M	0.80673	0.80607	0.2	-34	0.1	0.921	.
health	U	0.71509	0.69505	4.4		1.39	0.164	.
	M	0.71478	0.70312	2.6	41.8	1.51	0.13	.
Household size	U	2.902	2.8115	7.2		2.19	0.028	1.24*
	M	2.8888	2.7772	8.9	-23.2	5.47	0	1.28*
Proportion of people	U	0.41311	0.41966	-3.5		-1.11	0.269	1.03
	M	0.41362	0.42217	-4.6	-30.4	-2.73	0.006	1.03

* if variance ratio outside [0.98; 1.02] for U and [0.98; 1.02] for M

Source: Authors' elaboration based on CHARLS data.

Appendix 2: FE Estimation based on the actual enrolment status

Table A5: Full FE Estimation with PS weighting in Rural Areas - Enrolment

	lincp	lindi_inc	linc	lexp	p01e	p02e	mpi	mpi_edu	mpi_health	mpi_living	working	wwhour
Enrolment	0.0475	1.239***	0.201**	0.103***	-0.0325***	-0.0421***	-0.0398***	-0.0743***	-0.0324***	-0.0125***	0.00532	0.0783
	(0.0748)	(0.0820)	(0.0872)	(0.0268)	(0.0108)	(0.0126)	(0.00364)	(0.00836)	(0.00354)	(0.00384)	(0.00723)	(0.542)
married	-0.715***	-0.434***	-0.350*	0.255***	-0.0671***	-0.0971***	0.00736	0.00140	0.0178**	0.00249	0.0265*	-0.643
	(0.154)	(0.154)	(0.187)	(0.0624)	(0.0241)	(0.0263)	(0.00724)	(0.0165)	(0.00719)	(0.00705)	(0.0148)	(1.083)
health	0.500***	0.399***	0.103	-0.00639	-0.00502	0.000143	-0.00521	-0.0107	-0.00252	-0.00162	0.0449***	2.597***
	(0.0901)	(0.0952)	(0.0902)	(0.0283)	(0.0118)	(0.0132)	(0.00397)	(0.00913)	(0.00372)	(0.00410)	(0.00928)	(0.679)
hhsize	0.0490	0.167***	0.217***	-0.190***	0.0356***	0.0529***	-0.00901***	-0.0342***	-0.00210	0.00898***	0.00541*	0.383*
	(0.0306)	(0.0316)	(0.0415)	(0.0127)	(0.00507)	(0.00589)	(0.00129)	(0.00284)	(0.00139)	(0.00163)	(0.00300)	(0.224)
agedpop	0.253	2.342***	0.0912	0.615***	-0.185***	-0.203***	-0.192***	-0.411***	-0.0848***	-0.0794***	-0.0683**	-8.366***
	(0.272)	(0.310)	(0.303)	(0.103)	(0.0383)	(0.0440)	(0.0133)	(0.0312)	(0.0134)	(0.0131)	(0.0293)	(1.930)
_cons	2.535***	2.452***	6.896***	9.050***	0.0998***	0.128***	0.220***	0.360***	0.126***	0.174***	0.717***	30.51***
	(0.208)	(0.213)	(0.257)	(0.0846)	(0.0320)	(0.0351)	(0.00934)	(0.0211)	(0.00932)	(0.0101)	(0.0204)	(1.464)
N	27458	27458	19984	20292	20292	20292	27363	27431	27417	27377	27349	27458

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

Source: Authors' elaboration based on CHARLS data.

Table A6: Full FE Estimation with PS weighting in Urban Areas - Enrolment

	lincp	lindi_inc	linc	lexp	p01e	p02e	mpi	mpi_edu	mpi_health	mpi_living	working	wwhour
Enrolment	-0.246	0.131	-0.294	0.0968	-0.0147	-0.0410	-0.0208*	-0.0442*	0.00827	-0.0262**	-0.0415	-3.440*
	(0.361)	(0.381)	(0.275)	(0.0854)	(0.0298)	(0.0321)	(0.0108)	(0.0228)	(0.0128)	(0.0121)	(0.0319)	(1.799)
married	-0.336	-0.566	0.351	0.152	-0.0424	-0.0621	0.0194	0.0119	0.0478**	-0.00152	-0.0454	-0.955
	(0.452)	(0.544)	(0.417)	(0.141)	(0.0439)	(0.0551)	(0.0140)	(0.0268)	(0.0244)	(0.0183)	(0.0383)	(2.256)
health	0.853***	0.948***	0.394	-0.0403	0.0213	0.0220	-0.0165**	-0.0195	-0.0238**	-0.00599	0.0161	2.048
	(0.261)	(0.321)	(0.253)	(0.0614)	(0.0163)	(0.0209)	(0.00732)	(0.0144)	(0.0114)	(0.00829)	(0.0239)	(1.368)
hhsize	-0.0692	0.377***	0.0460	-0.163***	0.0139*	0.0359***	-0.000464	-0.00702	-0.00321	0.00877**	0.00295	0.516
	(0.106)	(0.119)	(0.0866)	(0.0287)	(0.00830)	(0.0126)	(0.00288)	(0.00636)	(0.00355)	(0.00352)	(0.00918)	(0.537)
agedpop	-1.326*	-0.772	-0.173	0.586***	-0.0472	-0.0217	-0.0626***	-0.116***	-0.0335	-0.0383	-0.189***	-5.956
	(0.732)	(0.832)	(0.790)	(0.187)	(0.0475)	(0.0714)	(0.0217)	(0.0424)	(0.0315)	(0.0242)	(0.0711)	(3.710)
_cons	3.310***	5.804***	8.320***	9.503***	0.0250	-0.00598	0.107***	0.0977***	0.109***	0.113***	0.520***	17.69***
	(0.595)	(0.691)	(0.556)	(0.183)	(0.0567)	(0.0752)	(0.0176)	(0.0372)	(0.0256)	(0.0209)	(0.0547)	(3.346)
N	6307	6307	4559	4898	4898	4898	6278	6293	6292	6279	6248	6307

