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**Urban Difference Perspective: Research on the Impact Effect of Home- and
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26 **Abstract:**

27 **Background:** Population aging and public health emergencies pose challenges to the
28 sustainability of healthcare systems for older adults. This study aims to assess the
29 resilience of urban healthcare system for older adults and to examine whether, how, and
30 under what conditions nationwide reforms in home and community care have enhanced
31 the resilience of this system.

32 **Methods:** Using the pilot program for reforming home- and community-based elderly
33 care services (PHC), rolled out in five batches from 2016, as a quasi-natural experiment,
34 we analysed 4774 city-year observations from Chinese prefecture-level and higher
35 cities over 2010–2024. The urban healthcare services resilience index (LCRI) is
36 constructed from two dimensions: service supply resilience and cost guarantee
37 resilience. Spatial analysis, kernel density estimation, and Dagum Gini decomposition
38 characterised its distributional evolution and regional disparities. A staggered
39 difference-in-differences (DID) model identified the average treatment effect, dynamic
40 effects, and transmission mechanisms, with multiple robustness tests.

41 **Results:** During the sample period, the overall urban LCRI rose steadily, areas with
42 low LCRI values contracted significantly, and regional disparities showed a fluctuating
43 trend toward narrowing. Its spatial distribution did not exhibit a typical “higher in the
44 east, lower in the west” gradient, but rather varied more in accordance with population
45 density. PHC significantly improved the LCRI, and the policy effects gradually
46 emerged and continued to accumulate as PHC progressed. Mechanism analysis
47 indicates that PHC primarily exerted its effects by stimulating healthcare supply and

strengthening cost coverage, as evidenced by an increase in the number of seats for community meal assistance services and care personnel, as well as a decrease in per capita healthcare expenditure. Heterogeneity analysis shows that the effects of PHC were more evident in cities with higher degrees of economic development, more advanced aging populations, abundant medical resources, well-developed digital infrastructure, and greater fiscal capacity.

Conclusions: PHC can enhance the LCRI by stimulating healthcare supply and strengthening cost coverage, with gains accumulating over time and concentrated in better-resourced cities. This study provides evidence at the urban level for enhancing the resilience of healthcare systems for the elderly.

Keywords: Healthcare services; Home and community care services; Healthcare equity; Spatial distribution; Kernel density analysis

Background

Population aging and increased life expectancy are reshaping global health systems and have made equitable access to sustainable care for older adults a central issue on the global health agenda. According to data from the World Health Organization, the global population aged 60 and older reached 1 billion in 2020 and is projected to rise to 1.4 billion by 2030 and 2.1 billion by 2050. The demand for care resulting from disability and cognitive impairment continues to grow, and its distribution is uneven across regions with varying resource endowments. Long-term care has evolved from a matter arranged by families into a public issue concerning health, finance, and equity, and its accessibility directly influences disparities in health outcomes among older adults. In recent years, public health emergencies and rising care costs have demonstrated that the equity and sustainability of the system are not determined by its static scale, but rather by its ability to maintain service accessibility during disruptions and to prevent families from falling into financial distress due to care expenses. Therefore, scale indicators such as the number of beds and the number of facilities can only indicate the size of the system; they cannot answer questions about who the system serves fairly or whether it can withstand shocks. It is against this backdrop that the concept of resilience from health systems research has been introduced into the field of health care services for older adults to describe the system's ability to maintain equity and accessibility, absorb shocks, and resume operations in the face of exogenous disturbances [1, 2]. Resilience represents a reserve of capacity built

up through sustained investment and may be distributed unevenly across different cities, manifesting primarily in two capacities: service supply redundancy and cost buffers. Accordingly, this paper defines the LCRI for older adults as the system's ability to maintain service provision, stabilize cost burdens, and ensure equitable and sustainable operations in the face of expanding demand or external shocks, and characterizes it from two dimensions: service provision resilience and cost protection resilience.

How to build this capacity and ensure it benefits cities at different stages of development is a common equity challenge facing all countries as they reform their elderly health care systems. The prevailing trend in international practice is highly consistent: shifting the focus of care from institutional settings to home and community-based care, and replacing high-cost institutional services with continuous care that is closely integrated into daily life. Since 2016, China has been advancing pilot reforms for home- and community-based elderly care services, using central lottery public welfare funds to provide incentive-based subsidies that support the construction of community care facilities, the establishment of service platforms, and the participation of social forces. The design of this initiative implicitly addresses disparities in regional resource allocation and represents a concrete implementation of the transition toward a de-institutionalized elderly health care system in China. Its phased implementation, supported by ongoing fiscal incentives, provides favorable conditions for identifying policy effects and examining their distribution patterns at the urban level. The key lies not in increasing the total volume of resources, but in simultaneously optimizing the structure of care provision and cost coverage, so that cities with different resource

endowments all have the opportunity to enhance their capabilities [3]. On the supply side, stable, targeted funding has driven the regular establishment of community service centers and professional staff, transforming care capacity into mobilizable reserves, which particularly benefits older adults in resource-scarce areas [4]. On the cost side, universal access to home- and community-based services replaces high-cost institutional care and reduces the marginal demand for medical services through health management, thereby lowering household out-of-pocket expenses [5]. It is evident that pilot programs may enhance the resilience of urban health and medical service systems for the elderly through two pathways: stimulating supply and ensuring cost coverage; however, whether this improvement can be achieved simultaneously across different cities remains to be seen.

Research related to this study primarily falls into two categories. The first category of studies examines the implementation effects of supply-side policies for elder care services, with research outcomes largely focusing on service accessibility, the health of older adults, unmet care needs, and the burden of family caregiving [6, 7]. Previous studies show that these pilot programs improve older adults' health, slow declines in daily living ability, and reduce unmet care needs [8, 9]. Expanding community care may also substitute for informal family care and reduce the use of intensive medical services [10, 11]. A second strand of the literature centers on the resilience of healthcare systems and long-term care frameworks, primarily addressing conceptual frameworks, evaluation indicators, and regional differences [12-14]. Overall, these two strands have not yet been effectively integrated: On the one hand, policy evaluations rarely treat the

system's combined capacity to maintain services and stabilize costs as an outcome variable, making it difficult to determine whether supply-side reforms have improved the system's scale or its resilience to disruptions. On the other hand, research on resilience largely remains at the cross-sectional or descriptive level, lacking causal identification based on quasi-experimental designs. Consequently, questions remain as to whether and to what extent reforms in home- and community-based care have enhanced the LCRI, through what mechanisms these effects are transmitted, and under what urban conditions such reforms are most effective.

Compared with existing research, this paper's marginal contributions are primarily reflected in four aspects. First, it expands the outcome variables for evaluating elderly care service policies from service quantity and health outcomes to the resilience of the elderly health care system. Second, it constructs the urban elderly LCRI based on two dimensions: service supply resilience and cost coverage resilience. This index provides a comparable, quantitative assessment of the resilience of the elderly health care system. Third, this study combines distributional analysis with policy effect identification. On the one hand, it uses spatial distribution, kernel density estimation, and the Dagum-Gini decomposition to illustrate the evolution of resilience levels and inter-city differences; on the other hand, it employs an interleaved difference-in-differences method to identify the net effects and dynamic impacts of policies. Descriptive findings and effect identification mutually corroborate one another, collectively painting a comprehensive picture of resilience enhancement. Fourth, this study identifies two transmission mechanisms: the stimulation of healthcare service supply and the strengthening of cost

coverage. At the same time, the study examines the heterogeneity of policy effects across different levels of economic development, degrees of population aging, healthcare resources, digital infrastructure, and fiscal capacity. This provides a reference for cities and countries at different stages of development to advance healthcare reforms for the elderly.

The rest of the study proceeds as outlined below. Section 2 outlines the policy backdrop, theoretical frameworks, and research hypotheses. Section 3 details the data, methodologies, and variables. Section 4 reports the distribution analysis, regional disparities, baseline results, and robustness tests. Section 5 looks into the mechanisms and urban heterogeneity. Section 6 explores the results and limitations. Section 7 concludes and presents policy implications.

Policy Background and Theoretical Analysis

Policy context of home- and community-based care reform in China

PHC is a representative policy initiative by the central government to advance supply-side reform in elderly care services, and it also serves as the institutional precursor to the current inclusive network of universal elderly care . Fig. 1 outlines the institutional evolution and key policy milestones of PHC. Evaluating the effectiveness of PHC not only helps summarize existing reform experiences but also informs the policy implementation for the subsequent expansion of inclusive elderly care services.

