When Institutions Fill the Gaps: Compensatory Effects of Long-Term Care Insurance on Mental Health among Rural Older Women in China

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Abstract

Background: Rural older women in China face intersecting disadvantages that elevate depressive symptoms. Long-Term Care Insurance (LTCI) has expanded rapidly, yet its mental health effects on this population remain underexamined through a gender lens.

Methods: We used five waves of CHARLS (2011-2020) with 2,193 rural women aged ⩾60. We employed a staggered difference-in-differences design, complemented by moderation analysis, heterogeneity tests, and time-dependent survival analysis. Robustness checks included instrumental variable estimation, Callaway-Sant'Anna DID, placebo tests, and baseline exclusion sensitivity.

Results: LTCI reduced depression scores by 0.45 points (p=0.028) and depression onset hazard by 36.1% (HR=0.639, p=0.009). Benefits were compensatory, concentrated among women lacking regular emotional and financial support from children and those with high social isolation. Heterogeneity analyses demonstrated a pronounced age gradient and a significant education gradient, while care-need and disability subgroups showed directionally consistent but underpowered effects. These findings were robust to all falsification tests.

Conclusion: LTCI confers meaningful mental health protection for rural older women through compensatory pathways that substitute for depleted informal support. However, benefits concentrate among younger-old and more-educated women, raising equity concerns. Gender-sensitive implementation with mental health screening, targeted outreach for less-educated women, and community-based enrollment assistance is essential to ensure policy equity.

Keywords: Long-term care insurance; Gendered institutional compensation; Compensatory substitution; Mental health; Older women

1. Introduction

The twenty-first century is characterized by a profound and unprecedented demographic transition toward population aging. Globally, the proportion of individuals aged 60 and above is projected to double by 2050, placing immense pressure on health systems, social security frameworks, and traditional models of intergenerational care[1]. China exemplifies this transformation on an accelerated scale. The population aged 60 and older has surpassed 280 million, nearly one-fifth of the total. The Chinese government has responded with ambitious policy reforms, most notably the staggered rollout of Long-Term Care Insurance (LTCI), a social insurance mechanism designed to subsidize formal care services and mitigate the financial risks associated with chronic disability and dependency [3][5]. A growing body of research has evaluated the effects of LTCI on healthcare utilization, medical expenditure, and financial protection [10][12][13][14]. However, the psychosocial consequences of this reform, particularly through a gender lens, remain inadequately understood.

The challenges of aging in China are most acute in rural regions, where decades of selective out-migration of younger adults have eroded the traditional family support infrastructure, leaving behind a population that is disproportionately elderly and female [2][3]. Rural older women occupy a uniquely precarious position at the intersection of multiple disadvantages. Having often spent their working lives in informal labor, many lack adequate pension coverage or sufficient financial assets for a secure retirement. Simultaneously, the erosion of filial piety and geographic separation have diminished the availability of informal caregiving. Due to deeply entrenched patriarchal gender roles, rural women have historically provided such care and, paradoxically, are now increasingly deprived of receiving it. [8] This confluence of economic scarcity, physical morbidity, and weakened social networks has precipitated a mental health crisis. Epidemiological evidence consistently documents elevated rates of clinically significant depressive symptoms

among rural older women in China, with prevalence estimates substantially higher than those observed among urban or male counterparts[4]. This heightened vulnerability can be conceptualized through the lens of gendered pathways to health, which posits that the distribution of illness is shaped by differential exposure and vulnerability to social, economic, and environmental stressors that accrue over the life course [7][8]. Despite the gravity of this challenge, the extent to which formal social policies such as LTCI can interrupt these gendered pathways remains a critical empirical gap.

A central theoretical question motivating this study concerns whether formal insurance substitutes for or complements pre-existing informal support structures. The compensatory substitution model predicts that formal LTCI coverage will yield the greatest psychological benefits for individuals whose informal support networks are weakest, by filling the void left by absent or diminished family resources.[70]. The complementary model, in contrast, predicts that formal care and informal support function synergistically, with individuals who already enjoy robust social ties deriving enhanced benefits from LTCI. Distinguishing between these two pathways carries direct implications for the targeting of LTCI outreach and the equitable distribution of policy benefits across subpopulations with varying levels of social capital. We hypothesize, based on the theoretical primacy of resource substitution in contexts of structural disadvantage [2], that LTCI will exhibit a compensatory pattern, conferring the most pronounced mental health benefits upon rural older women who lack regular emotional contact with their children, who receive no financial transfers, and who experience high levels of social isolation.

This study is expected make several distinct contributions. By focusing exclusively on rural older women, we move beyond gender-blind evaluations and examine LTCI as institutional compensation at the intersection of patriarchal care expectations and rural deprivation. We investigate moderating roles of emotional and financial support, social isolation, and pension coverage to clarify whether LTCI substitutes for or amplifies informal resources. A staggered difference-in-differences design reinforced by IV estimation, Callaway-Sant'Anna DID, and time-dependent survival analysis provides robust evidence on both depressive symptom severity and depression onset. Subgroup analyses by age, education, and functional status examine whether benefits are equitably distributed.

2. Methods

2.1 Data Source and Sample Construction

This study utilized data from the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative longitudinal survey of adults aged 45 and older and their spouses [15]. We employed five waves in 2011, 2013, 2015, 2018, and 2020. The baseline wave in 2011 established the pre-intervention health and socioeconomic profiles of respondents, while subsequent waves captured the dynamic changes following the staggered introduction of LTCI across pilot cities beginning in 2016 [16].

Our analytical sample was constructed through sequential exclusions from the full female CHARLS sample. We retained women who resided in rural areas at baseline, were aged 60 or older at baseline, and had non-missing observations on the CES-D scale and core covariates. Respondents who migrated across urban and rural boundaries during the observation period were excluded to avoid confounding LTCI effects with changing residential environments. The final sample comprised 2,193 rural older women contributing 8,803 person-wave observations, of whom 572 resided in cities that implemented LTCI pilot programs during the study period.

