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Dedication

To my mother, and in the loving memory of my beloved father.

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Chapter 1

Introduction

The economic and social factors play a critical role in determining individual and societal well-being. The chapters in this dissertation provide empirical analyses of key issues: women's bargaining power in Indonesia and its association with household budget allocation toward children; the impact of mobility of an individual on healthcare utilization and health outcomes in China; and the impact of health insurance integration on individuals' healthcare utilization.

The first chapter investigates the relationship between women's bargaining power and household budget allocation toward children in Indonesia. Women's ability to influence household decisions is a crucial determinant of children's health, education, and overall well-being. Using individual-level survey data, this chapter employs Ordinary Least Squares (OLS) regression together with the Multinomial Logit model to measure the extent of women's bargaining power and estimate its association with child nutrition, education, and health expenditures. By applying a robust analytical framework, this study sheds light on the relations through which how empowering women in household decision-making can connect to child outcomes through household budget allocation.

The second chapter examines urban-rural differences in and the effects of mobility on healthcare utilization and health outcomes in China using individual-level survey data from CHARLS (China Health and Retirement Longitudinal Study). As migration between rural and urban areas continues to increase, understanding how changes in location affect access to and use of healthcare services becomes essential. First, using pooled OLS models, this study estimates the relationship between the location of residence and health indicators. Second, a difference-in-differences (DiD) approach is employed to assess the impact of relocation from urban to rural areas and vice versa. By constructing treatment and control groups, this chapter identifies changes in healthcare utilization patterns following migration, contributing to the broader discourse on urbanization and healthcare accessibility.

The third chapter evaluates the effects of integrating two different health insurance schemes into a unified insurance system in China on healthcare utilization and health outcomes. Many countries are reforming their health insurance systems to enhance efficiency and ensure equitable access to healthcare. After showing descriptive associations between insurance schemes and healthcare variables, this study applies a Pooled OLS, a difference-in-differences approach to analyze the impact of transitioning from separate health insurance schemes to a unified system. By comparing the treatment and control groups—those who are affected by the introduction of the new insurance scheme because of the policy versus those who retained their original, unchanged plans—the analysis assesses the benefits of integration in terms of improved healthcare usage.

Together, these chapters provide a comprehensive examination of factors influencing women's decision-making power, household budget allocation, individuals' healthcare access, and health equity. The findings offer valuable policy insights into how empowering women, addressing migration-related healthcare challenges, and improving insurance systems can contribute to better health and economic outcomes for individuals and society at large. The empirical strategies applied in this thesis ensure robust and reliable estimates, facilitating a deeper understanding of these critical issues.

Chapter 2

Women's Bargaining Power and Household Budget Allocation to Human Capital: Evidence from the Indonesia Family Life Survey (IFLS) (with Rifai Afin and Dr. Péter Elek)

Abstract: In this paper, we explore the association of women's bargaining power with human capital investment within the household. Using data from the Indonesia Family Life Survey (IFLS), wave 5, we estimate the determinants of bargaining power with multinomial logit models and the association of bargaining power with food, bad goods, education, and health spending with OLS regression models. We find that the wife's higher education level increases the probability of her sole bargaining power in food spending and of joint husband-wife decision-making in education and health spending. The share of food spending is largest in households with joint decision making, the share of spending on bad goods is largest in households where women have no bargaining power, while the association of bargaining power with education and child health spending is more heterogeneous and domain-specific.

Keywords: women's bargaining power, budget allocation, household consumption, human capital investment, Indonesia

JEL: C31, D12, D13, I14, I24

2.1 Introduction

In the United Nations' Agenda for Sustainable Development Goals, key targets include achieving gender equality, empowering women, ensuring quality education, reducing poverty, and promoting health and well-being. A growing body of evidence shows that women's participation at the household level is essential to achieve these goals (Amugsi et al., 2016). Women's empowerment, particularly in the context of intra-household decision-making, plays a crucial role in shaping children's human capital outcomes, including nutrition, education, and health (Duflo, 2003, 2012).

While existing research highlights the importance of women's empowerment for child well-being, significant gaps still remain. First, measuring women's bargaining power remains a persistent challenge (Doss, 2013). Many studies rely on proxy variables that may not capture the nuanced ways in which women influence specific categories of household spending. Second, the underlying mechanisms through which women's bargaining power translates into child human capital investments are not fully understood. Doss (2013) mentions that the mechanism and causal relationship of women's bargaining power and child outcomes are not clear. Much of the literature focuses on final outcomes (e.g., child health or education levels), rather than the intermediate budgetary decisions that lead to them. Finally, questions of endogeneity – whether women's bargaining power is influenced by the same factors that determine spending – are often insufficiently addressed.

This paper seeks to fill these gaps by examining the relationship between women's intra-household bargaining power and household spending on children's human capital in Indonesia. Using nationally representative household survey data from 2015, we analyse how decision-making authority links with the share of household spending devoted to food, education, and health for children.

Thus, by examining these, this paper makes two contributions to the current literature. First, we use a detailed, domain-specific scoring method to capture women's bargaining power across four areas – food, bad goods, education, and health spending. Second, we focus on intermediate outcomes. Instead of final child outcomes, we focus on the allocation of resources, providing insight into the immediate pathways through which bargaining power may shape long-term child development.

We find that a wife's higher education level increases the probability of her sole decision-making in food spending and of joint husband-wife decision-making in education and health spending. The share of food spending is largest in households with joint decision making, the share of spending on bad goods is largest in households where women have no bargaining power, while the association of bargaining power with education and child health spending is more ambiguous. The share of education spending seems lower in households with better women's bargaining power, and joint decision-making seems to result in less household budget allocation to child health spending. These results suggest a complex relationship between women's empowerment and household resource allocation – one that may not always align with the assumption that more power is associated with more spending on child-related goods. Possible interpretations include differences in expenditure composition or prioritisation across categories, although the present analysis does not allow identification of the underlying behavioural mechanisms.

The remainder of this paper is organized as follows. Section 1 presents the institutional background and literature review. Section 2 outlines the methodology and data. Section 3 presents the results. Section 4 concludes with implications, discussions, and future research directions.

2.1.1 Institutional Background in Indonesia

Indonesia's social structure is deeply rooted in familial and communal values, with traditionally extended family systems and collective decision-making playing central roles. However, urbanization and economic shifts have gradually moved households toward more nuclear family arrangements. While Indonesia remains largely patriarchal – with male heads of households typically holding primary decision-making power – women's roles, though respected, often remain secondary.

Women's empowerment has improved in Indonesia, especially in the public sphere. Female political representation has increased notably, rising from 6% in 1955 to 17% by 2014, with notable progress in the 2019 elections (Aspinall et al., 2021; Indonesia, 2015, 2017). However, gender disparities in decision-making within households persist, particularly regarding the allocation of resources for children's needs. Labor force participation rate for women aged 15+ is 53.2% in Indonesia as of 2020 [1]. Further, fertility rate is 2.2 births per women as of 2021 [2].

Indonesia continues to face significant challenges in child health and education. Although stunting rates among children under five have declined from 40.4% in 2000 to 31% in 2022, malnutrition remains prevalent, with both under- and over-nutrition affecting children – especially boys (UNICEF et al., 2023a, 2023b). Educational attainment has improved, yet upper secondary and tertiary enrolment remains uneven across regions and income levels ("Education attainment - Adult education level - OECD Data", n.d.).

These dynamics create a complex setting in which women's bargaining power may critically shape household spending decisions. Faced with competing demands – such as child nutrition, education, healthcare, and non-essential goods like

[1] https://data.unwomen.org/country/indonesia
[2] https://data.worldbank.org/indicator/SP.DYN.TFRT.IN?locations=ID

tobacco – how resources are allocated within households reflects both gender dynamics and broader socioeconomic pressures.

2.1.2 Literature Review: Women's Bargaining Power and Child Human Capital

A growing body of literature shows that women's bargaining power within households plays a critical role in shaping investments in children's human capital. This work emphasizes that resource allocation may depend not only on total household income but also on intra-household control over decisions and resources. When women have greater bargaining power, allocations tend to shift toward child-centred goods, reflecting differences in preferences, information, and caregiving responsibilities (Doss, 2013). While early studies established the existence of such effects, more recent work highlights substantial heterogeneity across outcome domains and decision-making structures, underscoring the need for a more mechanism-driven synthesis.

Nutrition and Food Allocation

The most consistent evidence linking women's bargaining power to child outcomes emerges in the domain of nutrition. Across low- and middle-income countries, stronger maternal bargaining power is associated with more diverse, nutrient-rich diets and greater adherence to recommended feeding practices (Amugsi et al., 2016; S. Kulkarni et al., 2020; Lépine & Strobl, 2013). Meta-analyses and systematic reviews confirm positive average effects on child anthropometrics, while noting that results vary by region and by how empowerment is measured (Carlson et al., 2015; Pratley, 2016; Santoso et al., 2019).

Country-specific studies from Bangladesh, India, and Senegal show that greater maternal decision-making authority predicts improvements in height-for-age (HAZ), weight-for-age (WAZ), weight-for-length (WLZ), and mid-upper-arm circumference (MUAC) scores (Desai & Kiersten, 2005; Holland & Rammohan, 2019; Lépine & Strobl, 2013; Shroff et al., 2009, 2011). Similar gains are observed when women control productive assets or income streams (S. Kulkarni et al., 2021). When women enter paid work, their enhanced voice often raises household diet quality (Sangwan & Kumar, 2021). However, evidence from several Nepal and Indian studies finds little or even negative effects, plausibly because employment may reduce time available for childcare (Bose, 2011; Cunningham et al., 2019).