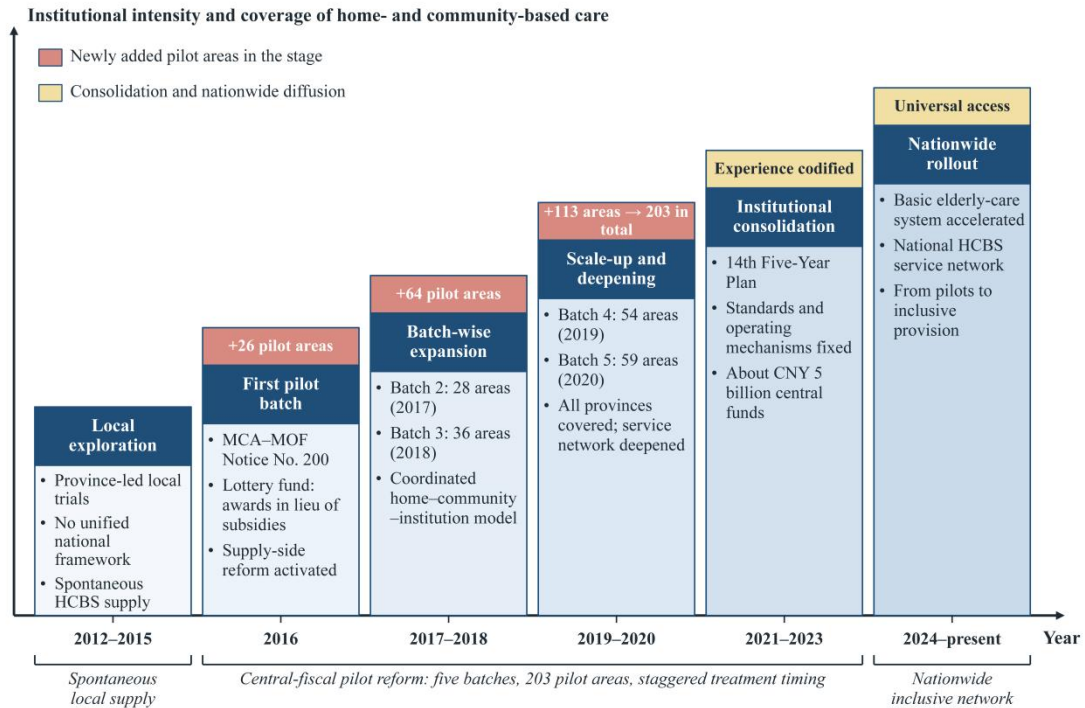


Fig. 1 Institutional Evolution of PHC in China and Key Policy Milestones

Fig. 2 further illustrates the pace of PHC’s implementation and its staggered treatment structure. The differences in the timing at which cities in each batch entered the treatment phase provide the necessary variation in treatment timing for the staggered two-way DID analysis.

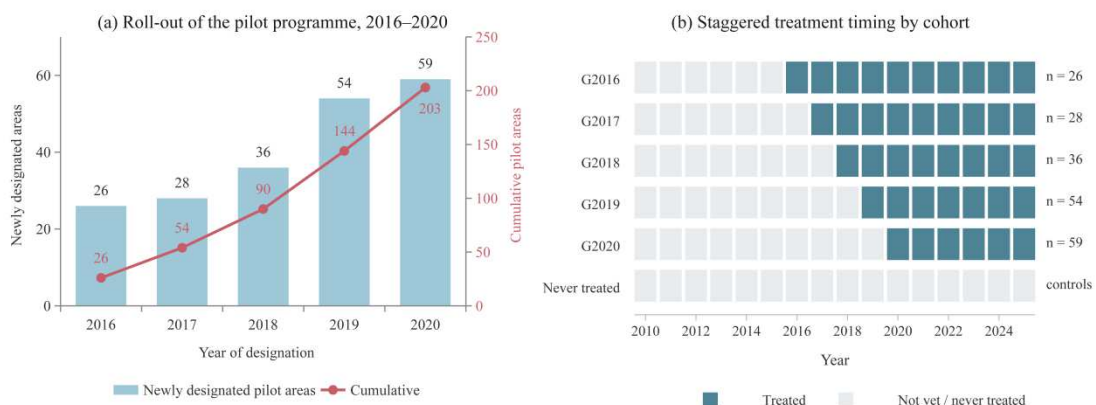


Fig. 2 Timeline of PHC and Allocation of Overlapping Implementation Phases

Conceptual framework and study hypotheses

Resilience is essentially a system's capacity to maintain core services, stabilize costs, and recover quickly in the face of disruptions; this capacity can only be gradually built up through sustained and predictable resource investments under normal conditions [15-17]. The institutional characteristics of PHC lie precisely in this: the central government's special lottery public welfare fund, through its "incentive-based funding" approach, provides local governments with stable, predictable dedicated funding and institutional support, transforming scattered, spontaneous local initiatives into sustained investments backed by standards, performance evaluations, and supporting measures [18]. Unlike one-time subsidies or purely demand-side subsidies, this approach simultaneously transforms both the supply structure and cost structure of the system, thereby affecting the system's overall capacity rather than a single outcome [19]. Evaluations of PHC have already shown that the pilots significantly slowed the decline in older adults' activities of daily living and reduced unmet care needs, while also improving their health status [20-22]; these widespread improvements at the individual level are a direct reflection of the alleviation of pressure at the system level. Based on this, we propose the following hypothesis:

Hypothesis 1. PHC significantly enhances the LCRI.

The aforementioned improvement in resilience can be broken down into two pathways: strengthening financial protection and enhancing care provision. The effect of strengthening financial protection stems from the fundamental characteristics of

long-term care risks: expenditures are highly uncertain and potentially catastrophic, and the ability to cushion these costs therefore constitutes a key pillar of resilience [23, 24]. This effect operates through price and health channels. Under the price channel, universal pricing and government procurement reduce out-of-pocket care costs. They also allow households to shift spending away from reactive medical treatment [25, 26]. Under the health channel, continuous community health management helps preserve older adults' health and reduces demand for intensive medical services [27]. Consistent with this, the expansion of long-term healthcare supply and subsidies has repeatedly been found to curb older adults' use of hospitalizations and medical services [28-30]. This process improves access to services, replaces some high-cost institutional and medical care, reduces household cash expenditure, and strengthens financial buffers. With this in mind, we propose the following hypothesis:

Hypothesis 2. PHC enhances the cost protection resilience dimension of the LCRI by reducing the economic burden of personal care and strengthening the stability of funding.

The healthcare supply activation effect manifests as the expansion and structural optimization of formal care services in the community. PHC established community meal centers, day care centers, and embedded elderly care facilities across local service grids. This reduced the distance and time required to obtain care and shifted some family-based informal care to accessible formal services [31]. Existing evidence also shows that community care reduces the time families spend on informal care, especially for older adults with greater care needs [32, 33]. At the same time, government

procurement and social participation have lowered entry barriers and operating risks for private elderly care facilities. They have also expanded the workforce of professional caregivers, social workers, and senior care assistants. However, whether this supply can truly be realized depends on the support provided by the allocation of medical resources and interdepartmental coordination [34, 35]. The significance of this goes beyond the current scale of the sector: service outlets and human resources that operate on a routine basis constitute the system's capacity for rapid mobilization and accessibility when demand surges. Fiscal incentives and subsidies support facilities and service platforms. They also attract social providers and expand the care workforce, thereby increasing supply reserves and improving accessibility. Consequently, the following hypothesis is put forward:

Hypothesis 3. PHC enhances the “service supply resilience” dimension of the LCRI by stimulating the supply of community care services, expanding the care workforce, and increasing supply redundancy and accessibility.

Fig. 3 summarizes the theoretical mechanism through which PHC affects the LCRI.

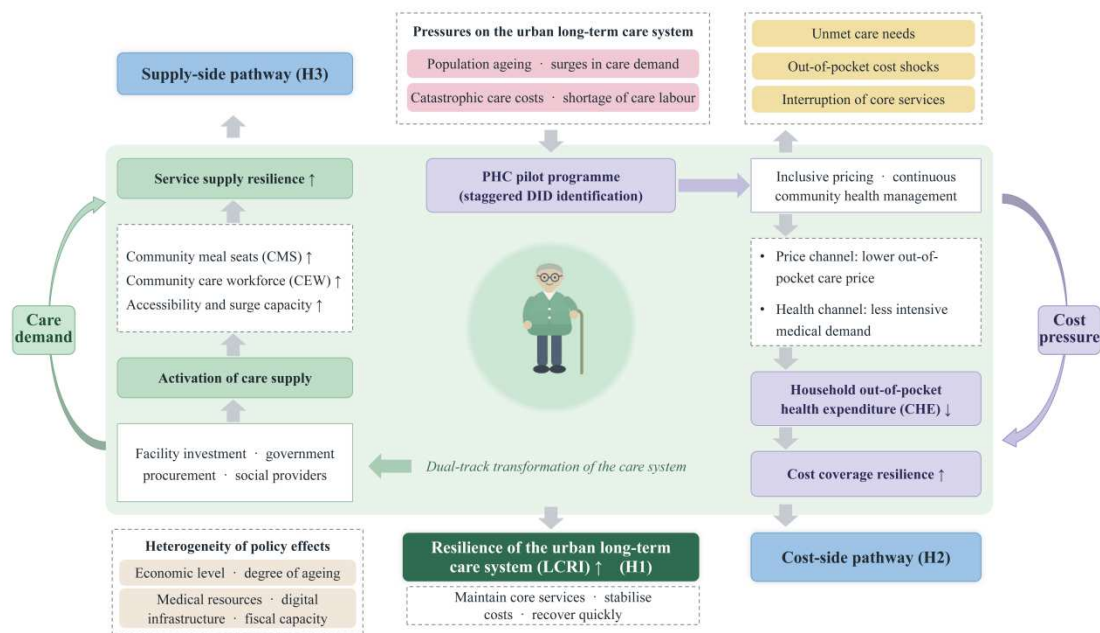


Fig. 3 Theoretical Framework of the Impact of PHC on the LCRI

Methods

Study design and data sources

Information was derived from three primary sources. First, national, provincial, and municipal statistical yearbooks and reports are used to construct the LCRI, mechanism variables, and controls. Second, five official lists along with supporting documents released by the Ministry of Civil Affairs and the Ministry of Finance have specified the pilot urban areas and their respective implementation timelines. Third, population yearbooks and city statistical bulletins provide supplementary data on population structure and public finance.

