Li et al. International Journal for Equity in Health (2024) 23:211
https://doi.org/10.1186/s12939-024-02297-y

International Journal for Equity in Health

RESEARCH Open Access

The impact of long-term care insurance on healthcare utilization and expenditures among middle-aged and older Chinese adults: a quasi-experiment study

Mengdie Li[1], Xiaoru Fan[2], Jushuang Li[1], Jun Wang[1], Ping Yin[3], Ruifei Zuo[4], Yao Jie Xie[5,6*] and Chun Hao[1,7*]

Abstract

Background Long-term care insurance (LTCI) is essential to alleviate the challenges of rapid aging. Research on LTCI in developing countries is limited and conclusions remain controversial. This study aims to empirically evaluate how the LTCI pilot in selected cities influences healthcare utilization and expenditures among middle-aged and older Chinese adults.

Methods Data was from 2013, 2015, and 2018 China Health and Retirement Longitudinal Study. 167 LTCI and 8225 non-LTCI group participants were identified. Propensity score matching difference-in-difference method was used to evaluate the net effect of LTCI. The robustness of the findings was tested using a placebo test.

Results In the pilot cities, around 17.8% of the population had LTCI coverage, with approximately 59.9% participating in urban employee medical insurance and 81.4% being urban residents. LTCI significantly reduced the monthly out-of-pocket outpatient expenditure by 313.764 yuan ($P<0.05$), but had no significant effects on the inpatient utilization and expenditure. Further analysis of vulnerable subgroup revealed that LTCI decreased monthly outpatient visits frequency, total outpatient expenditure, and out-of-pocket outpatient expenditure by 0.523 times, 643.500 yuan, and 302.367 yuan, respectively ($P<0.05$). Robustness tests confirmed the stability of these results.

Conclusions The LTCI coverage rate has remained low. While LTCI has contributed to reducing outpatient utilization and expenditure, its impact on controlling inpatient-related outcomes is limited. It is recommended to broaden LTCI coverage beyond existing participants to encompass more vulnerable populations, and improve awareness and quality of LTCI services to achieve a significant effect on inpatient care.

Keywords Long-term care insurance, Healthcare utilization, Healthcare expenditures, Propensity score matching difference-in-difference method, Middle-aged and older adults, China

*Correspondence:
Yao Jie Xie
grace.yj.xie@polyu.edu.hk
Chun Hao
haochun@mail.sysu.edu.cn
[1]Department of Medical Statistics, School of Public Health, Sun Yat-Sen University, Guangzhou, China
[2]Liwan District Center for Disease Control and Prevention, Guangzhou, China
[3]Sun Yat-sen University Cancer Center, Guangzhou, China
[4]Department of Applied Statistics, School of Mathematics, Northwest University, Xi'an, China
[5]School of Nursing, The Hong Kong Polytechnic University, Hong Kong SAR, China
[6]Research Centre for Chinese Medicine Innovation, The Hong Kong Polytechnic University, Hong Kong SAR, China
[7]Sun Yat-Sen Global Health Institute, Institute of State Governance, Sun Yat-Sen University, Guangzhou, China

Background

China is one of the countries aging most rapidly in the world, with a high annual growth rate [1]. By 2033, the country is poised to transform into a super-aged society, with individuals aged 65 and above constituting 20% of the total population [2]. Rapid aging presents many challenges. Regarding disease burden, ageing exacerbates the prevalence of non-communicable diseases and limitations in activities of daily living (ADLs) among the elderly [3]. As the nursing needs of older adults grow, family-based caring pattern proves insufficient [4]. Consequently, the elderly heavily rely on hospital services, straining healthcare resources. Furthermore, aging amplifies the economic burden on both governments and families. In China, between 2008 and 2017, the annual real total health expenditures surged by 12.2%, surpassing the annual real GDP growth rate [5]. Aging also results in a rapid rise in elderly population-to-working population ratio, in turn lead to an expanding deficit in social pension programs [6]. At the household level, this demographic shift heightens the risk of catastrophic health expenditures [7] and poverty [8, 9].

Drawing from experiences in other aging nations [10, 11], China launched a long-term care insurance (LTCI) trial program in 35 pilot cities in 2016. The program is a crucial attempt to address the challenges associated with aging. During the pilot phase, LTCI mandatorily covers individuals enrolled in the urban employee medical insurance (UEMI), a type of public basic medical insurance that can reimburse hospital costs. A few pilot cities have expanded coverage to include enrollees of the urban resident medical insurance (URMI) or the urban and rural resident medical insurance (URRMI), both of which are also types of the public basic medical insurance program. LTCI targets insured individuals with limitations in daily activities due to old age or illness, covering their costs of long-term care services at home or in specialized nursing facilities. The long-term care services include basic daily living care such as medication administration, assisted feeding, and supine care, as well as medical nursing services like oral care, balance training, and sputum suction, focusing on chronic condition rehabilitation. LTCI funds are primarily raised through public basic medical insurance pooled funds and individual contributions. In China, UEMI funds consist of pooled funds and medical savings account (MSA), while URMI and URRMI funds do not have an MSA. MSA of UEMI comprises contributions from individuals in full and approximately 30% from employers. For UEMI enrollees, LTCI individual contributions are annually transferred from their MSA of UEMI, totaling about 30 yuan (100 CNY = 13.89 USD), without requiring additional premiums. Enrollees of URMI or URRMI typically make personal payments for LTCI contributions, amounting to several dozen yuan annually. LTCI reimbursement for long-term care costs generally stands at around 70%, varying based on the city and care location (home or facility), with a maximum of 90%. Notably, LTCI funds are exclusively allocated for long-term care services and do not cover outpatient or inpatient services.

Developed countries introduced LTCI decades before China and have conducted extensive research on its impact. Existing studies on the pilot effect of LTCI policy have mainly focused on its economic and health effects. According to international experience, the implementation of LTCI may enhance the health status and quality of life of beneficiaries while lowering the utilization and cost of healthcare [12–14]. This may be due to beneficiaries receiving appropriate management at home or in long-term care facilities, thus avoiding hospital treatment [15, 16]. However, evidence from developed countries may not be applicable to developing countries due to variations in healthcare systems, income levels, LTCI policies, etc., among different countries or regions. Thus, it is imperative to evaluate LTCI's effects in China, as it holds substantial implications for policy implementation not only within China but also for other developing countries grappling with similar challenges tied to population aging.

