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Services and Cash: How Long-term Care Insurance Benefit Design Affects Household Behavior in China*

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Abstract

This study analyzes the effects of China's long-term care insurance (LTCI) benefit design on household consumption and intergenerational support. The program provides two benefit options: in-kind benefits (or services) and cash allowances. We introduce a conceptual framework to analyze economic decision making under the two types of LTCI benefits. Using an empirical framework that exploits variations in LTCI benefit designs across China's pilot cities, we find that both types of LTCI benefits increase household consumption and reduce medical expenditure. Specifically, 'mixed' benefits households – those with a choice between in-kind and cash benefits – significantly increase spending on food and housing, while households receiving services spend more on housing, transport, and clothing. Additionally, in-kind benefit recipients report receiving lower informal care from their children, implying a substitution with formal care. Households with mixed benefits experience a decline in financial support from children, suggesting a crowding-out of intergenerational transfers. Finally, we estimate income and substitution effects that are implicit in recipients' behavior to analyze welfare implications under China's LTCI.

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Keywords: Long-term Care Insurance, Benefit Design, In-kind Benefits, Cash Benefits, Household Consumption, Intergenerational Support

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1 Introduction

Globally, many countries are experiencing a significant demographic shift characterized by a rapidly aging population, as life expectancy increases and fertility rates decline. As populations age, the demand for long-term care (LTC) services grows, raising questions on how best to finance and deliver LTC services to meet this need. Due to the high fiscal cost of LTC and to alleviate the burden on families, there is growing recognition of the need for formal systems to finance LTC to complement the provision of informal care (Colombo et al., 2011).

China's population is rapidly aging. Between 2021 and 2040, the fraction of individuals aged 65 years and older is projected to grow from 13% to 26% (United Nations, 2023). Substantial financial and human resources are required to meet the LTC needs of the country's older population (Xu et al., 2019). In 2016, China introduced a pilot program for long-term care insurance (LTCI) with the aim of providing financial support and services for people with long-term disabilities. To meet the diverse care needs for both formal and informal care, pilot cities in China offer two types of benefits: *in-kind* (or services) benefits, and a mix of in-kind and *cash* benefits. With in-kind benefits, beneficiaries receive a broad range of services covering basic medical, nursing, home and residential care, with a portion of the service costs covered by the LTCI. Cash benefits, on the other hand, are lump-sum cash allowances, complemented by informal care provided by family members or purchasing the formal care themselves. In cities offering in-kind benefits, beneficiaries can only receive services; in cities offering mixed benefits, beneficiaries can choose either services or cash.

In this paper, we examine how the benefit design of China's LTCI program affects household behavior. We leverage the difference in design across cities to investigate its impact on household consumption of older Chinese, and on the receipt of financial support and informal care. We postulate that households respond differently to incentives embedded within different types of benefits. For example, the provision of in-kind benefits incentivizes beneficiaries to choose formal care. Recipients of cash, on the other hand, have the flexibility to allocate funds towards paying family members for informal care, or covering out-of-pocket medical expenses or general expenses.

We begin by analyzing conceptually household utility maximization decisions under the two types of LTC benefits. Having access to LTCI results in a price effect, which can be decomposed into two components: a substitution effect and an income effect. A key insight is that receiving cash represents solely an income effect, whereas receiving services encompasses an income effect and a substitution effect. Building on the conceptual model, we estimate an empirical model to evaluate the impact of the two types of LTCI benefits on household consumption and intergenerational support. Our data comes from the China Health and Retirement Longitudinal Study (CHARLS) and our empirical strategy uses the timing of LTCI roll-out across pilot cities, as well as information on the types of LTCI benefits that were introduced.

Our empirical results indicate that households that receive mixed benefits significantly increase their expenditure on food and housing, whereas households who receive in-kind benefits increase their expenditure on housing, transport and clothing. Beneficiaries of both types of benefits reduce medical related expenditure, suggesting a substitution away from medical services towards formal and informal LTC services. Overall, individuals who receive mixed LTCI benefits significantly increase their levels of non-medical consumption. We also find that beneficiaries who receive solely in-kind LTCI benefits reported a reduction in the amount of informal care provided by children, signaling a substitution of formal care for informal care, relieving the burden of care provision by family caregivers. Receiving mixed LTCI benefits, on the other hand, results in a significant reduction in the amount of financial support that an elderly household receives, indicating that cash benefits crowds out financial transfers from children.

This paper contributes to several strands of literature. First, a growing body of work has studied the effects of introducing LTCI predominantly from the experiences of high-income countries such as Germany, Japan and Korea (Courbage and Eeckhoudt, 2012; Geyer and Korfhage, 2015; Kim and Lim, 2015; Fu et al., 2017; Courbage et al., 2020), as well as that of China (Lei et al., 2022; Feng et al., 2020; Wang et al., 2021; Chen and Ning, 2022; Liu et al., 2023). Few studies investigate the implications of offering different types of LTCI benefits, with the exception of Costa-Font et al. (2018, 2022) on the Spanish experience. We contribute to the literature by providing insights on the implications of LTCI benefit design in China on household welfare. This research is especially relevant for policy makers in low- and middle-income countries (LMIC) looking to design public LTC programs, as LMICs face specific challenges that constrain their capacity to publicly provide LTC services (Cheng et al., 2023).

Second, we contribute towards the understanding of the theoretical underpinnings of consumer behavior regarding different types of LTC benefits. This is a domain where the body of work is very small. A study by Courbage and Eeckhoudt (2012) theoretically examines, from the perspective of a caregiver, the decision to depend on the formal LTC care system or directly providing care. Theoretical insights enhance our understanding of how LTCI benefit design affect the welfare of beneficiaries and their families, and also on the efficiency and sustainability of LTC programs.

Third, we contribute to the evidence base in China by examining the impact of LTCI on household well-being, intergenerational support and financial transfers. Previous research has studied its effects on health care use and medical expenses (Ma et al., 2019; Feng et al., 2020; Hou et al., 2021; Chen and Ning, 2022), health status and mortality risk (Lei et al., 2022), and consumption (Liu et al., 2023). None of these studies considered the implications of different types of LTCI design.

The remainder of this paper is organized as follows. Section 2 outlines the institutional background of the LTCI program and discusses the conceptual framework. Section 3 describes the data and Section 4 presents the econometric strategy. Section 5 discusses the empirical results and robustness checks. Section 6 analyzes the welfare implications and Section 7 concludes with a summary of our findings.

2 Background

2.1 The Impact of Long-term Care Insurance

Internationally, the introduction of LTCI resulted in improvements in physical and cognitive capacities of recipients in Germany (Büscher et al., 2010), Japan (Olivares-Tirado et al., 2012), and Korea (Lee et al., 2014). In China, studies have shown that LTCI resulted in improved physical and mental health (Lei et al., 2022), lowered out-of-pocket inpatient expenditures (Chen and Ning, 2022), and reduced hospital expenses (Feng et al., 2020). Having access to LTCI also enhances the welfare of recipients' families, alleviating financial burden on households (Zuchandke et al., 2010; Iwamoto et al., 2010; Kim and Lim, 2015; Choi et al., 2018), improves household savings (Ohinata and Picchio, 2020; Liu et al., 2023), and increases caregivers' labor force participation.

A small body of work examines on the effect of different types of LTC benefits predominantly in high income countries. In Italy, where public support for LTC is primarily in the form of cash benefits, LTC support was found to increase the receipt of informal care (Courbage et al., 2020). Spain, on the other hand, directly provides or subsidizes formal care and LTC support reduced the receipt of informal care provided by family members. The decision to rely on the formal LTC care system or caring for one's parents was shown to depend on the degree of altruism (Courbage and Eeckhoudt, 2012). Two Spanish studies, Costa-Font et al. (2018) and Costa-Font et al. (2022), find that caregiving allowances for informal care reduced hospital care use, increased the receipt of informal care, and increased cash transfers from parents to their offsprings. Both in-kind benefits and cash was found to reduce hospital admissions and hospital care use, though cash resulted in a smaller decline (Costa-Font et al., 2018). In Germany, providing cash benefits had a large negative effect on the labor supply of carers, whereas providing in-kind benefits had a small positive effect on labor supply (Geyer and Korfhage, 2015).

2.2 China's Long-term Care Insurance Pilot

In 2016, China introduced LTCI pilot programs across 15 cities. The program's objective is to provide financial assistance and services to individuals with long-term disabilities and is predominantly financed through the country's social health insurance programs. There are two criteria for eligibility to LTCI coverage. First, individuals have to be severely disabled for at least six months. The degree of disability is evaluated using the Barthel Activities of Daily Living index, and other disability assessments determined by pilot cities. Second, the pilot cities only provide LTCI benefits to individuals who are enrolled in the country's public medical insurance schemes: the Urban Employee Basic Medical Insurance (UEBMI) for urban employees and Urban-Rural Residents Basic Medical Insurance (URRBMI) for both urban and rural residents (Lei et al., 2022).[1]

Table 1 shows the pilot cities that have introduced LTCI between 2016 and 2017 that are captured in data from the CHARLS, which we used for the empirical analysis. The table also summarizes the two types of benefit packages: cities that provide a mix of in-kind and cash benefits, and others that

[1]In the 15 pilot cities, all cities provide LTCI coverage to urban employees covered under UEBMI. Six cities (e.g., Nantong and Shanghai) and Shandong province also offer LTCI coverage to both urban and rural enrollees under URRBMI, while Jilin province provides services to urban residents enrolled in URRBMI.

provide only in-kind benefits. More details are given in Table A1 of Appendix A. The LTCI program broadly covers services for basic daily living, medical and nursing care, institutional care, and home care (Feng et al., 2021). Many cities provide only in-kind benefits, with benefit generosity varying in terms of the coinsurance rates. Four cities provide mixed benefits, where beneficiaries can choose either services or cash. The cash allowance is set at approximately 450 RMB (US$68) per month, and comes with the condition that family caregivers provide informal care. In Jingmen, caregivers have to be trained in designated nursing institutions to be eligible; benefits are capped at 40 RMB (US$6) per day. Overall, the LTCI benefits are generous. The annualized value of cash benefits in 2018 amounted to 9,200 RMB (US$1400), which is approximately 88% of the average annual expenditure on caregiving for older adults requiring LTC based on estimates from data that available in the years prior to the introduction of LTCI (Liu et al., 2023).

Table 1: Type of Benefit Packages in Pilot Cities

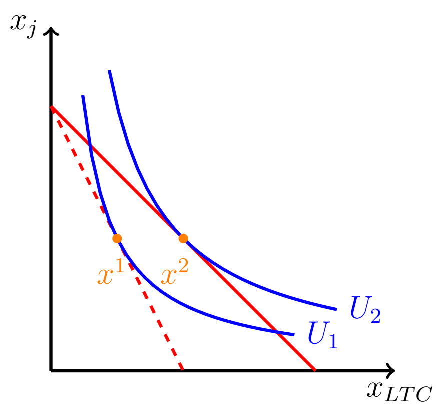
Province - City	Social Security Eligibility	In-kind Benefit	Cash Benefit
Mixed of In-kind and Cash Benefit			
Jiangxi - Shangrao	UEBMI	900 -1200 RMB/month;	450 RMB/person/month
Sichuan - Chengdu	UEBMI	70% - 75%	75%
Jiangsu - Xuzhou	UEBMI-URRBMI	30 - 48 RMB/day or 500 RMB/month	15 RMB/person/day
Hubei - Jingmen	UEBMI-URRBMI	70% - 80%, cap 100 - 150 RMB/day	cap 40 RMB/person/day
In-kind Benefit Only			
Zhejiang - Ningbo	UEBMI	40 RMB/day	
Shandong - Jinan	UEBMI	220 - 260 RMB/day, or cap 35 RMB/day	
Jilin - Jilin	UEBMI-URBMI (urban only)	70% - 80%	
Hebei - Chengde	UEBMI	70%	
Shanghai - Shanghai	UEBMI-URRBMI	85% - 90%	
Anhui - Anqing	UEBMI	40 - 50 RMB/day, or 750 RMB/month	
Guangdong - Guangzhou	UEBMI	75% - 90%, cap 115 - 120 RMB/day (Daily Living)	
Shandong - Linyi	UEBMI-URRBMI	75% - 90%	
Heilongjiang - Qiqihaer	UEBMI	50% - 60%	
Jiangsu - Suzhou	UEBMI-URRBMI	20 -30 RMB/day	

Note: This table lists all pilot cities that have launched the LTCI policy between 2016 and 2017 and are available in China Health and Retirement Longitudinal Study (CHARLS) data. UEBMI stands for Urban Employee Basic Medical Insurance for urban employees. URRBMI stands for Urban-Rural Residents Basic Medical Insurance, which provides coverage to both urban and rural residents. URBMI stands for Urban Residents Basic Medical. Percentages, where presented, refer to the co-insurance rate of eligible expenses.