2.2 Variable Definitions

The primary outcome variable was depressive symptoms measured by the Center for Epidemiologic Studies Depression Scale (CES-D), a widely validated 10-item instrument that assesses the frequency of depressive symptoms over the past week [17]. Each item is scored from 0 to 3, yielding a total score ranging from 0 to 30, with higher scores indicating more severe symptoms. A cutoff of 10 or above identified clinically significant depressive symptoms[18]. The CES-D has demonstrated satisfactory reliability and validity in Chinese older adult populations, with Cronbach's alpha typically exceeding 0.80[19].

The core explanatory variable was LTCI exposure, coded as 1 if the respondent resided in a city that had implemented an LTCI pilot program by the survey year and 0 otherwise. Pilot city status was verified through official documents issued by the Ministry of Human Resources and Social Security and city-level policy announcements.

Moderation variables captured distinct dimensions of pension coverage, family support and social integration. Emotional support was measured as a binary indicator of whether the

respondent had face-to-face contact with children at least once per week. Financial support was a binary indicator of whether the respondent received any financial assistance from children during the past year. [21] Social isolation was measured using a composite index ranging from 0 to 6, constructed from items assessing the frequency of social activities, community participation, and contact with non-family social networks, with higher scores indicating greater social isolation [22]. Pension coverage was defined as a binary indicator of whether the respondent received any public pension income. [23][62]

Control variables included age in years, marital status (married or partnered versus unmarried, widowed, or divorced), activities of daily living limitations (count of difficulties across six ADL items), chronic disease count (number of diagnosed conditions), and educational attainment (classified into four categories from illiterate to middle school and above[68]).

2.3 Empirical Strategy for Main Effects

• Two-Way Fixed Effects and Goodman-Bacon Decomposition

To estimate the causal effect of LTCI on depressive symptoms, we employed a multi-period difference-in-differences (DID) model that exploits the staggered timing of LTCI implementation across pilot cities [24]. As a benchmark, we first estimate a two-way fixed effects (TWFE) model of the form:

$$Y_{it} = \beta_0 + \beta_1 \cdot LTCI_{ct} + \beta_2 \cdot X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes the CES-D score for individual i at time t; LTCI_{ct} is the binary treatment indicator for city c at time t; X_{it}represents a vector of time-varying individual-level covariates including age, marital status, ADL limitations, and chronic disease count; μ_i captures individual fixed effects that absorb time-invariant unobserved heterogeneity. λ_t account for unobserved time-invariant heterogeneity and common time trends and ε_{it} is the idiosyncratic error term. The coefficient β represents the DID estimator of interest, capturing the average treatment effect of LTCI on CES-D scores under the parallel trends' assumption[31]. Standard errors are calculated using the Driscoll-Kraay method to accommodate cross-sectional and serial correlation at the city level, with additional inference based on 500 bootstrap replications.

Under staggered adoption, however, the TWFE estimator can be biased due to negative weighting (Goodman-Bacon, 2021). We therefore conduct a Goodman-Bacon decomposition of the TWFE model, which partitions the overall estimate into a weighted average of three types of 2×2 comparisons: (1) treated vs. never-treated; (2) early-treated vs. later-treated (using the later-treated as controls before their own treatment); and (3) later-treated vs. early-treated (using already-treated units as controls). The third type receives negative weights and constitutes the primary source of bias.

• Moderation Analysis

To examine the moderating roles of emotional support, financial support, and social isolation, we extended the baseline model by including interaction terms between LTCI and each moderator:

$$Y_{it} = \alpha + \beta_1 \cdot LTCI_{ct} + \beta_2 \cdot Moderator_{it}$$

$$+\beta_3 \cdot (LTCI_{ct} \times Moderator_{it}) + \gamma \cdot X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

The coefficient $\beta_3$captures the differential effect of LTCI across levels of the moderator variable, revealing whether the mental health benefits of LTCI are conditioned by family support structures and social integration [32].

• Subgroup Analysis

For subgroup analysis, we stratified the sample by age group, care need(binary), disability status(binary) and educational attainment(binary), reflecting the empirical distribution of the sample. to examine whether LTCI effects differed according to human capital endowments that may shape health literacy, information access, and ability to navigate the LTCI application process[33].

• Survival Analysis

To complement the primary analysis of continuous CES-D score changes, we employed survival analysis to estimate the effect of LTCI on the hazard of new-onset depression. Because LTCI exposure is time-varying, individuals are unexposed until the year their city implements the pilot program, treating LTCI as a baseline fixed covariate in a conventional Cox model would introduce immortal time bias (i.e., person-time before LTCI adoption would be incorrectly

classified as “treated”). We therefore used a time-dependent Cox proportional hazards model, which allows the exposure status to vary over time within the same individual [35].

To further tighten the control for age as the dominant risk factor for late-life depression, we adopted age as the time scale. Accordingly, the model handles left truncation, respondents enter the risk set at their baseline age (the age at which they were first observed) and are followed until the earliest of depression onset, death, loss to follow-up, or the end of the observation period, at which point they are right-censored. The time-dependent Cox model is specified as:

$$h_i(t|X) = h_0(t) \cdot exp(\beta \cdot LTCI_i(t) + \gamma \cdot X_i) \quad (3)$$

Where $h_i(t|X)$ is the hazard of first depressive episode at age t for individual is the non-parametric baseline hazard function; $LTCI_i(t)$ is a time-varying binary indicator that switches from 0 to 1 once the respondent’s city of residence has implemented LTCI; and X_i is a vector of baseline covariates (education, baseline ADL limitations, and entry age). The exponentiated coefficient exp(β) represents the hazard ratio associated with LTCI coverage, interpreted as the proportional change in the instantaneous risk of depression onset attributable to LTCI.