Empirical research on LTCI's impact on healthcare utilization and expenditure in China is relatively insufficient compared to studies in developed countries, and conclusions drawn from existing studies remain controversial. Some studies indicate that LTCI policy reduce inpatient utilization and costs [17, 18], but others show no impact [19–21]. Similarly, findings on outpatient utilization and costs are inconsistent. Some studies report negative effects of LTCI [19, 22], while Chen et al. [23] found no impact. However, it is important to note that these studies were mainly conducted in a few selected cities and not across 35 pilot cities. Previous studies have the following limitations. On the policy aspects, some studies do not accurately reflect the reality of the policy due to their selection of study populations, locations, and outcomes. LTCI eligibility in China is contingent upon the type of public basic medical insurance. However, most studies [17, 22, 24, 25] categorize all people in the pilot city as exposed to the LTCI policy, irrespective of their public basic medical insurance type. Furthermore, although the LTCI pilot is implemented in 35 cities, most research focuses on only a few specific cities, primarily Qingdao [22, 26], Shanghai [27], and Jingmen [17], which may deviate from the original intent of the policy. Evidence from these few pilot cities lack national representativeness due to variations in aging levels and LTCI policies among them. Additionally, the LTCI policy aims to enhance the well-being of beneficiaries. Research should not only focus on the policy's impact on total medical expenses but also on out-of-pocket (OOP) expenses. OOP expenses directly reflect the economic burden on beneficiaries and thus reflect the impact of LTCI on their well-being. Many studies have overlooked this aspect. On the methodological aspects, the statistical analysis methods used in many studies are not rigorous. Some studies [17, 18, 28] mistakenly used two-wave data for difference-in-difference (DID) analysis without verifying whether the data met the common trends assumption required for DID analysis, which may lead to biased results.

To sum up, this study aims to assess how LTCI implementation affects healthcare utilization and expenditures, particularly OOP costs, among middle-aged and older Chinese adults. First, we include as many pilot cities as possible to offer comprehensive insights beyond existing literature. Second, we identify LTCI groups based on the cities and the public basic medical insurance type. We next test the common trends assumption and evaluate the effect of LTCI using DID method. Finally, we conduct a discussion and make recommendations based on the findings.

Materials and methods

Study design

This study made use of the China Health and Retirement Longitudinal Study (CHARLS) [29] longitudinal data from 2013, 2015, and 2018. We applied DID with 2 periods and 2 groups framework to estimate the impact of LTCI policy by comparing average levels of healthcare utilization and healthcare expenditures between residents exposed and unexposed to the LTCI policy. China formally began to launch LTCI nationwide in 2016, therefore 2018 were the policy active period to estimate the effect of LTCI by comparing changes of outcome differences between residents exposed and unexposed to the LTCI policy before and after implementation. This DID estimation should be under the common trends assumption between two groups during the LTCI policy inactive period from 2013 to 2015.

Data source

As a nationally representative investigation of the Chinese middle-aged and older population aged 45 and up, CHARLS investigated over 17,000 participants in roughly 10,000 households in 150 counties across 28 provinces using a multistage probability-proportional-to-size sampling method [30].

There were two steps to define the included participants for analysis. The first step is to define the included cities. 35 locations were selected as LTCI policy pilot cities in China starting from 2016, and 21 of which were covered by CHARLS. 4 out of 21 pilot cities that implemented LTCI after March 2018 (CHARLS 2018 survey was carried out from the end of September) were excluded since we assumed that only pilot cities that implemented LTCI more than six months preceding the survey were affected by the policy. Furthermore, 3 pilot cities that deployed LTCI before 2016 were excluded because they partially implemented LTCI prior to the nationwide rollout. Finally, 14 pilot cities and 109 non-pilot cities were included in the final analysis, and the distribution of 14 included pilot cities is shown in Fig. 1 (Anqing, Binzhou, Chengdu, Chengde, Dezhou, Guangzhou, Jinan, Ningbo, Qiqihar, Shangrao, Suzhou, Shanghai, Jingmen, and Jilin). The second step is to define the included participants, as depicted in Fig. 2. The LTCI policy exposed group (LTCI group) included LTCI enrollees in the pilot city, while the LTCI policy unexposed group (non-LTCI group) included non-LTCI enrollees in the pilot city (e.g., participants not enrolled in UEMI in Guangzhou) and non-pilot city participants. There were 8392 valid individuals left after filling in missing values for per capita household expenditure with multiple interpolation and eliminating samples with other missing covariates and dependent variables, including 167 LTCI group participants and 8225 non-LTCI group participants (772 of the non-LTCI group participants from pilot cities and 7453 participants from non-pilot cities). Table A in supplementary material lists the LTCI policy's implementation time and coverage population for the 14 pilot cities.

Variable specifications

The following were the dependent variables: (1) healthcare utilization: inpatient visits frequency during last year and outpatient visits frequency during last month, and (2) healthcare expenditures: total and OOP inpatient expenditure during the last year and total and OOP outpatient expenditure during last month.

Covariates

Based on Andersen's model, a typical model for evaluating health service utilization, we included a range of covariates [31]. Andersen's model suggested that health service utilization was determined by predisposing factors, enabling factors, and need factors. Predisposing factors in this study included age, gender (male/ female), marital status (married/ others), and educational level (range from less than lower secondary education to tertiary education). Enabling factors included residents (urban/ rural residents), types of nursing (home and others/ aged care institutions), per capita household expenditure (quartile 1–4), area (east/ west/ central/ northeast), and types of public basic medical insurance (UEMI/ URMI/ URRMI/ New rural cooperative medical insurance (NCMI)/ Uninsured). Chinese residents were prohibited from having dual coverage in public basic medical insurance, therefore participants who self-reported having more than one type of basic medical insurance in a

Fig. 1 Distribution of 14 pilot cities in China

year were disqualified. Need factors included health status (the number of chronic diseases), self-reported health status (a 5-level options ranging from very good to very poor), and any difficulty in ADLs (yes/ no). ADLs difficulty indicated that the participants reported any difficulty with at least one activity or was unable to perform the activity. The ADLs included getting dressed, taking a bath or shower, getting in and out of bed, eating, using the toilet, and controlling urine and feces.

Statistical analysis

We conducted the analysis on both the entire participant pool and the vulnerable subgroup. We identified those most likely to need long-term care services as vulnerable subgroups (defined as participants aged ≥ 65 years, or those facing any difficulty in ADLs, or diagnosed with cancer, stroke, or memory-related diseases at the time of the 2015 wave survey).