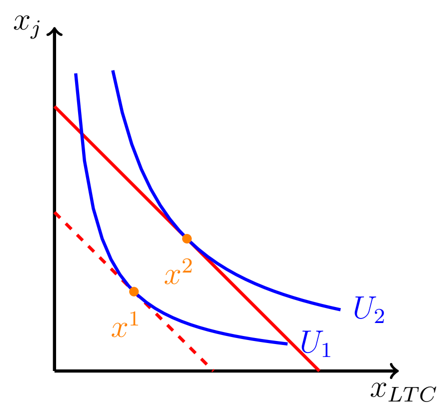
2.3 Conceptual Framework

We introduce a simple conceptual framework for analyzing economic decision-making in the context of LTCI that provides in-kind benefits and cash benefits. Consider a household making choices over levels of general consumption and LTC. The household's utility function $u(x)$ is constrained by budget $p \cdot x \leq y$, where p is the price vector of consumption bundles and y is the budget. The solution of the utility maximization problem, i.e., the Marshallian demand function, is $x^* = x^*(p, y)$, and the corresponding indirect utility function is $v(p, y) = u(x^*(p, y))$.

Consider two benefit options available to the household: 1) in-kind benefits and 2) cash benefits. Figure 1 illustrates how the chosen bundle (x_j, x_{LTC}) differ under the two options. The dashed line represents the budget constraint without LTCI, while the solid line represents the budget constraint under LTCI. The horizontal axis represents the quantity of LTC, and the vertical axis the consumption in item j.



(a) Effect of in-kind benefits



(b) Effect of cash benefits

Figure 1: Economic Decision for Two Types of LTCI Benefits

Panel (a) shows how the optimal bundle changes when in-kind benefits are offered. With in-kind benefits, the unit price of LTC declines resulting in the pivot of the budget line, allowing a higher level of LTC for every level of x_j . The household utility, shown by the indifference curves, rises from U_1 to U_2. Panel (b) on the other hand depicts the scenario when cash benefits are offered. Here, while the relative price of x_j and x_{LTC} remains unchanged, the offer of cash benefits results in an outward shift of the budget line; the optimal consumption bundle and the household utility adjust accordingly.

The two panels in Figure 1 illustrate different mechanisms in which in-kind and cash benefits affect household behavior. The first panel shows a change in the relative price (rotation of the budget line) and a higher purchasing power. The second panel shows only a change in purchasing power. This framework allows us to back out the substitution effect (SE) and the income effect (IE) of each good under the LTCI. The introduction of in-kind LTCI benefits affects the consumption of good x_j through a change in the relative price between x_j and x_{LTC} with the total effect described by the Slutsky's equation:

$$\underbrace{\frac{\partial x_j^*(p,y)}{\partial p_{LTC}}}_{\text{Total Effect}} = \underbrace{\frac{\partial x_j^h(p,u)}{\partial p_{LTC}}}_{\text{Substitution Effect}} + \underbrace{x_{LTC}^*(p,y)\cdot\left(-\frac{\partial x_j^*(p,y)}{\partial y}\right)}_{\text{Income Effect}}, \tag{1}$$

where the SE indicates the effect on the Hicksian demand in which the relative price changes but the utility level remains fixed, and the IE indicates the effect on consumption where the budget is expanded without a change in the relative price. For the case of a cash benefit, its effect on consumption x_j is entirely reflected by the IE since the relative price does not change.

Within the context of China's LTCI pilots, the price decline leads to an expected negative change in the SE for x_j due to a higher relative price of x_j to x_{LTC}. For the IE, the negative sign in the bracket suggests that the change in income moves in the opposite direction to the price. As a result, when the price of x_{LTC} declines, the IE of x_j is anticipated to be positive for a normal good but negative for an inferior good. Overall, the two types of LTCI benefits are expected to have different effects on household consumption. We apply these insights to examine if household consumption differs in pilot cities that offered mixed benefits compared with cities with in-kind benefits.

3 Data

To investigate the effects of LTCI on households' behaviors, we use data from the CHARLS. The CHARLS is a high-quality longitudinal survey that contains a nationally representative sample of residents ages 45 and older in China. It was launched in 2011 and covers 150 county-level units, surveying approximately 17,500 people in 10,000 households. Our research uses four waves of data from surveys that were conducted in 2011, 2013, 2015, and 2018.

The CHARLS has some advantages for analyzing the effect of long-term care insurance on household welfare. The survey contains information on municipality-level and county-level units, which permits us to identify the LTCI pilot cities. In addition, it provides comprehensive and high-quality data on demographic background, family characteristics, and various types of household spending, including medical costs and the consumption of necessities.

3.1 LTCI Eligibility

We define LTCI eligibility based on the year when LTCI was introduced in a respondent's city of resident, combined with public health insurance eligibility information as well as disability assessment.

First, an individual is eligible for LTCI coverage if the person is a resident of a pilot city and also covered by social health insurance (i.e., UEBMI for urban employees, and URRBMI for all residents or for urban residents only) as reported in Table 1. Second, to be eligible for long-term care, the individual would meet the assessment standard for *The Level of Disability in Long-term Care* issued by the National Healthcare Security Administration (NHSA). The assessment primarily uses the activities of daily living (ADL), an indicator of basic self-care tasks, to measure disability. We define individuals as "disabled" if they reported facing difficulties in any of the six ADLs - dressing, bathing, eating, getting in or out of bed, using the toilet, and controlling urination and defecation, which is in line with Liu et al. (2023). We, however, further define "disabled" if they remain disabled status in all waves of the longitudinal survey since they turn to disability for the first time to meet the defined long-term criteria. Finally, we consider a household as "treated" if it has at least one family member covered by the LTCI program. We further distinguish our treatment sample into those that receive in-kind LTC benefits, and those that receive a mix of in-kind and cash benefits. Households that make up the control group are those residing in cities that did not implement LTCI, or did not meet the health insurance and disability eligibility criteria.

3.2 Key Dependent Variables

The first set of outcome variables are the household's expenditures on clothing, food, housing, transportation, miscellaneous, and healthcare expenditures. We list the relevant items in the questionaire in Table 2. We then calculate the expense at the yearly level by taking into consideration the frequency at which the questions on household expenditure are asked,

$$Y = 52 \times Weekly + 12 \times Monthly + Annual,$$

where Y represents the household expenditure on clothing, food, housing, transportation, miscellaneous, and healthcare, respectively.

Table 2: Items in Questionnaire

	Item in Questionnaire		
	Weekly Expense	Monthly Expense	Annual Expense
Clothing			clothing and bedding
Food	food expenditure eating out spending beverage and tobacco		
Housing		water and electricity fuel (gas, coal, etc.) babysitters and servants	heating (centrally heated) furniture and durable goods property management
Transport		local transportation	long distance travel
Miscellaneous		toiletries and kitchen supplies telephone and internet usage	physical exercise make-up, facial, massage charge and tax (excluding income tax)
Medical			medical treatment (out-of-pocket)

Note: Data source: China Health and Retirement Longitudinal Study (CHARLS). We calculate the annual expenditure by $Y = 52 \times Weekly + 12 \times Monthly + Annual$, where Y represents the household expenditures on clothing, food, housing, transportation, and medical care, respectively.

The second set of outcome variables are the intergenerational support behaviour, including financial support and informal care. Financial support includes monetary and in-kind support from non-coresident children to their parents annually, while informal care refers to the time spend taking care of the parents by non-coresident family caregivers annually.

3.3 Descriptive Statistics

Based on the benefit packages adopted in pilot cities, the treatment group is further classified into categories: in-kind and mixed benefit. Control group are defined as those residing in cities that did not implement LTCI, or did not meet LTCI eligibility criteria, i.e. according to health insurance or disability status.

Table 3 summarizes the descriptive statistics for the treatment and control groups. The pre- and post-pilot comparison suggests that the LTCI policy has enhanced the consumption of daily necessities, which is generally larger in the treatment group than those in the control group. In addition, the increase of medical spending is less in the treatment group compared to those in the control, which may be driven by the implementation of LTCI. Furthermore, the magnitude effects for in-kind cities sand mixed cities are slightly different, which help us to analyze the corresponding policy implications.

Figure 2 shows the distribution of household consumption across treatment and control groups before and after the LTCI policy. It indicates that the treatment (i.e., in-kind and mixed groups) and the control groups share similar pattern in expenditures on most necessities, including clothing, food, housing, and transport in the pre-policy period.

To arrive at a precise estimate of the effect of LTC, we account for potential confounding factors by controlling for household demographic and socioeconomic covariates, including the age of disabled individuals, the average and variation of age of all household members, household income, and household size. Time-invariant covariates such as gender and education level of the disabled, are excluded from the model as they are absorbed by household fixed effects.

4 Empirical Strategy

4.1 Regression Model

To evaluate the impact of LTCI on the welfare of older adults and their family members, we exploit a two-way fixed effects (TWFE) DiD strategy with household fixed effects (FE) to the four-year panel data: the years 2011, 2013, and 2015 (before the introduction of LTCI) and the year 2018

Table 3: Summary Statistics

Household-level Statistics	Treatment Group: In-Kind Benefit (1) Pre-Pilot	(2) Post-Pilot	Treatment Group: Mixed Benefit (3) Pre-Pilot	(4) Post-Pilot	Control Group: Control (5) Pre-Pilot	(6) Post-Pilot
Annual Expense (RMB)						
Clothing	1447.8	2023.7	1905.3	2644.4	1183.3	1398.9
	(1971.9)	(2587.2)	(2523.6)	(2724.2)	(1813.1)	(2050.7)
Food	15185.4	17861.5	13011.4	21024.4	12525.7	16342.0
	(14207.1)	(15830.3)	(12052.8)	(14265.8)	(12436.9)	(15218.8)
Housing	3526.7	4848.4	2563.5	5204.2	2842.7	3602.0
	(3541.0)	(4205.8)	(2287.2)	(4864.7)	(3254.4)	(3630.7)
Transport	1355.0	2401.5	834.2	1534.4	862.2	1224.1
	(2711.3)	(3640.6)	(2237.2)	(3112.4)	(2039.0)	(2617.8)
Medical	1848.1	2960.2	2114.3	2689.8	2469.3	4875.8
	(4509.2)	(4818.5)	(4367.1)	(3114.1)	(5497.4)	(7412.1)
Miscellaneous	2826.6	3674.6	2818.1	4097	2737.3	2828.5
	(2808.1)	(3396.8)	(2853.5)	(3479.3)	(2991.1)	(2957.9)
Intergenerational Support						
Financial Support (RMB)	2176.4	3162.2	2209.7	3587.2	2493.5	3388.6
	(6458.8)	(7350.3)	(7268.5)	(9212.1)	(6195.5)	(7036.1)
Informal Care (Hours)	228.2	103.4	128.4	78.1	83.2	77.1
	(1817.9)	(435.0)	(1115.3)	(498.9)	(1057.7)	(472.3)
Covariate Characteristics						
Household Income (RMB)	29333.0	54863.7	30228.9	56640.1	16863.9	31487.8
	(32679.3)	(43501.9)	(32606.8)	(46564.1)	(25932.7)	(36482.6)
Household Age (Average)	54.9	56.0	55.1	56.8	58.4	60.6
	(8.80)	(8.38)	(8.53)	(7.38)	(9.23)	(9.18)
Household Age (SD)	1.79	1.64	1.60	1.39	2.18	2.10
	(1.89)	(1.76)	(1.69)	(1.18)	(2.15)	(2.06)
Household Size	3.17	3.15	3.07	3.24	3.32	3.31
	(1.42)	(1.41)	(1.62)	(1.64)	(1.64)	(1.72)
Observations	472	202	134	57	21242	7479

Note: This table presents the summary statistics across treatment and control groups. All statistics are calculated at the household-by-year level. All expenditures and income variables are measured in RMB. The exchange rate in 2016 between the US$ and Chinese RMB is set to US$100 = 664 RMB.