This survival analytic approach provides a clinically meaningful perspective by assessing LTCI’s effect on the incidence of new depression cases rather than changes in continuous symptom scores [35] and by properly accounting for the time-dependent nature of the policy intervention.

2.4 Robustness Checks

• Instrumental Variable Estimation

LTCI pilot city selection was non-random, likely prioritizing cities with stronger economic and healthcare infrastructure, which may independently affect mental well-being. To address this endogeneity concern, we employ a control function approach with a Probit first stage, using logged distance from the provincial capital to Qingdao as an instrument. The instrument is motivated by spatial decay in policy diffusion: cities closer to Qingdao adopted LTCI earlier through observational learning, while geographic distance exerts no direct effect on individual mental health. The Probit specification avoids the limitations of linear probability models for

binary endogenous variables. In the first stage, a Probit model estimates the LTCI participation decision:

$$Pr(LTCI_{it} = 1) = \Phi(\pi_0 + \pi_1 \cdot ln(Distance_i) + \gamma \cdot X_{it} + \lambda_t) \quad (4)$$

where Φ denotes the standard normal cumulative distribution function, $Distance_i$ is the spherical distance from the provincial capital to Qingdao, the pioneering city of LTCI institutionalization in China, X_{it}represents a vector of individual-level controls, and λ_t denotes year fixed effects. The instrument is motivated by spatial decay in policy diffusion theory, cities geographically closer to Qingdao are more likely to adopt LTCI earlier through observational learning and intergovernmental exchange, while geographic distance across cities exerts no direct effect on individual mental health conditional on covariates.

From the first-stage Probit model, we retrieve the predicted probability of LTCI participation, $\widehat{LTCI}_{it}$, and the residual $\hat{v}_{it} = LTCI_{it} - \widehat{LTCI}_{it}$. The second stage incorporates both the predicted probability and the residual into the main regression equation:

$$CES - D_{it} = \beta_0 + \beta_1 \cdot \widehat{LTCI}_{it} + \rho \cdot \hat{v}_{it} + \gamma \cdot X_{it} + \varepsilon_{it} \quad (5)$$

The inclusion of $\hat{v}_{it}$ as a control function provides a direct test of endogeneity: a statistically significant coefficient ρ indicates the presence of endogeneity, justifying the IV approach; an insignificant ρ suggests that OLS estimates may be consistent once the binary nature of LTCI adoption is appropriately modeled. Standard errors are clustered at the province level to account for within-province correlation in the error structure.

• Callaway-Sant'Anna Estimator

Under a staggered adoption, the conventional two-way fixed effects estimator may yield biased estimates in the presence of treatment effect heterogeneity. Specifically, the TWFE estimator constitutes a weighted average of group-time average treatment effects, where some weights may be negative, rendering the estimated coefficient difficult to interpret as a meaningful average treatment effect for the full sample. Hence, we cross-validate our findings using the group-time average treatment effect estimator proposed by Callaway and Sant'Anna (2021)[26]. This estimator uses "not-yet-treated" units as the comparison group, estimates treatment effects separately for each adoption cohort at each time period, and then aggregates these estimates into a

summary measure, thereby circumventing the negative weighting problem inherent in the TWFE estimator.

• Additional Checks

We further conduct the following robustness checks: (1) Placebo test, we randomly reassign LTCI treatment status across cities and re-estimate the DID model 1,000 times, constructing an empirical distribution of placebo coefficients against which to compare our estimated treatment effect. (2) Sample sensitivity analysis, we exclude respondents who exhibited depressive symptoms at baseline to rule out the possibility that our results are driven by mean reversion among initially depressed individuals. Results from these supplementary analyses are directionally consistent with our baseline findings, further reinforcing the robustness of our core conclusions.

All analyses were conducted using Stata version 17.0, with standard errors clustered at the city level to account for within-city correlation and potential serial correlation in individual-level outcomes. Statistical significance was assessed at the conventional 0.05 level using two-tailed tests, with marginal significance noted at the 0.05 to 0.10 level.

3. Results

3.1 Descriptive Statistics

The final analytical sample comprises 2,193 rural female respondents aged 60 years or above, contributing 8,803 person-wave observations across five survey waves (2011–2012, 2013, 2015, 2018, and 2020). Of these, 572 respondents received LTCI benefits at some point during the observation period. Table 1 presents the pooled descriptive statistics by treatment status. Respondents had a mean age of 70.6 years (SD=6.15) and a mean CES-D score of 8.08 (SD=5.94). The vast majority (80.6%) were married or had a partner. The mean educational attainment is 1.21(SD=0.49), which was low but consistent with reality.

In terms of health, respondents reported an average of 0.49 ADL limitations (SD=1.11) and 2.02 chronic conditions (SD=1.79). Family support was moderately prevalent: 69.3% maintained weekly contact with their children, and 78.2% received financial transfers from offspring. The mean social isolation score was 2.39 (SD=1.18), and 80.9% were covered by a pension. Baseline balance tests indicate that the treatment group was significantly younger, had lower baseline

CES-D scores, fewer ADL limitations, fewer chronic diseases, and higher marriage rates, consistent with the staged rollout of LTCI to relatively healthier cohorts in the initial implementation phase.