The relative strength of nutritional effects is consistent with the nature of food-related decisions. Food expenditures are frequent, divisible, and largely managed within the household, allowing women's preferences to translate more directly into outcomes when bargaining power increases. Moreover, nutritional investments yield immediate and observable returns, reinforcing maternal incentives to prioritize them. These features make nutrition particularly responsive to shifts in intra-household decision-making authority.

Education Outcomes

Evidence on educational outcomes is generally positive but less uniform. Maternal control over income or assets is associated with higher school enrolment, improved test scores, and greater educational spending (Carneiro et al., 2013; Chi & Qian, 2016; Qian, 2008). Evidence from China, Nicaragua, and Pakistan shows fewer grade repetitions when mothers have greater say in household decisions (Andrabi et al., 2012; Gitter & Barham, 2008). At the same time, some transfer programs find no advantage to channelling sources through mothers, and others report non-linear or gender-differentiated effects (Afoakwah et al., 2020; Benhassine et al., 2015).

Compared to nutrition, educational investments involve higher fixed costs, longer time horizons, and interaction with external institutions such as schools and labour markets. These features may attenuate the immediate impact of women's bargaining power, particularly when schooling decisions are normatively shared or dominated by fathers. As a result, increased maternal participation in decision-making may not always translate into effective control over educational choices, helping to explain the more heterogeneous findings in this domain.

Health Investments

Women's bargaining power is also linked to higher uptake of preventive care, immunization, and hygienic practices, contributing to lower child morbidity and mortality in countries including Ghana, Uganda, Vietnam, and Indonesia (Ganle et al., 2015; Novignon et al., 2019; Skoufias, 1999). Allocation effects appear especially pronounced for girls when household resources are scarce, suggesting that women's preferences may counteract gender-biased investment patterns (Duflo, 2003; Thomas, 1994).

Health investments occupy an intermediate position between nutrition and education. Preventive care often aligns closely with maternal preferences and caregiving roles, but access constraints, mobility restrictions, and the need for spousal cooperation can limit women's ability to act on these preferences. Consequently, empowerment may raise health investments most effectively when decision-making authority is accompanied by control over mobility and resources.

Measuring Bargaining Power and Decision-Making Structure

Women's empowerment is a widely acknowledged concept and a fundamental component of human rights. It is commonly understood as the process through which individuals acquire the ability to make meaningful choices and decisions in their lives (Kabeer, 1999). In the World Bank report (Mason & King, 2001), women's empowerment involves women's voice, expanding their access to education and healthcare, and ensuring equal access across key domains such as rights, resources, and voice. Further, this understanding is extended to women's access to economic opportunities, legal rights and political participation (Duflo, 2012). Moreover, empowerment is viewed as an ongoing process that entails gaining control over resources and strengthening individual and collective agency (Cornwall, 2016). Considering these, women's empowerment is shaped by a wide range of perspectives that highlight social, economic, and political transformations aimed at reducing gender inequalities and improving well-being.

In this study, women's empowerment is examined through women's bargaining power within the household, which reflects their ability to influence household resource allocation and decision-making.

Researchers measure women's bargaining power using a wide range of indicators, including participation in household decisions, control over expenditures, mobility, education, employment, wages, and asset ownership. Composite indices, such as the Women's Empowerment in Agriculture Index, integrate multiple domains of empowerment (Holland & Rammohan, 2019), while multidimensional frameworks emphasize empowerment in terms of resources, agency, and achievements (Huis et al., 2017). Other approaches emphasize social participation and workload as central components of women's bargaining power (S. Kulkarni et al., 2020). Divergent measures partly explain mixed findings and underscore the need for theory-driven, context-sensitive metrics.

Importantly, most empirical studies do not distinguish clearly between sole and joint decision-making, despite theoretical reasons to expect different effects. Sole decision-making may enable women to directly reallocate resources toward child-centred goods, whereas joint decision-making may reflect cooperative or symbolic participation in which women's preferences influence outcomes only when aligned with spousal interests. Failure to account for this distinction may contribute to mixed or attenuated estimates, particularly in domains such as education and healthcare that involve higher stakes or external actors.

Taken together, a large body of literature supports a generally positive, but not universal, relationship between women's bargaining power and children's human capital outcomes. Evidence is strongest and most consistent for nutrition, more heterogeneous for education, and context-dependent for health. These patterns suggest that the effectiveness of women's empowerment depends not only on the level of bargaining power but also on the type of investment and the structure of household decision-making.

Despite substantial empirical progress, recent studies continue to document unexplained heterogeneity across domains and contexts. Existing reviews largely aggregate outcomes and decision measures, offering limited insight into the mechanisms that govern when and how women's empowerment translates into improved child well-being. This paper addresses this gap by explicitly distinguishing between food, education, and health investments and by examining how sole versus joint decision-making shapes the translation of women's bargaining power into child human capital outcomes.

Theoretical expectations

Building on the literature reviewed above, we expect women's bargaining power to be differentially associated with expenditure shares across domains. In line with consistent evidence for nutrition, greater female decision-making authority—particularly in food-related decisions—is expected to be associated with a higher share of food expenditure and a lower share of bad goods. For education and health, where investments involve longer time horizons, institutional constraints, and often joint decision-making, the expected associations are less clear-cut and may vary by the structure of decision authority (sole versus joint). Accordingly, we anticipate more heterogeneous patterns for education and health spending shares than for food-related expenditures.

2.2 Data and Methodology

2.2.1 Data

The data we use in this study are the fifth wave of the Indonesia Family Life Survey (IFLS), implemented by RAND Social and Economic Well-being (Strauss et al., 2016a). The Indonesia Family Life Survey is a longitudinal household survey that provides comprehensive information on individual, household, and community characteristics. Initiated in 1993-1994 (Wave 1), the IFLS captures socioeconomic and demographic changes in Indonesia since the 1990s, with subsequent waves in 1997-1998 (Wave 2), 2000 (Wave 3), 2007-2008 (Wave 4), and 2014-2015 (Wave 5). Our study uses cross-sectional data from Wave 5, which is a representative survey of 83% of the Indonesian population (Strauss et al., 2016b). We use Stata 18.5 MP for analysis.

The sample is restricted to households with both a husband and a wife present, allowing for analysis of intra-household bargaining dynamics. Further, we include only households with children. The dataset combines household-level and child-level data. While food and bad goods consumption are measured at the household level, education and health expenditures are tracked individually for each child. Accordingly, we merge household and child-level datasets, where, for instance, parental education is a household-level variable, while a child's educational data is individual-specific.

The target sample includes children aged 14 or younger, as this is the age range covered in the child-level IFLS data. We exclude households with missing child information or with all children older than 14, as well as those whose children are neither biological, adopted, nor grandchildren. A flowchart detailing the data construction process is provided in Figure A.1 in the Appendix.

2.2.2 Variables

From IFLS-5, we extract variables indicating household consumption on food, children's healthcare and education, and expenditures on "bad goods" such as spending on betel nut for chewing, traditional drugs, tobacco, cigarettes, and alcoholic beverages from the survey. We treat spending on food, children's health, and education as proxies for household investment in human capital. Conversely, higher expenditures on bad goods are assumed to be negatively linked with such investments. Covering all commodities can make estimates less reliable because many household surveys do not accurately or thoroughly document consumption of items for all categories. Consequently, only the most significant commodity groupings or those with sufficient data quality are frequently included by researchers. For this reason, and for data quality reasons, we limit household expenditures to these categories, excluding durable and non-food items.

Dependent Variable

The primary outcome variable is the share of household expenditure allocated to food, bad goods, children's education, and healthcare. Unlike many studies that use final outcomes such as child anthropometric indicators (e.g., height-for-age or weight-for-height z-scores), we focus on these intermediate inputs to capture household investment in child well-being.

Control Variables

We control for a comprehensive set of household and individual characteristics, including age, education, employment, income, child's age, gender, health status, household size, income group, and urban/rural location.

Independent Variable (Bargaining Power)

The original IFLS survey interviewed respondents with questions about several different areas of household members' autonomy in decision-making. Respondents indicate who makes decisions across seventeen domains, including food purchases, clothing, education, healthcare, socializing, savings, and contraception. Answers can include one or multiple household members together. Our approach follows (Holland & Rammohan, 2019; Lépine & Strobl, 2013), using self-reported decision-making to construct a direct measure of women's bargaining power over sources and household matters. This method provides a practical, straightforward, data-driven approach that aligns with established literature.

To capture bargaining power, we focus on decision-making over three key areas: food expenditure, children's healthcare, and education – specifically, we use the survey questions "Who makes the decision on the food expenditure eaten at home; Who makes the decision on your children's healthcare spending; Who makes decision on your children's education spending in the family?". We construct a score based on whether the respondent (assumed to be the mother) is the sole decision-maker, co-decision-maker, or excluded from decision-making. If the mother solely decides on this specific domain, she is coded as having the highest bargaining power in that domain; if only the head (assumed to be the father) or other household members decide, bargaining power is coded as the lowest (see Table 2.1).

Due to data limitations, this study focuses on women's participation in household decision-making as the primary proxy for bargaining power. Other potentially relevant dimensions of empowerment, such as time use, and the division of household labor, are not being examined with the available data.

2.2.3 Empirical Model

Association of Expenditure Shares and Bargaining Power

This study examines how women's intra-household bargaining power is associated with household resource allocation toward investments in child human capital, focusing on expenditures on food, education, and health. Drawing on

Table 2.1: Survey response by mother/wife of the household in IFLS-5

Decision making	**WBP Score**	**Bargaining power scale**
"I" (alone) make a decision over the consumption.	3	Have full bargaining power over the consumption (Wife has full decision-making power).
"Me and my husband (spouse)" (together) make a decision over the consumption.	2	Have partial bargaining power over consumption (Wife and husband have joint decision-making power).
"Me and other members of the family" (altogether) make a decision over the consumption.	1	Have less partial bargaining power over consumption (Wife, husband and other household members shared decision-making power).
My husband (alone) and/or other members of the family, excluding the mother, make decisions.	0	Have no bargaining power over consumption (Wife has no decision-making power).