Propensity score matching difference-in-difference method (PSM-DID)

This study used the propensity score matching difference-in-difference approach (PSM-DID) to quantitatively assess if and how significantly the LTCI affected health service utilization and healthcare expenditures among adults in their middle and late years in China. Since enrollment in LTCI was not random, there may be heterogeneity between LTCI and non-LTCI groups. Firstly,

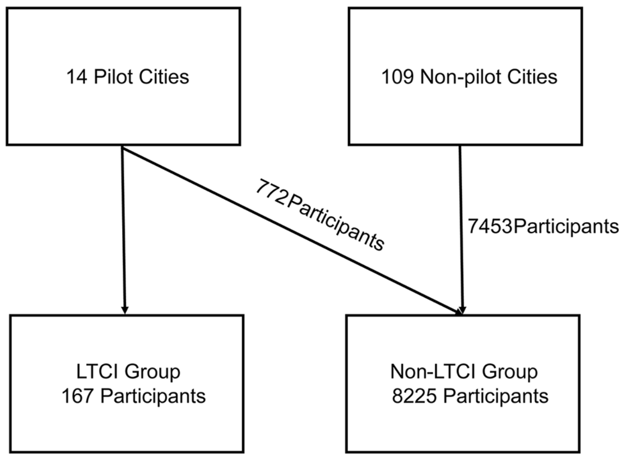

Fig. 2 Source and distribution of participants

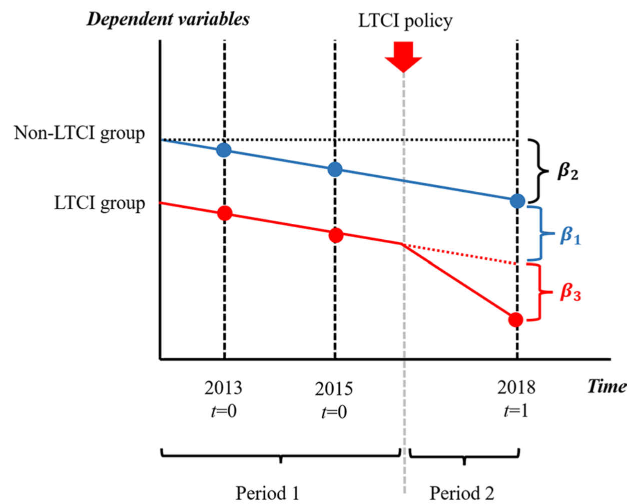

Fig. 3 Two-group, two-period DID design

this paper used the PSM method to control the heterogeneity of LTCI and non-LTCI groups. Secondly, DID was used on matched participants to estimate the effect caused by LTCI. All analyses were performed in *R*.

The PSM method was employed to generate new datasets in 2013, 2015, and 2018, ensuring comparability of multiple covariates between LTCI and non-LTCI groups using propensity scores (PS). PS is the conditional probability that a participant will be randomly assigned to the LTCI group based on observed covariates [32]. In this study, we calculated the PS using a logistic model as follows:

$$PS_{it} = \frac{\exp\left(\delta_0 + \delta x_{it}\right)}{1 + \exp\left(\delta_0 + \delta x_{it}\right)} \tag{1}$$

where x_{it} were a set of covariables matched; δ represented the logistic regression coefficients of the corresponding covariables; t could be 2013, 2015, or 2018.

To identify the participants in the non-LTCI group that shared the most PS with the LTCI group, nearest neighbor matching was used. We used 1:4 nearest neighbor matching to reduce the variance due to a large number of comparable non-LTCI participants [33]. Besides, to reduce matching bias, we set a caliper value equal to 0.2 times the standard deviation of the PS value [34]. The matched covariates included age, gender, marital status, educational level, residents, types of nursing, per capita household expenditure, area, types of basic medical insurance, number of chronic diseases, self-reported health status, and any difficulty in ADLs. The matched covariates should not differ significantly between the LTCI and non-LTCI groups if participants that failed the matching process were excluded. We checked the comparability of the covariates by comparing Standardized mean differences (SMD) [35] of covariates before and after matching, which were not influenced by data types and units of measure. Covariates were considered balanced when the absolute SMD was less than 0.25 [36], while Nguyen [37] proposed that the mean squared error was minimized when it was less than 0.10. Therefore this paper used 0.10 as the threshold for SMD.

Then, the DID regression would be done with the matched participants. The DID model is a quasi-experimental research design often used to study the effects of public health policy [38]. The form of the DID design in this study was two-group two-period. Participants in both groups were not exposed to LTCI in period 1, and LTCI policy only cover participants in the LTCI group but not the non-LTCI group in period 2. Differences for each group in the frequency and expenditure of inpatient and outpatient before and after the implementation of the LTCI were then calculated. The difference in aforementioned differences represented the net effect of the LTCI's implementation. The design and illustration of DID model is shown in Fig. 3. The regression model built in this paper was as follows:

$$\begin{aligned} y_{it} = {} & \beta_0 + \beta_1 * LTCI \\ & + \beta_2 * time + \beta_3 * LTCI * time + \delta x_{it} + \epsilon \end{aligned} \tag{2}$$

where y_{it} represent the six dependent variables including the annual inpatient visits frequency, annual total inpatient expenditure, annual OOP inpatient expenditure, monthly outpatient visits frequency, monthly total outpatient expenditure, and monthly OOP outpatient expenditure. *LTCI* represents a grouping dummy variable. If a participant belongs to the LTCI group, *LTCI*=1; otherwise, *LTCI*=0. $Time$ is a time dummy variable. As the LTCI policy was implemented after the 2015 wave, *time* is set as 1 for 2018 and 0 for 2013 and 2015. The interaction term *LTCI time* is the key explanatory variable of the model, which coefficient shows the effect of the LTCI.

x_{it} denote the covariables matched mentioned above and ϵ was the error term.