Table 1. Descriptive Statistics

Variable	Type	Overall_Mean (SD)	Control_Mean (SD)	Treatment_Mean (SD)
Age (years)	continuous	70.62(6.15)	70.42 (6.17)	73.42(5.16)
CES-D score	continuous	8.08 (5.94)	8.16 (5.96)	7.04(5.68)
Married/Has partner	binary	0.81(0.40)	0.80(0.39)	0.79(0.40)
Education Attainment	4-category	1.21(0.51)	1.22(0.51)	1.20(0.49)
ADL limitations	continuous	0.49 (1.11)	0.52 (1.12)	0.38(0.99)
Chronic disease count	continuous	2.02(1.79)	2.04 (1.78)	1.89(1.89)
Pension Coverage	binary	0.809(0.39)	0.80(0.40)	0.89(0.32)
Weekly contact with children	binary	0.693(0.46)	0.699(0.45)	0.601(0.49)
Received financial support	binary	0.782(0.41)	0.776(0.42)	0.873(0.33)
Social isolation	continuous	2.39 (1.18)	2.40 (1.17)	2.33(1.20)

Comparing treatment and control groups, respondents in LTCI pilot cities exhibited broadly similar baseline characteristics, though modest differences were observed in age distribution, education level, and baseline CES-D scores.

3.2 Main Effect of LTCI on Depressive Symptoms

LTCI reduced CES-D scores by 0.45 points ($p=0.028$) after adjusting for time-varying controls (Table 2). Decomposition revealed that 48.8% of the TWFE weight derived from problematic late-vs-early comparisons (average coefficient −0.330), explaining why the Callaway-Sant'Anna estimate (−0.949) was larger in magnitude.

Table 2. Effect of LTCI on Depressive Symptoms

	(1) TWFE	**(2) TWFE + Controls**
LTCI	-0.535**	-0.447*
	(0.270)	(0.238)
Has spouse	-0.591**	-0.604**
	(0.256)	(0.228)
Age		0.014
		(0.018)
ADL count		0.885***
		(0.111)
Chronic disease count		0.132
		(0.098)
Individual FE	Y	Y
Year FE	Y	Y
Observations	8,803	8,781
R^2 (within)	0.014	0.04
N(individuals)	2,193	2,193

*Note. Bootstrapped Driscoll-Kraay standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

Table 3. Goodman-Bacon Decomposition

Type	Weight	Average Coefficient	Weighted Contribution
Treated vs. Never	0.182	0.082	0.015
Early vs. Late	0.330	-0.093	-0.031
Late vs. Early (Negative Weight)	0.488	-0.330	-0.161
Overall (Decomposition)	1.000		-0.177
Actual TWFE Estimate			-0.447

The decomposition reveals that nearly half (48.8%) of the TWFE estimate derives from "Late vs. Early" comparisons, which is the problematic negative-weight comparisons identified by Goodman-Bacon (2021). These comparisons, where already-treated early-adopter cities serve as controls for later-adopting cities, systematically pull the TWFE estimate downward (average coefficient = −0.330), attenuating the true treatment effect.

The dominance of negative-weight comparisons (48.8% of total weight) explains why the TWFE estimate (−0.447) is substantially smaller than the Callaway-Sant'Anna estimate (−0.949), confirming that heterogeneity bias attenuates the estimated effect.

3.3 Parallel Trends Assessment

The validity of the DID identification strategy hinges on the parallel trends' assumption, which requires that treatment and control groups would have followed similar mental health trajectories in the absence of LTCI implementation.

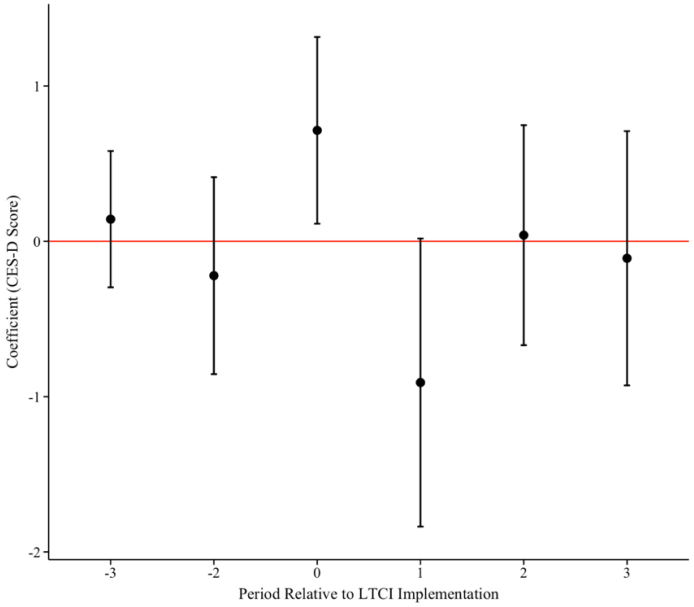


Figure 1. Event-Study Plot

Figure 1 presents the event-study coefficients plotting the dynamic effects of LTCI relative to the implementation year. In the pre-treatment period (three or more years before LTCI implementation), the estimated coefficients were close to zero and statistically insignificant, providing reassuring evidence that treatment and control groups followed parallel trends in CES-D scores prior to policy introduction. In the post-treatment period, coefficients became increasingly negative, suggesting that the mental health benefits of LTCI accumulated over time rather than manifesting immediately upon implementation. This dynamic pattern is consistent with the gradual nature of LTCI benefit take-up, as eligible individuals must learn about the program, complete application procedures, and begin receiving services before psychological benefits materialize [46].

3.4 Moderating Effects Results

Moderation results are presented in For financial support, the compensatory pattern was even more pronounced. The LTCI × financial support interaction was 1.422 ($p = 0.015$), and subgroup analyses revealed a stark contrast: LTCI reduced CES-D scores by 2.52 points ($p < 0.001$) among women receiving no financial transfers from children, compared with a negligible −0.093 ($p = 0.731$) among those who did, a 2.43-point between-group difference ($p < 0.001$).