Source: Authors' own elaboration.

economic theories of household behaviour, women's bargaining power—proxied by self-reported control over household decision-making—is hypothesized to shift spending toward child-oriented goods that more closely reflect maternal preferences (Lundberg et al., 1997; Thomas, 1990).

Our empirical specification draws on insights from Engel-curve and demand-system approaches—such as the Quadratic Engel Curve (QEC) and the Quadratic Almost Ideal Demand System (QUAIDS) (Banks et al., 1997) —which highlight that budget shares respond flexibly to total expenditure and preference shifters. While this framework motivates our empirical analysis, data limitations—most notably the absence of price information and the mixed household- and child-level structure of expenditures—preclude estimation of a fully specified demand system with adding-up, homogeneity, symmetry, and cross-equation restrictions. Accordingly, we adopt a reduced-form Engel-curve approach, in which women's bargaining power enters as a preference shifter in budget share regressions rather than as part of a structural demand system.

We estimate reduced-form Ordinary Least Squares (OLS) regressions of expenditure shares. As defined in the previous section, the empirical analysis focuses on four expenditure categories: food, bad goods, education, and health. These categories serve as proxies for household investments in child well-being. We assume women's bargaining power to be exogenous and estimate its association with expenditure shares using OLS. Women's decision-making authority is measured through self-reported control over spending decisions in the domains of food, child health, and education. This helps identify whether greater control by women corresponds with greater household investment in child-related goods. These intermediate outcomes offer valuable insights into how intra-household power dynamics connect with long-term human capital formation. Since bad goods are included among food-related items in the survey, bargaining power in food-related decisions is also used as the relevant measure for the estimation of the share of bad goods.

Expenditure shares are computed using total household expenditure as the common denominator. Given that food and bad goods expenditure are typically shared across the household, corresponding regressions are estimated at the household level. In contrast, health and education expenses are measured at the individual child level, allowing us to capture intra-household variation stemming from child-specific characteristics such as age, schooling status, and health needs.

More precisely, let $y_{(K_j)}$ denote the expenditure on category $K \in \{\text{food, bad goods}\}$ for household j and let $y_{(K_{ij})}$ denote the expenditure on category $K \in \{\text{education, health}\}$ for individual child i in household j. Let z_j represent total household spending, defined as the sum of expenditures across all four categories.

The corresponding expenditure shares are defined as

$$\omega_{(K_j)} = \frac{y_{(K_j)}}{z_j} \text{ for K} \in \{\text{food, bad goods}\} \tag{2.1}$$

$$\omega_{(K_{ij})} = \frac{y_{(K_{ij})}}{z_j} \text{ for K} \in \{\text{education, health}\} \tag{2.2}$$

To analyse the determinants of these budget shares, we estimate separate equations for each category, incorporating women's intra-household bargaining power, household-level controls, and, where relevant, child-specific characteristics. That is, for household-level outcomes $K \in \{\text{food, bad goods}\}$, we estimate

$$\omega_{(K_j)} = \alpha_K + \beta_K \phi_{(K_j)} + \gamma_K \log z_j + \sum_{l=1}^{L} \delta_{(l_K)} x_{(l_j)} + u_{(K_j)} \tag{2.3}$$

while, for child-level outcomes $K \in \{\text{education, health}\}$, the equation is

$$\omega_{(K_{ij})} = \alpha_K + \beta_K \phi_{(K_j)} + \gamma_K \log z_j + \sum_{l=1}^{L} \delta_{(l_K)} x_{(l_{ij})} + u_{(K_{ij})} \tag{2.4}$$

Here the term $\phi_{(K_j)}$ captures women's bargaining power in the household j in domain K. (In bad goods estimation, the bargaining power in food is used.) The variables x include household-level controls (e.g., household size, number of children, parental age, parental employment, residence type) and, for child-level outcomes (education, health), child characteristics such as age, gender, and schooling status. Finally, u is the error term.

The coefficient of interest, β_K, measures the association between women's bargaining power and the allocation of household resources across expenditure categories. These estimates should be interpreted as reduced-form relationships rather than structural demand parameters.

Determinants of Bargaining Power

In addition to the budget share analysis, we examine the socioeconomic correlates of women's bargaining power. For each domain $K \in \{\text{food, education, health}\}$, we estimate a multinomial logit model for $\phi_{(K_j)} \in \{0,1,2,3\}$, the bargaining power in the household j. That is, for each bargaining-power category $m \in \{0,1,2\}$, we define a category-specific linear index $S_{(K_{jm})}$ as a function of household and parental characteristics:

$$S_{(K_{jm})} = \alpha_{(K_m)} + \sum_{l=1}^{L} \theta_{(l_{K_m})}\, x_{(l_j)} \tag{2.5}$$

which enters the multinomial logit probability function. With category 3 as the reference group, the choice probabilities are:

$$\Pr\big(\phi_{(K_j)} = m \,\big|\, x_{(1_j)}, x_{(2_j)}, \ldots, x_{(L_j)}\big) = \frac{\exp\big(S_{(K_{jm})}\big)}{1 + \sum_{r=0}^{2} \exp\big(S_{(K_{jr})}\big)} \qquad \text{for } m = 0, 1, 2. \tag{2.6}$$

and

$$\Pr\big(\phi_{(K_j)} = 3 \,\big|\, x_{(1_j)}, x_{(2_j)}, \ldots, x_{(L_j)}\big) = \frac{1}{1 + \sum_{r=0}^{2} \exp\big(S_{(K_{jr})}\big)}. \tag{2.7}$$

This analysis provides descriptive evidence on the socioeconomic factors associated with women's bargaining power, but it is not intended to establish causal relationships.

2.3 Results

2.3.1 Descriptive Statistics

Table 2.2 presents summary statistics for key variables related to household expenditures, bargaining power, and control variables. On average, 65.5% of total expenditure is allocated to food, 9.1% to bad goods, 13.9% to education, and 2.0% to health.

Although approximately 67% of food expenditure decisions are made solely by the wife, decisions regarding education and health are predominantly made jointly by both husband and wife, accounting for about 58% and 62%, respectively. This means that in half of households, husband and wife make decisions over consumption together. Slightly more than half of husbands and wives have elementary or junior high school, and around 30% have a senior high school education. While 89% of husbands are employed, 42% of wives are employed. The average age of husbands and wives is 42 and 37 years, respectively. A larger proportion of households fall within the middle-income bracket, earning between 5 and 10 million Indonesian Rupiah (approximately USD 305 to 610, based on an exchange rate of 1 USD = 16,380.30 IDR).

Table 2.2: Summary statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Outcome variables					
Share of food expenditure	8834	0.655	0.207	0.006	1.000
Share of bad goods expenditure	8834	0.091	0.100	0.000	0.728
Share of education expenditure	14 127	0.139	0.165	0.000	0.928
Share of health expenditure	14 551	0.020	0.070	0.000	0.990
Treatment variables					
Wife's bargaining power in food					
No bargaining power	7785	0.133	0.340	0.000	1.000
Less partial bargaining power	7785	0.029	0.168	0.000	1.000
Partial bargaining power (joint)	7785	0.167	0.373	0.000	1.000
Full bargaining power	7785	0.671	0.470	0.000	1.000
Wife's bargaining power in education					
No bargaining power	7785	0.140	0.347	0.000	1.000
Less partial bargaining power	7785	0.030	0.171	0.000	1.000
Partial bargaining power (joint)	7785	0.581	0.493	0.000	1.000
Full bargaining power	7785	0.249	0.432	0.000	1.000
Wife's bargaining power in health					
No bargaining power	7785	0.092	0.288	0.000	1.000
Less partial bargaining power	7785	0.012	0.110	0.000	1.000
Partial bargaining power (joint)	7785	0.616	0.486	0.000	1.000
Full bargaining power	7785	0.280	0.449	0.000	1.000
Covariates					
Urban rural					
Rural	8834	0.424	0.494	0.000	1.000
Urban	8834	0.576	0.494	0.000	1.000

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Variable	Obs	Mean	Std. Dev.	Min	Max
Child age	14 127	6.621	4.275	0.000	14.000
Child gender (female = 1)	14 127	0.484	0.500	0.000	1.000
Husband age	8829	42.036	11.456	18.000	91.000
Husband's education					
No education	8785	0.027	0.162	0.000	1.000
Elementary, Junior high	8785	0.516	0.500	0.000	1.000
Senior high	8785	0.327	0.469	0.000	1.000
Higher education	8785	0.130	0.336	0.000	1.000
Husband's work status (employed = 1)	8827	0.891	0.312	0.000	1.000
Husband smoking (husband smokes = 1)	7748	0.694	0.461	0.000	1.000
Wife age	8832	37.641	10.642	15.000	83.000
Wife's education					
No education	8803	0.045	0.206	0.000	1.000
Elementary, Junior high	8803	0.554	0.497	0.000	1.000
Senior high	8803	0.281	0.450	0.000	1.000
Higher education	8803	0.120	0.325	0.000	1.000
Wife's work status (employed = 1)	8828	0.419	0.493	0.000	1.000
Wife smoking (wife smokes = 1)	8140	0.018	0.133	0.000	1.000
Child number	8834	1.706	0.818	1.000	8.000
Family size	8834	5.711	2.623	3.000	36.000
Income group					
0–5M	8834	0.299	0.458	0.000	1.000
5M–10M	8834	0.421	0.494	0.000	1.000
10M–15M	8834	0.171	0.376	0.000	1.000
15M+	8834	0.110	0.313	0.000	1.000
Education variables					
Child School type (Public = 1)	7440	0.804	0.397	0.000	1.000
Child School attendance	13 889	0.537	0.499	0.000	1.000
Health variables					
Child health status					
unhealthy	13 886	0.004	0.060	0.000	1.000
somewhat unhealthy	13 886	0.114	0.318	0.000	1.000
somewhat healthy	13 886	0.562	0.496	0.000	1.000
very healthy	13 886	0.321	0.467	0.000	1.000
Wife's health insurance (has insurance = 1)	8128	0.513	0.500	0.000	1.000
Husband's health insurance (has insurance = 1)	7735	0.515	0.500	0.000	1.000
Wife's health insurance – JKN (wife has JKN = 1)	8128	0.464	0.499	0.000	1.000