Statistical analysis

Spatial pattern analysis

Spatial distribution analysis is used to intuitively present the geographical pattern of the LCRI and its temporal changes [36]. Based on the calculated LCRI, this study denotes the LCRI of city i in year t as $LCRI_{it}$, and divides it into several grade intervals according to the natural breaks method or the quantile method. If the lower and upper bounds of the q th grade interval are c_{q-1} and c_q , respectively, then the spatial distribution category of city i in year t can be expressed as:

$$S_{it}=q, \quad \text{if } c_{q-1} \leq LCRI_{it} < c_q, \quad q=1,2,\dots,Q \quad (1)$$

where S_{it} denotes the resilience grade to which city i belongs in year t , and Q is the number of grades divided. By comparing the spatial distributions at different time points S_{it} , the spatial agglomeration, gradient differences, and evolutionary characteristics of high-resilience and low-resilience cities can be observed, providing a descriptive factual basis for the subsequent decomposition of regional differences and identification of policy effects.

Regional inequality analysis

To more comprehensively depict the regional disparities in the LCRI and their underlying causes, this study employs the Dagum Gini coefficient decomposition approach. Unlike the traditional Gini coefficient, which fails to account for overlapping regions, the Dagum version can break down the total disparity into three components:

intra-regional variance, inter-regional differences, and transvariation density, offering a more precise insight into the structural origins of LCRI variations across regions [37].

The overall Dagum Gini coefficient can be expressed as:

$$G = \frac{\sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{2n^2 \bar{y}} \quad (2)$$

where y_{ji} and y_{hr} denote the LCRI of cities in region j and region h , respectively; n_j and n_h are the numbers of cities in region j and region h , respectively; n is the total number of sample cities; $\bar{y}$ is the mean LCRI of the full sample; and k is the number of regions. Furthermore, the overall difference can be decomposed as:

$$G = G_w + G_{nb} + G_t \quad (3)$$

where G_w denotes the contribution of intra-regional differences, G_{nb} denotes the contribution of net inter-regional differences, and G_t denotes the contribution of transvariation density. On this basis, the study further explores the evolving patterns and contribution framework of LCRI disparities across the eastern, central, and western regions.

Distributional analysis

Kernel density estimation serves as a data-driven approach to describing probability distributions without assuming a specific functional form. Its advantage is that it does not presuppose a specific functional form of the overall distribution; instead, the shape of the density curve is determined by the sample data themselves. It is therefore suitable for characterizing the distributional position, shape, extension, and

polarization characteristics of the LCRI. Let the observed values of the LCRI be $x_i (i=1,2,\dots,n)$; then the kernel density estimator at any point x is:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x-x_i}{h}\right) \quad (4)$$

where n is the sample size, $K(\cdot)$ is the kernel function, and h is the bandwidth.

In this study, a Gaussian kernel is employed:

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right) \quad (5)$$

The bandwidth is determined according to the rule of thumb, and is re-estimated later using 1.5 times and 0.5 times the bandwidth to test the sensitivity of the distributional characteristics to bandwidth selection [38]. It should be emphasized that kernel density analysis characterizes descriptive facts at the distributional level, which are used to present stylized facts and provide an empirical background for causal analysis; the identification of the net policy effect still relies on the DID and event-study designs below.

Difference-in-differences analysis

PHC was implemented in five batches. Because the timing at which different cities entered PHC varied, a typical multi-period treatment structure was formed. To examine the causal impact of PHC on the LCRI, this study employs a staggered DID model [39]. The baseline model is specified below:

$$LCRI_{it} = \alpha + \beta PHC_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

Here, $LCRI_{it}$ denotes the LCRI for city i in year t . PHC_{it} equals 1 after city i

enters PHC in year t and 0 otherwise. β captures the average policy effect on the LCRI, and X_{it} is a vector of city-level controls. μ_i and λ_t denote city and year fixed effects, while ε_{it} is the error term. Robust standard errors for each regression are adjusted by clustering at the city level.

To verify the parallel-trends hypothesis and explore how policy impacts evolve over time, this study develops an event-study framework:

$$LCRI_{it} = \alpha + \sum_{k=-5, k \neq -1}^5 \beta_k D_{it}^k + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (7)$$

where D_{it}^k is a relative-time dummy variable, taking the value 1 when city i in year t is exactly k periods away from the year in which it entered PHC, and 0 otherwise; the period immediately before policy implementation ($k=-1$) is used as the reference group. If β_k in all pre-policy periods are not significantly different from zero, the parallel-trends assumption is supported; β_k in the post-policy periods characterize the dynamic changes in the policy effect.

To examine how the effect is transmitted, this study substitutes the dependent variable in Equation (6) with variables representing potential transmission paths, and develops the model below [40]:

$$M_{it} = \alpha + \theta PHC_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

where M_{it} sequentially denotes per capita healthcare consumption expenditure, the number of community meal-service places, and the number of community elderly care service workers; θ characterizes the average treatment effect of PHC on the corresponding mechanism variable.

Measures

Primary outcome: healthcare services resilience index

The measure of urban elderly healthcare services resilience index (LCRI) focuses on the system's potential level of resilience. In this study, we developed a comprehensive urban metric called the LCRI, which is built upon two key aspects: service supply resilience and cost coverage resilience. The former characterizes the system's supply capacity, redundancy, and accessibility when demand expands, while the latter characterizes the system's funding stability and cost-buffering capacity. These two dimensions complement each other, ensuring that the resilience assessment covers both the service supply side and the cost coverage side, thereby providing a relatively comprehensive portrayal of the urban healthcare service system for older adults' overall capacity to withstand disruptions and maintain sustainable operations. The indicator system consists of two dimensions and a total of 10 third-level indicators, all of which are available at the city level, as presented in Table 1.

The index is synthesized by determining weights using the entropy method and then performing a weighted aggregation.

Exposure: PHC pilot reform

The explanatory variable in this study is PHC. The treatment variable, PHC_{it} , is constructed as follows: it equals 1 once city i has been designated a PHC pilot at time t , and 0 otherwise.

373

374 **Table 1**

375 Indicator System for Evaluating the LCRI

Composite Index	Primary Indicators	Secondary Indicators	Indicator Definition	Attributes	Weight
LCRI	Resilience of Service Provision	Number of hospital and health center beds per 10,000 people	ln(Number of hospital and health center beds / Urban permanent resident population)	+	0.0022
		Number of elderly care facilities per capita	Number of elderly care facilities / Urban permanent resident population per 100,000	+	0.3414
		Number of healthcare professionals per 10,000 people	ln(Number of healthcare professionals / Urban permanent resident population)	+	0.0155
		Number of licensed physicians per 1,000 people	Number of licensed physicians / Urban permanent resident population	+	0.0328
		Number of hospitals and health centers per 1,000 people	Number of hospitals and health centers / Urban permanent resident population	+	0.1625
	Resilience of Cost Coverage	Number of elderly care beds per capita	Number of elderly care beds / Urban permanent resident population	+	0.3546
		Basic medical insurance coverage rate	ln(Number of participants in the basic medical insurance program for employees / Urban permanent resident population)	+	0.0114
		Per capita government spending on healthcare	Healthcare and family planning expenditures / Urban permanent resident population	+	0.0085
		Old-age insurance coverage rate	ln(Number of participants in the basic pension insurance program for urban employees / Urban permanent resident population)	+	0.0117
		Per capita disposable income	Per capita disposable income of urban residents	+	0.0594

376

377 *Covariates*

The selection of control variables follows two principles: first, they must influence both a city's care provision capacity and the probability of being selected for PHC; second, they must be reliably available at the city-year level. Accordingly, this study controls for the following city characteristics: Economic scale (GDP), urbanization rate (URB), digital infrastructure (MOB and BB), industrial structure (PRI and SEC), the extent to which a city engages with the wider economy (TRADE), and fiscal revenue and expenditure capacity (EXP and REV).

To address possible non-linear relationships between the control variables and the dependent variable, this study further includes the quadratic terms of the aforementioned control variables in the initial regression model [41].