The premise of applying the DID model is that, in the absence of the LTCI policy, both the LTCI and non-LTCI groups would have followed the same trend in the dependent variables (as shown in period 1 of Fig. 3), thereby meeting the common trends assumption. The coefficients of the interaction term *LTCI time* reflect the changes in the differences of the dependent variables between the LTCI and non-LTCI groups before and after LTCI pilot, eliminating the influence of time and other confounders on the results. If the common trends assumption was not met, we introduced the extended difference-in-difference-in-difference (DDD) model [38].

$$\begin{aligned} y_{it} =& \beta_0 + \beta_1 * LTCI + \beta_2 * time + \beta_3 * city \\ &+ \beta_4 * LTCI * time + \beta_5 * time * city \\ &+ \beta_6 * LTCI * city + \beta_7 * LTCI * time * city + \delta\, x_{it} + \epsilon \end{aligned} \quad (3)$$

For pilot cities, *city*=1; for non-pilot cities, *city*=0. In the pilot cities, *LTCI* is set as 1 for the LTCI group and 0 for non-LTCI group; in the non-pilot cities, *LTCI*=1 presents those with the UEMI; otherwise, *LTCI*=0. Whether the participant belongs to the pilot city is indicated by the city dummy variable *city*. The coefficients of the interaction term $LTCI^*time^*city$ represents the effect of the LTCI. The coefficients reflect the differences in changes of dependent variables differences between LTCI-eligible and non-eligible persons before and after the LTCI pilot, across pilot and non-pilot cities.

Robustness test

This study employed a placebo test [39] to assess the robustness of the DID and DDD results in the baseline analysis. The core idea of the placebo test involves creating fictitious exposure group to LTCI policy (fake LTCI group) and non-exposure group (fake non-LTCI group). If the coefficient of the interaction term remains statistically significant under the fictitious scenario, it suggests that the baseline estimation results are not robust and changes in the dependent variables may not be attributable to the impact of LTCI. Initially, participants from both LTCI and non-LTCI groups were pooled into an allocation pool, from which they were then randomly assigned to fake LTCI group or fake non-LTCI group. Subsequently, 500 regressions identical to those in the baseline analysis were conducted to observe the distribution of coefficients of the interaction term and their statistical significance under the fictitious scenario.

Results

The coverage of LTCI

In the CHARLS pilot city participants, 167 people were covered by LTCI and 772 were not. The coverage rate was about 17.8% in pilot cites. Of the LTCI enrollees, approximately 59.9% (100/167 in 2015) were UEMI participants and 81.4% (136/167) were urban residents.

Propensity score matching results

Before matching, the LTCI and non-LTCI participants differed significantly in 2013, 2015, and 2018 in terms of gender, education level, residents, per capita household expenditure, area, types of basic medical insurance, self-reported health status, and any difficulty in ADL (Table B in supplementary materials). After matching, there were no significant differences in all of the covariates in the matched participants between the LTCI and non-LTCI groups (Table C in supplementary materials). While not everyone in the LTCI group could match 4 non-LTCI group participants, the sample size varied from year to year, with sample sizes of 775, 759, and 741 in 2013, 2015, and 2018, respectively. Figure S1 in supplementary materials shows the visualization of SMD of covariates before and after nearest neighbor matching. All covariates in the three years met the condition that the SMD was less than 0.1. The above results showed that the two groups were balanced. The covariates in both groups of the vulnerable subgroup were also evenly matched.

Common trends test results

Figure 4 shows the results of the common trends test of the six dependent variables of entire population. All dependent variables meet the common trends assumption except for monthly outpatient visits frequency. Therefore, the DDD model was used to evaluate the effect of LTCI on monthly outpatient visits frequency, while the DID model was used to measure its effect on the other dependent variables. All dependent variables in vulnerable subgroup met the common trends assumption and DID model was used for analysis.

PSM-DID/DDD results of entire participants and vulnerable subgroup

Table 1, Column 2 (full table with covariates is in supplemental Table D) presents estimated coefficients of interaction term (*LTCI*time* for the DID model and *LTCI*time*city* for the DDD model) in the baseline model applied to all matched participants. These coefficients represent the net effect of LTCI on healthcare utilization and expenditures. The results indicate that the introduction of LTCI did not lead to a substantial alteration in inpatient utilization and expenditure. This includes annual inpatient visits frequency, annual total inpatient expenditure, and annual OOP inpatient expenditure. Regarding outpatient outcomes, LTCI demonstrated a significant reduction in monthly OOP outpatient expenditure by 313.764 yuan. However, there was no

