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Does the rural social pension alleviate urban-rural health inequality of opportunity? Evidence from China

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Abstract

Aim: To examine the impact of the New Rural Pension Scheme (NRPS) on health disparities between the urban and rural elderly in China.

Methodology: The authors constructed health inequality of opportunity (IOp) based on the ex-ante principle and utilised panel data from the China Health and Retirement Longitudinal Study (2015-2018), employing both difference-in-differences (DID) and propensity score matching DID methodologies to assess the impact.

Results: It was found that enrolment in the NRPS significantly enhanced health levels of the rural elderly and reduced health inequality of opportunity between the urban and rural elderly by 6.67%. The impact was more pronounced among lower-income and older age groups.

Implications and recommendations: The findings suggest that targeted social pension programmes can effectively reduce regional health disparities. Future research should explore the long-term sustainability of these effects and their applicability to other developing countries with similar urban-rural divides.

Originality/value: This study uniquely applied inequality of opportunity theory to distinguish between 'justifiable' and 'unjustifiable' health disparities, providing a more comprehensive understanding of urban-rural health inequalities and demonstrating the effectiveness of social pension programmes in addressing these disparities.

Keywords: health inequalities, social pension, inequality of opportunity (IOp), urban-rural disparities

1. Introduction

Reducing health inequalities is an important public health challenge. Health inequalities are evident not only in developed countries (Chetty et al., 2016; Bosworth, 2018), but are also prevalent in developing countries (Gwatkin, 2017). China, as the largest developing country, also faces significant health inequalities, particularly among the urban and rural elderly. Figure 1 illustrates the proportions of elderly populations and their corresponding mortality rates in China from 2011 to 2020. Rural elderly individuals experience a significant health disadvantage compared to their urban counterparts. The rural elderly not only have significantly higher mortality rates than their urban counterparts, but also age more severely.

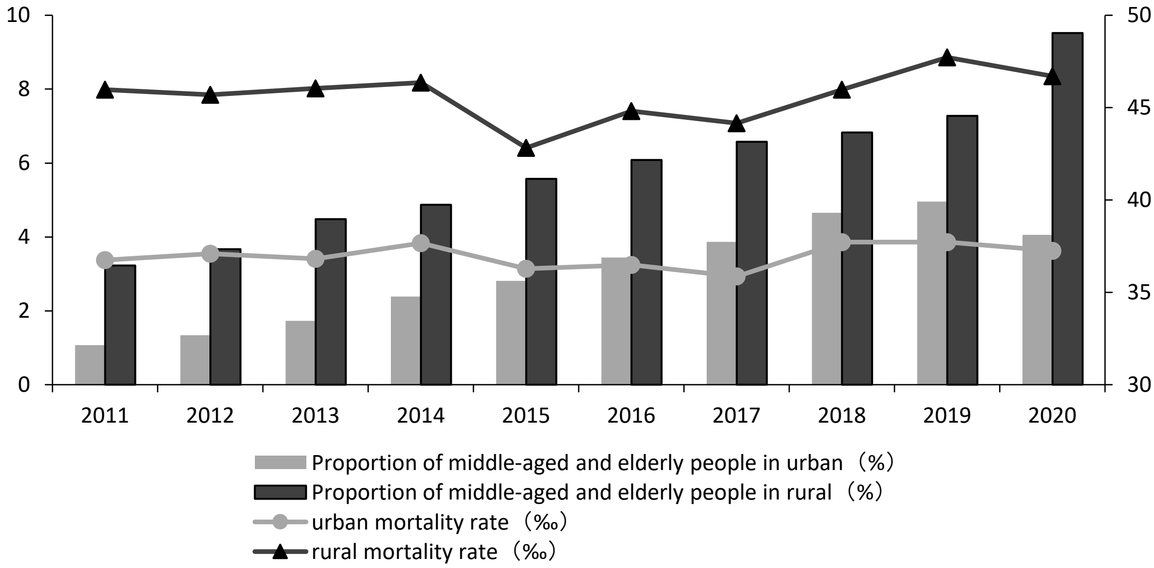


Fig. 1. Population proportion and mortality rate of the elderly in urban and rural areas from 2011 to 2020

Source: data from the National Bureau of Statistics of China.

Chinese policymakers are actively addressing health inequality. In October 2016, they promulgated the Healthy China 2030 blueprint, which explicitly set the goal of achieving health equity by 2023. Among the numerous policies targeting rural areas, the New Rural Pension Scheme (NRPS), designed for rural residents, has had a profound impact on the lives of the rural elderly. This significant social pension programme attracted widespread attention as soon as it was introduced. Abundant research indicates that the NRPS has had a significant effect on the rural elderly in terms of retirement, income, health, and well-being (Zhang et al., 2015; Zhang et al., 2016; Huang, & Zhang, 2021; Li et al., 2022). However, research examining whether the NRPS can effectively mitigate or even eliminate health inequality between urban and rural areas remains limited.

To investigate the impact of NRPS on urban-rural health inequalities, it is crucial to accurately measure the health disparities between urban and rural areas. Previous studies have primarily utilised absolute health differences between the urban and rural populations (Smith et al., 2008; Abdesslam, 2012; Cohen et al., 2018; Tang et al., 2024). However, these absolute differences may inherently include 'justifiable' disparities, and indiscriminately reducing them could potentially lead to more severe inequities (Ma et al., 2017). This study employs inequality of opportunity (IOp) to distinguish between 'justifiable' and 'unjustifiable' health disparities, thereby providing a more comprehensive understanding of the sources and structure of urban-rural health inequalities.

Following the establishment of a methodology for estimating urban-rural health disparities, The authors utilised data from the China Health and Retirement Longitudinal Study (CHARLS) to estimate the actual health levels of rural elderly individuals and the urban-rural health IOp, based on the ex-ante compensation principle for the years 2015 and 2018, and found that the actual health levels of the rural elderly increased by an average of 25.00%. Next, the difference-in-differences (DID) and propensity scorematching-difference-in-differences (PSM-DID) identification methods were applied to assess the impact of enrolment in the NRPS on the actual health of the rural elderly and the urban-rural health IOp. It was found that enrolment in NPRS leads to the enhancement of actual health levels of the rural elderly and a reduction in the urban-rural health IOp. Specifically, enrolment in the NRPS was associated with a 9.58% improvement in the average actual health level of the rural elderly and a 6.67% reduction in the average urban-rural health IOp when employing PSM-DID with controls for individual characteristics and province fixed effect. The benchmark results remained robust even after conducting sensitivity analyses by altering matching methods and changing the explanatory variables. Lastly, the authors conduct a heterogeneity analysis of income and age, finding that the impact of enrolment in the NRPS on the urban-rural health IOp was more pronounced among low-income and older individuals.