Potential pathway variables

This study examines two pathways: activating healthcare supply and strengthening cost coverage. Per capita healthcare expenditure (CHE) measures the financial burden of family care. Community meal service seats (CMS) measure service capacity, while community care workers (CEW) measure workforce supply.

Table 2 presents descriptive statistics for every variable included in the analysis.

Table 2
Statistical Summary of Variables

Type of Variable	Variable Symbol	Variable Definition	Sample Size	Mean	Standard Deviation	Minimum Value	Maximum Value
Dependent variable	<i>LCRI</i>	Resilience of the urban healthcare service system	4774	0.08	0.04	0.02	0.66
Independent Variable	<i>PHC</i>	Pilot program for reforming home- and community-based elderly care services	4774	0.20	0.40	0	1
	<i>CHE</i>	per capita healthcare expenditure	4774	4.63	0.03	4.57	4.81
Mechanism variable	<i>CMS</i>	Number of Meal Seats in the Community	4774	3.09	3.10	0	11.12
	<i>CEW</i>	Number of Community Elderly Care Service Staff	4774	1.91	2.14	0	9.44
	<i>GDP</i>	Regional Gross Domestic Product	4774	16.42	1.00	13.15	19.66
	<i>URB</i>	Urbanization Rate	4774	0.55	0.17	0.13	1
	<i>MOB</i>	Number of Mobile Phone Subscribers	4774	5.67	0.78	3.19	8.11
	<i>BB</i>	Number of Broadband Subscribers	4774	4.08	1.05	0.65	6.73
Control variables	<i>PRI</i>	Share of Primary Industry Value Added in GDP	4774	0.13	0.08	0.01	0.5
	<i>SEC</i>	Share of Secondary Industry Value Added in GDP	4774	0.43	0.11	0.09	0.9
	<i>TRADE</i>	Total Imports and Exports	4774	8.99	2.24	0.08	15.17
	<i>EXP</i>	General Public Budget Expenditures	4774	14.82	0.73	11.71	17.73
	<i>REV</i>	General Public Budget Revenues	4774	13.81	1.08	9.9	17.57

Results

Descriptive findings and geographic distribution of the LCRI

This study calculated LCRI values for China's cities at the prefecture level and above spanning the period 2010–2024. Table 3 reports the measurement results. Fig. 4

shows their spatial distribution in 2010, 2015, 2020, and 2024. Overall, during the sample period, the LCRI remained generally low but showed a steady upward trend. While there were some fluctuations from year to year, significant differences existed among cities, and the spatial distribution exhibited strong disparities.

Based on the annual measurement results, the average LCRI in Chinese cities from 2010 to 2024 ranged between 0.0521 and 0.1375, remaining overall in the lower range, suggesting that their LCRI scores still have much room to grow. Specifically, the average in 2010 was 0.0521. Thereafter, it generally showed a steady upward trend, rising to 0.0765 by 2018 and further increasing to 0.0917 and 0.0929 in 2019 and 2020, respectively; in 2021, the average rose to 0.1375, the highest value during the sample period; it subsequently declined slightly, reaching 0.0873, 0.0887, and 0.0843 in 2022–2024, respectively, and stabilized at a relatively high level. It should be noted that in 2021, the high value was accompanied by a simultaneous rise in both the standard deviation (0.0841) and the maximum value (0.6551), while the median rose only from 0.0840 to 0.1084. This indicates that the sharp increase in the annual mean was primarily driven by extreme values from a small number of cities and does not represent a general leap in the overall level. Overall, the LCRI underwent an evolution during the study period, progressing from a steady rise to a temporary peak in 2021 and then stabilizing at a high level; the level at the end of the sample period showed a marked improvement compared to the beginning.

Table 3

Annual LCRI Results for Chinese Cities

Year	Mean	Median	Standard Deviation	Minimum	Maximum
2010	0.0521	0.0698	0.0308	0.0172	0.3898
2011	0.0554	0.0506	0.0262	0.0191	0.2647
2012	0.0552	0.0528	0.0179	0.0209	0.1771
2013	0.0611	0.0579	0.0212	0.0223	0.2157
2014	0.0658	0.0614	0.0224	0.0247	0.2057
2015	0.0734	0.0628	0.0521	0.0281	0.5883
2016	0.0733	0.0690	0.0250	0.0344	0.3046
2017	0.0723	0.0677	0.0224	0.0359	0.1744
2018	0.0765	0.0711	0.0226	0.0395	0.2335
2019	0.0917	0.0836	0.0354	0.0446	0.2634
2020	0.0929	0.0840	0.0431	0.0440	0.5099
2021	0.1375	0.1084	0.0841	0.0497	0.6551
2022	0.0873	0.0835	0.0218	0.0483	0.2306
2023	0.0887	0.0859	0.0201	0.0432	0.1955
2024	0.0843	0.0812	0.0193	0.0478	0.1847

Looking further at the distribution characteristics, the median was lower than the mean in most years during the sample period, suggesting that the distribution has a noticeable positive skew, with a small number of cities with high LCRI values significantly driving up the overall mean. The standard deviation fluctuated over the sample period, rising significantly in 2015 and 2020–2021 due to sharp increases in individual cities' LCRI values. In other years, it mostly remained within the range of 0.02–0.035, before falling back to 0.0193 by 2024, indicating that the absolute differences among cities had narrowed somewhat. In terms of extremes, the maximum value was significantly higher in some years, reaching 0.6551 in 2021, indicating that a few cities had much higher LCRI values; the minimum value gradually rose from 0.0172 in 2010 to 0.0478 in 2024, indicating that cities with lower LCRI values are also steadily improving; however, absolute disparities among cities persist, and regional development imbalances remain pronounced.

In terms of spatial distribution, Fig. 4 presents the LCRI classification results for four representative years. In 2010, the lowest category covered more than half of the country's land area, while the highest covered less than 10 percent. By 2015, these shares had changed to about one-quarter and nearly 20 percent. In 2020 and 2024, the lowest tier covered less than 10 percent, while the highest expanded to about one-third and nearly 40 percent, respectively. This overall shift from lower to higher tiers is corroborated by the rise in mean values shown in Table 3 and the rightward shift of the main peak in the kernel density shown in Fig. 5, indicating that the improvement in LCRI values during the sample period was widespread and not limited to a few regions.

In terms of spatial patterns, the distribution of the LCRI does not follow the typical economic gradient of “high in the east, low in the west,” but rather shows greater differentiation along lines of population density. In 2010, contiguous high-ranking areas were mainly found in sparsely populated regions such as Heilongjiang, eastern Inner Mongolia, and northern Xinjiang. Densely populated areas, including the Huanghuaihai Plain, the middle and lower reaches of the Yangtze River, and South China, generally fell into the two lowest categories. This pattern is directly related to the per capita calculations of the LCRI's three-tier indicators: in regions with smaller population bases, the same stock of resources corresponds to higher per capita levels. It should be emphasized that Fig. 4 presents the classification results in terms of area, which visually magnifies a few geographically vast cities in the west; their placement in higher tiers does not imply an overall advantage for the western region. In terms of

the number of cities, the relative disadvantage of the western region persists, a point corroborated by the Gini coefficient decomposition results in Section 4.2.