Social isolation similarly moderated the LTCI effect ($\beta = -0.427$, $p = 0.025$). Women with high isolation experienced a 1.18-point reduction in depressive symptoms ($p = 0.004$), whereas their low-isolation counterparts showed no discernible benefit. This suggests that professional home visits and community-based care encounters facilitated by LTCI provide alternative channels of interpersonal interaction for women whose social networks have contracted.

In contrast, pension coverage showed no significant interaction with LTCI ($\beta = −0.101$, $p = 0.850$), though pension receipt itself independently protected mental health ($\beta = −0.611$, $p < 0.001$). This null interaction suggests parallel rather than synergistic protective pathways: pensions mitigate generalized economic insecurity, while LTCI addresses care-specific burdens. Table 4. The interaction between LTCI and emotional support was positive and significant ($\beta = 1.386$, $p = 0.003$), indicating that LTCI-associated reductions in depressive symptoms were concentrated among women lacking regular contact. Subgroup estimates confirmed this pattern that the LTCI effect reached −0.64 points among women without weekly contact but approached zero among those with regular contact (between-group difference $p = 0.055$).

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Table 4. Moderating Effects of Emotional/Financial Support and Social Isolation

	(1) Emotional Support	**(2) Financial Support**	**(3) Social Isolation**	**(4) Pension coverage**
LTCI	-0.412 (0.269)	-0.383 (0.260)	-0.446 (0.237)	-0.675 (0.583)
Moderator (centered)	-0.154 (0.231)	-0.340 (0.176)	0.173 (0.126)	-0.611***(0.186)
LTCI × Moderator	1.386** (0.459)	1.422* (0.582)	-0.427* (0.191)	-0.101(0.538)
Has spouse	-0.608 (0.228)	-0.594 (0.228)	-0.609 (0.228)	-0.386(0.281)
ADL count	0.882 (0.111)	0.873 (0.111)	0.884 (0.111)	0.750***(0.083)
Chronic disease count	0.131 (0.098)	0.133 (0.098)	0.132 (0.098)	0.247**(0.071)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2 (within)	0.033	0.033	0.033	0.163

*Notes: Sample restricted to women with at least one living child. Robust standard errors clustered at the city level are reported in parentheses. All models include individual and year fixed effects. *** p<0.001, ** p<0.01, * p<0.05.*

Taken together, the moderation analyses reveal that the mental health benefits of LTCI among rural older women are not uniformly distributed. Instead, the protective effects are most pronounced among those with the weakest emotional bonds, the most limited economic resources, and the sparsest social ties, which manifests a distinct compensatory gradient. These findings not only deepen our understanding of the mechanisms through which LTCI operates but also offer preliminary empirical guidance for the targeted deployment of long-term care resources.

3.5 Heterogeneity Analysis Results

Table 5 reports results from heterogeneity analyses stratified by age group, care need status, and disability status. With respect to age, the protective effect of LTCI exhibits a pronounced age gradient. The treatment effect is strongest and highly significant among women aged 60 to 70 years (β=-1.960, SE=0.417, p<0.001), remains significant for the 70 to 75 year cohort (β=-1.149, SE=0.486, p=0.018), becomes marginally significant for ages 75 to 80 (β=-1.072, SE=0.580, p=0.064), and is statistically indistinguishable from zero for those aged 80 years and above (β=0.253, SE=0.857, p=0.768). This nonlinear pattern reflects a "window of optimal benefit" wherein LTCI confers the greatest mental health protection during the life stage when functional decline has begun to generate tangible care needs yet the individual retains sufficient cognitive and physical capacity to navigate formal care systems. For the oldest old subgroup, the null effect may be attributable to ceiling effects in depressive symptomatology and diminished psychological responsiveness to policy interventions due to entrenched coping mechanisms.

Table 5. Heterogeneity Analysis Results

Dimension	Subgroup	β	SE	P_value
Age	Age 60-70	-1.960	0.417	<0.001
Age	Age 70-75	-1.149	0.486	0.018
Age	Age 75-80	-1.072	0.579	0.064
Age	Age 80+	0.253	0.857	0.768
Caregiver	Needs Care	-1.588	0.870	0.068
Caregiver	No Care Need	-0.918	0.311	0.003
Disability	Disabled	-1.307	0.812	0.107
Disability	Non-disabled	-1.016	0.362	0.005
Education Attainment	Educated	−2.786	1.106	0.012
Education Attainment	Illiterate	-0.357	0.279	0.255

Regarding care need status, women with instrumental activity of daily living limitations exhibit a substantively large but marginally significant treatment effect (β=-1.588, SE=0.870, p=0.068). Women without care needs present a smaller but more precisely estimated significant effect (β=-0.918, SE=0.311, p= 0.003). This directional pattern aligns with theoretical expectations that groups with greater care needs derive larger benefits from LTCI, although within group heterogeneity and relatively smaller sample sizes may attenuate statistical significance.

With respect to disability status, the treatment effects for both the disabled group and the non-disabled group are directionally negative, with coefficient magnitudes of negative 1.307 (SE=0.812, p=0.107) and negative 1.016 (SE=0.362, p= 0.005). Although the estimate for the disabled group does not reach conventional significance thresholds, the directional consistency across both groups supports the theoretical prediction that LTCI protects mental health across the full spectrum of functional ability, with larger magnitude benefits accruing to those facing more severe functional limitations.

As for education attainment, the protective effect of LTCI exhibits an education gradient. Women with primary education or above experienced a substantially larger and statistically significant reduction in depressive symptoms ($\beta = -2.786$, SE = 1.106, p = 0.012) compared with their illiterate counterparts, for whom the estimated effect was modest and did not reach conventional significance ($\beta = -0.357$, SE = 0.279, p = 0.255). The difference in coefficient magnitude between the two subgroups suggests that health literacy, administrative navigational capacity, and information access may act as enabling mechanisms that amplify the psychological returns to LTCI coverage.