This paper contributes to two strands of literature. Firstly by extending the existing research on IOp, whereas previous research predominantly focused on examining income and health IOp (Davillas, & Jones, 2020; Hufe et al., 2022; Shi et al., 2022). These studies mainly analysed many circumstances about individual advantages and then ascertained the contributions of these factors to IOp employing the Shapley decomposition method. However, only limited publications investigated the impact of a policy targeting populations with adverse circumstances on health IOp. Secondly, by extending the existing literature on the effect of enrolment in the NRPS in the field of health research. Given that the NRPS targets rural residents, prior health-related research mostly focused on the rural individual health outcomes resulting from this policy. In addition to the previously mentioned studies, Du et al. (2022) examined the impact of NRPI on delaying cognitive decline among the rural elderly. Qian and Li (2020) investigated the effect of enrolment in the NRPS benefits on the health behaviour of the rural elderly, whilst Zheng and Fang (2018) explored the effect of enrolment in the NRPS on subjective well-being of the rural elderly. Only one study was closely related to the topic of this paper, but it employed the ex-post compensation principle to investigate the impact of the enrolment in the NRPS on urban-rural health IOp (Zhang, & Chen, 2022). Overall, there is little research that examines the impact of the enrolment in the NRPS on urban-rural health IOp based on the ex-ante compensation principle.

The rest of this paper is structured as follows: Section 2 provides a general introduction to the institutional background and IOp. Section 3 explains the data source and variables definition, and model specification. Section 4 reports the baseline empirical results, the robustness tests and the heterogeneity analysis. Section 5 summarises the main findings and concludes.

2. NRPS and urban-rural health IOp

2.1. Development and status of the NRPS

To effectively ensure the social care for elderly rural residents, the Chinese government initiated the NRPS pilot programme in 2009. By the end of 2012, the NRPS was extended to almost all counties and county-level administrative regions across the country, covering a substantial population of 460 million. The NRPS operates on a voluntary enrolment basis and primarily targets rural residents who are not covered by the urban employee basic pension insurance system. The eligibility criteria for the NRPS are that rural elderly individuals have accumulated 15 years of contributions or that their children make contributions. When they reach the age of 60, they start to receive NRP. The NRPS benefits consist of three main components: government subsidies, collective allowances, and individual contributions. Specifically, the central government provides a basic pension of no less than 55 RMB per person per month, while local governments provide additional subsidies of no less than 30 RMB per person per year in 2009.

In 2014 the Chinese government merged the NRPS with the Urban Residents Pension Scheme to create the Urban-Rural Resident Social Pension (URRSP). The basic framework of URRSP closely resembles the previous NRPS, with similar financing, entitlements, management, and supervision practices. As of the end of 2013, the total number of participants in URRSP nationwide reached 498 million, with only 23.99 million being urban residents. This implies that the majority of participants in the URRSP were rural residents, while the number of urban residents covered was relatively small. Given that the primary focus of this paper are rural residents, for the sake of consistency and unity, the merged residents' insurance is still referred to as the NRPS in this paper.

Table 1. Overview of the New Rural Pension Scheme

	(1)	(2)	(3)	(4)	(5)	(6)
Year	Minimum basic pension (Yuan/month)	Number of insured (million)	Number of claimants (million)	Average claim amount (Yuan)	Per capita disposable income (Yuan)	Pension replacement rate (%)
2009	55.00	869.10	155.60	–	5153.20	–
2010	55.00	1027.68	286.26	700.06	5919.00	11.83
2011	55.00	3264.35	892.18	658.72	6977.30	9.44
2012	55.00	4836.95	1338.22	859.13	7916.60	10.85
2013	55.00	4975.01	1412.23	954.73	9429.60	10.12
2014	70.00	5010.75	1474.17	1065.82	10488.90	10.16
2015	70.00	5047.22	1480.03	1430.17	11421.70	12.52
2016	70.00	5084.71	1527.03	1408.29	12363.40	11.39
2017	70.00	5125.50	1559.79	1520.85	13432.40	11.32
2018	88.00	5239.20	1589.80	1836.39	14617.00	12.56
2019	88.00	5326.60	1603.19	1942.56	16020.70	12.13
2020	88.00	5424.38	1606.82	2088.04	17131.50	12.19
2021	88.00	5479.74	1621.33	2291.33	18930.90	12.10

Source: data from the China Statistical Yearbook and Ministry of Human Resources and Social Security for the years 2010 to 2022, as well as the Statistical Bulletin on the Development of Human Resources and Social Security for the years 2009, 2018, and 2021. The statistical indicators in the table are reported in accordance with the social endowment insurance for urban and rural residents from 2014.

Table 1 presents essential information regarding the NRPS. One can easily observe that the NRPS is facing the problems of sustainability risk and insufficient protection, although it has made great progress since its introduction. Specifically, the first column of Table 1 shows the amount of basic pension provided by the central government equivalent to the fiscal transfer and is adjusted every four or five years to 88 Yuan per person per month in 2021. Columns (2) and (3) show the number of participants in the programme and the number of beneficiaries respectively. While the number of participants has been steadily increasing, the number of beneficiaries has undergone rapid growth. As a result, the ratio of participants to recipients declined from 3.66 in 2011 to 3.38 in 2021. The last three columns depict the average annual NRPS benefits, per capita disposable income, and the ratio between the two. Since the formal implementation of the NRPS in 2011, the proportion of the NRPS benefits to rural per capita disposable income fluctuated between 9.44% and 12.56%. This suggests that coverage of the NRPS could be improved.

2.2. Urban-rural health IOp

Measuring the urban-rural health disparity can be approached through various methods, with the most direct being the comparison of observed health indicators between urban and rural areas. However, this approach not only overlooks differences in individual efforts within each group, but also obscures the influence of circumstances in urban or rural areas. To comprehensively assess the urban-rural health disparity, the authors adopted Roemer's theory of IOp. Building upon Rawls' *A Theory of Justice* (1971), Roemer (1998, 2002, 2018) systematically expounded upon the theory of IOp. According to this theory, an individual's advantage is determined by two components: uncontrollable factors termed circumstances (c) and controllable factors termed effort (e).