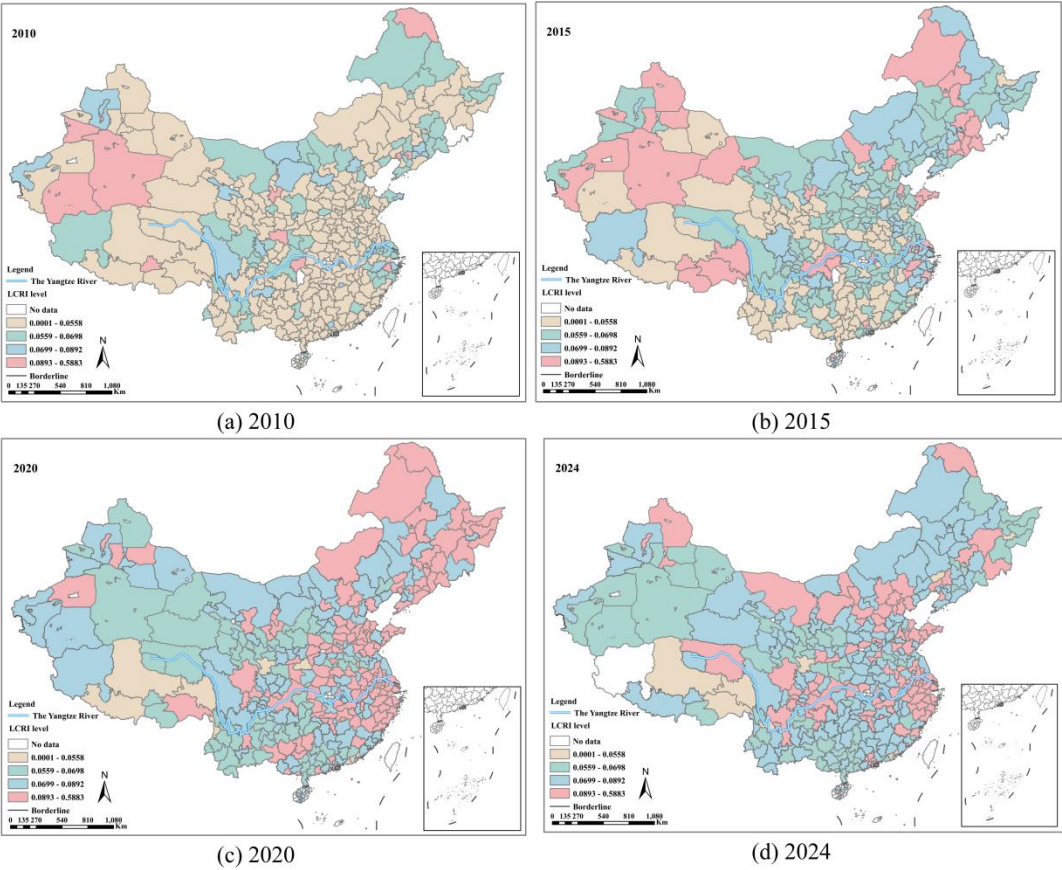


Fig. 4 Spatial Distribution of the LCRI in China

From an evolutionary perspective, the improvement in the LCRI has followed distinct phases. From 2010 to 2015, improvements were concentrated in the Northeast, Northwest, and several provincial capitals. Changes in the densely populated central and eastern regions were limited. From 2015 to 2020, improvement spread to the Northwest, Southwest, and most of South China, while persistently low-scoring areas contracted. From 2020 to 2024, the pattern stabilized. High-level areas became more

contiguous, and the remaining low- and medium-level cities were scattered across Central and Southwest China. Overall, the LCRI underwent a transition from generally low levels to a nationwide improvement during the sample period. Spatial disparities also shifted from an early-stage structural gap characterized by “overall low levels in densely populated areas” to localized, dispersed shortcomings in the later stage. This provides a descriptive foundation for the subsequent examination of policy effects and their regional variations.

Regional inequalities and distributional patterns

Tables 4 and 5 display the Dagum Gini coefficient for the LCRI along with the outcomes of its decomposition. Overall, the aggregate variation in the LCRI fluctuated from 0.2049 to 0.1229 between 2010 and 2024, reaching a peak of 0.2884 in 2021. The trend generally showed a narrowing of this variation, indicating that disparities among cities have narrowed overall, though regional imbalances persist.

Transvariation was generally one of the largest sources of overall variation, contributing about 30% to 50%, particularly in the early years. Within-group variation remained relatively stable at around 30% to 35%. Between-group variation rose from 17.32% in 2010 to 41.06% in 2019 and stood at 29.74% in 2024, indicating its growing importance. This indicates that the overall variation in the LCRI stems not only from development gaps among eastern, central, and western China but also from the spatial

overlap among these regions, with the impact of interregional disparities increasing over time.

Table 4

Results of the Dagum Gini Coefficient Decomposition of Regional Disparities

Year	Overall Difference	Intra-regional Contribution	Intra-regional (%)	Inter-regional Contribution	Inter-regional (%)	Transvariation Density Contribution	Transvariation (%)
2010	0.2049	0.0720	35.1287	0.0355	17.3180	0.0974	47.5533
2011	0.2011	0.0701	34.8407	0.0426	21.2067	0.0884	43.9525
2012	0.1608	0.0536	33.3282	0.0325	20.2334	0.0747	46.4384
2013	0.1698	0.0572	33.6912	0.0337	19.8510	0.0789	46.4578
2014	0.1713	0.0578	33.7252	0.0203	11.8225	0.0933	54.4523
2015	0.2194	0.0780	35.5376	0.0462	21.0539	0.0952	43.4085
2016	0.1637	0.0528	32.2750	0.0345	21.0819	0.0764	46.6431
2017	0.1608	0.0491	30.5570	0.0581	36.1090	0.0536	33.3340
2018	0.1497	0.0452	30.1938	0.0578	38.6282	0.0467	31.1780
2019	0.1930	0.0568	29.4460	0.0792	41.0585	0.0569	29.4955
2020	0.1824	0.0564	30.9188	0.0497	27.2573	0.0763	41.8240
2021	0.2884	0.0888	30.7900	0.1113	38.6049	0.0883	30.6052
2022	0.1331	0.0415	31.1639	0.0415	31.1731	0.0501	37.6630
2023	0.1243	0.0389	31.3047	0.0357	28.7044	0.0497	39.9909
2024	0.1229	0.0389	31.6761	0.0365	29.7351	0.0474	38.5889

The western region had the greatest intraregional variation, although it declined over the sample period. Disparities in the central region were initially small, increased briefly, and then fell. The eastern region showed relatively small and stable disparities, generally ranging from 0.13 to 0.20. This indicates that not only is the overall LCRI in the western region relatively low, but the issue of internal development imbalances was also more pronounced in the early stages of the sample period; however, internal disparities across all regions generally tended to converge over time.

As for differences across regions, the disparity between the eastern and western areas remained the most pronounced overall, followed by the Central–West gap, while

the East–Central gap was relatively smaller. From an evolutionary perspective, all three gaps generally showed a fluctuating trend toward narrowing, with the East–West gap decreasing from 0.2255 in 2010 to 0.1365 in 2024; during this period, the East–Central and Central–West gaps spiked abnormally in 2021, primarily due to significant fluctuations in the LCRI within the central region that year. Overall, the most striking difference in the LCRI exists between the eastern and western regions, serving as the main driver of interregional inequalities. Consequently, reducing this structural divide between the east and west should be a central focus in tackling national regional disparities.

Consequently, regional disparities in the LCRI have generally shown a fluctuating trend toward narrowing. In terms of composition, the system is primarily characterized by a leading contribution from ultra-high-density areas and an increase in inter-group contributions over time. Among interregional disparities, the East–West gap is the most pronounced, followed by the Central–West gap, while the East–Central gap is relatively smaller; moreover, internal disparities within the western regions were relatively more pronounced in the early stages of the sample period. This indicates that future efforts should focus on enhancing overall adaptability while narrowing structural differences. Specifically, efforts should focus on narrowing the development divide between eastern and western areas, as well as promoting coordinated growth across different regions.

Table 5
Dagum Gini Coefficients Within and Between Regions

Year	Eastern	Western	Central	East-West	East-Central	Central-West
2010	0.1585	0.2792	0.1218	0.2255	0.1505	0.2153
2011	0.1621	0.2618	0.1254	0.2173	0.1576	0.2110

Year	Eastern	Western	Central	East-West	East-Central	Central-West
2012	0.1605	0.1819	0.1132	0.1815	0.1484	0.1519
2013	0.1597	0.2009	0.1167	0.1889	0.1522	0.1647
2014	0.1411	0.1979	0.1553	0.1783	0.1503	0.1814
2015	0.1483	0.3124	0.1260	0.2446	0.1445	0.2355
2016	0.1302	0.1735	0.1579	0.1740	0.1559	0.1695
2017	0.1581	0.1340	0.1519	0.1824	0.1743	0.1475
2018	0.1491	0.1193	0.1421	0.1728	0.1629	0.1359
2019	0.1989	0.1415	0.1797	0.2255	0.1950	0.1896
2020	0.1504	0.1634	0.1925	0.1894	0.1735	0.2033
2021	0.1958	0.2814	0.2869	0.2478	0.3206	0.3266
2022	0.1326	0.1106	0.1334	0.1392	0.1337	0.1402
2023	0.1253	0.1068	0.1189	0.1375	0.1277	0.1206
2024	0.1290	0.1071	0.1138	0.1365	0.1287	0.1142

In addition, Fig. 5 shows the kernel density estimates of the LCRI in 2010, 2015, 2020, and 2024. Overall, the LCRI has a mainly unimodal distribution. Its main peak shifted from about 0.05 in 2010 to about 0.08 between 2020 and 2024, indicating a general improvement. The curve was flatter in 2015 and 2020. By 2024, the peak had risen and narrowed, showing renewed convergence at a higher level. A distinct right tail was present in every year and grew longer over time, indicating that a small number of cities with high LCRI values continued to lead the pack. The distribution never formed a stable bimodal or multimodal structure, suggesting that no significant polarization has yet emerged; instead, it exhibits only a slight tendency toward tiered differentiation.