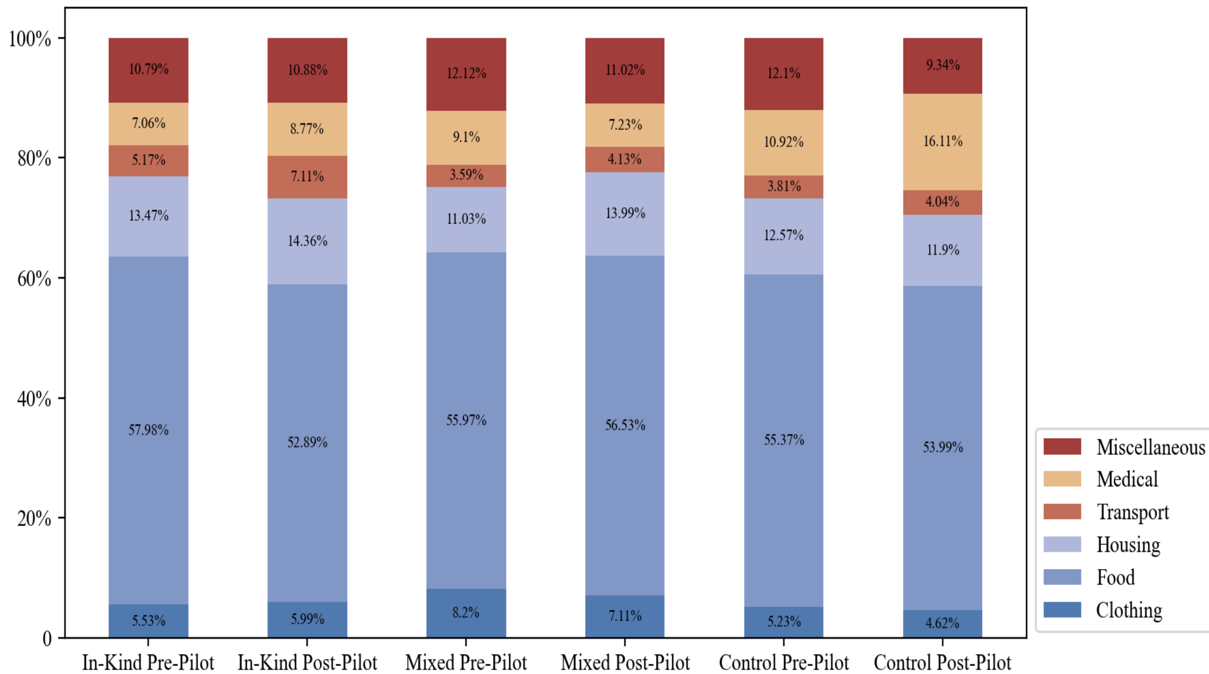


Figure 2: Distribution of Household Consumption across Treatment and Control Groups

Note: This figure presents the share of consumption in each item over the total consumption. The share is calculated based on the summary statistics presented in Table 3.

(after its introduction). Consider the living expenditure Y_{it} of household i in year t. The effect of the LTCI pilot is captured through a conventional Difference-in-Difference (DiD) model with two-way fixed effects,

$$Y_{ict} = \beta \cdot Treat_{ic} \times Post_t + X_{it}\gamma + \lambda_i + \delta_t + \varepsilon_{ict}, \tag{2}$$

where Y_{ict} denotes the outcome variables of household i living in the city c in year t, including various types of household annual spending listed in Table 3. The coefficient β captures the average treatment effect of the LTCI pilot on household behaviours, including consumption decision and intergenerational support. $Treat_{ic}$ is a dummy variable for household treatment status. In our setting, the treatment group consists of households with older adults covered by LTCI in the pilot city c, and the control group is formed of those households without family members covered by LTCI. Hence $Treat_{ic}$ equals 1 if an older adult in household i is eligible for LTCI coverage, and 0 otherwise. As discussed in Section 3.1, individual eligibility for LTCI coverage is based on the type of individual's public health insurance and the assessment of disability. $Post_t$ is a binary variable taking a value of 1 for 2018 and a value of 0 for 2011, 2013, and 2015.

X_{it} is a vector of household time-varying characteristics that include the household income, household size, average age within the household, and the standard deviation of household age to control for the variation in household age. Household fixed effects, λ_i, account for all time-invariant factors that may affect the outcome variables. δ_t is year fixed effects, and ε_{it} is a random error term. Standard errors are clustered at the city level to account for possible correlation in outcomes across different households in the same city.

4.2 Identification

The identification of a DiD model requires two assumptions. One is that the policy is exogenous to households. The other presumption is that the treatment group and the control group are comparable. We argue that our data satisfy these assumptions, so the coefficient estimate in the DiD model is identified. We discuss these two aspects below.

First, the policy is assumed to be exogenous to households, where the bias is caused by households' self-selection. Specifically, biases may occur if individuals migrate from a non-pilot city to a pilot city for the purpose of being eligible for LTCI. However, the issue of selective migration is likely not to be significant for a LTCI program. A household with long-term disabled people usually lacks the mobility to be able to migrate, and eligibility for LTCI coverage further depends on local requirements for public health insurance that are largely pre-determined due to the social security record in China.

Second, the key identifying assumption of the DiD approach requires common parallel trends between treatment and control groups before the treatment period. As the DiD model uses samples in the control group to represent the counterfactual scenario — how the observed outcomes would evolve in the absence of the intervention, we use an event study regression to test the parallel trends. Consider the following equation:

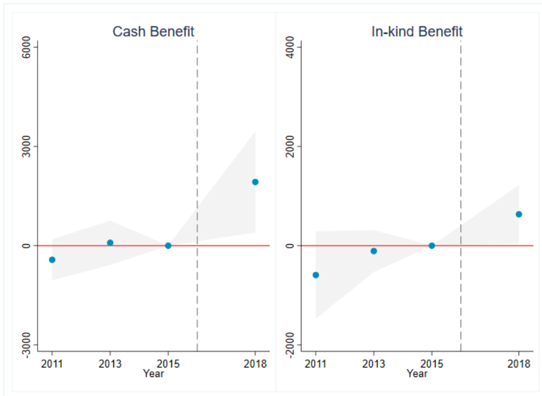
$$y_{ict} = \sum_{\tau \neq 2015} \beta_\tau \cdot Treat_{ic} \times \mathbf{1}\{t = \tau\} + X_{it}\gamma + \lambda_i + \delta_t + \varepsilon_{ict} \tag{3}$$

where everything is identical to Equation 2 except the inclusion of the interaction of $Treat_{ic}$ times the indicator of each year. β_τ captures the difference between the treatment group and the control group in year τ. Due to perfect co-linearity, we normalize β_{2015} to 0 so that each β_τ is interpreted as the gap in the difference between that discussed above in year τ and that in year 2015. With such a normalization operation, each β_τ is interpreted as any additional difference in year τ beyond the difference in the outcome Y_{it} between two groups in the year 2015.

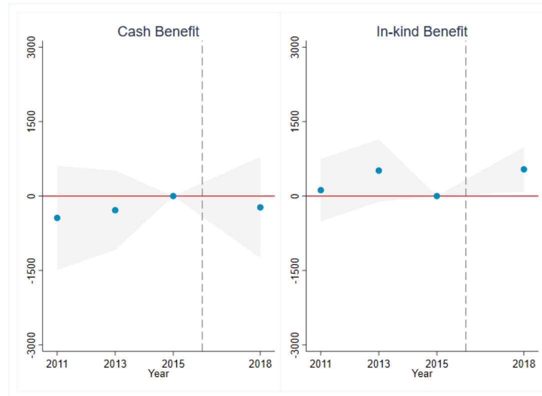
5 Results

5.1 Testing Parallel Trends

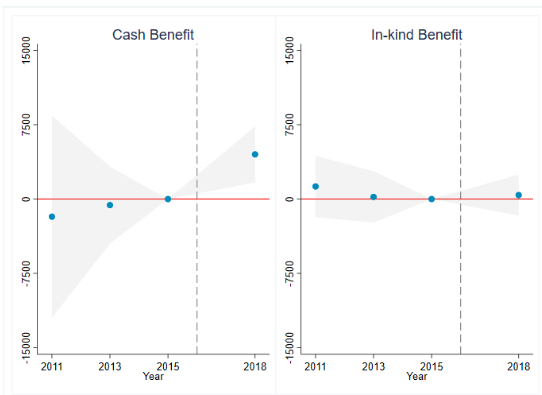
We first assess the validity of the parallel trends assumptions using an event study analysis. In the event study, the coefficient β_{2015} is normalized to 0. Hence, each coefficient estimate is interpreted as how the gap in outcomes between the treatment group and the control group in each year deviates from the reference year of 2015. If the coefficient estimate of β_τ ($\tau < 2015$) is not rejected to be null, we conclude that the pre-intervention outcomes in the treatment and control groups are not significantly different. Hence, we conclude that the parallel trends assumption is valid.



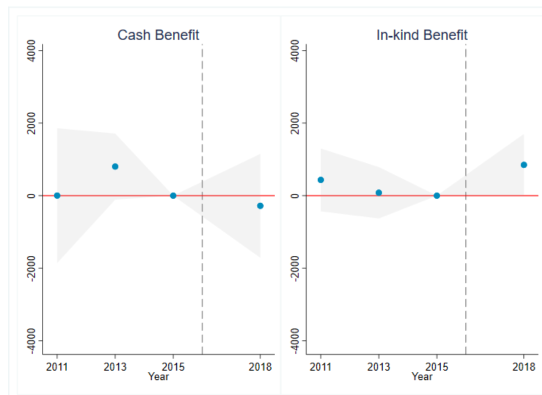
(a) Housing



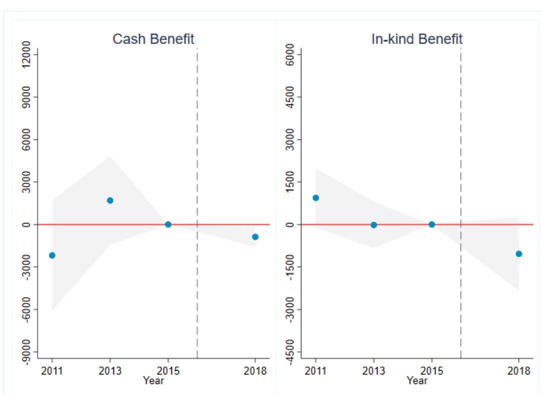
(b) Clothing



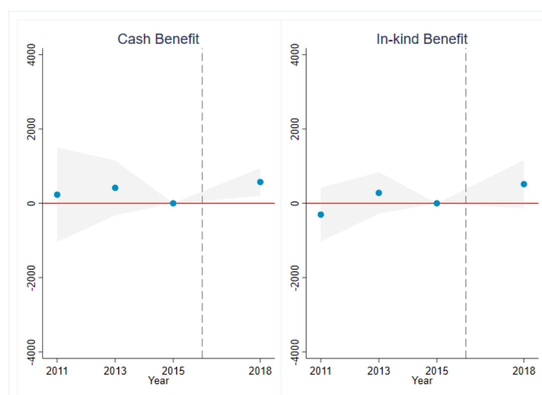
(c) Food



(d) Transportation



(e) Medical



(f) Miscellaneous

Figure 3: Event Study of Outcomes: Patterns of Necessities Expenditure

Note: This figure presents the event study described by Equation (3). Each subfigure represents the event study of a type of household spending. The dots represent the coefficient estimates, with β_{2015} normalized to zero. The left axis represents the estimate for mixed cities and the right axis for in-kind cities. All estimators incorporates control variables as in the main specification. The segments represent 95% confidence intervals. Regressions are weighted by household size. Standard errors are heteroskedasticity-robust and clustered at the city level.

Figure 3 presents the results of Equation 3 with each dependent variable Y_{it}. All sub-figures indicate that the differences between the treatment and control groups in 2011 and 2013 do not significantly differ from 0, for cities with either mixed or in-kind benefits, supporting the null hypothesis that the trends in the treatment group before the policy do not significantly differ from those in the control group. Based on this evidence, a DiD model is appropriate to identify the causal effect of the LTCI pilot policy.

5.2 Main Results

Table 4 shows the estimates of the impact on household consumption across different categories. All regressions control for household covariates, household fixed effects, and year fixed effects; heteroskedasticity robust standard errors clustered at the city level is calculated.