In the framework of this theory, differences in individual advantages resulting from circumstances are considered unjust, whereas differences resulting from effort-based factors are considered fair. If the disparities among individuals in a society are solely attributable to effort and are independent of the circumstances, there is no IOp in that society. IOp can be divided into the principles of compensation and encouragement. The compensation principle primarily emphasises compensating for differences caused by the circumstances when efforts are the same. Conversely, the encouragement principle highlights that, under similar circumstances, varying degrees of effort should lead to different advantages. In the study of social justice, the compensation principle is considered more reasonable than the encouragement principle (Fleurbaey, & Schokkaert, 2009). Therefore, the compensation principle to assess urban-rural health IOp was adopted in this study.

Under the compensation principle, the measurement of IOp can be categorised into ex-ante compensation, which does not require information about individual effort, and ex-post compensation, which does require information about individual effort. Consequently, the methods for measuring IOp differ between the two. The following section introduces the specific measurement methods for both and analyses which method is more suitable for this paper.

2.2.1. Ex-post compensation principle

The principle of ex-post compensation primarily involves the construction of an individual's counterfactual health level in an ideal situation, taking into account individual circumstances and effort information. Subsequently, the magnitude of IOp is obtained by subtracting the actual health level from the counterfactual health level. This difference is also known as the fairness gap. For the sake of brevity, the term 'fairness gap' is used later to denote urban-rural health IOp. The authors followed the existing literature (Rosa Dias, 2009; Trannoy et al., 2009; Fleurbaey, & Schokkaert, 2011), and the measure of the fairness gap is as follows:

$$h_t = f(c_t, e_t, u) \tag{1}$$

Firstly, by fixing c_i as c^* in the ideal circumstance (residing in urban areas), a counterfactual health distribution, $h_i^* = f(c^*, e_i, u_i)$ is defined to eliminate the just shortfall. The fairness gap is then measured by taking the difference between this counterfactual health level and the actual health level. Specifically, the measurement method assumes that the specific functional form of health level h_i of individual i can be represented as

$$h_i = \alpha + \beta c_i + (\gamma + \lambda c_i) e_i + u_i, \quad (2)$$

where the factor in regard to residence is a dummy variable equal 1 if residence is urban, and 0 if residence is rural. Considering that the marginal return of inputs for health capital is likely to be different due to urban-rural disparities, an interaction term between the two is added to equation (2). Assuming that urban is the ideal circumstance ($c^* = 1$), the fairness gap is the difference between the counterfactual health level of the rural individual in urban and his/her actual health level

$$fg_i = h_i^* - h_i = \hat{\beta}(1 - c_i) + \hat{\lambda}(1 - c_i) e_i, \quad (3)$$

where fg_i is the urban-rural health fairness gap when $c_i = 0$. Finally, based on the ex-post compensation principle, the fairness gap is:

$$fg_i = \hat{\beta} + \hat{\lambda} e_i. \quad (4)$$

2.2.2. Ex-ante compensation principle

Similar to the ex-post compensation principle, the ex-ante compensation principle also necessitates a measurement of counterfactual health level when estimating the fairness gap, subsequently subtracting it from an individual's actual health level. In contrast, the ex-ante compensation principle does not require information about an individual's effort. It should be noted, though, that this does not imply a disregard for individual effort levels. In fact, the ex-ante principle of compensation requires that the individual's advantage (health) be proportional before and after compensation. In other words, it allows for different efforts to correspond to different individual advantages (health); the specific measurements are described below.

Firstly, since the resources available within a given society are certain, the fair distribution and the actual distribution utilise the same resources. The authors followed the IOp measurement literature and ruled out creatio ex nihilo (Hufe et al., 2022):

$$\textstyle\sum_N h_i = \sum_N {h_i}^*, \quad (5)$$

where h_i is the actual health level of individual i, and h_i^* is the counterfactual health level of individual i under fair distribution.

Secondly, the study defined the specific counterfactual health distribution of rural individuals. According to Fleurbaey and Peragine (2013), Ramos and Van de Gaer (2016), and Hufe et al. (2022), the levels of an individual's health should not be correlated with his or her circumstances which implies that the distribution of urban and rural individual health should be the same on average, thereby satisfying:

$$\frac{1}{N_u} \sum h_i^{u*} = \frac{1}{N_r} \sum h_j^{r*} = \mu_N, \quad (6)$$

where h_i^{u*} denotes the counterfactual health levels of urban individuals, h_j^{r*} the counterfactual health levels of rural individuals, and μ_N represents the mean of the overall distribution of actual health levels of urban and rural. Similarly, $\frac{1}{N_r} \sum h_j^{r*} = \mu^{r*}$ is the mean of the distribution of the counterfactual health of rural individuals, and $\frac{1}{N_r} \sum h_j^{r} = \mu^{r}$ is the mean of the distribution of the actual health of rural individuals.

Subsequently, it was established that an individual's health level should remain proportional before and after compensation. This regulation adheres to the fundamental principles of IOp, which involve preserving health disparities resulting from individual efforts. Within the same circumstances, the authors believe that effort should be respected and that counterfactual health levels of rural individuals should be proportional to actual health levels

$$\frac{h_j^{r*}}{\mu^{r*}} = \frac{h_j^{r}}{\mu^{r}}. \quad (7)$$

Hence, the counterfactual health level of rural individuals is

$$h_j^{r*} = h_j^r \frac{\mu^{r*}}{\mu^r}, \tag{8}$$

whereas, the fairness gap based on the ex-ante compensation principle is

$$fg_i = h_j^{r*} - h_j^r. \tag{9}$$

The ex-post compensation principle formally reflects better the impact of individual effort on health by taking individual effort information into account, but it also leads to a series of problems, such as whether the type of individual health function is reasonable, and whether effort information is omitted. These issues can potentially distort the measurement of health IOp. In addition, in policy practice, governments often directly compensate individuals in disadvantaged circumstances without considering effort-related information (Fleurbaey, & Peragine, 2013). Lastly, the existing body of literature predominantly employs the ex-ante approach for measuring health IOp, which is relatively more mature and well-established. Therefore, the authors adopted the ex-ante compensation principle that aligns more logically with policy implementation when examining the effect of the enrolment in the NRPS on urban-rural health IOp.