3.6 Robustness Checks

Instrumental Variable Estimation Results

Table 6 (Shown in Supplementary materials) reports results from the IV estimation employing a control function approach with a Probit first stage[25]. In the first stage Probit model, the coefficient on log transformed distance to Qingdao is negative and statistically significant (β =-1.131, SE=0.051, p<0.001), with a linearized F statistic of 59.57, which substantially exceeds the Stock and Yogo critical value of 16.38 for 10 percent maximal instrumental variable bias, confirming that geographic distance constitutes a strong instrument.[69]

Table 6. Instrumental Variable Estimation Results

Stage	Variable	Coefficient	SE	P_value
First (Probit)	iv_dist_ln	-1.131	0.051	P<0.001
	age	0.004	0.006	0.503
	has_spouse	-0.055	0.070	0.431
	ADL	-0.072	0.028	0.010

Second (CF)	LTCI_prob	-4.737	0.977	P<0.001
	LTCI_resid	-0.203	0.390	0.603
	age	-0.014	0.025	0.560
	has_spouse	-0.960	0.234	P<0.001
Diagnostics	F-statistic	59.57		
	Endogeneity_test_p	0.603		
	Observations	7871		
	Effect_SD	0.806		

The second-stage control function estimate yields a coefficient of −4.737 (SE = 0.977, $p < 0.001$) on the predicted probability of LTCI participation. This estimate represents the local average treatment effect (LATE) among compliers: women whose LTCI adoption was induced by geographic proximity to the pioneering city. The LATE is substantially larger than the OLS estimate, consistent with particularly pronounced gains among compliers. The residual term coefficient is −0.203 and statistically insignificant ($p = 0.603$), failing to reject the null hypothesis of no endogeneity in the Probit specification.

Callaway-Sant'Anna DID Estimation Results

Table 7. Callaway-Sant'Anna Estimation

Parameter	Estimate	Std. Error	95% Confidence Interval	Observations
Overall ATT	−0.9489	0.3120	[−1.560, −0.338]	4,822

The CS-DID estimate of −0.95 points on the CES-D scale is directionally consistent with our main TWFE estimate and confirms that LTCI significantly reduces depressive symptomatology among rural older women. The CS-DID estimate is larger in magnitude than the TWFE estimate, suggesting that the TWFE estimator may indeed have been attenuated by heterogeneous treatment effects across different adoption cohorts. This confirms robustness to staggered adoption bias. (Table 7) (Shown in Supplementary materials)

Placebo test and sensitivity analysis

The placebo test results, presented in Table 8 (Shown in Supplementary materials), demonstrate that the estimated LTCI coefficient of -0.448 falls in the left tail of the empirical distribution of

placebo coefficients, with only 6% of placebo estimates being more negative than the actual estimate (p=0.06). This provides suggestive evidence against the null hypothesis of no treatment effect, though it falls marginally short of the conventional 0.05 significance threshold.

Table 8. Placebo test and sensitivity analysis

Test	LTCI_Coeff	P_value
Excl baseline depressed	-0.389	0.248
Placebo	-0.448	0.06

When respondents who were depressed at baseline (CES-D>10) were excluded from the analysis, the LTCI coefficient remained directionally negative and similar in magnitude to the main estimate, indicating that results are not driven by regression to the mean among initially depressed individuals. This indicates that results reflect genuine policy-induced improvements rather than mean reversion [42].

3.7 Survival Analysis Results

Main Effect of LTCI on Depression Incidence

Table 9 presents the main effect of LTCI on depression onset risk. In the preferred time-dependent Cox specification with age as the time scale, LTCI coverage was associated with a statistically significant 36.1% reduction in the hazard of depression onset (HR = 0.639, 95% CI: 0.458–0.893, p = 0.009). This effect was robust to alternative control specifications, including the addition of baseline chronic conditions (HR = 0.651, 95% CI: 0.467–0.908, p = 0.011; see Appendix Table). The clinical significance of this effect is substantial: a 36% reduction in depression hazard corresponds to approximately 4.5 additional depression-free years over a 10-year horizon for a typical 70-year-old rural woman, assuming a baseline cumulative incidence of 35%.[6]

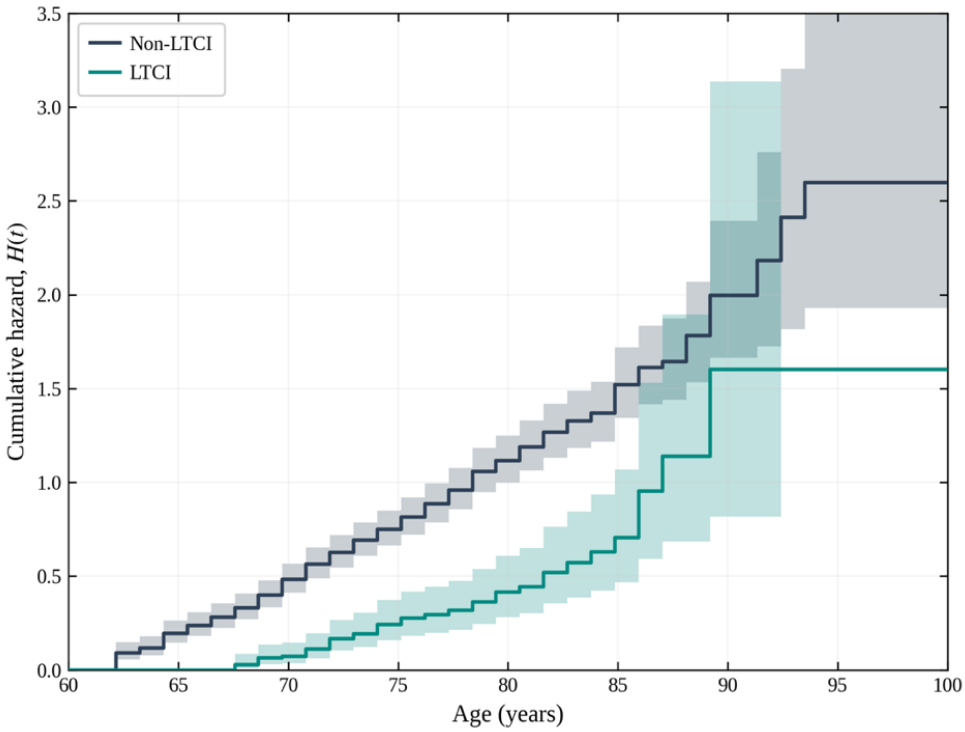


Figure 2. Main Effect of LTCI on Depression Incidence (Nelson-Aalen Figure)