(continued on next page)

Variable	Obs	Mean	Std. Dev.	Min	Max
Husband's health insurance – JKN (husband has JKN = 1)	7735	0.463	0.499	0.000	1.000

Note: Education and health expenditure are measured on the child level, food and bad goods expenditure are measured on the household level. Descriptive statistics of the treatment variables and of the non-child-specific covariates are shown on the household level. Descriptive statistics of the child-specific covariates are shown at the child level.

Source: Authors' own calculation from Strauss et al., 2016a, 2016b.

2.3.2 Determinants of Women's Bargaining Power

First, we identify the covariates that are associated with varying levels of women's bargaining power using a multinomial logit model. Here, the primary dependent variable is the categorical variable of Women's Bargaining Power (WBP), disaggregated across three domains: food, education, and health. (We keep the category with minimal bargaining power despite its relatively small sample size.) Independent variables include a range of socio-demographic indicators, such as the educational attainment, employment status, and age of both spouses, as well as urban residency and total household expenditures.

Women's Bargaining Power in Food Spending

As shown in summary statistics (Table 2.2) , most food expenditure decisions are made solely by wives, followed by joint decisions between husbands and wives. While the parameter estimates of the multinomial logit model are reported in the Appendix for reference (Table A.1), we focus here on the average marginal effects (see Table 2.3). These results indicate that higher levels of wife education sharply reduce the likelihood of women having no say in food expenditure and significantly increase their chances of having full decision-making power. Education thus emerges as a key factor in enhancing women's autonomy. Employment also increases women's bargaining power, though it tends to promote more joint decision-making rather than full autonomy. Furthermore, residing in urban areas is associated with a decreased likelihood of women having no say in food-related decisions and an increased likelihood of women having full decision-making authority. In high-income households, women are more likely to have full control over food expenditure decisions and less likely to share or lack decision-making power.

Women's Bargaining Power in Education Spending

Based on average marginal effects from the multinomial logit model (see Table 2.4), as a wife's education increases, the probability of no power in education spending decreases significantly, with a strong shift toward joint decision-making. However, a higher level of education does not significantly increase full (sole) bargaining power. This implies educated women are more likely to share power rather than dominate decisions in children's education spending. An increasing level of the husband's education sharply boosts joint decision-making while reducing the wife's sole authority. With the husband more highly educated, the bargaining structure over child education spending becomes more collaborative rather than matriarchal. Considering individual characteristics, a slightly older wife is less likely to decide alone and slightly more likely to have no say over the spending. Wife employment discourages no bargaining power for women.

Women's Bargaining Power in Health Spending

According to the average marginal effects shown in Table 2.5, the education level of the wife is the clearest driver of shared decision making over child health spending. A higher level of schooling for either wife or husband sharply raises the probability that medical spending on children is discussed and decided together, while it lowers the chances of both "wife has no say" and "wife decides alone". Resources and environment, for example, income, urban living, larger families, push the balance towards greater wife autonomy, not toward joint de-

Table 2.3: Average marginal effects for women's bargaining power in food

	Bargaining power			
VARIABLES	No (WBP in Food = 0)	Partial (less) (WBP in Food = 1)	Partial (joint) (WBP in Food = 2)	Full (WBP in Food = 3)
Wife age	-0.0005	0.0010**	-0.0000	-0.0004
	(0.0009)	(0.0004)	(0.0010)	(0.0012)
Wife's Education (baseline: no education)				
Elementary, Junior high	-0.0992***	-0.0236**	-0.0107	0.1335***
	(0.0295)	(0.0118)	(0.0261)	(0.0333)
Senior high	-0.1537***	-0.0172	-0.0079	0.1788***
	(0.0310)	(0.0133)	(0.0280)	(0.0357)
Higher education	-0.1647***	0.0038	0.0267	0.1342***
	(0.0328)	(0.0166)	(0.0318)	(0.0398)
Wife works	-0.0326***	-0.0001	0.0196**	0.0130
	(0.0078)	(0.0039)	(0.0089)	(0.0111)
Husband age	-0.0003	0.0001	-0.0024**	0.0026**
	(0.0008)	(0.0004)	(0.0009)	(0.0012)
Husband's Education (baseline: no education)				
Elementary, Junior high	0.0077	0.0011	-0.0386	0.0299
	(0.0238)	(0.0098)	(0.0338)	(0.0380)
Senior high	-0.0134	0.0025	-0.0501	0.0611
	(0.0251)	(0.0110)	(0.0351)	(0.0397)
Higher education	-0.0184	0.0036	-0.0337	0.0485
	(0.0280)	(0.0121)	(0.0376)	(0.0430)
Husband works	-0.0133	0.0015	0.0064	0.0053
	(0.0134)	(0.0059)	(0.0148)	(0.0184)
Income Group (baseline: 0–5M)				
5M–10M	-0.0044	-0.0028	-0.0118	0.0190
	(0.0092)	(0.0047)	(0.0105)	(0.0130)
10M–15M	-0.0034	0.0023	-0.0165	0.0176
	(0.0123)	(0.0062)	(0.0136)	(0.0171)
15M+	-0.0090	0.0034	-0.0309*	0.0365*
	(0.0156)	(0.0076)	(0.0161)	(0.0209)
Child number	0.0020	-0.0051*	-0.0015	0.0046
	(0.0049)	(0.0026)	(0.0056)	(0.0069)
Urban	-0.0104	-0.0040	-0.0118	0.0261**
	(0.0081)	(0.0042)	(0.0091)	(0.0114)
Observations	7748	7748	7748	7748

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' own calculations.

cision making. Employment of spouse empowers joint decision-making; however aging exhibits lower bargaining power of woman and less joint decision-making.

Table 2.4: Average marginal effects for women's bargaining power in education

VARIABLES	Bargaining power			
	No (WBP in Education = 0)	Partial (less) (WBP in Education = 1)	Partial (joint) (WBP in Education = 2)	Full (WBP in Education = 3)
Wife age	0.0024***	0.0022***	-0.0028**	-0.0018
	(0.0009)	(0.0005)	(0.0013)	(0.0011)
Wife's Education (baseline: no education)				
Elementary, Junior high	-0.0302	0.0156***	0.0187	-0.0042
	(0.0242)	(0.0055)	(0.0327)	(0.0272)
Senior high	-0.0654**	0.0285***	0.0592*	-0.0223
	(0.0262)	(0.0077)	(0.0354)	(0.0296)
Higher education	-0.0994***	0.0192**	0.1283***	-0.0481
	(0.0274)	(0.0089)	(0.0391)	(0.0334)
Wife works	-0.0249***	-0.0006	0.0141	0.0114
	(0.0080)	(0.0040)	(0.0114)	(0.0101)
Husband age	0.0012	-0.0002	-0.0032***	0.0023**
	(0.0008)	(0.0004)	(0.0012)	(0.0010)
Husband's Education (baseline: no education)				
Elementary, Junior high	0.0019	0.0093	0.1240***	-0.1351***
	(0.0221)	(0.0112)	(0.0395)	(0.0393)
Senior high	0.0246	0.0009	0.1851***	-0.2106***
	(0.0240)	(0.0117)	(0.0413)	(0.0409)
Higher education	0.0420	0.0112	0.2425***	-0.2957***
	(0.0277)	(0.0131)	(0.0442)	(0.0419)
Husband works	0.0109	0.0074	0.0018	-0.0201
	(0.0123)	(0.0052)	(0.0187)	(0.0167)
Income Group (baseline: 0–5M)				
5M–10M	0.0022	0.0131***	-0.0060	-0.0093
	(0.0100)	(0.0042)	(0.0133)	(0.0116)
10M–15M	-0.0030	0.0206***	-0.0293*	0.0116
	(0.0122)	(0.0060)	(0.0175)	(0.0156)
15M+	0.0122	0.0212***	-0.0757***	0.0423**
	(0.0157)	(0.0075)	(0.0217)	(0.0203)
Child number	-0.0009	-0.0042*	-0.0085	0.0135**
	(0.0050)	(0.0025)	(0.0070)	(0.0061)
Urban	0.0069	0.0045	-0.0478***	0.0364***
	(0.0083)	(0.0041)	(0.0116)	(0.0102)
Observations	7748	7748	7748	7748

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' own calculations.