3. Methodology

3.1. Data sources

The authors utilised the China Health and Retirement Longitudinal Study (CHARLS) for the analysis. CHARLS is a biennial national survey designed to collect representative data from Chinese individuals aged 45 and older, encompassing various health indicators, insurance coverage information, and other individual characteristics. The survey's design was inspired by the Health and Retirement Study (HRS) in the United States.

The baseline data for CHARLS at national level originates from 2011, and it has since expanded to include four waves of panel data, spanning 2011, 2013, 2015, and 2018. In late 2012, the Chinese government announced that the NRPS achieved near-universal coverage across rural China. To ensure equal enrolment opportunities in the NRPS for all respondents, the study excluded data from 2011 and 2013 and retained only the nationally representative tracking data from 2015 and 2018.

Given the primary focus of the study on the elderly population, the analysis was restricted to individuals aged 60 and above. The examination of urban-rural disparities in elderly health opportunities necessitated the use of both urban and rural samples, whilst in the following analysis of the impact of enrolment in the NRPS on urban-rural health IOp, the authors used exclusively the rural sample.

3.2. Variable construction

3.2.1. Measure of actual health level

Measuring individual actual health levels forms the basis for assessing urban-rural health IOp. This study employed the frailty index as a proxy for actual health status as it offers a more comprehensive metric for assessing health. The frailty index quantifies an individual's frailty by calculating the proportion of health indicators for which they exhibit unhealthy values, encompassing various symptoms, signs, and abnormalities related to the health and quality of life of middle-aged and elderly individuals (Yang, & Lee, 2010). There is no universally accepted number of required variables, but typically it ranges between 30 to 70 variables. The frailty index's values range from 0 to 1, with higher values indicating poorer health conditions.

Given that this study employs data from the CHARLS, it primarily encompassed six modules: (1) self-assessment of health; (2) instrumental activities of daily living; (3) activities of daily living (ADL); (4) functional limitations; (5) mini-mental state examination; (6) chronic disease morbidity. These six modules comprise a total of 41 health variables, and the specific formula is as follows

$$FI = \frac{\sum_{k=1}^{n} d_i}{n}, \tag{10}$$

where *FI* represents the frailty index, $n = 41$ represents the use of a total of 41 variables, and $d_i = 1$ – health variable i in a state of health deficit, otherwise $d_i = 0$. The frailty index is a continuous variable with values ranging from 0 to 1, where a higher frailty index indicates a poorer health condition of the respondents.

3.2.2. Measure of urban-rural health fairness gap

In this paper the fairness gap serves as a proxy for rural-urban health opportunity inequality measured based on the ex-ante compensation principle. Table 2 presents the estimated actual health level and fairness gap based on the ex-ante compensation principle. It was found that from 2015 to 2018, both rural and urban actual health levels experienced improvements, and the fairness gap narrowed. Specifically, as shown in the first row of Table 2, the actual health level of rural individuals improved from 0.32 in 2015 to 0.24 in 2018, indicating an average health improvement of 25.00%. The last two rows represent the counterfactual health level of rural individuals and the fairness gap, estimated using equations (5) to (9). It can be seen that the fairness gap decreased from -0.018 in 2015 to -0.014 in 2018, representing an average reduction of 22.22%. This is in line with the fact that the Chinese government was continuously promoting rural-urban integration in recent years, thus narrowing the rural-urban gap.

Table 2. Estimation of the actual health and the health fairness gaps

	2015		2018	
	Mean	Std. deviation	Mean	Std. deviation
Actual health in rural	0.3168	0.1479	0.2434	0.1313
Counterfactual health	0.2993	0.1398	0.2296	0.1238
Health fairness gap	-0.0175	0.00820	-0.0138	0.00750

Notes: Counterfactual health levels for rural residents are calculated based on the ex-ante compensation principle. The fairness gap is equal to the counterfactual health level minus the actual health level.

Source: data from the CHARLS.

3.3. Model specification

The difference-in-difference (DID) method is a commonly employed technique in economics for assessing policy effects. The specific regression equation used in this study is as follows:

$$y_{it} = \beta_0 + \beta_1 \times NRPS_i \times Time_t + \beta_2 \times NRPS_i + \beta_3 \times Time_t + \gamma \times X_{it} + \nu_i + \varepsilon_{it}, \tag{11}$$

where subscript i represents rural elderly individuals, t denotes time, and y_{it} represents both the actual health status of rural elderly individuals and the equity gap. $NRPS_i$ indicates the enrolment status of rural elderly individuals in the NRPS. If individual i enrols in the NRPS, then $NRPS_i$ equals 1, otherwise it equals 0. $Time_t$ represents the year, where $Time_t = 1$ corresponds to 2018, and $Time_t = 0$ corresponds to 2015. The authors excluded samples that had already claimed the rural pension from NPRS in 2015. Consequently, the examined group consisted of individuals who did not claim the rural pension from NPRS in 2015 but did so in 2018, while the control group comprised individuals who did not claim the rural pension from NPRS in either 2015 or 2018.

X_{it} represents other time-invariant control variables that affect the actual health level of rural elderly individuals, which includes gender, age, and education, following Huang and Zhang (2021), while ν_i represents province fixed effects, which account for differences among provinces that remain unchanged over time. These differences may include economic conditions, lifestyle habits, and other provincial disparities. The coefficient of interest is denoted as β, which represents the estimated impact of enrolment in the NRPS on the actual health level of rural elderly individuals and urban-rural health IOp.

The NRPS explicitly stipulates that enrolment is entirely based on voluntary choice, potentially introducing a 'self-selection' issue in the actual enrolment levels. If the division between the treatment group and the control group is influenced by individual characteristics, there may be concerns regarding internal validity. In other words, relying solely on the DID method might not satisfy the assumption of random assignment between the treatment and control groups, potentially leading to biased estimation results. To address this concern, the authors further assessed the impact of enrolment in the NRPS on the actual health levels of rural elderly and the fairness gap using a propensity score matching with difference-in-differences (PSM-DID) model.