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

Source: Authors' elaboration based on CHARLS data.

Endnotes

[1] Based on the World Bank estimates, the poverty rate (US$1.90) changed from 11.2% in 2010, 7.9% in 2011, 6.5% in 2012, 1.9% in 2013, 0.7% in 2015, 0.5% in 2016, 0.4% in 2017, 0.3% in 2018 and further down to 0.1% in 2019 (https://data.worldbank.org/indicator/SI.POV.DDAY?locations=CN Retrieved 7 June 2022). The reason for such a dramatic poverty reduction in recent years, in particular, from 2009 to 2015 is an important area of research the present study sheds light on.

[2] National Bureau of Statistics of China: https://data.stats.gov.cn/english/easyquery.htm?cn=C01 Retrieved 7 June 2022.

[3]1 US Dollar = 6.8279 Chinese Yuan Renminbi on 12/31/2011: https://www.exchangerates.org.uk/historical/USD/31_12_2009; Retrieved on 7 June 2022.

[4] Zhang et al. (2020) used only the 2015 data of CHARLS, while Huang and Zhang (2021) used the 2011 and 2013 waves of the CHARLS to be combined with the 2010 and 2012 waves of the CFPS (the China Family Panel Studies). These studies focused only on rural areas. Our study is unique as we use the panel for the entire nation covering both rural and urban areas based on the 2011, 2012, and 2015 waves of CHARLS, the period when poverty reduced dramatically.

[5] The latest wave of 2018 survey data was recently released but we have not included it because the identification of our econometric analysis relies on the phased introduction of the programme in 2011-15 where the program coverage increased stage by stage and our method cannot be credibly applied to the panel of 2015-2018 as nearly all the eligible people had already accessed the programme in 2015. That is, the 2015 wave is regarded as 'the fully-developed case' because, in 2014, the NRSP in rural areas and URPP in urban areas were unified as UPBRP and the universal pension system was fully developed and more consistent by 2014. However, the analysis of the 2018 wave or any future wave using a different

estimation method could be an important topic for future research.

[6] CHARLS website: http://charls.pku.edu.cn/pages/about/sample/en.html. Retrieved 8 June 2022.

[7] If N is the total population of all the county-level units and 150 is the number of counties to be sampled, then an interval is defined as n=N/150

[8] Some dwellings had multiple households living in them. In these cases, CHARLS randomly chose one household that had an age-eligible member. Thus, some variation exists in the number of completed household surveys in each PSU. This is corrected by using the sampling weights.

[9] If a household had more than one person older than 40 and met our residence criterion, they randomly selected one of them.

[10] Among different matching algorithms, Kernel matching is applied here and it compares the outcome of each participant to a weighted average of the outcomes of all non-participants where the weight depends on the distance between the two sample points (Heinrich et al., 2010). The advantage of the Kernel matching estimator is to minimize information loss (Caliendo and Kopeinig, 2008). The weights are then smoothed using a standard normal distribution. The use of other matching algorithms has not changed the final results significantly.

[11] See Machado and Silva (2019) for details. We use a Stata command, *xtqreg* written by Silva (https://www.stata.com/meeting/uk19/slides/uk19_santos.pdf Retrieved 8 June 2022).

[12] NBS: Statistical Bulletin of National Economic and Social Development, 2011, 2013, 2015.

[13] A full set of the results including the estimated coefficients of control variables will be provided on request.

[14] It should be noted that the FE result (at the mean) and the quantile FE result at the median

do not necessarily match. This is because (i) the distribution of most of the variables, such as income, is skewed towards the left and (ii) estimation methods are different where the panel quantile regression reflects the location-scale model (Machado, and Silva, 2019).

[15] It should be noted that for income or consumption P10 (the 10th percentile) represents the poorest households, while for poverty measures P10 represents the richest households.