We present the results in three panels. The first panel comprises cities with mixed benefits and control cities. Here, the estimates represent the effect of having access to LTCI that covers both in-kind and cash benefits. Having LTCI that offers mixed benefits has a positive effect on expenditure for food and housing, and a negative effect on medical expenditure. Specifically, having access to LTCI results in an increase of food expenditure by 5067 RMB (USD $602) and an increase of housing expenditure by 2027 RMB (USD $305). Additionally, having LTCI with mixed benefits results in a reduction in medical expenditure by 1272 RMB (USD $192). The observed reduction in medical expenditure is not likely driven by an improvement in health status as our sample comprise respondents with long-term disabilities. Rather, it likely arises from a substitution away from medical services towards formal and informal LTC services. However, the effect on consumption of clothing, transportation, and miscellaneous items is not significant.

The second panel of Table 4 presents the results for the sub-sample of in-kind benefit cities and control cities. Having LTCI that offers in-kind benefits has a positive effect on expenditure for clothing, housing, and transport, and a negative effect on medical expenditure. While these effects are on the whole qualitatively similar to those observed from mixed benefit cities, we observe that having LTCI with in-kind benefits results in a weakly significant increase in transport expenditure whereas we do not find an effect for mixed benefits. This result likely arises from the need to incur higher transportation costs to access formal LTC services provided in designated facilities, whereas cash benefits come with the flexibility of seeking informal care at home, reducing the need to travel. Having in-kind LTC benefits results in a decrease in medical expenditure, which similar to the case of mixed benefits, suggests a substitution away from medical services towards LTC services.

Table 4: Impact of LTCI Coverage on Household Consumption

	(1) Clothing	(2) Food	(3) Housing	(4) Transport	(5) Medical	(6) Miscel.	(7) Total	(8) Non-Med.
Sub-sample Cities: Mixed Benefits + Non-pilot								
Treat × Post	-219.6	5066.7**	2026.8***	-483.6	-1272.0**	519.5	5783.7	6909.9*
	(588.9)	(2000.2)	(683.6)	(541.1)	(632.3)	(385.6)	(5529.1)	(4018.6)
Observations	24976	24976	24976	24976	24976	24976	24976	24976
R-square	0.59	0.59	0.57	0.57	0.49	0.56	0.64	0.66
Sub-sample Cities: In-kind Benefits + Non-pilot								
Treat × Post	342.5**	239.6	847.2***	769.6**	-1338.0**	554.3*	1600.8	2753.2
	(158.5)	(1077.3)	(265.7)	(367.2)	(572.7)	(284.5)	(2769.8)	(1852.5)
Observations	26714	26714	26714	26714	26714	26714	26714	26714
R-square	0.59	0.59	0.58	0.58	0.49	0.56	0.64	0.67
Full Sample Cities: In-kind Benefits + Mixed Benefits + Non-pilot								
DiD × Mixed	-241.2	4900.0**	2032.2***	-491.9	-1272.5**	529.6	5562.4	6728.7*
	(589.0)	(2003.1)	(682.0)	(540.8)	(630.1)	(386.7)	(5534.1)	(4021.0)
DiD × In-kind	346.7**	281.3	837.8***	770.3**	-1314.0**	553.4*	1707.9	2789.5
	(159.0)	(1071.4)	(265.2)	(365.9)	(574.5)	(283.7)	(2755.9)	(1843.9)
p-value of Testing Mixed = In-kind	[0.33]	[0.04]	[0.10]	[0.06]	[0.97]	[0.97]	[0.53]	[0.38]
Observations	27797	27797	27797	27797	27797	27797	27797	27797
R-square	0.59	0.59	0.58	0.58	0.49	0.56	0.64	0.67
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster - City	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the impact of LTCI coverage on household consumption, including clothing, food, housing, transport and miscellaneous. Each column represents the expenditure on the corresponding item (in Chinese Yuan). The control variables include the average age and the standard deviation of age within a household, household income, and household size. Regressions are weighted by household size. Heteroskedasticity-robust standard errors, shown in parentheses, are clustered at the city level. * p<0.1, ** p<0.05, *** p<0.01.

We also estimate the impact on the aggregate expenditure. In the seventh column, we report the results for total consumption, which is the sum of expenditures across all categories in previous columns. The findings suggest a positive effect on total consumption, although it is not statistically significant. This provides some evidence of improved well-being due to LTCI coverage. However, there is variation in the magnitude of the effect between the mixed benefit and in-kind benefit packages, indicating that the mixed benefit package incentivizes greater every-day consumption compared to the in-kind benefit package. Total non-medical consumption is presented in the last column. Having access to LTCI with mixed benefit has a large effect on non-medical consumption, resulting in an improvement of the welfare level of beneficiaries.

In the third panel, for completeness, we pool the two subsamples comprising mixed and in-kind benefit cities together with control cities and re-estimated the DiD regression with separate indicators for identifying mixed and in-kind benefit cities. While the subsample analyses are more flexible specification-wise as they allow the coefficient on the control covariates to vary across the subsample of mixed or in-kind cities, the pooled model restricts these to be the same. This approach eliminates potential bias arising from different estimates of fixed effects in each subsample regression. Comparing the results in this panel and previous panels, the estimates from the pooled model are very similar to the subsamples.

An additional advantage of incorporating both mixed and in-kind benefit cities into a unified regression model is the ability to conduct statistical tests to determine whether the coefficient estimates for the two types of packages differ significantly. Consequently, our analysis includes the p-value for testing the equality of these coefficient estimates within the panel. The outcomes of such tests have policy implications regarding the efficacy of the two benefit types. Notably, our results indicate that the null hypotheses are significantly rejected at a 10% level for expenditure on food, housing, and transportation.

5.3 Robustness Check

We conduct a set of robustness checks using recently developed methods for robust inference in DID models. While the initial DiD estimate is based on TWFE regression, recent literature has identified issues with traditional TWFE estimates (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2020; Borusyak et al., 2022). These methodologies account for treatment heterogeneity and dynamic effects, serving to assess the robustness of the TWFE estimate. The results, shown in Figure B1 in Appendix B, display estimates from various methods, which support the validity of the primary DiD result and strengthen confidence in the findings.

We employ an additional method to assess robustness. The DiD estimate may be biased due to the influence of a specific city, particularly since our treatment group consists of only a few cities. To address this, we implement a "leave-one-out" strategy, conducting DiD regressions while excluding one city at a time. In Figure B2, we categorize the estimates into two groups, separated by a purple dashed line. Estimates for mixed benefit cities are above the line, while those for in-kind benefit cities are below. The first estimate in each group serves as our benchmark, corresponding to the main results. Our findings indicate that the leave-one-out approach yields DiD results within the 95% confidence interval of the main results for both groups, confirming that no single pilot city unduly influences our results.

In additional, we use an event-study approach to evaluate the random selection of pilot cities by the government. Utilizing data from the China City Yearbook (2011–2019), we consider various city-level statistics, including total population, GDP per capita, social security enrollment, number of hospitals, beds, and medical staff, which are key indicators of elder care and long-term care. We define treatment and control groups based on city selection for the pilot LTCI project in 2016. The event study is represented by the following equation:

$$y_{ct} = \sum_{\tau \neq 2016} \beta_\tau \cdot Treat_c \times \mathbf{1}\{t = \tau\} + \varepsilon_{ct}.$$

In this regression, β_τ measures the difference between pilot and non-pilot cities. A significant β_τ, particularly for $\tau < 2016$, suggests potential selection bias; otherwise, we cannot reject the assumption of exogenous selection. As illustrated in Figure B3, we find no significant differences in city-level characteristics impacting long-term care between pilot and non-pilot cities, thus ruling out endogenous selection of pilot cities.

Finally, we assess the sensitivity and reliability of our results, as presented in Table B1. In the first panel, we regress the outcome variable while excluding all control covariates. This approach is necessary because control covariates may be influenced by the policy, potentially biasing the DiD estimates. The consistency of treatment effects in this specification indicates that the main model estimates are not heavily influenced by specific control variables. The subsequent panels further confirm the reliability of our main results. The second panel mirrors the main specification but employs an unweighted regression, yielding similar findings without adjusting for household size. Finally, we focus solely on long-term disabled families, which eliminates the possibility that non-disabled households in the control group distort the DiD results. The stability of these findings reinforces the reliability of our conclusions derived from the DiD approach.

5.4 Impact on Intergenerational Supports

We also examine the impact of LTCI coverage on household behavior especially intergenerational support by analyzing sub-samples based on the benefit packages and conducting DiD analysis for cities with in-kind benefits and cities with mixed benefits, respectively. The results are presented in Table 5, with different panels representing either sample division or interaction.

The first column presents the results for informal care provided by children. We find that receiving LTCI has no significant effect on the provision of informal care in pilot cities with mixed benefits. On the contrary, in cities that offered solely in-kind benefits, receiving LTCI results in a reduction in the amount of informal care provided by children by 94 hours annually, accounting for 41 percent of the average number of informal care hours (228 hours) recorded by households in in-kind cities before the LTCI policy. This result indicates that LTCI services facilitate the substitution of formal care for informal care, relieving the demands for care provided by family caregivers.

Unlike the case of informal care, the receipt of mixed LTCI benefits results in a significant reduction in the amount of financial support that an elderly household receives. Specifically, households in mixed benefit pilot cities report receiving an average of 1070 RMB (USD $161) less per year from their children, a reduction of 48 percent of the average amount of financial support that a household usually receives.

6 Decomposing Price Effects

We use the conceptual framework outlined in Section 2 to estimate income and substitution effects that are implicit in recipients' behavior, when receiving cash versus in-kind benefits, to analyze

Table 5: Impact on Intergenerational Supports

	(1) Informal Care (Hours)	(2) Financial Support
Sub-sample: Mixed Benefits + Non-pilot		
Treat × Post	-82.9	-1018.8*
	(178.1)	(530.4)
Observations	24976	24976
R-square	0.40	0.52
Sub-sample: In-kind Benefits + Non-pilot		
Treat × Post	-93.2**	282.9
	(40.9)	(352.6)
Observations	26714	26714
R-square	0.39	0.52
Full Sample: In-kind Benefits + Mixed Benefits + Non-pilot		
DiD × Mixed	-80.1	-1070.1**
	(178.1)	(530.9)
DiD × In-kind	-94.1**	305.5
	(40.9)	(350.5)
p-value of Testing Mixed = In-kind	[0.94]	[0.02]
Observations	27797	27797
R-square	0.39	0.52
Other Controls	Yes	Yes
Household Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Note: This table presents the impact of LTCI coverage on household behavior, including informal care and financial support from family caregivers. The control variables include the average age and the standard deviation of age within a household, household income, and household size. Cluster-robust standard errors, shown in parentheses, are clustered at the city level. * p<0.1, ** p<0.05, *** p<0.01.

the welfare implications under China's LTCI. To facilitate this, we can write down the following estimating equation:

$$Y_{it} = \beta_1 \cdot 1\{Cash_i\} \times Post_t + \beta_2 \cdot 1\{In\text{-}kind_i\} \times Post_t + X_{it}\gamma + \lambda_i + \delta_t + \varepsilon_{it}, \tag{4}$$

where $1\{Cash_i\}$ and $1\{In\text{-}kind_i\}$ are indicators of whether the treatment group receives cash or in-kind benefits. From Eq. (4), β_1 captures the pure income effect and β_2 the total effect of a price change. Hence, the substitution effect is given by $\beta_2 - \beta_1$.

Estimating Eq. (4) requires us to identify a subgroup that receives only cash benefits; in practice our sample of mixed benefit recipients receives both cash and services. To this end, we assume that the conditional probability of receiving cash, in our sample of mixed benefit recipients, is approximately 0.5. This is based on the government's design of the LTCI being actuarially fair - these assumptions are detailed in Appendix C. Hence the generalized DiD model in Eq. (4) is modified as

$$\begin{aligned} Y_{it} =& \beta_1 \cdot \big(0.5 \times 1\{Mixed_i\}\big) \times Post_t \\ &+ \beta_2 \cdot \big(1\{In\text{-}kind_i\} + (1-0.5) \times 1\{Mixed_i\}\big) \times Post_t + X_{it}\gamma + \lambda_i + \delta_t + \varepsilon_{it}, \end{aligned} \tag{5}$$

where β_1 and β_2 are still respectively the income and total effects under price change; $\beta_2 - \beta_1$ again represents the substitution effect.