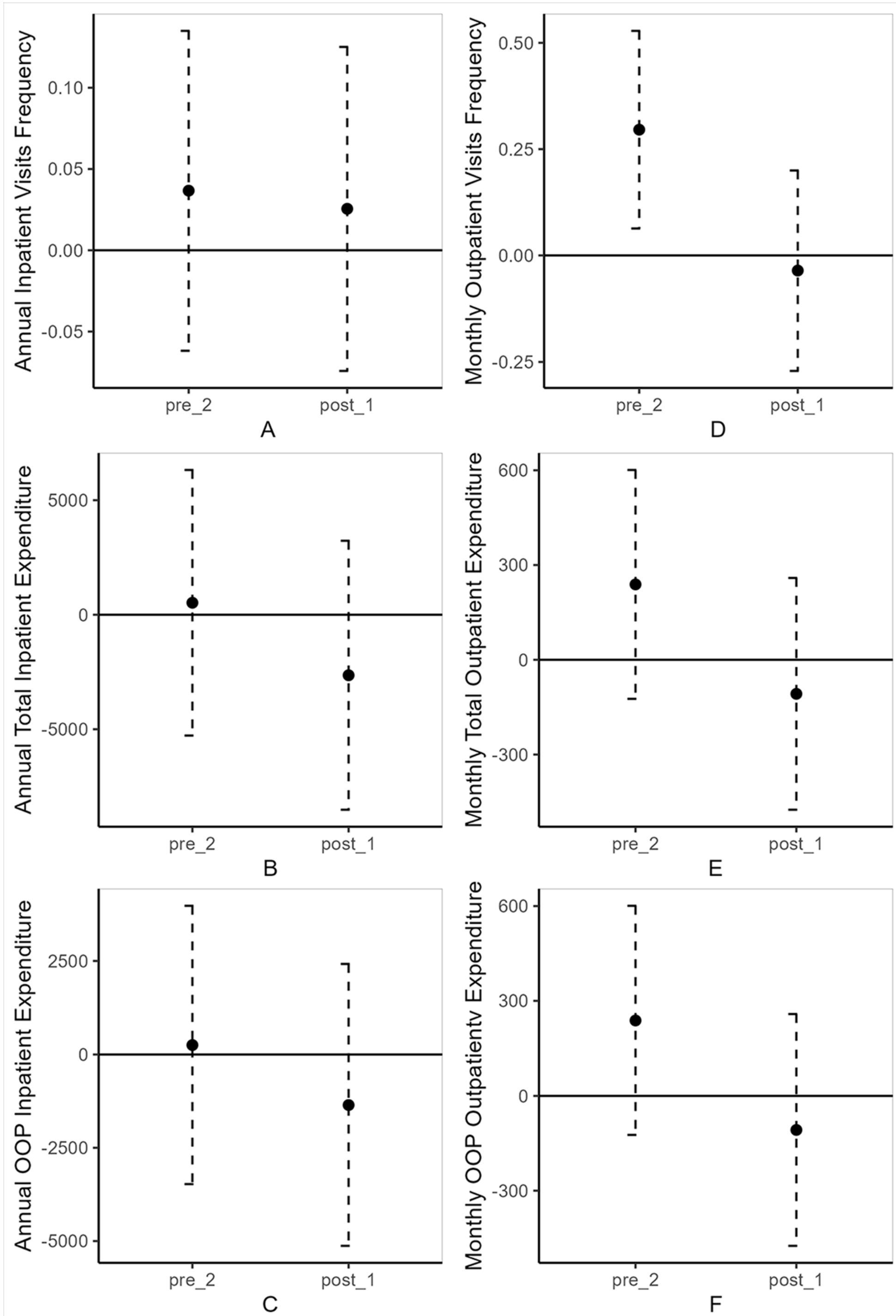

Fig. 4 Results of common trends test. *Notes* **A**, common trends test result of annual inpatient visits frequency; **B**, common trends test result of annual total inpatient expenditure; **C**, common trends test result of annual OOP inpatient expenditure; **D**, common trends test result of monthly outpatient visits frequency; **E**, common trends test result of monthly total outpatient expenditure; **F**, common trends test result of monthly OOP outpatient expenditure. pre_2, 2013; post_1, 2018. *Abbreviations OOP* Out-of-pocket

statistically significant impact on monthly outpatient visits frequency and monthly total outpatient expenditure.

Table 1, Column 3 shows the estimated coefficients for DID model applied to vulnerable matched participants. The DID results demonstrated that the implementation of LTCI significantly decreased outpatient utilization and expenditure for the vulnerable population. The reduction included a 0.523 decrease in monthly outpatient visits

Table 1 The effects of LTCI on health care utilization and expenditures

Variables	Entire participants	Vulnerable participants
Annual inpatient visits frequency	-0.029 (0.059)	-0.163 (0.124)
Annual total inpatient expenditure	-4200.206 (4019.114)	-2275.684 (2090.300)
Annual OOP inpatient expenditure	-2105.069 (2493.747)	-1514.678 (1133.278)
Monthly outpatient visits frequency	-0.489 (0.314)	**-0.523*(0.264)**
Monthly total outpatient expenditure	-343.087 (214.589)	**-643.500*(321.799)**
Monthly OOP outpatient expenditure	**-313.764*(144.168)**	**-302.367*(120.900)**

Notes *$p<0.05$. Statistically significant results were bolded. Standard errors were in parentheses. The PSM-DDD method was used to measure the effect of long-term care insurance on monthly outpatient visits frequency among entire participants, as it did not meet the common trends test. The PSM-DID method was used for the remaining outcome variables. All expenditures are measured in Chinese CNY. 100 CNY = 13.89 USD

Abbreviations OOP Out-of-pocket

frequency, a decrease of 643.500 yuan in monthly total outpatient expenditure, and a decrease of 302.367 yuan in monthly OOP outpatient expenditure.

Robustness test results

We conducted placebo tests on both the full population and the vulnerable subgroup. The results show that, across the 500 regressions for all dependent variables, the average estimated coefficients are not statistically significant, meaning the effects of the fake LTCI policy are close to zero. Figure 5 presents the placebo test results for the four dependent variables that had statistically significant coefficients in the baseline regression. This indicates that the baseline analysis results are robust, and the changes in the differences of the dependent variables between the LTCI and non-LTCI groups was indeed caused by the LTCI policy.

Discussion

This study found that LTCI's coverage remains low in pilot cities. This study discovered that LTCI reduced monthly OOP outpatient expenditure for middle-aged and older Chinese adults. However, it didn't significantly affect outpatient visits frequency, total outpatient expenditure and inpatient outcomes. In the vulnerable subgroup, LTCI decreased three outpatient outcomes but did not affect inpatient results.

Unlike other aging countries like Japan, China had a low LTCI coverage rate. LTCI is mandatory for all Japanese citizens aged 40 and above, whereas China differs in this regard. LTCI was piloted in only 35 cities in China, predominantly covering UEMI enrollees across all pilot cities and including URMI or URRMI enrollees in only a few cities.

Similar to previous research in China [22], this study found that LTCI significantly reduced monthly OOP outpatient expenditure for middle-aged and elderly adults. LTCI also reduced outpatient visits frequency and total outpatient expenditure, though not statistically significant [17]. Similarly to the situation in South Korea, studies have shown that LTCI has no impact on outpatient visit frequency [40] but reduces the medical expenses per visit [41]. In the vulnerable subgroup, reductions were significant for all there outpatient outcomes. One potential mechanism is that LTCI reimburses for daily living care and medical nursing services, which partially substitute for outpatient services. Since services used by insured individuals cannot be covered by different social insurance plans simultaneously, and because LTCI offers a high reimbursement rate and greater convenience compared to outpatient services, participants prefer to seek for long-term care services [42]. Besides, LTCI policies may reduce beneficiaries' risk of disease [43, 44] and outpatient emergencies [45, 46] by offering care services, indirectly lowering outpatient expenses. These findings indicate that LTCI could assist in easing the financial burden of outpatient for beneficiaries. However, there are also studies with different results. Chen et al. [23] found that LTCI had no impact on OOP outpatient expenditure, while Hou et al. [19] found that LTCI improved outpatient utilization and cost. The heterogeneity in the results may be due to differences in the cities analyzed and the definition of the LTCI group. Chen et al. covered only two pilot cities and did not exclude Qingdao from their analysis—where LTCI was implemented partially before LTCI's nationwide launch in 2016—when using the DID method. The partial implementation in Qingdao may have confounded the assessment of the national implementation effects. Hou et al. did not assess the covariate balance between the LTCI and non-LTCI groups, which could lead to confounding effects.