2.3.3 Effects of Bargaining Power on Spending Shares

Table 2.6 presents the results from the baseline models of spending shares, which include only the treatment variable (women's bargaining power) and the log of

Table 2.5: Average marginal effects for women's bargaining power in health

VARIABLES	**Bargaining power** No (WBP in Health = 0)	Partial (less) (WBP in Health = 1)	Partial (joint) (WBP in Health = 2)	Full (WBP in Health = 3)
Wife age	0.0008	0.0015***	-0.0026**	0.0004
	(0.0007)	(0.0003)	(0.0012)	(0.0011)
Wife's Education (baseline: no education)				
Elementary, Junior high	-0.0135	0.0099***	0.0146	-0.0110
	(0.0181)	(0.0031)	(0.0318)	(0.0290)
Senior high	-0.0302	0.0107**	0.0724**	-0.0529*
	(0.0199)	(0.0042)	(0.0345)	(0.0315)
Higher education	-0.0232	0.0052	0.1119***	-0.0939***
	(0.0225)	(0.0045)	(0.0382)	(0.0349)
Wife works	-0.0133**	-0.0012	0.0216*	-0.0071
	(0.0066)	(0.0025)	(0.0112)	(0.0104)
Husband age	0.0020***	-0.0006**	-0.0033***	0.0019*
	(0.0007)	(0.0003)	(0.0012)	(0.0011)
Husband's Education (baseline: no education)				
Elementary, Junior high	-0.0131	0.0030	0.0943**	-0.0842**
	(0.0203)	(0.0075)	(0.0392)	(0.0381)
Senior high	-0.0052	0.0010	0.1570***	-0.1528***
	(0.0218)	(0.0079)	(0.0410)	(0.0397)
Higher education	-0.0061	0.0013	0.2228***	-0.2179***
	(0.0240)	(0.0086)	(0.0437)	(0.0417)
Husband works	-0.0090	-0.0012	0.0412**	-0.0311*
	(0.0108)	(0.0037)	(0.0187)	(0.0174)
Income Group (baseline: 0–5M)				
5M–10M	-0.0108	0.0048*	0.0011	0.0049
	(0.0080)	(0.0027)	(0.0131)	(0.0121)
10M–15M	-0.0010	0.0079**	-0.0148	0.0079
	(0.0104)	(0.0039)	(0.0172)	(0.0160)
15M+	0.0100	0.0094*	-0.0519**	0.0330
	(0.0133)	(0.0052)	(0.0215)	(0.0205)
Child number	0.0003	-0.0051***	-0.0090	0.0138**
	(0.0041)	(0.0019)	(0.0070)	(0.0064)
Urban	0.0112	0.0053**	-0.0526***	0.0361***
	(0.0069)	(0.0025)	(0.0114)	(0.0106)
Observations	7748	7748	7748	7748

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' own calculations.

total spending. In the estimation of child-level shares (education and health), the standard errors are clustered at the household level. As indicated earlier, we use bargaining power in food spending as the main treatment variable in the estimation of the share of bad goods spending.

Table 2.6: Effects of women's bargaining power on spending shares (baseline OLS results)

VARIABLES	(1) Share of food	(2) Share of bad goods	(3) Share of education	(4) Share of health
WBP in food = 1 (less partial)	0.0348**	-0.0202***		
	(0.0140)	(0.0064)		
WBP in food = 2 (partial [joint])	0.0076	-0.0069		
	(0.0080)	(0.0043)		
WBP in food = 3 (full)	-0.0103	-0.0077**		
	(0.0066)	(0.0034)		
WBP in education = 1 (less partial)			0.0209**	
			(0.0096)	
WBP in education = 2 (partial [joint])			-0.0048	
			(0.0042)	
WBP in education = 3 (full)			-0.0026	
			(0.0047)	
WBP in health = 1 (less partial)				-0.0065
				(0.0059)
WBP in health = 2 (partial [joint])				-0.0027
				(0.0026)
WBP in health = 3 (full)				-0.0047*
				(0.0027)
Log of total spending	-0.1067***	-0.0240***	0.0313***	0.0102***
	(0.0035)	(0.0018)	(0.0023)	(0.0017)
Constant	2.3339***	0.4770***	-0.3542***	-0.1386***
	(0.0553)	(0.0290)	(0.0364)	(0.0262)
Observations	7,785	7,785	12,717	12,971
R-squared	0.117	0.026	0.016	0.009

Note: The baseline category of WBP is "no bargaining power".
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Standard errors are clustered at the household level.
Source: Authors' own calculations.

According to the results, women's involvement in the household budget decision decreases the allocation toward bad goods in the family at each level of involvement compared to no participation. For instance, the difference is -0.007 between partial (joint) participation and no participation, and also between full participation and no participation, which is substantial relative to the average bad goods spending share of 0.091 (see Table 2.2). Compared to no female decision-making, the share of food spending is larger under partial (joint) decision-making and less partial decision-making, but lower under full female decision-making. (Although only the individual coefficient of less partial decision making is significant, the difference of the parameter of partial and full decision making is also significantly positive.)

Since we know from the multinomial logit results that women's bargaining power is associated with other explanatory variables (that may independently influence the spending shares), in Table 2.7, we add control variables for household demographics, employment, and other economic factors to the spending share equations. Here, the results for food spending and bad goods spending are similar to those of Table 2.6, although the levels of significance may differ. For education, compared to households in which women report no bargaining power, the budget share allocated to education is lower in households where women exhibit greater decision-making authority. A similar pattern emerges for health expenditures, where joint decision-making is associated with a smaller share devoted to child health.

In addition, greater bargaining power may be associated with a reallocation toward other child-oriented inputs—such as improved food consumption or reductions in bad goods—suggesting shifts in the composition of child-related investments rather than lower overall commitment to children's welfare.

Table 2.7: Effects of women's bargaining power on spending shares (OLS regression results with multiple control variables)

VARIABLES	**(1)** **Share of food**	**(2)** **Share of bad goods**	**(3)** **Share of education**	**(4)** **Share of health**
WBP in food = 1 (less partial)	0.0348**	-0.0160**		
	(0.0140)	(0.0065)		
WBP in food = 2 (partial [joint])	0.0065	-0.0064		
	(0.0080)	(0.0043)		
WBP in food = 3 (full)	-0.0102	-0.0058*		
	(0.0066)	(0.0034)		
WBP in education = 1 (less partial)			-0.0147**	
			(0.0067)	
WBP in education = 2 (partial [joint])			-0.0010	

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VARIABLES	(1) Share of food	(2) Share of bad goods	(3) Share of education	(4) Share of health
			(0.0029)	
WBP in education = 3 (full)			-0.0062*	
			(0.0033)	
WBP in health = 1 (less partial)				-0.0093
				(0.0061)
WBP in health = 2 (partial [joint])				-0.0044
				(0.0028)
WBP in health = 3 (full)				-0.0038
				(0.0028)
Urban	-0.0108**	-0.0077***	0.0235***	-0.0022
	(0.0045)	(0.0023)	(0.0021)	(0.0013)
Family size	0.0014	0.0018***	-0.0030***	-0.0007**
	(0.0010)	(0.0005)	(0.0005)	(0.0003)
Husband works	-0.0147*	-0.0055	-0.0031	-0.0078***
	(0.0078)	(0.0039)	(0.0034)	(0.0026)
Wife works	0.0158***	-0.0114***	-0.0032	-0.0024*
	(0.0045)	(0.0022)	(0.0021)	(0.0013)
Wife age	-0.0008***	-0.0012***	0.0004***	-0.0001
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Wife's insurance JKN				0.0014
				(0.0015)
Husband's insurance JKN				-0.0026*
				(0.0015)
Log of total spending	-0.1055***	-0.0207***	-0.0061***	0.0175***
	(0.0037)	(0.0018)	(0.0018)	(0.0016)
Number of children			-0.0269***	-0.0089***
			(0.0012)	(0.0008)
Child age (baseline: 6 years for education and 0 for health)				
0			-0.1214***	
			(0.0048)	
1			-0.1258***	-0.0102**
			(0.0049)	(0.0050)
2			-0.1237***	-0.0217***
			(0.0048)	(0.0045)
3			-0.1204***	-0.0210***
			(0.0049)	(0.0047)
4			-0.0898***	-0.0269***
			(0.0055)	(0.0045)
5			-0.0183***	-0.0295***
			(0.0062)	(0.0044)
6				-0.0369***
				(0.0043)
7			0.0661***	-0.0396***
			(0.0070)	(0.0042)

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VARIABLES	(1) Share of food	(2) Share of bad goods	(3) Share of education	(4) Share of health
8			0.1115***	-0.0428***
			(0.0065)	(0.0040)
9			0.1128***	-0.0423***
			(0.0064)	(0.0041)
10			0.1080***	-0.0420***
			(0.0065)	(0.0043)
11			0.1139***	-0.0428***
			(0.0065)	(0.0040)
12			0.1168***	-0.0425***
			(0.0066)	(0.0043)
13			0.1644***	-0.0441***
			(0.0073)	(0.0042)
14			0.1866***	-0.0488***
			(0.0075)	(0.0041)
Female (child gender)			0.0100***	-0.0034***
			(0.0020)	(0.0012)
Child health status (Baseline: very unhealthy)				
somewhat unhealthy				-0.0124
				(0.0153)
somewhat healthy				-0.0298**
				(0.0151)
very healthy				-0.0327**
				(0.0151)
Constant and model stats				
Constant	2.3500***	0.4734***	0.2661***	-0.1546***
	(0.0567)	(0.0294)	(0.0282)	(0.0280)
Observations	7,782	7,782	12,564	11,933
R-squared	0.121	0.044	0.519	0.076

Note: The baseline category of WBP is "no bargaining power".

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Standard errors are clustered at the household level.

Source: Authors' own calculations.