Subgroup-Stratified Analysis

Table 9 (shown in Supplementary materials) presents LTCI hazard ratios stratified by baseline levels of four moderators. The pattern of results provides convergent validation of the compensatory resource framework identified in the TWFE-DID moderation analysis.

Table 9. Subgroup-Stratified Hazard Ratios: LTCI and Depression Onset

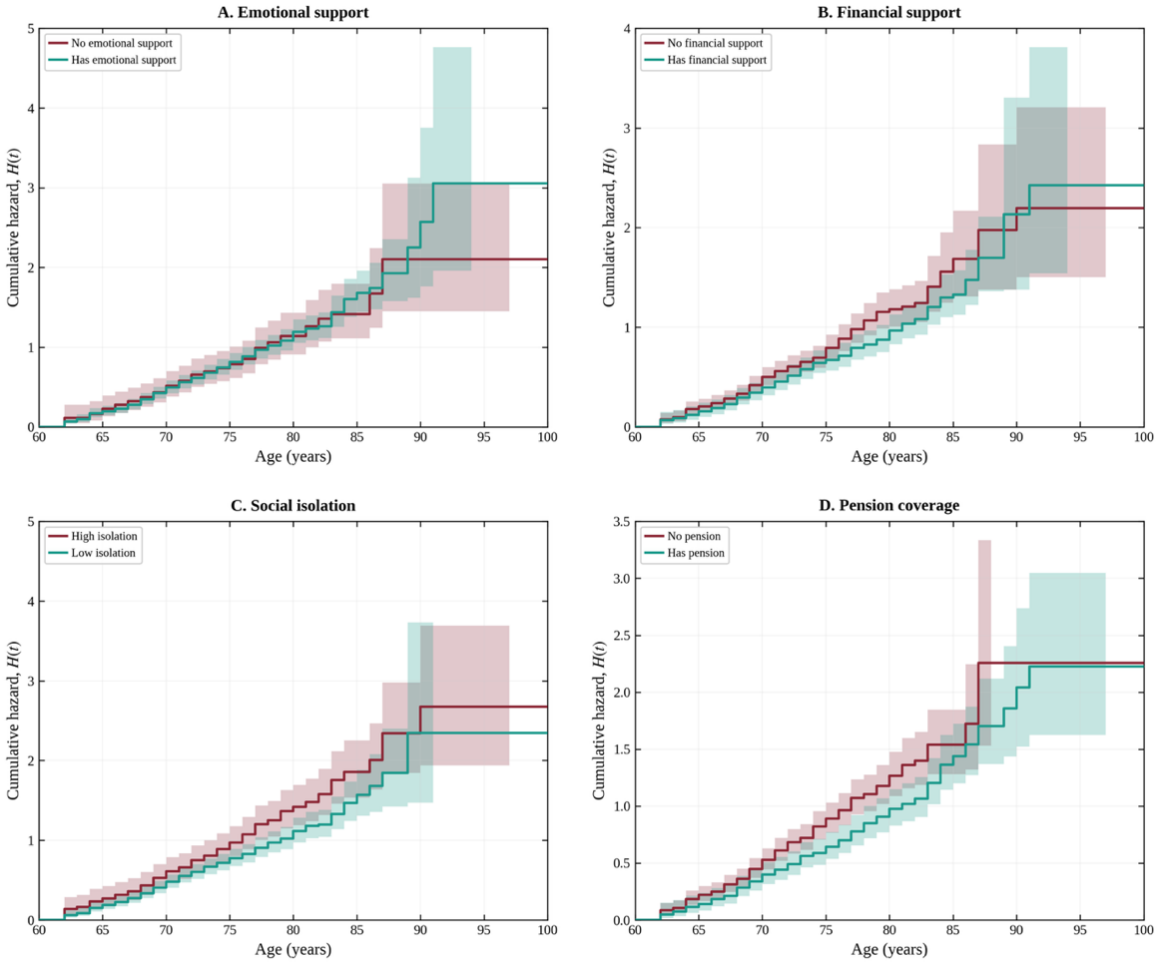


Figure 3. Subgroup-Stratified Analysis by Four Moderators (Nelson-Aalen Figure)

Consistent with the DID moderation results, LTCI hazard ratios were systematically lower among subgroups with weaker informal support. The protective effect was strongest for women without financial transfers (HR=0.547, p=0.020) and those with high social isolation (HR=0.413, p=0.017), while pension coverage showed no effect modification, further supporting the compensatory interpretation.

Subgroup	N	Events	HR	95% CI	P-value
Overall	1,122	438	0.639	0.458–0.893	0.009
Emotional support					

Has weekly contact	863	339	0.678	0.466–0.986	0.042
No weekly contact	259	99	0.497	0.235–1.049	0.067
Financial support					
Receives financial support	578	216	0.726	0.465–1.132	0.158
No financial support	544	222	0.547	0.328–0.910	0.020
Social isolation					
Low isolation	735	272	0.759	0.518–1.112	0.157
High isolation	387	166	0.413	0.199–0.855	0.017
Pension coverage					
Has pension	574	204	0.653	0.408–1.045	0.076
No pension	548	234	0.650	0.402–1.050	0.078

Notes: Time-dependent Cox models with age as time scale. All models control for baseline ADL limitations, education, and entry age. Standard errors clustered at individual level.