This study found no significant impact of LTCI on inpatient utilization and expenditure, both in the overall population and in the vulnerable subgroup. These findings align with investigations conducted in China [19–21]. The possible reasons are as follows. Firstly, LTCI doesn't reimburse hospitalization expenses like medical insurance does. Instead, it can only indirectly reduce inpatient visits frequency and costs by offering healthcare services to improve the health status of beneficiaries. The too short duration of the LTCI pilot in China to achieve notable improvements in health levels might explain why there wasn't a significant effect [18]. Secondly, participants requiring hospitalization typically have more severe illnesses, leading them to be cautious in selecting medical facilities. Due to the traditional trust in hospitals

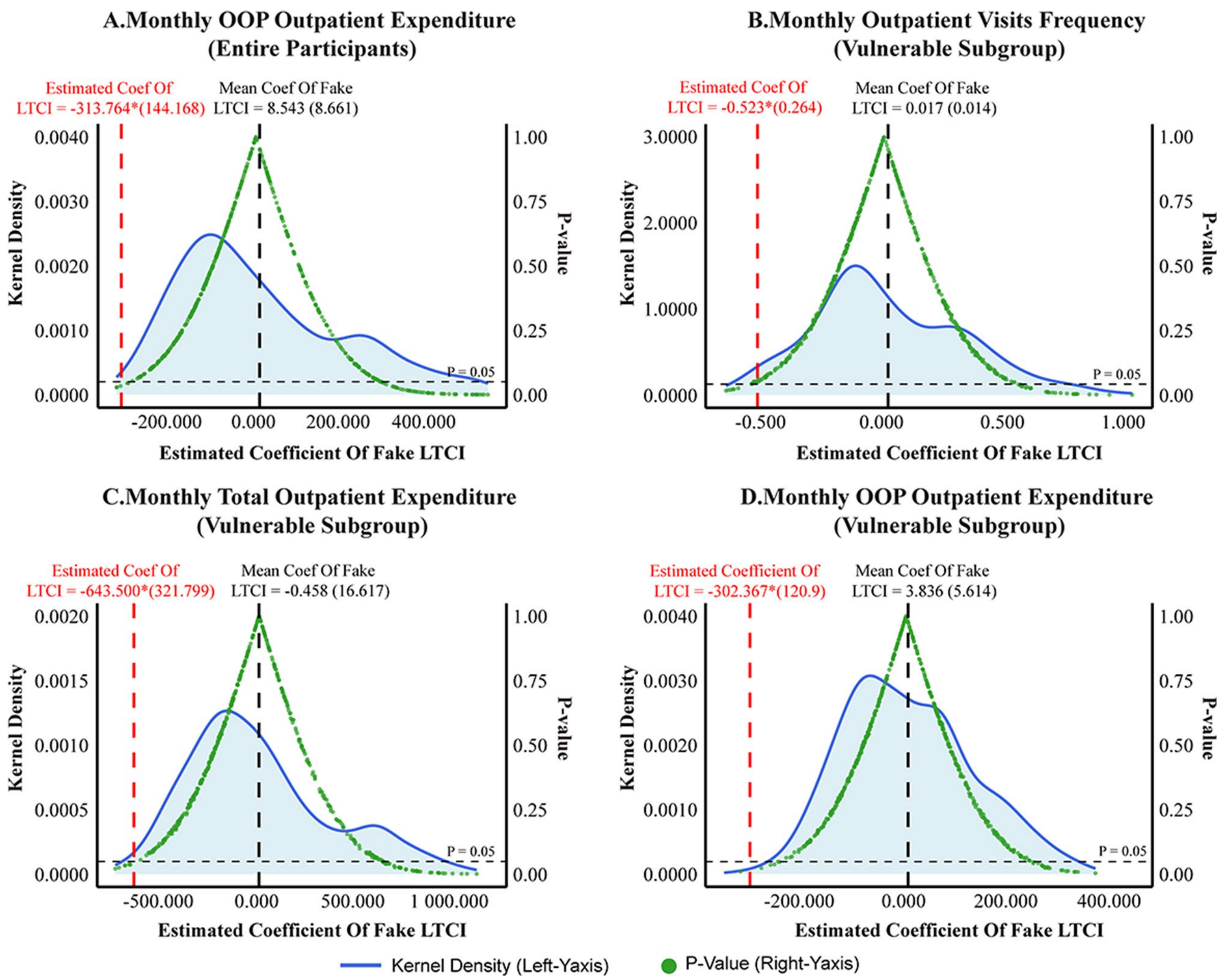

Fig. 5 Results of placebo tests. *Notes* **A**, Kernel density and P-values of simulated coefficients for monthly OOP outpatient expenditure (entire participants); **B**, Kernel density and P-values of simulated coefficients for monthly outpatient visits frequency (vulnerable subgroup); **C**, Kernel density and P-values of simulated coefficients for monthly total outpatient expenditure (vulnerable subgroup); **D**, Kernel density and P-values of simulated coefficients for monthly OOP outpatient expenditure (vulnerable subgroup). Red vertical dashed line, The estimated coefficients (standard errors) in the baseline analysis. Black vertical dashed line, The mean estimated coefficients (standard errors) in the 500 times simulation. Statistically significant coefficients were marked with * Abbreviation: OOP Out-of-pocket

and the limited quality assurance of LTCI services [47], people prefer to choose hospital services rather than LTCI services. Thirdly, LTCI service providers might identify health issues needing hospitalization and offer health education to the disabled and their families [48]. This can raise their awareness of health management, leading to increased demand for hospitalization [49, 50]. As a result, the inpatient utilization and expenditure did not significantly decrease. Some studies had findings that differed from this one. Deng et al. [17] and Yang et al. [28] found that LTCI reduced the frequency and expenditure of inpatient. These studies analyzed data from the 2015 and 2018 waves of CHARLS. Since there is only one wave of data available before the implementation of LTCI, and the common trends test requires data from at least two waves prior to policy implementation, these studies did not perform this test. This omission may lead to improper use of DID analysis and potentially biased outcomes.

Based on the previous description of the coverage rate and the results of the LTCI's impact, this study makes some recommendations. Firstly, expand LTCI's coverage to ensure equity in policy. Presently, most LTCI participants in China are urban residents and those from higher socio-economic backgrounds, like UEMI participants. However, rural populations experience more aging, severe health issues, and face higher risks of poverty due to illness compared to urban areas [51]. It's vital to broaden policy coverage beyond current pilot participants and prioritize rural areas with weaker healthcare infrastructure. Secondly, summarize the pilot experience and establish a referral mechanism between hospitals and LTCI nursing facilities for necessary patient transfers. This initiative may raise awareness of LTCI services and decrease unnecessary hospitalizations.