Specifically, the authors employed a series of covariates to calculate propensity scores for matching, ensuring that the probability of samples entering the treatment group and control group is similar. This approach effectively controls for differences in observable characteristics between the two groups, thereby approximating the assumption of random assignment between the treatment and control groups. These covariates, referenced from previous studies by Ma et al. (2017) and Zhang and Chen (2022), encompass income, nutrition, education attainment, medical insurance, age, gender, marriage status, smoking status, drink status, frequency of physical exercise, number of children, availability of tap water, toilet type (squat or other), and household neatness. Table 3 provides descriptive statistics for these variables.

Table 3. Descriptive statistics

	Mean	Std. deviation	Min	Max	N
Dependent variable					
Actual health	0.2625	0.1414	0.0146	0.9423	3,892
Fairness gap	-0.0148	0.0079	-0.0520	-0.0008	3,892
Independent variable					
Claim_NRP	0.5529	0.4973	0	1	3,892
Controls					
Income	7.0435	2.8796	0	14.4532	3,885
Nutrition	3.6694	1.4873	0	8.2000	3,859
Education attainment	4.6280	5.1563	0	16	3,892
Medical insurance	0.3769	0.2213	0	1	3,814
Age	68.9677	6.8089	60	97.2658	3,701
Gender	0.5570	0.4968	0	1	3,892
Marriage	0.7495	0.4334	0	1	3,892
Children	3.5455	1.7273	0	12	3,892
Drinking	0.2590	0.4381	0	1	3,892
Smoking	0.2618	0.4397	0	1	3,892
Exercise	0.8656	0.3411	0	1	3,892
Availability of tap water	0.7280	0.4450	0	1	3,890
Toilet style	0.7882	0.4097	0	1	3,890
Neatness	3.1610	1.0670	1	5	3,734

Notes: Actual health is proxied by the frailty index. Claim_NRP represents those claiming the New Rural Pension (Yes=1). Income is represented by the natural logarithm of the annual per capita household income. Nutrition is represented by the natural logarithm of per capita weekly food consumption. Medical insurance is proxied by reimbursement rate. Educational attainment is represented by the number of years of education. Marriage is coded as 1 for married and 0 for other. Children are proxied by the number of elderly children. Drinking is coded as 1 for drinking this year, 0 for other. Smoking is coded as 1 for smoking this year, 0 for other. Exercise is coded as 1 for exercising frequently this year, 0 for other. Availability of tap water is coded as 1 for having tap water, 0 for other. Toilet style is coded as 1 for squatting, 0 for sitting. Neatness is scored from 1 to 5, with 1 representing 'very neat' and 5 representing 'very untidy'.

Source: data from the CHARLS.

4. Empirical results

4.1. Baseline regressions

4.1.1. The impact of enrolment in the NRPS on actual health level

Table 4 reports the baseline estimates of the impact of enrolment in the NRPS on the actual health level of the rural elderly. The study found a significant improvement in the actual health level of rural elderly individuals upon enrolment in the NRPS, regardless of the model specification. Columns (1) to (4) in Table 4 represent results with no control variables and province-fixed effects, province-fixed effects without control variables, control variables without province-fixed effects, and both control variables and province-fixed effects, respectively. Panel A presents estimates based on the DID method, while Panel B presents estimates based on the PSM-DID method.

In particular, in column (4) of Panel A which includes both control variables and province-fixed effects under the DID approach, the effect of enrolment in the NRPS significantly narrowed the fairness gap by 0.024 units. Correspondingly, the estimate under the PSM-DID method in Panel B is 0.023 units in the fourth column. Given that the average actual health level of rural elderly in 2018 is 0.24, the enrolment in the NRPS is equivalent to reducing urban-rural health IOp by 9.58%.

Table 4. Impact of enrolment in the NRPS on actual health for rural residents

	Actual health			
	(1)	(2)	(3)	(4)
Panel A: DID				
NRPS × Time	-0.0245**	-0.0250**	-0.0237**	-0.0242**
	(0.0103)	(0.0104)	(0.0102)	(0.0103)
NRPS	-0.0606***	-0.0859***	-0.0606***	-0.0873***
	(0.0085)	(0.0095)	(0.0085)	(0.0096)
Time	0.0322***	0.0292***	0.0267***	0.0222**
	(0.0092)	(0.0095)	(0.0090)	(0.0093)
Controls	No	No	Yes	Yes
Province FE	No	Yes	No	Yes
R^2	0.0643	0.1303	0.1049	0.1716
Observations	3,892	3,701	3,892	3,701
Panel B: PSM-DID				
NRPS × Time	-0.0198*	-0.0237**	-0.0183	-0.0226**
	(0.0117)	(0.0114)	(0.0116)	(0.0112)
NRPS	-0.0662***	-0.0872***	-0.0666***	-0.0885***
	(0.0100)	(0.0106)	(0.0100)	(0.0106)
Time	0.0250**	0.0269***	0.0188*	0.0198*
	(0.0104)	(0.0104)	(0.0103)	(0.0102)
Controls	No	No	Yes	Yes
Province FE	No	Yes	No	Yes
R^2	0.0678	0.1320	0.1044	0.1720
Observations	3,446	3,446	3,446	3,446

Notes: The coefficient of interest is negative which means that the enrolment in the NRPS enhances the actual health because the actual health is proxied by the frailty index which is closer to zero implying the individual is more healthy. Standard errors are clustered at the household level. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. In Panel A, control variables are gender, age, education, marriage, and children. In Panel B, control variables are income, nutrition, healthcare accessibility, medical insurance, education attainment, age, gender, marriage, children, smoking, drink, exercise, availability of tap water, toilet style, and neatness.

Source: data from the CHARLS.

4.1.2. Impact of enrolment in the NRPS on the fairness gap

Table 5 reports the baseline estimates of the impact of enrolment in the NRPS on the fairness gap. It was found that enrolment in the NRPS significantly reduces the fairness gap. In Table 5, columns (1) to (4) represent different specifications, including no control variables and province-fixed effects, province-fixed effects without control variables, control variables without province-fixed effects, and both control variables and province-fixed effects. Panel A presents the estimates based on the DID method, while Panel B those based on the PSM-DID method.

In particular, the fourth column of Table 5, which includes both control variables and province fixed effects under the DID method, shows that enrolment in the NRPS significantly narrows the fairness gap by 0.0013 units. This result is consistent with the corresponding estimate in Panel B. Considering that the average fairness gap in 2018 was -0.018, the effect of enrolment in the NRPS is equivalent to reducing urban-rural health IOp by 6.67%.