Table 6 shows the estimated components of price effects on household expenditures. Each column corresponds to a separate regression, with household spending on clothing, food, housing, and miscellaneous as dependent variables. We omit transportation and medical expenses here since, as seen in our main results, recipient behavior for these items are benefit-specific hence the inference from a decomposition analysis is less likely to be accurate.

The first estimate, β_1, represents the income effect on household spending. For households with cash benefits, the LTCI coverage does not significantly affect their consumption of clothing, whereas it leads to a statistically significant increase in their expenditures on food and housing. Hence, for the disabled household, there is no significant income effect on household consumption of clothing and miscellaneous, whereas it has an economically and statistically significant income effect in increasing household expenses on other items. Specifically, the income effect of LTCI coverage is associated with a 9519 RMB (US$1434) increase in spending on food. The income effect of LTCI coverage also leads to an increase in housing expenditure by 3227 RMB (US$486). All these results suggest that households could release the economic burden of consuming more beyond necessities through the income effect.

The second estimate, β_2, captures the total effect of LTC in-kind benefit on families' expenditures. This estimate is the actual impact of the price change, through which is the most popular LTCI compensation. The results suggest that LTC price change does not significantly affect household consumption of food and miscellaneous, whereas it leads to a statistically significant increase in expenditures on clothing, housing, and miscellaneous, with respectively 23%, 26%, and 20% increase compared with the average consumption of the treated household in the pre-policy period. In the economic frame regarding the change of Marshallian demand due to the price decline, this effect is the sum of the income effect and the substitution effect. Hence, we use the coefficient estimates of β_1 and β_2 to obtain the corresponding substitution effect.

Furthermore, the difference between β_2 and β_1 represents the substitution effect from the LTCI policy, capturing the change in household consumption patterns due to changes in the prices of LTC services. The LTCI coverage leads to a decrease in the price of LTC services, households with LTCI coverage would substitute food and housing with LTC services, while consumption patterns for all other items remain not significant.

We conduct two further analyses with this model. First, our DiD analyses also allow us to calculate the cross-price elasticity with respect to the price of LTC. Table 6 suggests that almost all these daily consumptions are complements, where clothing, housing, and miscellaneous have a large magnitude of cross-price elasticity. In contrast, food consumption is very inelastic accordingly. We also provide more discussion about the cross-price elasticity and the implication of welfare in market equilibrium in Appendix D. Second, for a set of heterogeneity analyses, we analyze how the effects vary across different household income levels and on the distributional assumptions on the choice probabilities. These analyses show that the effect sizes do not vary significantly – these are discussed in detail in Appendix E.

Table 6: Decomposing price effects on household expenditures

Parameter	Interpretation	(1) Clothing	(2) Food	(3) Housing	(4) Miscellaneous
β_1	Income Effect	-829.2	9518.7**	3226.6**	505.8
		(1192.2)	(4130.3)	(1387.9)	(820.5)
β_2	Total Effect	346.7**	281.3	837.8***	553.4*
		(159.0)	(1071.4)	(265.2)	(283.7)
$\beta_2 - \beta_1$	Substitution Effect	1175.9	-9237.5	-2388.7	47.6
p-value	Testing $\beta_2 - \beta_1 = 0$	[0.34]	[0.04]	[0.10]	[0.96]
$\overline{Y}$	Pre-mean of Treated	1490.3	14608.0	3269.2	2701.6
$\beta_2/\overline{Y}$	Total %Δ of Outcome	23%	2%	26%	20%
$\frac{\beta_2/\overline{Y}}{\%Reimburse}$	Cross-price Elasticity	0.32	0.027	0.36	0.28
Other Controls		Yes	Yes	Yes	Yes
Household Fixed Effects		Yes	Yes	Yes	Yes
Year Fixed Effects		Yes	Yes	Yes	Yes
Observations		27797	27797	27797	27797
R-square		0.59	0.59	0.58	0.56

Note: This table presents the DiD estimate, with each column representing the household expenditure on the corresponding item (in Chinese Yuan). The control variables include the average age and the standard deviation of age within a household, household income, and household size. Cluster-robust standard errors, shown in parentheses, are clustered at the city level. * p<0.1, ** p<0.05, *** p<0.01.

7 Conclusion

This research paper examines the heterogeneous effects of different benefit schemes under China's Long-Term Care Insurance (LTCI) on household consumption decisions and welfare. With the aim of addressing the increasing demand for long-term care services, China introduced a pilot program of LTCI in 2016. The program seeks to provide funds or services for basic living and medical care to individuals with long-term disabilities. However, informal care provided by family members has traditionally been the primary source of assistance for older people in need of care in China. This study investigates the impact of LTCI benefit packages on household consumption choices and overall welfare, considering the unique context of strong family ties in the country.

By leveraging the variation in LTCI benefit designs across pilot cities in China, this paper develops a theoretical model to analyze household utility-maximizing decisions and the comparative statics under LTCI policies. Subsequently, a Difference-in-Differences (DiD) approach is employed to evaluate the effects of LTCI policies on household consumption forms that are closely related to daily life in the Chinese context, including clothing, food, housing, transportation, and medical items. The analysis considers the different implications arising from mixed benefit packages and in-kind benefits, allowing for the estimation of total effects, substitution effects, and income effects.

Our findings reveal that LTCI significantly improves household welfare by alleviating financial burdens and increasing consumption of essential goods. The results suggest that the LTCI pilot policy enhances daily non-medical consumption, which is in line with Liu et al. (2023). Specifically, the LTCI pilot program significantly increases annual consumption on clothing and housing expenditures. Income effects are observed in food, housing, and miscellaneous expenditures. The impacts on transportation and medical expenditures vary across the benefit packages faced by the households. Our findings also confirm the substitutability of formal for informal care in China, consistent with previous studies on LTCI in China (Lei et al., 2022). The robustness checks, heterogeneity analysis, and placebo tests conducted further support the validity and consistency of the baseline results. our results also indicate the LTC policy has heterogeneous effects on intergenerational support. Specifically we provide suggestive evidence that it is the LTC in-kind benefit, rather than the cash benefit, mitigates the burden of informal care on family caregivers, whereas the cash benefit may crowd out the financial transfer from non-coresident children.

This paper enriches the current body of research on LTCI by delving into the underexplored area of the implications of offering varied types of LTCI benefits, focusing on the differentiation between in-kind and cash benefits. The majority of existing studies have analyzed the implementation and outcomes of LTCI, yet the impacts of distinct benefit designs have rarely been investigated, except for a few studies on Spain's LTCI system. Our research fills the gap by exploring the influence of LTCI benefit designs in China on the welfare of households, providing vital insights for policymakers in low- and middle-income countries who grapple with the challenges of offering public LTC services. This exploration is particularly critical as it widens the scope of empirical data regarding the impacts of LTCI on the well-being and financial decisions of families in China, where the economic strain of elder care profoundly affects both individuals and their family.

Furthermore, our study advances both the theoretical and empirical discourse on consumer behavior in relation to diverse LTC benefits, venturing beyond the predominantly studied areas of healthcare consumption, medical expenditures, and intergenerational support. By delineating the outcomes of in-kind versus cash benefits, this paper not only adds to the empirical literature but also deepens the theoretical understanding of the economic considerations involved in LTC care choices, shedding light on the complex interplay between LTCI benefit design, the welfare of recipients, and the long-term viability of LTC schemes. This comprehension is indispensable for devising LTC policies that are both efficacious and sustainable, addressing the intricate needs of the globally aging population. The study's findings underscore the importance of tailoring LTCI benefit packages to better accommodate the varied responses of households with disabled members, guiding the formulation of future policies to publicly finance LTC for the elderly in a manner that enhances household welfare and informs equitable LTCI policy development.

References

Borusyak, K., X. Jaravel, and J. Spiess (2022). Revisiting event study designs: Robust and efficient estimation. *Available at SSRN 2826228*.

Büscher, A., B. Holle, S. Emmert, and A. Fringer (2010). Home care counseling for recipients of cash payments in the German long-term care insurance. *Zeitschrift Fur Gerontologie Und Geriatrie 43*(2), 103–110.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230.

Chen, H. and J. Ning (2022). The impacts of long-term care insurance on health care utilization and expenditure: Evidence from China. *Health Policy and Planning 37*(6), 717–727.

Cheng, T., W. Yip, and Z. Feng (2023). Public provision and financing of long-term care: case studies in middle- and high-income countries. *Geneva: World Health Organization ISBN: 978-92-4-008633-3*.

Choi, J. W., E.-C. Park, S. G. Lee, S. Park, H.-G. Ryu, and T. H. Kim (2018). Does long-term care insurance reduce the burden of medical costs? a retrospective elderly cohort study. *Geriatrics & gerontology international 18*(12), 1641–1646.

Colombo, F., A. Llena-Nozal, J. Mercier, and F. Tjadens (2011). Help wanted? providing and paying for long-term care. *Paris: Organisation for Economic Co-operation and Development. OECD Health Policy Studies*.

Costa-Font, J., S. Jimenez-Martin, and C. Vilaplana (2018). Does long-term care subsidization reduce hospital admissions and utilization? *Journal of Health Economics 58*, 43–66.

Costa-Font, J., S. Jiménez-Martín, and C. Vilaplana-Prieto (2022). Do public caregiving subsidies and supports affect the provision of care and transfers? *Journal of Health Economics 84*, 102639.

Courbage, C. and L. Eeckhoudt (2012). On insuring and caring for parents' long-term care needs. *Journal of Health Economics 31*(6), 842–850.

Courbage, C., G. Montoliu-Montes, and J. Wagner (2020). The effect of long-term care public benefits and insurance on informal care from outside the household: Empirical evidence from Italy and Spain. *The European Journal of Health Economics 21*, 1131–1147.

de Chaisemartin, C. and X. D'Haultfoeuille (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review 110*(9), 2964–96.

Feng, J., Z. Wang, and Y. Yu (2020). Does long-term care insurance reduce hospital utilization and medical expenditures? evidence from china. *Social Science & Medicine 258*, 113081.

Feng, Z., X. Zhuang, and G. Elena (2021). Understanding China's long-term care insurance pilots: Key features, challenges and prospects. *China: An International Journal 19*(3), 168–187.

Fu, R., H. Noguchi, A. Kawamura, H. Takahashi, and N. Tamiya (2017). Spillover effect of Japanese long-term care insurance as an employment promotion policy for family caregivers. *Journal of Health Economics 56*, 103–112.

Geyer, J. and T. Korfhage (2015). Long-term care insurance and carers' labor supply–a structural model. *Health Economics 24*(9), 1178–1191.

Hou, Y., Y. Wang, S. Yan, W. Zhang, L. Zhang, and J. Yao (2021). Impacts from long-term care insurance on medical service utilization, medical burden and health of middle-aged and elderly people: An empirical research based on the DID method (in Chinese). *Chinese Journal of Health Policy 14*, 35–40.

Iwamoto, Y., M. Kohara, and M. Saito (2010). On the consumption insurance effects of long-term care insurance in Japan: Evidence from micro-level household data. *Journal of the Japanese and International Economies 24*(1), 99–115.

Kim, H. B. and W. Lim (2015). Long-term care insurance, informal care, and medical expenditures. *Journal of Public economics 125*, 128–142.

Lee, T. W., E. Yim, E. Cho, and J. Chung (2014). Cognitive function, behavioral problems, and physical function in long-term care insurance beneficiaries with dementia in south korea: comparison of home care and institutional care services. *Journal of the American Geriatrics Society 62*(8), 1467–1475.

Lei, X., C. Bai, J. Hong, and H. Liu (2022). Long-term care insurance and the well-being of older adults and their families: Evidence from China. *Social Science & Medicine*, 114745.

Liu, H., J. Ma, and L. Zhao (2023). Public long-term care insurance and consumption of elderly households: Evidence from China. *Journal of Health Economics 90*, 102759.

Ma, C., Q. Yu, Z. Song, and H. Chen (2019). Long-term care insurance, the control of medical expenses and "value-based health care" (in Chinese). *China Industrial Economics 12*, 42–59.

Ohinata, A. and M. Picchio (2020). Financial support for long-term elderly care and household saving behaviour. *Oxford Economic Papers 72*(1), 247–268.

Olivares-Tirado, P., N. Tamiya, and M. Kashiwagi (2012). Effect of in-home and community-based services on the functional status of elderly in the long-term care insurance system in Japan. *BMC Health Services Research 12*(1), 1–10.

Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics 225*(2), 175–199.