Limitations

Our study had two limitations. Firstly, we employed self-reported survey data, which may be prone to recall bias. In the survey, CHARLS also investigated the respondent's spouse. If the respondent was unable to answer, CHARLS designated the spouse or adult children as proxy respondent, reducing bias to some extent. Secondly, as a quasi-experiment, this study may involve confounding effects in causal inference. Similar to other studies [18, 23, 28], we matched and corrected for covariates that likely influenced the outcomes.

Conclusions

The empirical results of this study suggested that the introduction of LTCI reduced the OOP outpatient expenditure but did not affect other outcomes among Chinese middle-aged and elderly people. Similarly, LTCI reduced outpatient but not inpatient outcomes in vulnerable population. Based on our findings, improvements in LTCI policy are needed.

Abbreviations

LTCI	Long-term care insurance
ADLs	Activities of daily living
DID	Difference-in-difference
OOP	Out-of-pocket
CHARLS	China Health and Retirement Longitudinal Study
UEMI	Urban employee medical insurance
URMI	Urban resident medical insurance
URRMI	Urban and rural resident medical insurance
MSA	Medical savings account
NCMI	New rural cooperative medical insurance
PSM-DID	Propensity score matching difference-in-difference method
PS	Propensity scores
SMD	Standardized mean differences
DDD	Difference-in-difference-in-difference method

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12939-024-02297-y.

Supplementary Material 1

Acknowledgements

We thank the CHARLS research and field team and every participant in the study for their contributions. We thank the long-term care insurance research group from School of Public Administration and Policy, Renmin University of China for providing China pilot long-term care insurance policy database (CLIP). We thank Yuzhou Gu (Guangzhou Center for Disease Control and Prevention, Guangzhou, China) for supervising the study.

Author contributions

CH and YJX were both corresponding authors for this manuscript. M-DL analyzed data, interpreted data and wrote the manuscript. X-RF and J-SL analyzed data, interpreted data and revised the manuscript. JW, PY and R-FZ checked the statistical results and revised the manuscript. YJX and CH developed study protocol, supervised the study, and revised the manuscript.

Funding

Supported by the National Natural Science Foundation of China (grant number #71974212, #72204059) and Science and Technology Program of Guangzhou, China (grant number #202201010078).

Data availability

The datasets generated and analyzed during the current study are available in the CHARLS repository, https://charls.pku.edu.cn/.

Declarations

Ethics approval and consent to participate

Ethical approval for main household survey in all the CHARLS waves was granted from the Institutional Review Board at Peking University (IRB00001052-11015). During the fieldwork, each respondent who agreed to participate in the survey was asked to sign two copies of the informed consent, and one copy was kept in the CHARLS office, which was also scanned and saved in PDF format. The survey were in accordance with the ethical standards delineated in the 1964 Declaration of Helsinki and its subsequent amendments.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 19 February 2024 / Accepted: 2 October 2024
Published online: 14 October 2024

References

1. Han Y, He Y, Lyu J, Yu C, Bian M, Lee L. Aging in China: perspectives on public health. Global Health J. 2020;4:11–7.
2. Luo Y, Su B, Zheng X. Trends and challenges for population and health during population aging - China, 2015–2050. China CDC Wkly. 2021;3:593–8.
3. Chen X, Giles J, Yao Y, Yip W, Meng Q, Berkman L, et al. The path to healthy ageing in China: a Peking University-Lancet Commission. Lancet. 2022;400:1967–2006.
4. Yang X, Hao Y, George SM, Wang L. Factors associated with health-related quality of life among Chinese caregivers of the older adults living in the community: a cross-sectional study. Health Qual Life Outcomes. 2012;10:143.
5. Yip W, Fu H, Chen AT, Zhai T, Jian W, Xu R, et al. 10 years of health-care reform in China: progress and gaps in Universal Health Coverage. Lancet. 2019;394:1192–204.
6. OECD. (2024), Old-age dependency ratio (indicator). doi: 10.1787/e0255c98-en (Accessed on 04 February 2024) [Internet]. theOECD. [cited 2024 Feb 4]. http://data.oecd.org/pop/old-age-dependency-ratio.htm
7. Cylus J, Thomson S, Evetovits T. Catastrophic health spending in Europe: equity and policy implications of different calculation methods. Bull World Health Organ. 2018;96:599–609.
8. Murphy A, Palafox B, Walli-Attaei M, Powell-Jackson T, Rangarajan S, Alhabib KF, et al. The household economic burden of non-communicable diseases in 18 countries. BMJ Glob Health. 2020;5:e002040.
9. Li Y, Wu Q, Xu L, Legge D, Hao Y, Gao L, et al. Factors affecting catastrophic health expenditure and impoverishment from medical expenses in China: policy implications of universal health insurance. Bull World Health Organ. 2012;90:664–71.
10. Coe NB, Goda GS, Van Houtven CH. Family spillovers and long-term care insurance. J Health Econ. 2023;90:102781.
11. Chen L, Xu X. Effect evaluation of the long-term care insurance (LTCI) system on the health care of the elderly: a review. J Multidiscip Healthc. 2020;13:863–75.
12. Lee TW, Yim ES, Choi HS, Chung J. Day care vs home care: effects on functional health outcomes among long-term care beneficiaries with dementia in Korea. Int J Geriatr Psychiatry. 2019;34:97–105.