4. Discussion

4.1 Summary and Interpretation

Our findings provide robust evidence that LTCI significantly reduces both depressive symptom severity and the incidence of new-onset depression among rural older women. The effect size of roughly 7 percent of baseline SD is comparable to other social policy mental health interventions in low- and middle-income settings, carrying substantial public health significance given the large population of potential beneficiaries.

4.2 Theoretical Contributions

The primary theoretical contribution of this study is the identification of a consistent compensatory substitution mechanism. Across emotional contact, financial transfers, and social integration, the psychological benefits of LTCI were systematically concentrated among women

with the weakest informal resources. This convergent pattern indicates that formal institutional support can substitute for depleted family care rather than merely complement it.

Cohen and Wills (1985) posited that social support buffers stress, with strongest protection emerging under high stress exposure. Our results demonstrate that formal institutional resources can fulfill an analogous function when informal support has eroded. In rural China, where labor out-migration has structurally weakened intergenerational support, LTCI operates as a societal compensatory mechanism, delivering the greatest relief to women most affected by the withdrawal of traditional resources. This aligns with Hammarström's (2014)[8] resource substitution thesis but advances it by providing quasi-experimental evidence of the causal pathway.

The gender-specific dimension merits emphasis. Existing studies of LTCI effects on mental health have predominantly employed gender-pooled samples, obscuring the distinct pathways through which insurance coverage may operate for women versus men[11]. The compensatory pathway we identify is activated precisely because rural older women in China occupy a structurally disadvantaged position at the intersection of age-related care needs, limited economic autonomy, and the erosion of patriarchal family obligations. [8][9]. For this population, LTCI selectively redresses the psychological consequences of social deprivation, functioning as an institutional counterweight to cumulative disadvantages over the female life course. The finding that formal care visits can partially substitute for family-based interpersonal contact suggests that LTCI's therapeutic component extends beyond functional care delivery to the psychosocial benefits of human interaction. [54].

In contrast to the family-support moderators, pension coverage showed no effect modification. This null interaction supports an interpretation of parallel protective pathways. Pensions mitigate generalized economic insecurity through unconditional income transfers, whereas LTCI addresses care-specific burdens including functional dependence, caregiving costs, and the anxiety of unmet care needs. The absence of synergy between these two institutional supports implies that comprehensive social protection requires both income security and care service coverage, as neither alone is sufficient.

The heterogeneity patterns further reinforce the compensatory mechanism. The pronounced age gradient, with the strongest effects among women aged 60–70 and null effects above 80, suggests a window of optimal benefit when care needs have emerged but navigational capacity

remains intact. The education gradient is consistent with the inverse care law [48]: those most in need of care face the greatest barriers to accessing it. These patterns underscore that the compensatory function of LTCI is itself conditioned by individual capacity to navigate formal systems, a dimension not fully captured in the original resource substitution thesis.

4.3 Policy Implementation

The concentration of LTCI benefits among younger-old and more-educated women raises equity concerns. Women aged 80 and above, and those without formal education, derived negligible benefits, suggesting that the current implementation model may inadvertently widen existing mental health disparities. Mechanisms likely include health literacy barriers, administrative complexity in enrollment, and unequal access to program information. Community-based enrollment assistance and simplified application procedures are essential to reduce these barriers. Proactive outreach targeting socially isolated and less-educated subgroups can ensure that those most likely to benefit from LTCI actually receive it. Integrating mental health screening into routine LTCI service delivery would further help identify beneficiaries at elevated risk and connect them with appropriate psychosocial support.

4.4 Limitations

Several limitations of this study should be acknowledged. First, the reliance on observational data means that causal estimates depend on the validity of the parallel trends assumption, and unobserved confounders cannot be entirely ruled out. [62]. Second, binary LTCI exposure measurement does not capture variation in benefit generosity, service intensity, or implementation quality across pilot cities.[63] Third, measures of emotional support and social isolation, while multidimensional, are relatively coarse and may not fully capture the quality of interpersonal relationships. [64] Fourth, the CES-D assesses self-reported symptoms rather than clinically diagnosed depression and may be influenced by cultural response patterns. [65] Fifth, differential attrition related to mental health trajectories could introduce selection bias.[66] Last, the follow-up period of up to five years may be insufficient to capture the full long-term mental health effects of LTCI coverage. [71]

5. Conclusion

This study demonstrates that LTCI confers meaningful mental health protection for rural older women in China through compensatory substitution, with the largest benefits among those with weakest informal support. However, benefits concentrate among younger-old and more-educated women, raising equity concerns that unmodified expansion may widen disparities. Gender-sensitive implementation integrating mental health screening, community-based enrollment assistance, and targeted outreach to isolated and less-educated subgroups is essential to ensure this landmark policy protects China's most vulnerable older women.

Authorship Contribution Statement

Zhangbo An, Conceptualization, Methodology, Data curation, Formal Analysis, Writing-original draft;

Qihui Xie, Conceptualization, Methodology, Validation, Supervision, Reviewing and Editing;

Hongying Zhang, Data curation, Validation and Supervision;

Yuwu Xie, Methodology, Data curation, Formal Analysis

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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Data and Ethics Statement

This study uses publicly available data from the China Health and Retirement Longitudinal Study (CHARLS), accessible at http://www.charls.pku.edu.cn/en. CHARLS was endorsed by the Biomedical Ethics Committee of Peking University (IRB00001052-11015). The authors do not have permission to share the raw data directly.

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