United Nations (2023). World population prospects. *New York: United Nations Department of Social and Economic Affairs, Population Division (https://population.un.org/wpp/Download/).*

Wang, Q., G. A. Abiiro, J. Yang, P. Li, and M. De Allegri (2021). Preferences for long-term care insurance in China: results from a discrete choice experiment. *Social Science & Medicine 281*, 114104.

Xu, X., X. Huang, X. Zhang, and L. Chen (2019). Family economic burden of elderly chronic diseases: Evidence from China. In *Healthcare*, Volume 7, pp. 99. Multidisciplinary Digital Publishing Institute.

Zuchandke, A., S. Reddemann, S. Krummaker, J. Von Der Schulenburg, and M. Graf (2010). Impact of the introduction of the social long-term care insurance in germany on financial security assessment in case of long-term care need. *The Geneva Papers on Risk and Insurance-Issues and Practice 35*(4), 626–643.

Online Appendix for Publication

A Details of LTCI Packages in Pilot Cities

Table A1: Type of Benefit Packages in Pilot Cities

Province - City	Social Security Eligibility	In-kind Benefit	Cash Benefit
Mixed of In-kind and Cash Benefit			
Jiangxi - Shangrao	UEBMI	Home Care: 900 RMB/month; Institution: 1200 RMB/month	450 yuan/person/month
Sichuan - Chengdu	UEBMI	Institution: 70%; Home Care: 75%	75% of officially evaluated expenses
Jiangsu - Xuzhou	UEBMI-URRBMI	Institution: 48 RMB/day; Nursing Home: 30 RMB/day; Home Care: 500 RMB/month	15 RMB/person/day
Hubei - Jingmen	UEBMI-URRBMI	Home Care: 80%, cap 100 RMB/person/day; Nursing Home: 75%, cap 100 RMB/person/day; Institution: 70%, cap 150 RMB/person/day	cap 40 RMB/person/day
In-kind Benefit Only			
Zhejiang - Ningbo	UEBMI	40 RMB/day	
Shandong - Jinan	UEBMI	Institution: 220 - 260 RMB/day; Home Care and Nursing Home: cap 35 RMB/day	
Jilin - Jilin	UEBMI-URBMI	80% (UEBMI) or 70% (URBMI)	
Hebei - Chengde	UEBMI	70%	
Shanghai - Shanghai	UEBMI-URRBMI	Home Care: 90%; Institution: 85%	
Anhui - Anqing	UEBMI	Institution: 50 RMB/day; Nursing Home: 40 yuan/day; Home Care: 750 yuan/month	
Guangdong - Guangzhou	UEBMI	Institution: 75%, Daily Living: cap 120 RMB/day; Home Care: 90%, Daily Living: cap 115 yuan/day	
Shandong - Linyi	UEBMI-URRBMI	Institution: 75% - 85%; Home Care: 90%	
Heilongjiang - Qiqihaer	UEBMI	Institution: 60%; Nursing Home: 55%; Home Care: 50%	
Jiangsu - Suzhou	UEBMI-URRBMI	Institution: severe 26 RMB/day, moderate 20 RMB/day; Home Care: severe 30 RMB/day, moderate 25 yuan/day	

Note: This table lists all pilot cities that have launched the LTCI policy between 2016 and 2017 and are available in China Health and Retirement Longitudinal Study (CHARLS) data. UEBMI stands for Urban Employee Basic Medical Insurance for urban employees. URRBMI stands for Urban-Rural Residents Basic Medical Insurance, and URBMI stands for Urban Residents Basic Medical. Institution, Nursing Home and Home Care stand for benefit package from institution care, nursing home care, and home care, respectively. Percentages, where presented, refer to the co-insurance rate of eligible expenses.

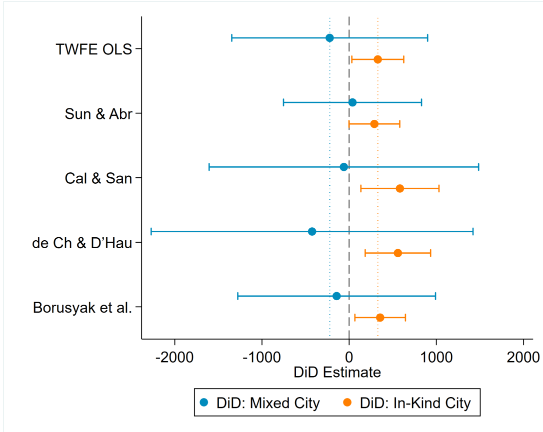
B Robustness Check

This section displays a serious of robustness checks. We first propose robustness checks of the DiD estimate using recently developed techniques. These approaches incorporate treatment heterogeneity and dynamic effects and are used to check whether the TWFE estimate in the empirical setting is robust. As shown in Figure B1, these alternative estimators reinforce the validity of the main DiD result and enhance the overall confidence in the findings.

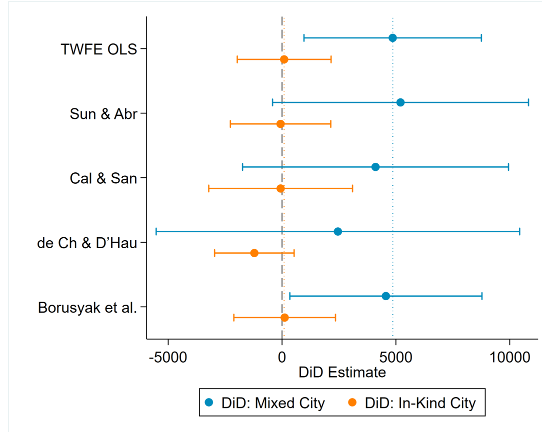
We then use a "leave-one-out" strategy, where we run the DiD regressions by excluding one specific city in each iteration to check if there exists any bias generated by a specific city. The results are presented in Figure B2, we divide the estimate into two groups, separating them by the purple dashed line. Above the line are the estimates of the effect in the mixed benefit cities, iterating one-by-one, and below are those of the in-kind benefit cities. Figure B2 suggests that our results are not accidentally driven by any single special pilot city.

Furthermore, we adopt an event-study approach to test whether the pilot cities were randomly selected by the government. As shown in Figure B3, there are no differences between the pilot and non-pilot cities in city-level characteristics that could affect long-term care, including total population, GDP per capita, number of enrollees in UEBEI and UEBMI, number of hospitals, number of beds, and number of medical staff. Hence, we rule out the possibility that the pilot cities were endogenously chosen.

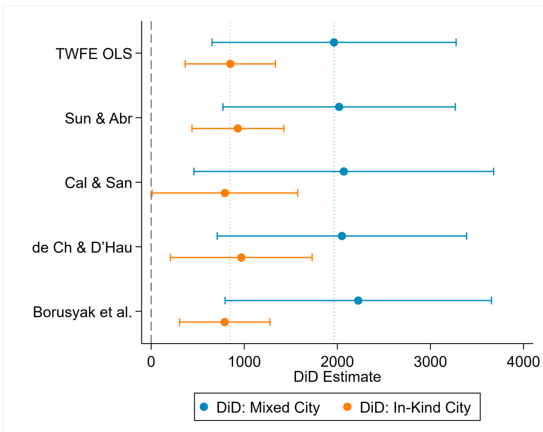
Finally, we check the sensitivity and reliability of our main regression result with different empirical specifications to check if the results are sensitive to different settings. The results are presented in Table B1.



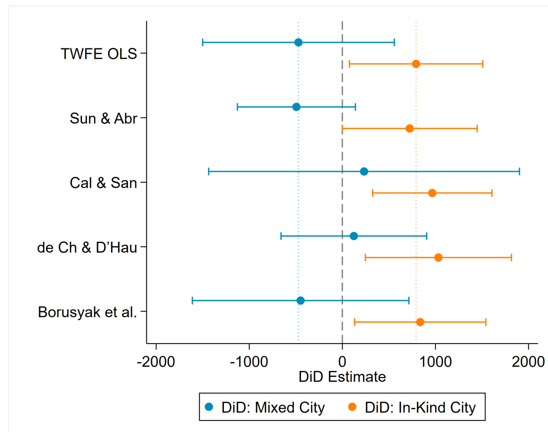
(a) Clothing



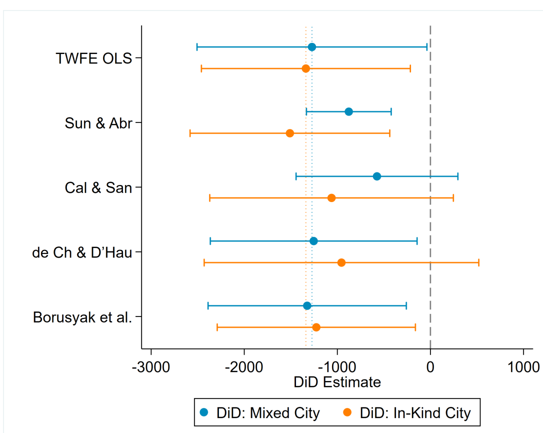
(b) Food



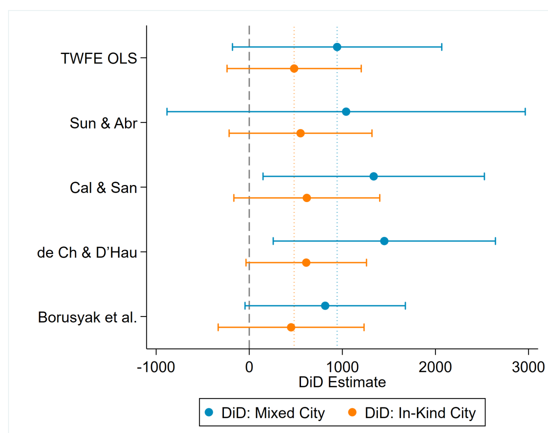
(c) Housing



(d) Transportation



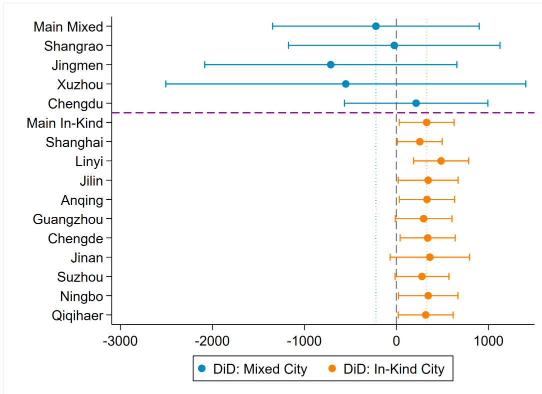
(e) Medical



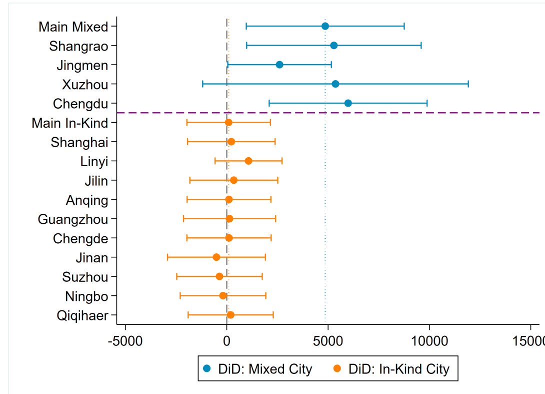
(f) Miscellaneous

Figure B1: Robustness Check Using Modern DiD Techniques

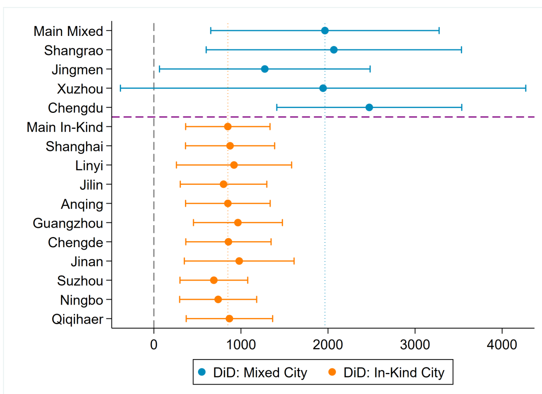
Note: The figure presents the results of robustness check of staggered difference-in-differences (DiD) estimates. Each dot represents an estimate from the corresponding method. The two-way fixed effect estimator (TWFE) is exactly the main DiD result. The remaining four estimators respectively follow four research papers: Sun and Abraham (2021), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfoeuille (2020), and Borusyak et al. (2022). All estimators incorporate control variables as in the main specification. The segments represent 95% confidence intervals. Regressions are weighted by household size. Standard errors are heteroskedasticity-robust and clustered at the city level.