Having full bargaining power and less partial control compared to no bargaining power does not make a difference in significance in how much households allocate to health spending. As far as the other variables are concerned, urban households spend a smaller share on bad goods but allocate a larger share to education compared to their rural counterparts (See Table 2.7). Larger households dedicate a greater share of their budget to food, reflecting increased overall demand. However, they tend to allocate less to education and health, likely due to resource constraints. Spending on bad goods is relatively higher, which may further reduce investment in essential categories such as education and health. Households with older wives allocate slightly less to food, likely reflecting shifts in consumption preferences. These women appear to place greater emphasis on education spending while reducing expenditures on bad goods. Wealthier households (with higher total spending) allocate a smaller proportion of their budget to food and bad goods, and a larger proportion to health. Households with female and older children spend more on education but less on health, while, understandably, less is spent on health if the child is healthier.

To further assess whether the estimated effects reflect age-related expenditure needs rather than bargaining dynamics per se, we examine how health and education expenditure shares vary across children's age groups. Appendix Table A.4 reports the summary of expenditure shares by single-year child age. We observe a noticeable decline in health expenditure shares between ages five and six, which continues until approximately age eight. This pattern is consistent with declining early-childhood medical needs, such as vaccinations and treatment for common early-life illnesses. In contrast, education expenditure shares increase sharply between ages four and five and again between ages six and seven, corresponding to the transition into organized childcare and formal primary schooling. These discontinuities suggest are consistent that age-related institutional and developmental thresholds may play an important role in shaping expenditure allocation.

Motivated by these patterns, we conduct additional analyses using age-restricted subsamples. For health expenditure shares, we estimate the OLS model separately for children aged five and below. Among younger children, the estimated effect of women's bargaining power is slightly stronger than in the full sample, although only full women's bargaining power remains statistically significant. For education expenditure shares, we estimate the model for children aged five and above—those more likely to be enrolled in organized childcare or school—and find stronger and statistically more significant effects compared to the full sample. These results, reported in Appendix Table A.5, are also consistent with the main results reported in Table 2.7, even with the age cut.

To better capture the possibly income-dependent effects of women's bargaining power on spending shares, we compare the average spending shares by bargaining power and income group in Figure 2.1 . Although the estimates are noisy (as reflected by the large confidence intervals), the figures by and large reinforce the results of Tables 2.6 and 2.7. Within relatively lower income households (with income between 5M and 10M) – where spending constraints are more likely to be important – joint decision making is related to the largest food spending without considering less partial bargaining power due to its smallest sample size, followed by no bargaining power, and then by full bargaining power of the mother (Figure 2.1a). In lower-income households, women's absence in decision-making is associated with higher spending on bad goods (Figure 2.1b). A stronger differentiation is observed across bargaining power for education spending shares (Figure 2.1c). In relatively wealthier groups (income in the range 10M-15M), joint decision-making households spend the most on education, while the opposite is true for poorer households (income less than 5M). Health spending share is low across all groups, with greater variation at higher income levels. Interestingly, in mid- and higher-income groups, households with no female power spend more on health, while female-only and joint decision households show consistently lower health shares (Figure 2.1d). Finally, the figure again shows that food and bad goods spending shares are negatively correlated, while education does not show specific patterns across income groups, and child health spending share shows slightly positive, but more stable patterns related to income level. Taken together, these patterns suggest that the association between women's bargaining power and expenditure shares varies across income groups, consistent with income-dependent

Engel effects and potentially reflecting differing budget constraints across the distribution.

Robustness checks

As robustness checks, we estimate alternative specifications that account for the fractional nature of expenditure shares and the prevalence of zero expenditures.

First, we implement a fractional logit model for expenditure shares. Overall, the coefficient estimates reported in Appendix Table A.6 yield findings that are broadly consistent with the main OLS results, with some differences in statistical significance across specifications, but generally exhibiting similar signs to those reported in Table 2.7.

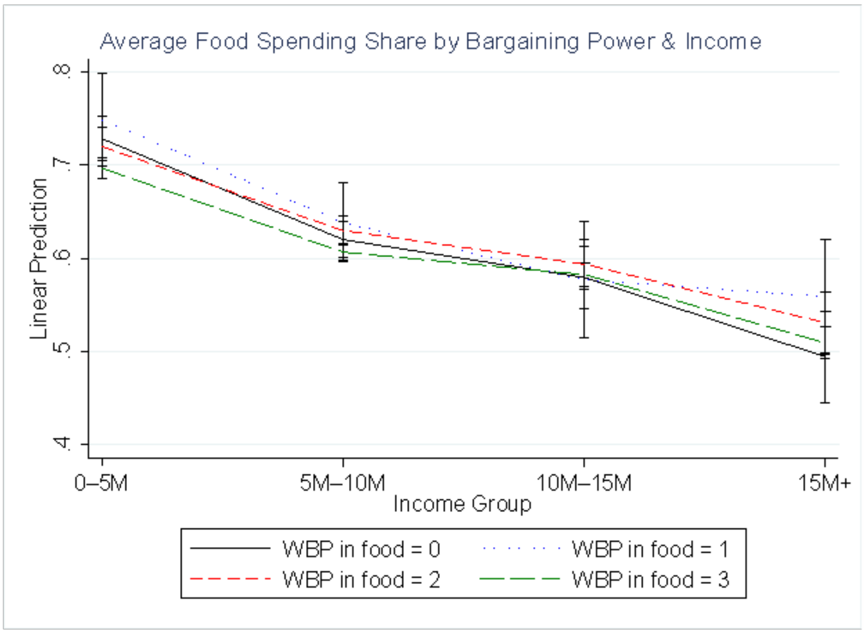
Given the mass of zeros in bad goods, education, and health budget shares, we also estimate a two-part model for robustness. (Since the distribution of food spending share lacks zeros and has a very small number of ones, we only perform these exercises for the other three spending categories.) The first part models the probability of a positive share in the given category using a probit specification. In the second part, conditional on positive spending, we estimate the magnitude of the share using OLS applied to a log transformation of the budget share. The results are found in Appendix Tables A.7 and A.8. The estimated parameters are overall consistent with the baseline findings and do not substantially alter the main conclusion of the paper. For instance, the probit equation for the bad goods yields statistically significant parameters of the same sign as in Table 2.7, while the parameters are not significant – although of the expected sign – in the second part of the model.

2.4 Conclusion and Discussion

This study examines the association between women's intra-household bargaining power and household budget allocation, with particular attention to expenditures

Figure 2.1: Average spending shares by women's bargaining power and income group

(a) Food spending



(b) Bad goods spending

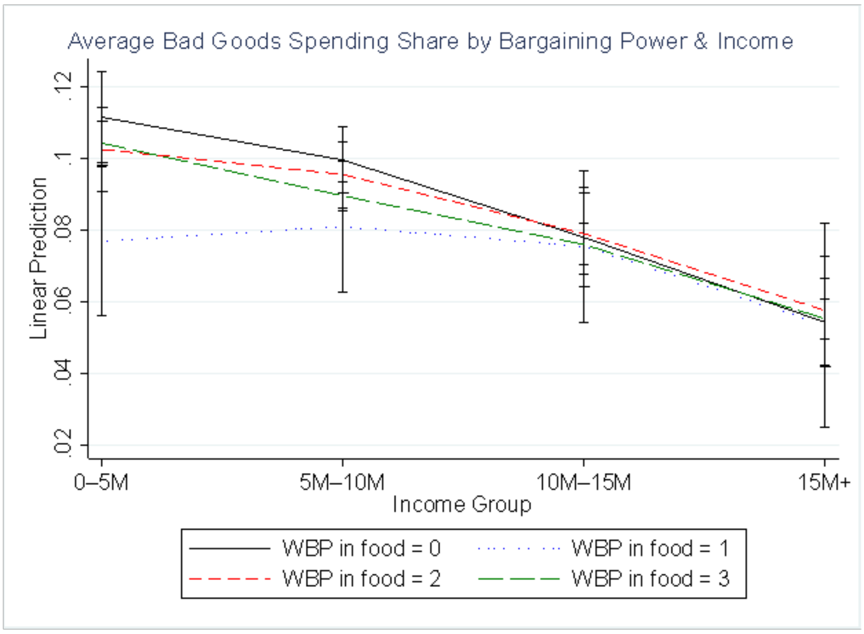
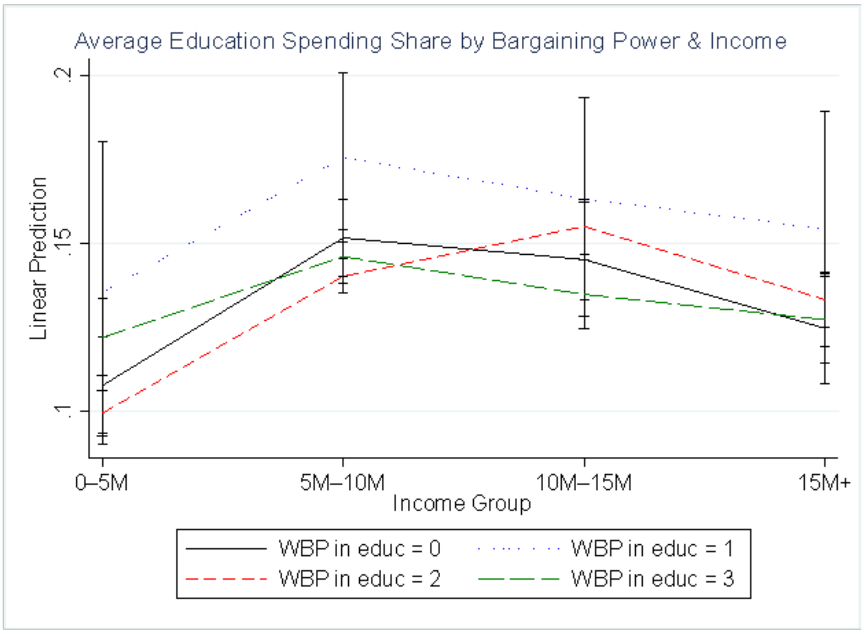
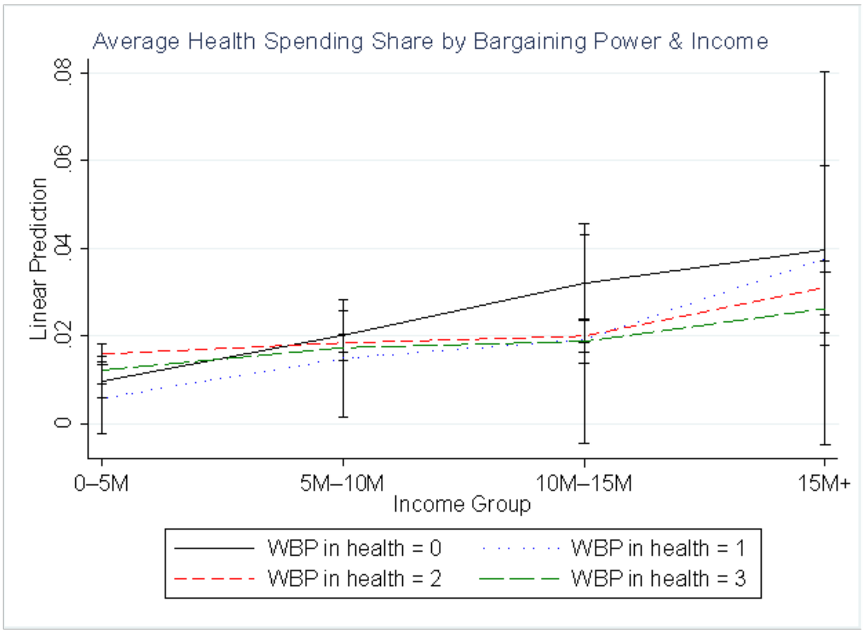