Table 5. Impact of enrolment in the NRPS on health fairness gap for rural elderly

	Health fairness gap			
	(1)	(2)	(3)	(4)
Panel A: DID				
NRPS × Time	0.0013**	0.0014**	0.0013**	0.0013**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
NRPS	-0.0018***	-0.0016***	-0.0015***	-0.0012**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Time	0.0030***	0.0044***	0.0030***	0.0045***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Controls	No	No	Yes	Yes
Province FE	No	Yes	No	Yes
R^2	0.0525	0.1198	0.0937	0.1617
Observations	3,892	3,701	3,892	3,701
Panel B: PSM-DID				
NRPS × Time	0.0011*	0.0013**	0.0010	0.0012**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
NRPS	-0.0014**	-0.0015***	-0.0010*	-0.0011*
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Time	0.0033***	0.0045***	0.0033***	0.0045***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Controls	No	No	Yes	Yes
Province FE	No	Yes	No	Yes
R^2	0.0555	0.1212	0.0927	0.1617
Observations	3,446	3,446	3,446	3,446

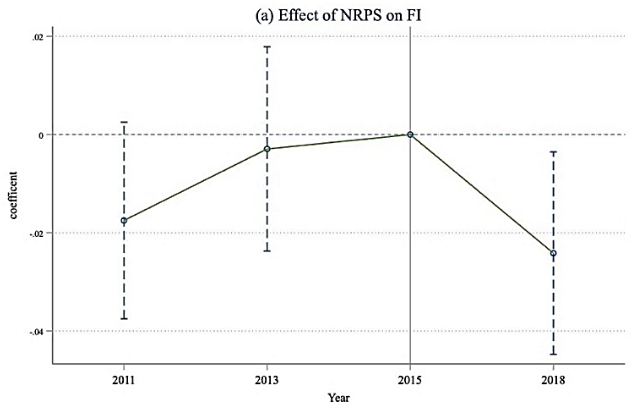
Notes: The coefficient of interest is negative which means that the enrolment in the NRPS reduces the health fairness gap because the health fairness gap approaches zero implying IOp decreases. Standard errors are clustered at the household level. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. In Panel A, control variables are gender, age, education, marriage, and children. In Panel B, control variables are income, nutrition, health care accessibility, medical insurance, education attainment, age, gender, marriage, children, smoking, drink, exercise, availability of tap water, toilet style, and neatness.

Source: data from the CHARLS.

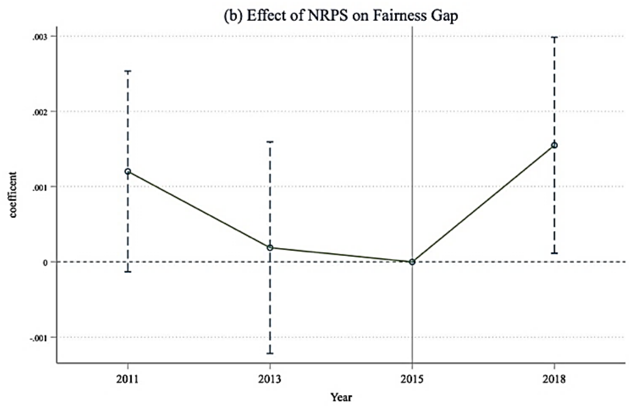
4.2. Robustness tests

4.2.1. Parallel trends test

To test for pre-trends the authors curated thoroughly the CHARLS data from 2011 and 2013, merging it with the baseline regression sample. Next, an event study method was implemented to estimate the year-wise changes in actual health and urban-rural health IOp. In Figure 2, there are no significant differences between the treatment group and control group, hence the identification design satisfies the parallel trends assumption.



Panel A: Effect of NRPS on health level



Panel B: Effect of NRPS on urban-rural health fairness gap

Fig. 2. Parallel trends test

Source: data from the CHARLS.

4.2.2. Matching performance

Good matching performance is the key to guarantee the validity of PSM-DID. Figure 3 reports the standard deviations of the covariates before and after matching, and shows that matching effectively narrowed the differences in observable characteristics between the treatment and control groups. In particular, the standard deviations of educational attainment, age, availability of piped water, gender, and type of latrine are all outside of 10 percent before matching, and all the variables are within 10 percent of each other after matching. This implies that the matching is better and satisfies the balance assumption.

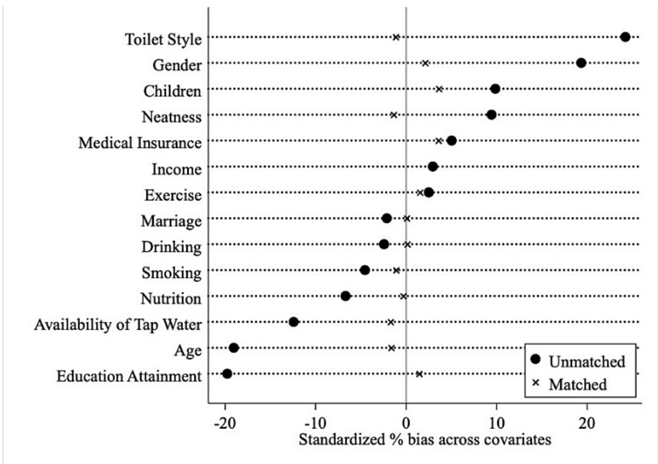


Fig. 3. Standard deviation of covariates before and after matching

Source: data from the CHARLS.

4.2.3. Alternative matching methods

Due to the potential variation in estimation results that may arise from different matching methods in PSM-DID, the authors conducted a series of robustness checks by employing alternative matching techniques. Table 6 presents the results of re-estimating the baseline model after altering matching methods. It was found that, irrespective of the matching methods employed, the results remained consistent with those of the baseline results. In particular, columns (1) and (2) altered the bandwidth for kernel matching in the baseline model from 0.06 to 0.02, revealing that enrolment in the NRPS significantly enhances individual actual health level by 0.023 units and significantly reduces the fairness gap by 0.0013 units. Columns (2) and (3) switched the matching method in the baseline model to neighbour 1:2 matching, revealing that enrolment in the NRPS significantly improves individual actual health level by 0.031 units and significantly reduces the fairness gap by 0.0017 units. Finally, the last two columns replaced the baseline model's matching method with radius matching, finding that enrolment in the NRPS significantly promotes individual actual health level by 0.022 units and notably reduces the fairness gap by 0.0012 units. These results collectively indicate that changing the matching method does not significantly alter the baseline estimation results.