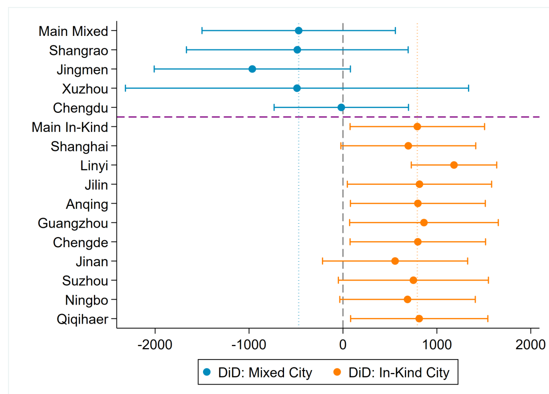
(a) Clothing



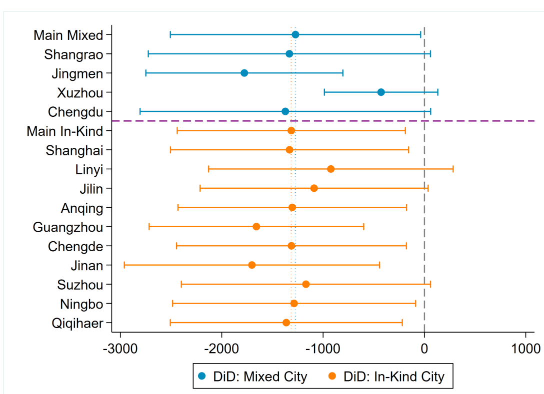
(b) Food



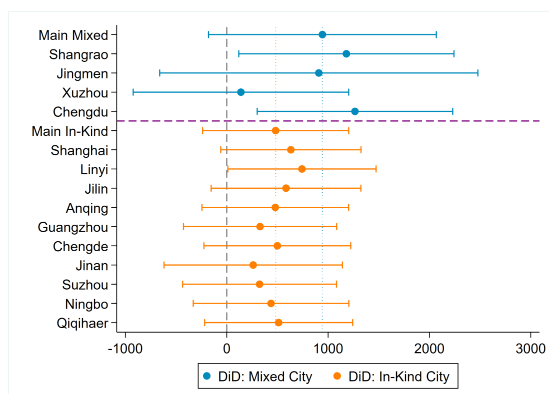
(c) Housing



(d) Transportation



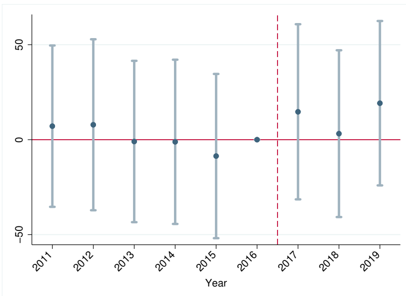
(e) Medical



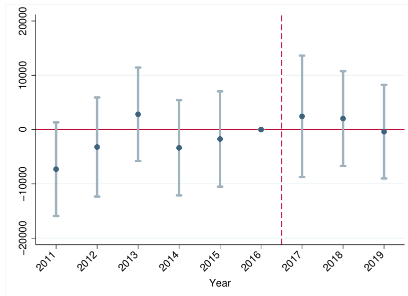
(f) Miscellaneous

Figure B2: Robustness Check with Leave-One-Out Approach

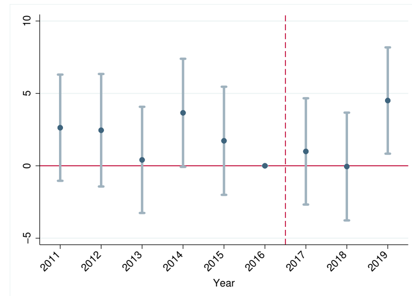
Note: The figure presents the results of a robustness check using the leave-one-out approach. Each dot represents the regression excluding sample data in the city labeled on the y-axis. The orange dot line and blue dot line respectively represent the coefficient estimate in the main results. The vertical dashed line represents zero, and the horizontal dashed line separates the mixed cities and in-kind cities. All estimators incorporate control variables as in the main specification. The segments represent 95% confidence intervals. Regressions are weighted by household size. Standard errors are heteroskedasticity-robust and clustered at the city level.



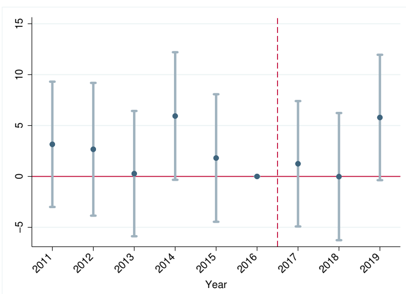
(a) Population



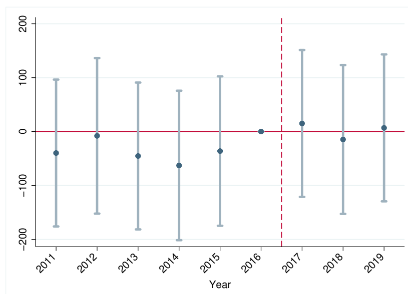
(b) GDP per Capita



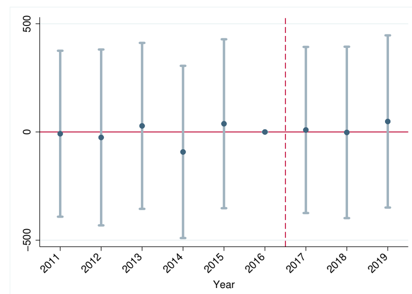
(c) Staff of Health and Security



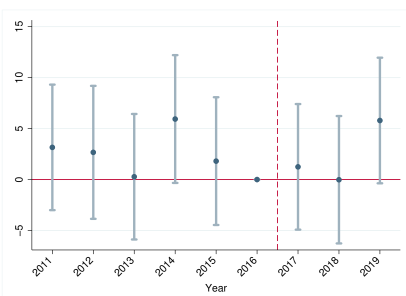
(d) Staff of Public Administration



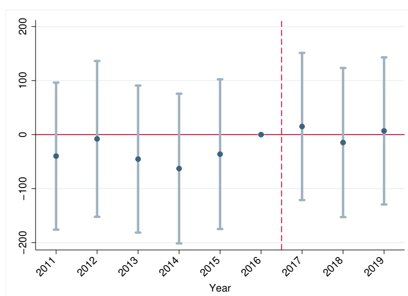
(e) UEBEI



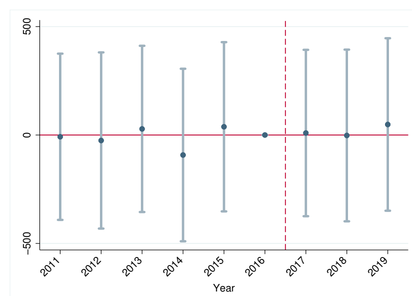
(f) UEBMI



(g) Number of Hospitals



(h) Number of Medical Beds



(i) Number of Medical Staff

Figure B3: Test of Pilot City Selection

Note: This figure depicts the event study at the city level. Each subfigure represents the event study of an indicator of social welfare. The dot represents the coefficient estimates, with β_{2016} normalized to zero. The bars represent 95% confidence intervals. The vertical dashed line marks the introduction of the LTCI pilot project.

Table B1: Sensitivity - Impact of LTCI Coverage on Household Consumption

	(1) Clothing	(2) Food	(3) Housing	(4) Transport	(5) Medical	(6) Miscellaneous
No Control Covariates						
DiD × Mixed	-98.7	5822.1***	2228.7***	-397.6	-1252.8*	746.6*
	(598.1)	(2152.7)	(709.8)	(555.4)	(637.6)	(401.2)
DiD × In-Kind	381.8**	414.5	873.8***	793.0**	-1323.7**	596.5**
	(173.5)	(1096.7)	(235.6)	(379.7)	(573.7)	(300.0)
Other Controls	No	No	No	No	No	No
Observations	27797	27797	27797	27797	27797	27797
R-square	0.58	0.52	0.57	0.57	0.49	0.55
No Regression Weight						
DiD × Mixed	273.7	5005.5***	1857.7***	-94.0	-1206.3	653.3**
	(272.9)	(1406.9)	(458.7)	(383.6)	(770.0)	(280.9)
DiD × In-Kind	252.7**	-81.4	667.4**	726.5**	-1251.0**	401.5**
	(115.1)	(1048.1)	(262.8)	(336.5)	(494.7)	(202.3)
Regression Weight	No	No	No	No	No	No
Observations	27797	27797	27797	27797	27797	27797
R-square	0.59	0.57	0.55	0.57	0.47	0.54
Sub-sample - Disabled Household Only						
DiD × Mixed	-174.0	4081.3**	1933.8***	-595.9	-944.6	298.3
	(596.0)	(1974.5)	(680.2)	(540.4)	(656.2)	(395.9)
DiD × In-Kind	404.1**	-636.9	640.2**	621.2**	-893.5	232.2
	(167.6)	(1155.9)	(271.0)	(310.1)	(588.3)	(324.5)
Observations	7419	7419	7419	7419	7419	7419
R-square	0.64	0.53	0.59	0.63	0.52	0.60
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster - City	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the impact of LTCI coverage on household consumption, including clothing, food, housing, transport and miscellaneous. Each column represents the expenditure on the corresponding item (in Chinese Yuan). The control variables include the average age and the standard deviation of age within a household, household income, and household size. Regressions are weighted by household size. Heteroskedasticity-robust standard errors, shown in parentheses, are clustered at the city level. * p<0.1, ** p<0.05, *** p<0.01.

C Derivation of Income/Substitution Effect

In our framework, for the pilot city with mixed benefits, a household chooses the option that obtains a higher overall utility level. The analytical change of utility level is described below. For Option 1), the marginal gain in utility is through the change in price, i.e.,

$$\Delta^p v(p, y) = v\left(p, p^{LTC} \cdot (1-r), y\right) - v(p, y) \approx -\frac{\partial v(p, y)}{\partial p^{LTC}} \cdot rp^{LTC},$$

where r is the reimbursement rate for LTCI in-kind benefits. For Option 2), the marginal gain in utility is through the income effect, i.e.,

$$\Delta^y v(p, y) = v\left(p, y+m\right) - v(p, y) \approx \frac{\partial v(p, y)}{\partial y} \cdot m,$$

where m is the amount of cash.

Estimating the value offered by the two types of LTCI benefits requires us to make an additional assumption. Such an assumption permits us to separate the value of having access to cash benefits versus in-kind benefits, which we are not able to identify purely from the data as we only observe cities with in-kind and mixed benefits and not cities with solely cash benefits.

Assumption 1 *The government is actuarial fair in the LTCI design, i.e., $x^*_{LTC}(p, y) \cdot rp^{LTC} = m$. In words, the expected amount of government expenditure reimbursed by the LTCI should equal to the amount of lump-sum cash benefit.*

Assumption 1 suggests that when the government chooses which plan to provide, it should not differ a lot in the budget of public finance; the government expenditure should be similar for either option provided. For simplicity, we do not consider the moral hazard problem between the government and residents in terms of how residents respond to the policy and how the government takes this incentive into account.

This assumption also makes the Slutsky's equation in Equation (1) hold in terms of the amount of expenditure. Specifically, multiplying the change of price for both sides generates

$$\frac{\partial x_j^*(p,y)}{\partial p_{LTC}} \cdot rp^{LTC} = \frac{\partial x_j^h(p,u)}{\partial p_{LTC}} \cdot rp^{LTC} + x_{LTC}^*(p,y) \cdot \left(-\frac{\partial x_j^*(p,y)}{\partial y}\right) \cdot rp^{LTC}, \tag{C1}$$

with the actuarial fair assumption that $x_{LTC}^*(p,y) \cdot rp^{LTC} = m$, the rp^{LTC} in the last term could be rewritten as $\frac{m}{x_{LTC}^*(p,y)}$. Hence, plugging it into the equation generates

$$\underbrace{\frac{\partial x_j^*(p,y)}{\partial p_{LTC}} \cdot rp^{LTC}}_{\Delta x_j \text{ with In-kind Benefit}} = \underbrace{\frac{\partial x_j^h(p,u)}{\partial p_{LTC}} \cdot rp^{LTC}}_{\text{Substitution Effect}} + \underbrace{m \cdot \left(-\frac{\partial x_j^*(p,y)}{\partial y}\right)}_{\Delta x_j \text{ with Cash Benefit}} \tag{C2}$$

Equation (C2) implies that, under the actuarial fair assumption, the substitution effect can be directly obtained by the difference between the effect in cities with cash benefit and in-kind benefit. Hence, as long as we can separate the effect of the cash benefit in the sample data of cities with mixed benefits, we can estimate the substitution effect by taking the difference.