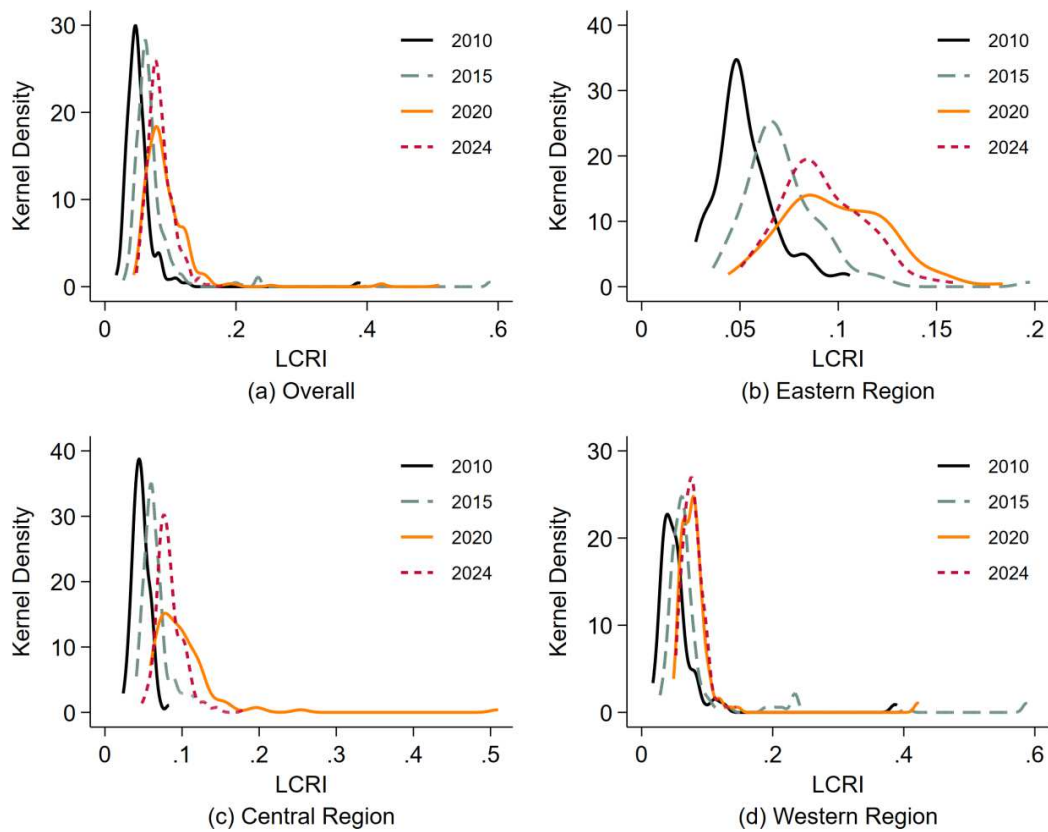


Fig. 5 Kernel Density Estimation Results for the LCRI

When viewed regionally, the eastern area shows the most scattered kernel density curve distribution, with its primary peak gradually shifting significantly to the right as time progresses, along with the appearance of several secondary peaks and a relatively extended right tail. This suggests that the eastern area shows a high average LCRI, yet it also features the largest fluctuations in LCRI figures across its cities; certain urban centers have attained a high LCRI, whereas others stay at a middle level. For the central area, its distribution shows a tighter spread, as the kernel density curve mainly clusters within the low-middle and middle value intervals. Over time, the primary peak moves to the right, while the high-value tail remains relatively underdeveloped. This suggests that despite some internal disparities in the central region, the overall pattern tends to

converge towards the mid-range level. In contrast, the western region shows a more intense concentration of lower figures, accompanied by a long tail at the higher end. Its main peak within the low-value range is comparatively high, and several secondary peaks persist on the right-hand side. This suggests notable internal differences within the Western Region, where cities with low LCRI scores coexist alongside a limited number of cities with high LCRI scores, leading to a more distinct division within the area.

In addition to the above findings, the analysis of kernel density estimation combined with the Gini coefficient decomposition method proposed by Dagum reveals that the LCRI experienced a consistent upward trend throughout the study period, while regional structural differences still exist. The distribution patterns across the Eastern, Central, and Western regions are distinct from one another. The eastern region has the most scattered data points, the Central region shows a concentration in the middle, while the Western region features a cluster at lower values with a pronounced trailing tail. Each of the three regions presents predominantly single-peak distributions, with their primary modes gradually shifting toward the right as time progresses. Notably, none of the regions exhibit a stable bimodal distribution. When decomposing the Gini coefficient, transvariation is found to be the primary driver of overall disparities. The contribution of interregional variations has also risen, particularly the divide between the eastern and western regions. This indicates that the LCRI's distribution and changes, along with regional differences, cannot be attributed to arbitrary variations. Instead, they stem from the joint influence of various factors, such as regional development

foundations, fiscal capabilities, demographic traits, and the external environment. Building on this, the remainder of this study will further explore the identification of policy effects, the examination of mechanisms of action, and heterogeneity analysis to reveal the causal impact of PHC on the LCRI.

Estimated effect of PHC on the LCRI

Table 6 presents the baseline regression findings, where both columns account for fixed effects of city and year. Column (1) includes only the first-order terms of the control variables; the estimated coefficient for PHC is 0.0060, which is significantly positive at the 1% level. Column (2) additionally incorporates the quadratic terms of the control variables; the estimated coefficient of PHC is 0.0044, showing a statistically significant positive relationship at the 10% significance level. Based on these findings, the baseline regression indicates that PHC has a robust positive impact on the LCRI. These results provide strong evidence in favor of Hypothesis 1.

Although an increase of about 0.006 is small in absolute terms, it is statistically meaningful given the LCRI mean of about 0.08 and its limited variation. The gradual increase is also consistent with resilience being a capacity built over time. The direction of the control variables is largely consistent with expectations, and the core coefficients remain stable after including quadratic terms, indicating that the results are not sensitive to the specified model form. However, Table 6 reflects only the average treatment effect;

its dynamic characteristics still need to be examined using the event study model discussed below.

Table 6

Baseline Regression Results

Variables	(1)	(2)
	<i>LCRI</i>	<i>LCRI</i>
<i>PHC</i>	0.0060*** (0.0023)	0.0044* (0.0026)
Controls	YES	YES
Controls ²	NO	YES
Year	YES	YES
City	YES	YES
N	4774	4774

Note: Robust standard errors are presented within parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% thresholds.

Sensitivity analyses

Parallel trends assessment

Before implementing policy interventions, researchers must ensure that the treatment and control groups follow identical trends to meet the assumptions of the DID framework, which is crucial for reliable test results. To verify this assumption, this study employs the event-study model specified in Equation (7), and the empirical results are presented in Fig. 6. Prior to the policy's enforcement, the dynamic effect coefficients for each phase were statistically insignificant, showing minor fluctuations around zero. This implies that the treatment and control groups maintained a parallel trend before the PHC initiative took effect. Following the policy's introduction, the

dynamic effect coefficients rose steadily, turning significantly positive over time, which implies that the policy's impacts unfolded gradually and grew in magnitude as PHC initiatives advanced. This result is consistent with the parallel trends hypothesis, indicating that the policy's impact began to manifest and strengthen as PHC continued to develop.

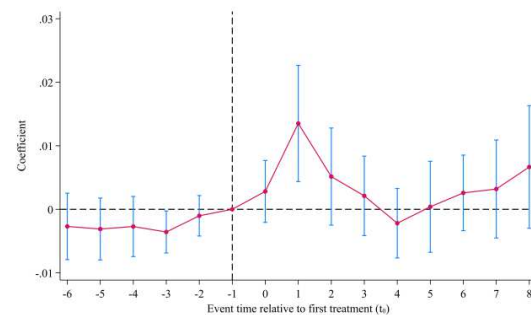


Fig. 6 Parallel Trends Check

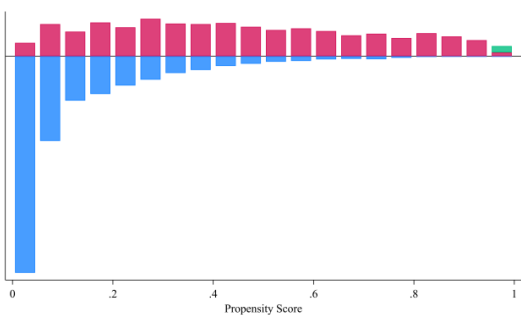


Fig. 7 PSM Common Support

Propensity score-matched DID analysis

To reduce potential biases caused by pre-existing disparities in measurable attributes across pilot and non-pilot cities, the research adopts propensity score matching combined with difference-in-differences (PSM-DID) to ensure the robustness of the results. As shown in Fig. 7, the scores of the treatment and control groups overlap significantly, with only a small number of treatment group samples falling outside the support region, indicating minimal loss of sample representativeness. Following the matching process, the standardized deviations of each covariate showed a sharp decline, effectively erasing intergroup disparities. After re-estimation based on the matched samples, the impact of PHC on the LCRI remains significantly positive, and the

magnitude of the effect is close to that of the baseline regression. This suggests the initial findings hold steady even after accounting for potential selection biases.

Placebo analysis

To eliminate the potential impact of random factors or unmeasured variables on the estimation outcomes, this study adopts a randomization approach for the placebo test: an equal number of cities to the real pilot cities are randomly chosen to serve as a “dummy treatment group,” with “dummy policy dates” also randomly assigned. After the dummy policy variable is constructed, the model is re-estimated, and this simulation process is repeated 500 iterations, with the results presented in Fig. 8.