Figure 2.1: Average spending shares by women's bargaining power and income group (continued)

(c) Education spending



(d) Health spending



Note: WBP denotes women's bargaining power in the domains of food, education, and health. The variable is coded as follows: 0 = no bargaining power; 1 = partial (less) bargaining power; 2 = partial (joint) bargaining power; and 3 = full bargaining power. Source: Authors' own calculations.

on food, bad goods, education, and health—key channels through which households invest in child human capital. The effects are heterogeneous across domains of decision-making, particularly between sole and joint decisions with spouses.

Women's bargaining power appears to be positively correlated with education, employment, and urban residence. Socio-economic and demographic characteristics, including income level and household composition, also play a central role in shaping spending patterns. Among middle-income households, joint decision-making over education is associated with higher education investment, indicating potential complementarities in spousal cooperation. In addition, greater women's bargaining power is consistently associated with a lower share of household resources devoted to bad goods, a pattern consistent with shifts toward alternative consumption categories .

Overall, the findings indicate that intra-household bargaining dynamics are systematically associated with the composition of household expenditure. The effects are not uniformly positive across all child-related categories; rather, women's bargaining power appears to be linked to reallocations within the household budget. In particular, while greater bargaining power is associated with lower spending on bad goods, its relationship with education and health shares is negative, suggesting shifts in expenditure composition rather than straightforward increases in all child-related investments. These patterns underscore the importance of distinguishing between absolute expenditure levels and relative budget shares when evaluating household investment behaviour.

Policy relevance

Given the associational nature of the analysis, the policy implications should be interpreted with appropriate caution. Nonetheless, the findings offer policy-relevant insights by highlighting domains in which women's decision-making authority is systematically linked to household investment behaviour. Policies aimed at strengthening women's bargaining position—through legal frameworks, access to education, labour market opportunities, or financial inclusion—may be associated with changes in household expenditure allocation across categories relevant to child development.

The strong association between women's education and bargaining power across decision-making domains highlights female schooling as an important correlate of women's agency and household expenditure allocation, with potential intergenerational implications. Similarly, the patterns observed for joint decision-making suggest that policies promoting educational attainment for both spouses may be associated with more cooperative decision-making over children's schooling, particularly in middle-income households.

Finally, the observed associations for health expenditures point to domains where institutional constraints and access barriers may interact with women's decision-making authority, especially in rural and low-income settings where women's decision-making authority may be more constrained. While causal pathways remain to be established, these patterns point to areas where complementary policy interventions could be explored.

Limitations and Future Research

Several limitations should be acknowledged. First, this study relies on expenditure shares as proxies for child outcomes. In this research, we do not use any specific children's nutrition, education, or health standardized measurement or index for defining the outcome; however, we assume that the main channel to improve children's outcome is through spending on those specific items in the household budget. Future research should incorporate standardized measures to assess actual improvements in child welfare.

Second, the measure of bargaining power is based on self-reported decision-making indicators, which, although grounded in observed behaviour, may be subject to reporting bias and endogeneity.

Third, the analysis, although controls for a rich set of explanatory variables, does not fully address issues of causal identification. Unobserved heterogeneity and omitted variable bias may influence the estimated effects. Future research should seek to exploit exogenous variation – such as legal reforms or natural experiments – to strengthen causal claims and explore heterogeneity across institutional or cultural contexts.

Chapter 3

The Geographic Variations In Utilization of Healthcare Services In China: Evidence From The China Health and Retirement Longitudinal Study (CHARLS)

Abstract:

Background: This study examines the key drivers of geographic variation in healthcare utilization in China among adults aged 45 and older, with a focus on disparities in outpatient and inpatient services. **Methods:** Using nationally representative panel data, I apply econometric techniques, including fixed effects and difference-in-differences models, to analyze regional differences in healthcare use and the role of rural–urban mobility. **Results:** On the demand side, socioeconomic status, health condition, insurance type, gender, and age strongly influence access to care. Rural residents are more likely to use outpatient services, whereas urban residents have a higher probability of inpatient admission. In wealthier regions, inpatient utilization is significantly lower, while outpatient use remains stable. On the supply side, infrastructure capacity also shapes utilization patterns, though demand-side factors play a more dominant role. Migration between rural and urban areas does not independently affect utilization once fixed effects are considered. Instead, economic context, declining self-rated health, and broader temporal trends are the main drivers of increasing outpatient and inpatient use. **Conclusions:** Despite progress from recent health reforms in China, institutional frictions and structural imbalances continue to shape healthcare utilization. To promote equity and efficiency, future reforms should prioritize integrating insurance systems, improving benefit portability, and balancing investments between outpatient and inpatient care.

Key Words: geographic variation, regional variation, CHARLS, China, healthcare utilization, health status

3.1 Background

While extensive research, particularly in the U.S., has documented regional variation in healthcare spending and utilization, the underlying causes—especially the balance between supply-side and demand-side influences—remain contested. International evidence is sparse and mixed, with variations in how decentralization and system structure shape healthcare use. This study addresses this gap by synthesizing and comparing provincial patterns in healthcare variation, offering an understanding of how geographic variation and population characteristics intersect to influence healthcare utilization.

While urban residents in many countries utilize significantly more healthcare than rural populations, this disparity often reflects systemic inequalities rather than differences in health needs. Understanding whether supply-side capacity or demand-side constraints drive these differences is critical for improving equitable healthcare access, especially in the context of decentralizing health systems or designing targeted interventions. China's healthcare utilization patterns reflect both progress and persistent inequality. Outpatient services are becoming more equal across regions and residence types, while inpatient care still reveals structural and geographic disparities not explained by income alone.

This study investigates the determinants of regional variation in healthcare utilization among Chinese adults over 45 years of age, assessing whether such variation contributes to disparities and reflects geographic heterogeneity in service access. Therefore, I have the following research questions:

- What explains geographic (urban/rural or provincial) variation in healthcare utilization and health outcome and how large is the effect of geographic variation among middle-aged and older adults in China?
- How do individual characteristics (e.g., education, insurance, age) and supply-side factors (e.g., provincial health infrastructure) influence healthcare use and health status?
- What is the effect of migration (urban-to-rural or rural-to-urban) on healthcare utilization and health outcomes?

There is a large body of literature on the geographic variation in healthcare utilization in the USA, Switzerland, Canada, Germany, and Japan. The literature offers a lack of insight into provincial level patterns of healthcare utilization in China, so the magnitude of geographic variation remains largely unknown. Whereas certain countries show pronounced regional disparities in access to healthcare services, others exhibit only minimal geographic variation, resulting in relatively uniform patterns of utilization nationwide.

This study makes several contributions. First, I investigate differences in healthcare utilization across provinces and between urban and rural areas. Using panel data, I examine whether utilization is primarily influenced by demand-side (individual) or supply-side factors. Second, I employ multiple outcome measures, including inpatient visits, outpatient visits, and healthcare spending, to capture utilization comprehensively. I also incorporate alternative measures of individual health status and covariates related to health conditions. Finally, I analyze rural-to-urban migration to disentangle the relative roles of supply and demand in shaping healthcare use.

The remainder of the paper is organized as follows. Next, the institutional background on the Chinese healthcare system is presented, followed by current literature and existing empirical studies in different countries. Section 2 explains the methodology and data that are used in this paper. Section 3 discusses the results of this research. Conclusion and discussion are presented in Section 4.