Table 6. Robustness test of alternative matching methods

	Matching methods					
	Kernel (bwidth=0.02)		Neighbour (k=2)		Radius (calliper=0.05)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Actual health	Fairness gap	Actual health	Fairness gap	Actual health	Fairness gap
NRPS × Time	-0.0232**	0.0013**	-0.0312***	0.0017***	-0.0224**	0.0012*
	(0.0112)	(0.0006)	(0.0118)	(0.0007)	(0.0113)	(0.0006)
NRPS	0.0200*	-0.0011*	0.0241**	-0.0013**	0.0198*	-0.0011*
	(0.0102)	(0.0006)	(0.0103)	(0.0006)	(0.0103)	(0.0006)
Time	-0.0879***	0.0045***	-0.0807***	0.0041***	-0.0887***	0.0046***
	(0.0106)	(0.0006)	(0.0104)	(0.0006)	(0.0107)	(0.0006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1721	0.1619	0.1804	0.1706	0.1736	0.1633
Observations	3,442	3,442	2,212	2,212	3,415	3,415

Notes: The coefficient of interest is negative which means the enrolment in the NRPS reduces the health fairness gap because the health fairness gap approaches zero implying IOp decreases. Standard errors are clustered at the household level. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Control variables are income, nutrition, healthcare accessibility, medical insurance, education attainment, age, gender, marriage, children, smoking, drink, exercise, availability of tap water, toilet style, and neatness.

Source: data from the CHARLS.

4.2.4. Alternative dependent variables

The choice of key variables used to measure the fairness gap can potentially influence the main regression outcomes. To address this concern, additional estimation was conducted on the baseline model by substituting the core variables used to construct the fairness gap. Table 7 presents the results of re-estimating the baseline model after replacing the dependent variables. In the first two columns, the authors replaced the proxy variables for urban and rural from residence with household registration (hukou), whilst in the last two columns the frailty index was replaced with health indicators based on PCA. Panel A shows the estimates based on the DID model, and Panel B the estimates based on the PSM-DID model. It was found that both substitutions are consistent with the benchmark results.

Table 7. Robustness test of alternative dependent variables

	Hukou		PCA	
	Actual health	Fairness gap	Actual health	Fairness gap
	(1)	(2)	(3)	(4)
Panel A: DID				
NRPS × Time	-0.0242**	0.0013**	-0.2091**	0.6057**
	(0.0103)	(0.0006)	(0.0878)	(0.2918)
NRPS	0.0222**	-0.0012**	0.1465*	-0.3636
	(0.0093)	(0.0005)	(0.0771)	(0.2286)
Time	-0.0873***	0.0045***	0.0512	-0.0924
	(0.0096)	(0.0005)	(0.0814)	(0.2746)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.1716	0.1617	0.0674	0.0684
Observations	3,701	3,701	3,701	3,701
Panel B: PSM-DID				
NRPS × Time	-0.0226**	0.0012**	-0.2143**	0.6501**
	(0.0112)	(0.0006)	(0.0954)	(0.3156)
NRPS	0.0198*	-0.0011*	0.1377*	-0.3499
	(0.0102)	(0.0006)	(0.0837)	(0.2483)
Time	-0.0885***	0.0045***	0.0472	-0.1299
	(0.0106)	(0.0006)	(0.0895)	(0.2997)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.1720	0.1617	0.0664	0.0670
Observations	3,446	3,446	3,446	3,446

Notes: The coefficient of interest is negative which means the enrolment in the NRPS reduces the health fairness gap because the health fairness gap approaches zero implying IOp decreases. Standard errors are clustered at the household level. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. In Panel A, control variables are gender, age, education, marriage, and children. In Panel B, control variables are income, nutrition, healthcare accessibility, medical insurance, education attainment, age, gender, marriage, children, smoking, drink, exercise, availability of tap water, toilet style, and neatness.

Source: data from the CHARLS.

According to the estimates from the PSM-DID model, substituting household registration for the residential location showed that enrolment in the NRPS significantly increased the actual health level of the rural elderly by 0.023 units and significantly reduced the fairness gap by 0.0012 units. Similarly, when replacing the frailty index with health indicators constructed using PCA, the PSM-DID estimates indicates that enrolment in the NRPS significantly improved the actual health level of rural elderly individuals by 0.21 units and notably narrowed the fairness gap by 0.65 units. These results suggest that the baseline estimates remained robust even when altering the key variables used to measure the dependent variable.

4.3. Heterogeneity analysis

Due to the potential heterogeneous impact of the enrolment in the NRPS on urban-rural health IOp across income and age groups, the authors conducted a heterogeneous analysis based on different income and age categories. Table 8 reports the effect of enrolment in the NRPS on the fairness gap for distinct income and age cohorts. It was found that the narrowing effect of enrolment in the NRPS on the fairness gap was primarily observed among relatively lower-income and older age groups.

Table 8. Heterogeneity analysis of income and age for the rural elderly

	Fairness gap				
	Income			Age	
	<33	33~66	>66	<75	>=75
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
NRPS × Time	0.0033***	0.0014	0.0004	0.0008	0.0035**
	(0.0011)	(0.0011)	(0.0012)	(0.0006)	(0.0014)
NRPS	0.0015	0.0039***	0.0045***	0.0047***	0.0037***
	(0.0011)	(0.0010)	(0.0010)	(0.0006)	(0.0012)
Time	-0.0014**	-0.0008	-0.0009	-0.0009	-0.0027**
	(0.0007)	(0.0010)	(0.0011)	(0.0006)	(0.0012)
Controls	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
R^2	0.1292	0.1681	0.1872	0.1478	0.1516
Observations	1,034	1,428	1,237	2,939	761
Panel B: PSM-DID					
NRPS × Time	0.0029***	0.0011	0.0007	0.0007	0.0039***
	(0.0011)	(0.0012)	(0.0013)	(0.0007)	(0.0015)
NRPS	0.0025**	0.0040***	0.0037***	0.0047***	0.0037***
	(0.0011)	(0.0011)	(0.0011)	(0.0007)	(0.0013)
Time	-0.0014*	-0.0003	-0.0014	-0.0007	-0.0030**
	(0.0008)	(0.0011)	(0.0012)	(0.0006)	(0.0013)
Controls	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
R^2	0.1358	0.1691	0.1971	0.1453	0.1599
Observations	1,055	1,293	1,096	2,740	705

Notes: The coefficient of interest is negative which means the enrolment in the NRPS reduces the health fairness gap because the health fairness gap approaches zero implying IOp decreases. Standard errors are clustered at the household level. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. In Panel A, control variables are gender, age, education, marriage, and children. In Panel B, control variables are income, nutrition, healthcare accessibility, medical insurance, education attainment, age, gender, marriage, children, smoking, drink, exercise, availability of tap water, toilet style, and neatness.