13. Moon S, Park HJ, Sohn M. The impact of long-term care service on total lifetime medical expenditure among older adults with dementia. Soc Sci Med. 2021;280:114072.
14. Choi JW, Park E-C, Lee SG, Park S, Ryu H-G, Kim TH. Does long-term care insurance reduce the burden of medical costs? A retrospective elderly cohort study. Geriatr Gerontol Int. 2018;18:1641–6.
15. Serrano-Alarcón M, Hernández-Pizarro H, López-Casasnovas G, Nicodemo C. Effects of long-term care benefits on healthcare utilization in Catalonia. J Health Econ. 2022;84:102645.
16. Crawford R, Stoye G, Zaranko B. Long-term care spending and hospital use among the older population in England. J Health Econ. 2021;78:102477.
17. Deng X, Liao J, Peng R, Chen J. The impact of long-term care insurance on medical utilization and expenditures: evidence from Jingmen, China. Int J Environ Res Public Health. 2022;19:12275.
18. Lei X, Bai C, Hong J, Liu H. Long-term care insurance and the well-being of older adults and their families: evidence from China. Soc Sci Med. 2022;296:114745.
19. Hou Y, Wang Y, Yan S, Zhang W, Zhang L, Yao J. Impacts from long-term care insurance on medical service utilization, medical burden and health of middle-aged and elderly people: an empirical research based on the DID method. Chin J Health Policy. 2021;14(9):35–40. [in Chinese].
20. Gao X, Yue Z. The impact of long-term care insurance on medical expenditure for middle-aged and elderly people in China: empirical analysis based on CHARLS. Xinjiang State Farms Econ. 2022;348(02):38–46. [in Chinese].
21. Man X, Ma C. Effect of long-term care insurance on health condition, medical expenditure and family care of the urban elderly in China: a CHARLS data analysis. Chin J Public Health. 2023;39:971–5.
22. Ma C, Yu Q, Song Z, Chen H. Long-term care insurance, the control of medical expenses and value based Health Care. Industrial Econ. 2019;381(12):42–59. [in Chinese].
23. Chen H, Ning J. The impacts of long-term care insurance on health care utilization and expenditure: evidence from China. Health Policy Plan. 2022;37:717–27.
24. Ma G, Xu K. Value-based health care: long-term care insurance for out-of-pocket medical expenses and self-rated health. Int J Environ Res Public Health. 2022;20:192.
25. Tang Y, Chen T, Zhao Y, Taghizadeh-Hesary F. The impact of the long-term Care Insurance on the medical expenses and Health Status in China. Front Public Health. 2022;10:847822.
26. Yu X, Liu H, Yang W. Long-term care insurance's impacts on medical expenditure——Based on synthetic control research on Qingdao case. Insurance Stud. 2019;370(2):114–27. [in Chinese].
27. Feng J, Wang Z, Yu Y. Does long-term care insurance reduce hospital utilization and medical expenditures? Evidence from China. Soc Sci Med. 2020;258:113081.
28. Yang S, Guo D, Bi S, Chen Y. The effect of long-term care insurance on healthcare utilization of middle-aged and older adults: evidence from China health and retirement longitudinal study. Int J Equity Health. 2023;22:228.
29. China Health and Retirement Longitudinal Study [Internet]. [cited 2023 Sep 2]. http://charls.pku.edu.cn/
30. Zhao Y, Hu Y, Smith JP, Strauss J, Yang G. Cohort profile: the China Health and Retirement Longitudinal Study (CHARLS). Int J Epidemiol. 2014;43:61–8.
31. Andersen RM. Revisiting the behavioral model and access to medical care: does it matter? J Health Soc Behav. 1995;36:1–10.
32. Rosenbaum PR, Rubin DB. The central role of the propensity score in observational studies for causal effects. Biometrika. 1983;70:41–55.
33. Caliendo M, Kopeinig S. Some practical guidance for the implementation of propensity score matching. J Econ Surv. 2008;22:31–72.
34. Austin PC. An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivar Behav Res. 2011;46:399–424.
35. Zhao Q-Y, Luo J-C, Su Y, Zhang Y-J, Tu G-W, Luo Z. Propensity score matching with R: conventional methods and new features. Ann Transl Med. 2021;9:812.
36. Stuart EA. Matching methods for causal inference: a review and a look forward. Stat Sci. 2010;25:1–21.
37. Nguyen T-L, Collins GS, Spence J, Daurès J-P, Devereaux PJ, Landais P, et al. Double-adjustment in propensity score matching analysis: choosing a threshold for considering residual imbalance. BMC Med Res Methodol. 2017;17:78.
38. Wing C, Simon K, Bello-Gomez RA. Designing difference in difference studies: best practices for public health policy research. Annu Rev Public Health. 2018;39:453–69.
39. Wan J, Nie C, Zhang F. Does broadband infrastructure really affect consumption of rural households? – a quasi-natural experiment evidence from China. China Agricultural Economic Rev. 2021;13:832–50.
40. Costa-Font J, Jimenez-Martin S, Vilaplana C. Does long-term care subsidization reduce hospital admissions and utilization? J Health Econ. 2018;58:43–66.
41. Cho Y-M, Kwon S. Effects of public long-term care insurance on the medical service use by older people in South Korea. Health Econ Policy Law. 2023;18:154–71.
42. Zhang Y, Yu X. Evaluation of long-term care insurance policy in Chinese pilot cities. Int J Environ Res Public Health. 2019;16:3826.
43. Lee TW, Yim E, Cho E, Chung J. Cognitive function, behavioral problems, and physical function in long-term care insurance beneficiaries with dementia in South Korea: comparison of home care and institutional care services. J Am Geriatr Soc. 2014;62:1467–75.
44. Wang J, Guan J, Wang G. Impact of long-term care insurance on the health status of middle-aged and older adults. Health Econ. 2023;32:558–73.
45. Rapp T, Chauvin P, Sirven N. Are public subsidies effective to reduce emergency care? Evidence from the PLASA study. Soc Sci Med. 2015;138:31–7.
46. Di Pollina L, Guessous I, Petoud V, Combescure C, Buchs B, Schaller P, et al. Integrated care at home reduces unnecessary hospitalizations of community-dwelling frail older adults: a prospective controlled trial. BMC Geriatr. 2017;17:53.
47. Feng Z, Glinskaya E, Chen H, Gong S, Qiu Y, Xu J, et al. Long-term care system for older adults in China: policy landscape, challenges, and future prospects. Lancet. 2020;396:1362–72.
48. Bailey MJ, Goodman-Bacon A. The War on Poverty's experiment in Public Medicine: Community Health Centers and the mortality of older americans. Am Econ Rev. 2015;105:1067–104.
49. Takahashi M. Insurance coverage, long-term care utilization, and health outcomes. Eur J Health Econ. 2023;24:1383–97.
50. Kim H, Mitra S. The economic and health effects of long-term care insurance: new evidence from Korea. J Econ Ageing. 2022;23:100412.
51. Zhou Y, Guo Y, Liu Y. Health, income and poverty: evidence from China's rural household survey. Int J Equity Health. 2020;19:36.

Publisher's note