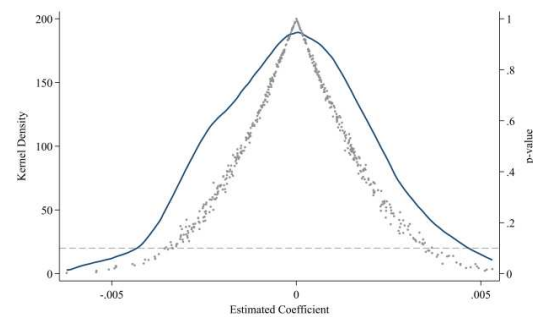


Fig. 8 Placebo Test

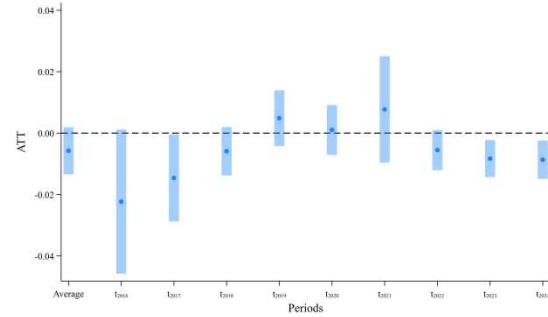


Fig. 9 Callaway–Sant’Anna Dynamic Effect

The dummy estimated coefficients exhibit a kernel density distribution centered approximately at 0, with the vast majority concentrated near zero; their corresponding p-values are mostly greater than 0.1, suggesting policy effects are generally insignificant under random conditions. By comparison, the actual estimated

coefficients lie in the right-hand tail of the dummy coefficient distribution, distinctly beyond the clustered area, which implies that the policy impacts detected in this study cannot be attributed to random occurrences or unaccounted variables.

Alternative staggered DID estimation

Traditional two-way fixed effects models in staggered DID settings might suffer from bias when treatment impacts are heteroskedastic. To address this, this study adopts the Callaway–Sant’Anna method to re-examine dynamic treatment effects. As illustrated in Fig. 9, the estimates are insignificant before the policy but gradually become positive and significant afterward. This pattern aligns with prior event-study outcomes and indicates that the core results are not skewed by the “bad comparison” issue.

Additional sensitivity analyses

To further confirm the stability of the baseline findings, this study carried out sensitivity analyses, such as removing the four municipalities directly under the central government and other special samples, implementing two-tailed truncation on the dependent variable at the 1% and 99% percentiles, and employing the instrumental variables (IV) approach to tackle possible endogeneity issues. Table 7 reports the outcomes of these robustness checks. In Column (1), after excluding the four municipalities directly under the central government and other special cases, the PHC coefficient is 0.0063 and is significant at the 1% level, indicating that the findings are

not driven by cities with special administrative statuses or those with larger economic scales. In Column (2), after applying two-sided truncation at the 1% and 99th percentiles to the dependent variable, the PHC coefficient is 0.0060 and remains significant at the 1% level, indicating that the results are not affected by outliers. To tackle potential endogeneity, Column (3) adopts the IV approach, with the interaction between “the scope of Confucian cultural influence” and national PHC intensity serving as the instrumental variable. This instrumental variable is significantly positively correlated with PHC implementation, and the direct effect of historical and cultural endowments on current LCRI values can be accounted for by city fixed effects. The two-stage estimation results show that PHC’s effect on the LCRI remains at 0.0060 and is significantly positive at the 1% level, indicating that the baseline conclusions remain robust after addressing the issue of endogeneity.

Table 7

Results of Other Robustness Checks

Variables	(1)	(2)	(3)
	Excluding Samples	Winsorization	IV
<i>PHC</i>	0.0063*** (0.0023)	0.0060*** (0.0017)	0.0060*** (0.0023)
Controls	YES	YES	YES
Controls²	NO	NO	NO
Year	YES	YES	YES
City	YES	YES	YES
N	4705	4774	4774

Extended Analysis

Potential pathways

Cost protection pathway

PHC may not only directly affect the operational performance of the elderly care service system but may also play an indirect role by replacing high-cost care options and reducing older adults' reliance on intensive medical services. Based on this, this study further examines the transmission mechanism of PHC from the perspective of cost burden, choosing CHE as the mechanism variable.

As presented in the first column of Table 8, the findings from the mechanism analysis reveal that when CHE serves as the dependent variable, the estimated coefficient of PHC is -0.0059 , showing a statistically significant negative relationship at the 5% significance level. This implies that PHC has significantly reduced residents' out-of-pocket healthcare expenses. This is consistent with theoretical expectations and suggests that PHC does not function solely through the provision of services itself but also further strengthens the system's cost-coverage capacity through two pathways: the substitution of care modes and the early resolution of medical needs. Hypothesis 2 is supported.

PHC replaces some high-cost institutional and medical care with accessible community and home care. It shifts care needs from hospitals and nursing homes to community and household settings, reducing out-of-pocket expenditure. Continuous health management also supports earlier detection and intervention, which lowers demand for intensive medical services. As fixed medical expenses fall, households retain a larger financial buffer against rising demand and external shocks.

Service supply pathway

Another channel through which PHC operates is by expanding resources on the supply side. The injection of central government incentive and subsidy funds may not only improve the operational quality of existing services but also play an indirect role by expanding facility capacity and increasing the care workforce. Based on this, this study further examines the impact pathways of PHC from the perspectives of facility supply and workforce supply, selecting the number of CMS and the number of CEW as mechanism variables, respectively.

The results of the mechanism analysis for CMS and CEW are presented in Columns (2) and (3) of Table 8. Specifically, the estimated PHC coefficients are 0.5026 and 0.4193, respectively, both of which are positive and statistically significant at the 1% level. PHC therefore expanded both facility capacity and workforce supply. This suggests that PHC does not function solely through fiscal investment itself but also enhances the system's responsiveness to demand shocks through two pathways: improving facility accessibility and alleviating labor constraints. Hypothesis 3 is supported.

First, PHC's special funds and supporting policies promote community meal centers, day care centers, other service facilities, and information platforms. This directly improves the spatial accessibility and capacity of community care, enabling older adults to receive basic care within a shorter service radius. Second, by relaxing entry requirements, purchasing services, and providing operational subsidies, PHC has

encouraged the participation of social forces, thereby expanding the workforce of professional caregivers and support staff and alleviating the most pressing labor constraints in care services. Together, these measures create a clear transmission process. Central government funding supports facilities and platforms, attracts social providers, and expands the workforce. The resulting supply reserves can be mobilized when demand rises.

Table 8

Results of the Mechanism Tests

Variables	(1)	(2)	(3)
	Cost Protection Mechanism	Healthcare supply Mechanism	
	<i>CHE</i>	<i>CMS</i>	<i>CEW</i>
<i>PHC</i>	-0.0059** (0.0024)	0.5026*** (0.1425)	0.4193*** (0.0973)
Controls	YES	YES	YES
Controls ²	YES	YES	YES
Year	YES	YES	YES
City	YES	YES	YES
N	4774	4774	4774

Subgroup analyses

Subgroup analyses by economic development and population aging

External heterogeneity is analyzed based on the economic environment and demographic conditions of each city, including economic level (measured by GDP) as well as the extent of population aging, which is represented by the share of individuals aged 65 or more in the total population. Table 9 presents these findings.

Table 9

Results of the External Heterogeneity Tests

Variables	<i>EDL</i>		<i>PAL</i>	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
<i>PHC</i>	0.0057** (0.0029)	0.0078 (0.0056)	0.0100*** (0.0033)	-0.0019 (0.0033)
Controls	YES	YES	YES	YES
Controls²	YES	YES	YES	YES
Year	YES	YES	YES	YES
City	YES	YES	YES	YES
N	2372	2402	2386	2388

In terms of economic development level (EDL), the PHC coefficient of the higher-tier group stood at 0.0057, which was statistically significant at the 5% significance level, while the corresponding value for the lower-tier group stood at 0.0078, but not significant. A possible reason is that the positive effect of PHC on the LCRI is consistently identified only in developed cities with a high degree of marketization and well-established privately operated elderly care facilities; the strength of this effect in less developed cities requires more precise testing. In the population aging level (PAL) dimension, the coefficient for the “deeply aged” group was 0.0100, showing a marked positive relationship at the 1% significance level, with a magnitude roughly double that of the economic level grouping; the coefficient for the “mildly aged” group was −0.0019, which was not significant and had a negative sign. The differences in coefficient magnitude and sign suggest that the same policy investment produces larger gains in the LCRI in cities with severe population aging and more urgent care needs.

Subgroup analyses by health resources, digital infrastructure, and fiscal capacity

Internal heterogeneity is examined based on a city's own resource endowments and capacity conditions, including medical resource endowments (MRE) (as determined by the count of beds in hospitals and health centers per 10,000 individuals), the level of digital infrastructure (DIL) (measured by the number of mobile phone subscribers), and fiscal capacity (FIS) (measured by the fiscal self-sufficiency rate). Table 10 presents the findings.