While we cannot directly observe the choice of each household in the mixed cities, we take advantage of the revealed preference that the household is making a choice decision between such two options. We acknowledge some unobserved shocks in the trade-off and therefore consider choice-specific idiosyncratic shocks before the decision $\varepsilon^{\{\Delta p, \Delta y\}}$ with type 1 extreme value distribution. Although, in general, it can be any distribution such that $(\varepsilon^{\Delta p} - \varepsilon^{\Delta y})$ is with mean 0 and is symmetric at 0, we use type 1 extreme value distribution only because it has analytical solutions. The probability of choosing cash benefits is then

$$\begin{aligned}
\text{Prob}(\Delta^y | r, m) &= \frac{\exp(\Delta^y v(p,y))}{\exp(\Delta^y v(p,y)) + \exp(\Delta^p v(p,y))} \\
&= \frac{\exp(\frac{\partial v(p,y)}{\partial u} \cdot m)}{\exp(\frac{\partial v(p,y)}{\partial u} \cdot m) + \exp(-\frac{\partial v(p,y)}{\partial p^{LTC}} \cdot rp^{LTC})} \\
&= \frac{1}{1 + \exp\left(\frac{\partial v(p,y)}{\partial y} \cdot \left(-\frac{\partial v/\partial p}{\partial v/\partial y} \cdot rp^{LTC} - m\right)\right)},
\end{aligned}$$

where the term $-\frac{\partial v/\partial p}{\partial v/\partial y}$ is exactly the Marshallian demand according to the Roy's Identity, i.e., $x^*(p,y) = -\frac{\partial v/\partial p}{\partial v/\partial y}$. Hence, the equation above is then

$$\text{Prob}(\Delta^y|r,m) = \frac{1}{1+\exp\left(\frac{\partial v(p,y)}{\partial y}\cdot(x^*_{LTC}(p,y)\cdot rp^{LTC}-m)\right)}. \tag{C3}$$

This conditional choice probability reflects the condition of whether a household would choose the cash benefit or the in-kind benefit based on the reimbursement rate and the amount of cash benefit. With the actuarial fair condition that $x^*_{LTC}(p,y)\cdot rp^{LTC} = m$, the conditional plan choice probability should be

$$\text{Prob}(\Delta^y|r,m) = \frac{1}{1+\exp\left(\frac{\partial v(p,y)}{\partial y}\cdot 0\right)} = \frac{1}{2}. \tag{C4}$$

We next use this conditional choice probability to investigate the effect of the LTCI pilot through empirical analysis.

Given this derived probability, according to the law of large number, the fraction of choosing cash benefit should be close to the conditional choice probability. Hence, we use a continuous exposure to the cash benefits option obtained from Equation (C4) as a generalized DiD model, i.e., the conditional probability of choosing the cash benefits option. Our regression model is then,

$$\begin{aligned} Y_{it} = &\beta_1\cdot\big(\text{Prob}(\Delta^y|r,m)\times 1\{Mixed_i\}\big)\times Post_t \\ &+\beta_2\cdot\big(1\{In\text{-}kind_i\}+(1-\text{Prob}(\Delta^y|r,m))\times 1\{Mixed_i\}\big)\times Post_t + X_{it}\gamma+\lambda_i+\delta_t+\varepsilon_{it}. \end{aligned} \tag{C5}$$

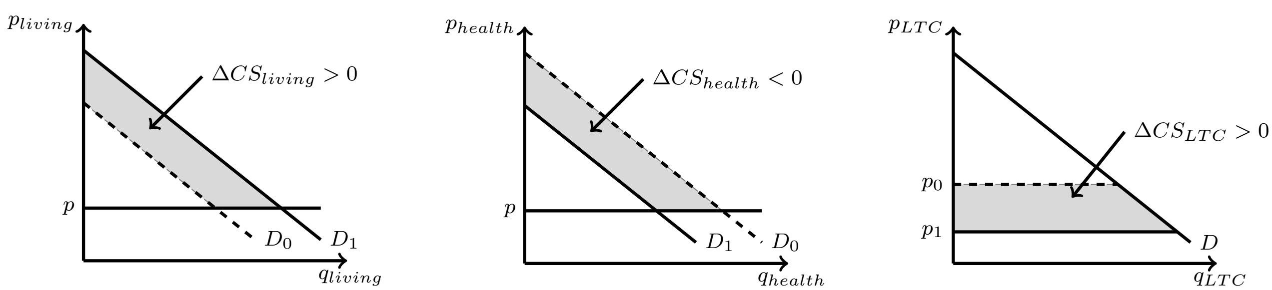
D Implication of Market Equilibrium

According to the definition, the cross-price elasticity is the percentage change of demand of a good due to one percentage change of LTC's price. Hence, the equation to calculate the cross-price elasticity is

$$\eta_{LTC,Y} = \frac{\%\Delta Q_Y}{\%\Delta p_{LTC}} = \frac{(p_Y \cdot \Delta Q_Y)/(p_Y \cdot Q_Y)}{\%\Delta p_{LTC}} = \frac{\beta_2/\overline{Y}}{\%Reimburse}.$$

Such elasticity is positive when a good is a complement to LTC and negative when the good is a substitute. The magnitude of the elasticity reflects the ability of complementarity/substitution.

We interpret the cross-price elasticity in each partial equilibrium in Figure D1. Each subfigure shows how demand and the quantity of demand are affected by the introduction of the LTCI program. The corresponding changes in demand yield a series of changes in consumer surplus. Panel (a) describes the equilibrium in the market for clothing, food, housing, transportation, and miscellaneous. Panel (b) is the equilibrium in the market for medical utilization. In panels (a) and (b), we assume that the price level does not change because of the regulated prices and the comparatively small number of beneficiaries of the LTCI program. Panel (c) suggests a decline in the cost of LTC due to the LTCI pilot when we assume a free adjusted supply in this market.



(a) Living Cost (b) Healthcare (c) Long-term Care

Figure D1: Partial Equilibrium in Each Market

Note: This figure presents the ideal demand and welfare change in each market. The shadowed areas are the change in welfare. Panel (a) describes the equilibrium in the market for clothing, food, housing, transportation, and miscellaneous. Panel (b) is the equilibrium in the market for medical utilization. In panels (a) and (b), we assume that the price level does not change because of the regulated prices and the comparatively small number of beneficiaries of the LTCI program. Panel (c) suggests a decline in the cost of LTC due to the LTCI pilot when we assume a free adjusted supply in this market.

Combining these figures makes it possible to calculate the net consumer welfare change due to the introduction of the LTCI. Our contribution is to quantify the magnitude with which the demand curves shift. If the price level remains fixed, the shift of a demand curve due to a 1 percent change in the price of LTC exactly represents the cross-price elasticity. Hence, the horizontal distance between D_0 and D_1 is the cross-price elasticity multiplied by the rate of reimbursement.

Unfortunately, this paper is not able to calculate the net consumer welfare change due to the data limitation. However, our estimate contributes to the literature by quantifying the magnitude of the shift in demand, which is the cross-price elasticity. Future work could extend our results. For instance, the demand curves or own-price elasticity of the demand could be estimated as suggested in Figure D1. Based on our results, researchers could calculate the net consumer welfare change and estimate an optimal reimbursement for the LTCI program to maximize consumer welfare.

E Heterogeneity

In this part, we analyze how the effect might vary across different household income levels. We first separate the high-income group and the low-income group according to the long-run household income. In such separation, the group is time-invariant. We run DiD regressions with the baseline specification for each group separately, reporting the results in Table E1. There are two panels in the table, with each representing the DiD estimates with sub-sample data by group. As above, each column represents the regression with corresponding dependent variables.

Table E1: DiD Results with Income Heterogeneity

	(1) Clothing	(2) Food	(3) Housing	(4) Miscellaneous
Sub-sample: Income Above Median				
β_1: Income Effect	-988.2	5146.2	2459.8*	1338.0
	(1700.3)	(5201.4)	(1327.8)	(1538.0)
β_2: Total Effect	367.4	-237.3	535.4	231.5
	(281.0)	(1955.9)	(362.0)	(465.5)
Observations	14153	14153	14153	14153
R-square	0.60	0.59	0.58	0.56
Sub-sample: Income Below Median				
β_1: Income Effect	-578.6	16040.9**	4372.0**	-567.0
	(626.8)	(7792.4)	(2111.4)	(1371.4)
β_2: Total Effect	358.3**	1189.7	1295.2***	985.1***
	(166.9)	(1255.3)	(307.0)	(145.6)
Observations	13644	13644	13644	13644
R-square	0.53	0.55	0.55	0.53
Other Controls	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Note: This table presents the DiD estimate through sub-sample analyses. Each panel represents the DiD results using corresponding sub-sample data. Each column represents the expenditure on the corresponding item (in Chinese Yuan). The control variables include the average age and the standard deviation of age within a household, household income, and household size. Cluster-robust standard errors, shown in parentheses, are clustered at the city level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Each column displays a similar pattern to the main results, indicating that the results do not strongly differ between the high- and low-income groups. Notably, the magnitude in the low-income panel is larger than that for the high-income group, suggesting that the release of economic burden from the LTCI is more effective for the low-income household than the high-income household. While some estimates display opposite signs against the main result, these estimates are neither significant in the main result nor in this heterogeneity analysis.

In addition, we also relax the assumption of actuarial fair condition in the equation of the probability of choosing the in-kind benefit option. In the real world, it is also plausible that such probability is an increasing function of household income because high-income households are more likely to choose in-kind benefits as their opportunity cost of providing informal caregiving is higher than those of low-income households. For this consideration, we construct a heterogeneous probability for each household with disabled that lives in the pilot city with options of the cash-benefit and the in-kind benefit. Since we do not observe the actual choice, it is not possible to identify the conditional choice probability. Instead, we use the normal cumulative distribution function of the standardized long-run household income (data minus sample mean and then divided by sample standard deviation), i.e.,

$$\text{Prob}(\Delta_i^y) = \Phi\left(\frac{y_i - \overline{y}}{\sigma_y}\right).$$

where y represents the household income, $\overline{y}$ represents the sample mean of y, and σ_y is the sample standard error of y. We use such probability to re-construct the DiD estimate through

$$\begin{aligned} Y_{it} =& \beta_1 \cdot \big(\text{Prob}(\Delta_i^y) \times 1\{Mixed_i\}\big) \times Post_t \\ &+ \beta_2 \cdot \big(1\{In\text{-}kind_i\} + (1 - \text{Prob}(\Delta_i^y)) \times 1\{Mixed_i\}\big) \times Post_t + X_{it}\gamma + \lambda_i + \lambda_t + \varepsilon_{it}, \end{aligned}$$

which is identical to the previous specification except for the construction of $\text{Prob}(\Delta_i^y)$.

Table E2 presents the corresponding DiD results with the heterogeneous conditional choice probability. All estimates display similar results to our main specification. Hence, we conclude that the price decomposition estimate does not heavily rely on the assumption of homogeneous conditional choice probability.

Table E2: DiD Results with Heterogeneous Exposure in the Mixed City

	(1) Clothing	(2) Food	(3) Housing	(4) Miscellaneous
β_1: Income Effect	-252.3	6905.6**	2772.9***	951.2
	(892.0)	(2765.8)	(831.6)	(640.5)
β_2: Total Effect	306.2**	402.6	846.4***	508.3*
	(153.5)	(1055.0)	(259.8)	(278.8)
$\beta_2 - \beta_1$: Substitution Effect	558.5	-6503.0	-1926.5	-442.9
p-value	[0.54]	[0.04]	[0.03]	[0.56]
Other Controls	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	27797	27797	27797	27797
R-square	0.59	0.59	0.58	0.56

Note: This table presents the DiD estimate through the heterogeneous probability of choosing cash-benefit in the mixed city. Each column represents the expenditure on the corresponding item (in Chinese Yuan). The control variables include the average age and the standard deviation of age within a household, household income and household size. Cluster-robust standard errors, shown in parentheses, are clustered at the city level. * p<0.1, ** p<0.05, *** p<0.01.