Source: data from the CHARLS.

Columns (1)-(3) present the responses of different groups categorised by tertiles of income. The enrolment in the NRPS had a significant impact on reducing the fairness gap among the bottom third of income earners, irrespective of whether the DID or PSM-DID method was employed. To be more precise, the enrolment in the NRPS reduced the urban-rural health IOp by 0.0029 units for the bottom third income group, while its impact on other income groupings was not statistically significant. This phenomenon could be attributed to the limited amount of the NRPS benefits, which makes lower-income groups more reliant on the NRPS compared to higher-income ones.

The last two columns show the responses of the 60-75 age group and the 75 and older age group. The enrolment in the NRPS had a more pronounced effect on the 75 and older age group, whether analysed using the DID or PSM-DID method. In particular, the enrolment in the NRPS decreases urban-rural health IOp by 0.0039 units for the 75 and older age group, while it was not statistically significant for the 60-75 age group. This discrepancy could be attributed to the relatively limited income of the elderly aged 75 and above compared to those aged 60-75, leading the former to be more reliant on the NRPS.

To sum up, these results suggest that the enrolment in the NRPS has a heterogeneous impact across different income and age groups, with a more substantial effect on reducing urban-rural health IOp among lower-income and older age cohorts. This outcome highlights the importance of considering income and age disparities when assessing the implications of the NRPS on health outcomes.

5. Conclusion

Eliminating regional health inequality is a matter of great concern for policymakers. This paper provides evidence from China that a policy targeting unfavourable regions for protection can reduce regional health inequality. Based on Roemer's theory of inequality of opportunity and utilising panel data from the China Health and Retirement Longitudinal Study covering the years 2015 to 2018, the authors employed the methods of difference-in-differences and propensity score-matched DID to investigate the impact of enrolment in the New Rural Pension Scheme on health inequality of opportunity among the urban and rural elderly. Following Roemer's theory, the authors initially discuss the distinction between ex-ante and ex-post compensation principles for measuring health inequality of opportunity, ultimately opting for the ex-ante compensation principle to assess urban-rural health inequality of opportunity.

Next, through empirical analyses, it was found that the enrolment in the NRPS significantly enhances the health level of rural elderly individuals and substantially reduces urban-rural health inequality of opportunity. In particular, the enrolment in the NRPS was associated with an approximate 9.58% improvement in health level and a 6.67% reduction in urban-rural health inequality of opportunity on average. The authors conducted robustness tests, including altering matching methods and replacing explanatory variables, and found consistent results with the baseline estimates. In the heterogeneous analysis, the paper discerned that the impact of the enrolment in the NRPS on urban-rural health inequality of opportunity was more pronounced among low-income and older individuals.

The study by Zhang and Chen (2022) is most closely aligned with the presented research topic, however their principle for measuring health inequality of opportunity differed: this study employed an ex-ante approach, whereas theirs utilised an ex-post method. They found that the NRPS mitigates approximately 8.13% of the health IOp between the urban and rural elderly, which is largely consistent with the findings of this study. Ma et al. (2017) also investigated the impact of public policy on health IOp among the urban and rural elderly, but focused on the integration of urban and rural medical insurance systems. They discovered that such integration reduced health IOp between urban and rural areas by approximately 24-28%. The more substantial impact of insurance integration compared to the NRPS can be attributed to its more direct influence on the health of rural residents.

This paper holds substantial policy implications. Firstly, similar social security programmes targeted at populations in disadvantaged circumstances, e.g. rural, not only enhance the health of these groups but also narrow health opportunity inequality among different circumstances. Therefore, policymakers should consider welfare changes between groups in addition to the direct effects of policies when assessing policy benefits, otherwise they may underestimate policy effectiveness. Secondly, as society continually pursues fairness and justice, future policy evaluations should pay greater attention to the inequality of opportunity among different groups.

There are still some limitations in this paper, mainly that the investigated conditions were only urban and rural, whilst future research could incorporate the effects of other circumstances. Moreover, future policy assessments could give greater consideration to the issue of inequality.

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Appendix

Introduction to the variables used in constructing the fragility index

When constructing the frailty index, the following indicators were used:

(1) Self-assessment of health: "How do you perceive your overall health?" Ratings of very good, good, fair, poor, and very poor are denoted as 0.2, 0.4, 0.6, 0.8, and 1, respectively.

(2) Instrumental activities of daily living: "Do you experience difficulties in tasks such as managing money, taking medication, shopping, cooking, making phone calls, and housekeeping?" Difficulties are denoted as 1, while the absence of difficulties is defined as 0.

(3) Activities of daily living: "Do you experience difficulties in activities like bathing, getting out of bed, using the toilet, eating, dressing, and making decisions?" Difficulties are denoted as 1, while the absence of difficulties is denoted as 0.

(4) Functional limitations: "Do you face difficulties in activities such as walking 100 meters, climbing stairs, reaching up, getting up from a chair, bending down or kneeling, picking up a coin, and lifting a 10-kilogram weight?" Difficulties are denoted as 1, while the absence of difficulties is denoted as 0.

(5) Mini-mental state examination: "Can you accurately answer questions about the current year, the current month, the current date, the current season, the day of the week, your current memory status, the ability to draw a picture seen, and the level of depression?" Similar to self-rated health, ratings of very good, good, fair, poor, and very poor are denoted as 0.2, 0.4, 0.6, 0.8, and 1, respectively. Correct answers are denoted as 0, while incorrect answers are denoted as 1.

(6) Chronic disease morbidity: "Are you diagnosed with conditions such as hypertension, hyperlipidemia, hyperglycemia, malignancies, chronic lung diseases, liver diseases, heart diseases, strokes, kidney diseases, gastrointestinal diseases, emotional and mental issues, memory-related diseases, rheumatism, and asthma?" Presence of each condition is denoted as 1, while absence is denoted as 0.