Table 10

Results of the Internal Heterogeneity Tests

Variables	<i>MRE</i>		<i>DIL</i>		<i>FIS</i>	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
<i>PHC</i>	0.0076** (0.0038)	0.0037 (0.0035)	0.0056** (0.0028)	0.0041 (0.0049)	0.0068** (0.0026)	0.0035 (0.0044)
Controls	YES	YES	YES	YES	YES	YES
Controls²	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
City	YES	YES	YES	YES	YES	YES
N	2371	2403	2383	2391	2001	2773

A consistent pattern emerges across all three dimensions: in the groups with higher medical resource endowments, more developed digital infrastructure, and stronger fiscal capacity, the PHC coefficients are 0.0076, 0.0056, and 0.0068, in each case showing a statistically significant positive association at the 5% significance level; while the corresponding coefficients for the lower-end groups are also positive, none are significant. The effect of PHC on the LCRI is consistently identified in cities with stronger resources and implementation capacity. Abundant medical resources support the integration of community care and healthcare. Better digital infrastructure helps convert policy resources into accessible services. Stronger fiscal capacity also improves

the implementation of central government funding. In general, the impact of PHC on the LCRI is more significant in urban areas with greater economic prosperity, more advanced aging populations, abundant medical resources, well-developed digital infrastructure, and strong fiscal capacity.

Discussion

Geographic inequalities and health equity implications

The results of the analysis of measures and distributions indicate that the improvement in urban LCRI is not a homogeneous process. The spatial distribution does not follow an economic gradient of high values in the east and low values in the west, but rather diverges along lines of population density. Given the same stock of resources, sparsely populated areas correspond to higher per capita levels. This suggests that resource inputs do not automatically translate into equitable service capacity; the interaction between resource allocation methods and population structure warrants greater attention from policymakers. The Dagum Gini decomposition reveals that although overall disparities have fluctuated and narrowed, the east-west gap has consistently been the primary source of inequality, and the contribution of interregional disparities has increased over time. This indicates that regional inequality does not resolve naturally but requires sustained governance interventions. Estimates of the core density further indicate that the distribution has not yet become polarized, but a right-

tail skew persists, with a small number of cities continuing to lead. This pattern remains in a malleable phase, representing a critical window of opportunity to strengthen equitable governance and prevent the solidification of disparities [42]. These findings suggest that advancing the development of the Elderly LCRI should not focus solely on raising the national average but should also incorporate equity considerations within the framework of universal health coverage. Differentiated resource allocation helps bridge structural disparities across regions, which is a crucial step toward building a more equitable and resilient society [43].

Interpretation of subgroup differences

PHC plays a significant role in promoting urban elderly LCRI, primarily through two channels. The first channel is the stimulation of healthcare supply, and the second is the strengthening of cost coverage. Targeted investments on the supply side promote the regular deployment of service outlets and professional personnel, while universal access to services on the cost side reduces the financial burden on households. However, this promotional effect is not evenly distributed. Heterogeneity tests show that the policy effects can be consistently identified only in certain cities. These cities share common characteristics: a high level of economic development, ample fiscal resources, abundant medical resources, and well-developed digital infrastructure. The institutional root cause of this disparity lies in the “incentives in lieu of subsidies” design, whereby central government incentives primarily support investments during the project launch

phase. Subsequent operations and service procurement still rely on local fiscal resources and market capacity; consequently, resource endowments constitute a threshold determining whether the policy's effects can be fully realized. Cities with more advanced aging populations have responded more actively to the policy, indicating that demand pressures can stimulate local willingness to implement the policy and allocate resources. Based on this, policy expansion should prioritize needs while also addressing capacity gaps [44]. Efforts should be directed toward cities facing greater aging pressures, while also providing complementary support to cities with weaker fiscal and market capacity.

Implications for policy and practice

The findings discussed above have implications that extend beyond a single country. First, the resilience of home- and community-based care stems from simultaneous improvements in supply redundancy and cost buffers; therefore, traditional evaluation metrics centered on the number of beds and facilities may systematically misjudge the effectiveness of reforms, making it essential to incorporate service accessibility and the financial burden on families into routine monitoring. Second, the effects accumulate gradually as PHC progresses rather than manifesting immediately. This suggests that care reforms driven by project-based, one-time investments struggle to build resilience; a stable and predictable mechanism for sustained, routine funding is key. This is particularly important for low- and middle-

income countries that primarily rely on special-purpose grants or short-term pilot programs to advance care reforms [45]. Third, the effectiveness of reforms is constrained by local fiscal matching funds and market capacity. Without capacity-building arrangements targeting vulnerable regions, the expansion of universal care policies may raise overall standards while simultaneously widening regional disparities in resilience.

Limitations of the study and future directions

This paper identifies two areas for future research. First, the resilience index developed in this study is synthesized from publicly available statistical data and primarily reflects the system's capacity reserves. Future research could integrate micro-level care data to further characterize the system's actual recovery rate. Second, the heterogeneity analysis currently relies on group-based regression. Future studies could introduce formal tests of differences in coefficients across groups and, combined with a longer observation window, dynamically track the evolution of policy effects. Looking ahead, as healthcare data infrastructure improves, the academic community can further explore methods for measuring resilience at the individual level. Such approaches can identify disparities in benefits across different groups, providing more detailed empirical evidence to support the design of targeted healthcare policies. This holds significant practical implications for advancing reforms in elderly healthcare systems across countries at different stages of development.

Conclusions and Policy Implications

Conclusions

To summarize the key findings of this study, they can be outlined as follows: (1) Over the sample period, the LCRI generally increased steadily; areas with low LCRI values shrank significantly; and overall regional disparities narrowed, although spatial imbalances persisted. Because the indicators are measured per capita, their distribution follows population density rather than the usual east-west gradient. (2) PHC significantly improved the LCRI, and its effect accumulated over time. The result remains robust across a series of robustness checks, including outlier exclusion, sample trimming, PSM-DID estimation, placebo tests, Callaway and Sant'Anna estimation, and instrumental-variable analysis. (3) The program increased community meal service seats and elderly care staff while reducing per capita healthcare expenditure. It therefore strengthened both healthcare supply and cost coverage. (4) The effects were concentrated in cities with stronger economies, more advanced aging, better medical and digital resources, and greater fiscal capacity.

Policy Recommendations

Building on the findings presented above, this study puts forward four policy recommendations. First, the reform of home- and community-based care should be treated as a routine institutional arrangement for building resilience rather than a phased project. Stable and predictable fiscal investment should be used to maintain the normal operation of community service centers and care personnel, thereby enabling the sustained accumulation of supply reserves and cost buffers. Second, policy expansion should balance efficiency and equity: while leveraging the capacity and exemplary role of developed cities, targeted funding and capacity-building support should be provided to cities with high levels of aging but weak fiscal and market capacity, thereby preventing excessive disparities in policy benefits across cities. Third, efforts should be coordinated on both the supply and cost sides: while expanding community facilities and professional care staff, the level of out-of-pocket expenses for families should be stabilized through inclusive pricing and government procurement of services, and digital platforms should be leveraged to enhance the accessibility and availability of services. Fourth, resilience should be incorporated into the standard evaluation criteria for elderly care service reforms. Beyond metrics like the count of beds and available amenities, the system should simultaneously monitor supply excess, accessibility, and cost burdens, thereby providing a comparable evaluation basis for the deinstitutionalization of elderly healthcare service systems worldwide.

Abbreviations

LCRI healthcare services resilience index

928	PHC	pilot program for reforming home- and community-based elderly care services
929	PAL	population aging level
930	EDL	economic development level
931	MRE	medical resource endowments
932	DIL	digital infrastructure level
933	FIS	fiscal capacity
934	CHE	per capita healthcare expenditure
935	CMS	community meal service seats
936	CEW	community elderly care service workers
937	GDP	gross domestic product
938	URB	urbanization rate
939	MOB	mobile phone subscribers
940	BB	broadband subscribers
941	PRI	share of primary-industry value added in GDP
942	SEC	share of secondary-industry value added in GDP
943	TRADE	total imports and exports
944	EXP	general public budget expenditures
945	REV	general public budget revenues
946	DID	difference-in-differences
947	PSM	propensity score matching
948	PSM-DID	propensity score matching difference-in-differences
949	IV	instrumental variable

950

951 **Declarations**

952 **Ethical approval and consent to participate**

953 Not applicable. This study used publicly available aggregated city-level
954 statistical data and did not involve human participants, human tissue, or individual-
955 level personal data.

956 **Consent for publication**

957 Not applicable.

958 **Availability of data and materials**

959 The datasets used and analyzed during the current study are available from the
960 corresponding author upon reasonable request.

961 **Competing interest**

962 The authors declare that they have no known competing financial interests or
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970 **Authors’ contributions**

Xinlei Zou: Conceptualization, Formal analysis, Investigation, Data curation, Software, Visualization, Project administration, Writing – original draft. Zijie Wang: Validation, Interpretation of results, Writing – review & editing. Guoqing Zhai: Methodological discussion, Interpretation of results, Writing – review & editing. Fangxia Pan: Methodology, Validation, Data curation, Supervision, Funding acquisition, Writing – review & editing. All authors read and approved the final manuscript.

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