3.1.1 China's Healthcare Reform: Progress and Persistent Challenges

China's healthcare system has experienced major reforms aimed at expanding access and improving quality. Since the 2009 reform plan, which allocated CNY850 billion (US$124 billion), the government has sought to address inequalities, particularly between urban and rural areas, and to ensure basic healthcare for all by 2012 (Z. Chen, 2009; S. Wang et al., 2009). Before the reform, the system faced numerous challenges, including inequitable spending, unaffordable access, limited insurance coverage, inefficient service delivery, and a high reliance on out-of-pocket payments (Z. Chen, 2009; Hsiao, 2004; Hu et al., 2008; W. Yip & Hsiao, 2009).

Following the 2009 reform, notable progress was made. By 2012, over 90% of the population had health insurance coverage. Public health spending increased, particularly in poorer regions, and basic services such as screening and vaccinations became free. An essential medicines list was also implemented in primary care with zero-profit margins (W. C.-M. Yip et al., 2012). From 2000 to 2017, government health spending rose significantly, reducing out-of-pocket payments from 50% to 28%. Insurance enrollment and resource efficiency improved, and some urban–rural health gaps narrowed (Meng et al., 2019; W. Yip et al., 2019).

Despite these advances, challenges persisted—regional disparities, inefficiencies in public hospitals, and rising healthcare costs, high out-of-pocket expenses (Meng et al., 2012; Wagstaff et al., 2009; W. Yip et al., 2019). Furthermore, primary healthcare continues to suffer from low quality, poor chronic disease management, antibiotic overuse, limited workforce capacity, and weak integration with hospitals, contributing to inefficient care and poor outcomes (X. Li et al., 2020; G. Liu et al., 2017). Persistent urban–rural disparities and challenges from urbanization, population aging, and hospital cost control highlight ongoing systemic issues (Jakovljevic et al., 2023).

China faces a rising burden of non-communicable diseases (NCDs), including cancer, cardiovascular diseases, and diabetes, exacerbated by urbanization, aging, unhealthy lifestyles, and environmental risks (P. Gong et al., 2012; He et al., 2005; L. Wang et al., 2005). Although life expectancy has increased, regional disparities in mortality remain, especially in poorer, rural, and polluted northern provinces (Murray et al., 2020; Zhou et al., 2016). Air pollution alone contributes to 10–15% of DALYs in many provinces, particularly affecting respiratory health (Ferrari et al., 2024).

Overall, while China has expanded healthcare access and insurance coverage, significant challenges in quality, equity, and sustainability persist, especially in managing NCDs and strengthening primary care.

3.1.2 Literature Review on Geographic Variation of Healthcare Utilization

A substantial body of literature has explored healthcare spending, particularly in the United States, with a strong emphasis on Medicare expenditures. While this research has yielded significant insights into healthcare costs and utilization, the role of geographic variation remains complex and not fully understood (Skinner, 2011). Geographic patterns in health outcomes are often shaped more by behavioral, socioeconomic, and environmental factors—such as dietary habits and smoking—than by healthcare utilization itself (S. C. Kulkarni et al., 2011).

Regional differences in Medicare spending have drawn particular attention. Y. Song et al. (2010) found that when Medicare beneficiaries moved from low- to high-intensity regions, healthcare utilization increased—reflected by more diagnoses and testing—without improvements in survival, raising concerns about the effectiveness of high-intensity care. Similarly, Clemente et al. (2019) highlighted inefficiencies in Medicare and Medicaid, indicating that higher expenditures do not consistently lead to better health outcomes.

Geographic variation also extends to diagnostic practices. Welch et al. (2011) reported significant differences in the prevalence of chronic disease diagnoses across 366 U.S. hospital referral regions (HRRs). Chandra and Staiger (2007) found that in regions with high treatment intensity, outcomes improved for patients suited to intensive care but worsened for those who were not. Their findings suggest that both supply and demand-side factors—including regional care specialization—drive healthcare utilization.

Finkelstein et al. (2016) estimated that approximately 40–50% of geographic variation in Medicare spending stems from patient characteristics and preferences, while the remainder is attributable to supply-side factors such as physician behavior and healthcare infrastructure. Further, Finkelstein et al. (2021) demonstrated that geographic location significantly influences elderly mortality, highlighting place-based effects on health outcomes.

Physician discretion plays a major role in regional variation. Currie et al. (2016) emphasized that variability in physician decision-making contributes to differences in spending and outcomes. Cutler et al. (2019) similarly concluded that physician beliefs about appropriate care were the most significant factor driving regional variations, whereas patient preferences had a minor role. Supporting this, Baker et al. (2014) attributed 23% of spending variation to supply factors, 12% to patient health and income, and only 5% to patient preferences. Doyle (2011) found that visitors to high-spending regions in Florida experienced lower inpatient mortality, largely due to advanced diagnostic services and teaching hospitals—benefits not observed among local residents.

Studies from other countries offer further context. In Canada, Lavergne et al. (2016) found that healthcare spending variation in British Columbia was largely explained by demographic and socioeconomic factors. Di Matteo and Di Matteo (1998) identified population aging as the primary driver of regional healthcare expenditure variation across Canadian provinces.

In Japan, regional disparities in healthcare utilization are limited due to its centralized healthcare system. Studies by Ibuka et al. (2020), Jin et al. (2022), and Kusunoki and Yoshikawa (2024) found minimal regional variation in general utilization but noted geographic trends in long-term care expenditures, with higher spending in western regions. Conversely, Shirakura et al. (2024) observed significant disparities in inpatient spending among older adults, driven largely by the distribution of healthcare resources.

In Europe, Rabbe et al. (2022) reported that Germany had the highest hospital-driven variation but low overall regional disparities. The Netherlands showed mixed results, while Italy demonstrated high regional variation linked to healthcare access, regional policies, and patient preferences. Giannoni and Hitiris (2002) found that income levels and population aging primarily explained Italian regional disparities, consistent with findings from de Vries et al. (2018) in the Netherlands, where individual demand-side characteristics dominated.

Decentralization has mixed effects. In Spain, Costa-Font and Pons-Novell (2007) found that fiscal competition among autonomous communities increased healthcare spending in certain regions. Similarly, Crivelli et al. (2006) reported that territorial decentralization in Switzerland contributed to spending disparities, while Camenzind (2012) highlighted both demand and supply-side drivers. Reich et al. (2012) identified supplier-induced demand due to specialist density, contributing to higher costs. In Norway, geographic variation remains significant that place-based factors accounted for 50% of healthcare utilization variation, especially among lower-educated individuals (Godøy & Huitfeldt, 2020).

In lower- and middle-income countries, disparities are often driven by socioeconomic inequalities. In India, Banerjee (2021) found a rural–urban gap in healthcare utilization, with higher usage among urban and educated elderly populations. In China, C. H. Gong et al. (2016) and P. Cao and Pan (2024) highlighted the importance of socioeconomic status, urbanization, and insurance type in healthcare access and utilization. Migrants, in particular, face access barriers due to the Hukou system, type of migration and destination (Hou et al., 2019; Mou et al., 2015). Geographic differences in self-rated health were also observed across Chinese provinces, with urban and economically advanced areas reporting better outcomes (Yiengprugsawan et al., 2019).

Overall, the literature shows that geographic variation in healthcare utilization and spending is shaped by a complex interplay of demand-side (patient needs and preferences) and supply-side (provider behavior and system characteristics) factors. While some countries experience high regional disparities driven by decentralization or local policies, others, like Japan and Germany, exhibit more uniform patterns due to centralized governance or systemic regulation. Understanding the balance between these factors is essential for designing equitable and efficient healthcare systems.

3.2 Methods

3.2.1 Data

In this study, I use survey data from the China Health and Retirement Longitudinal Study (CHARLS). The survey offers comprehensive individual-level data on socio-economic and health factors for individuals aged 45 and older. CHARLS features a representative sample encompassing 150 counties/districts and 450 villages/urban communities, reaching between 17,000 and 21,000 individuals across various provinces in each wave (Zhao et al., 2014). The data is panel-structured data with 5 waves. Each wave is conducted at intervals of 2 to 3 years. First wave covers 17708 individuals in 10257 households. In this study, I use individual-level panel data from wave 1 to wave 5 (Zhao et al., 2023). I limit the sample to individuals aged between 45 and 85 years.

3.2.2 Variables

Dependent variables

The main outcome variables in this research refer to how much healthcare is utilized by an individual. The first type of outcome variable is a binary variable that determines whether an individual utilizes outpatient or inpatient care (1 if yes, 0 if no). Inpatient and outpatient utilization were operationalized using two survey items. Outpatient visits were identified based on respondents' reports of having sought or received care from hospitals, health centers, clinics, or individual practitioners within the past month. Inpatient care was measured by whether respondents reported having been hospitalized within the previous year.

The second type of variable is the total number of outpatient and inpatient visits if visited. This shows how many times an individual visits the hospital. The third type of outcome variable is the continuous variable measuring the total healthcare spending on outpatient and inpatient care by an individual. Health spending was assessed through corresponding questions on medical expenditures. For outpatient care, respondents were asked to report the total costs associated with all visits during the past month. Inpatient expenditures were measured by the reported total cost of hospitalizations in the past year. Costs included payments made directly to hospitals—such as ward fees—but excluded non-medical expenses, including wages paid to hired nurses, transportation, and accommodation for patients or accompanying family members.

Price is not adjusted. To avoid high skewness and kurtosis, I use the logarithm of expenditure (defined only for positive values). In addition to healthcare utilization, I include indicators of health status as outcome variables. Health can be measured in different ways thus I use self-reported health status [1] from the survey as a subjective health measure, the presence of chronic diseases such as hypertension and diabetes as self-reported indicators, and the systolic measurement of blood pressure as an objective health measure. However, due to data coverage in the survey, systolic measurements are provided only for the first three waves but not for waves four and five.

Explanatory variables

Independent variables are classified into demand-side and supply-side factors. Demand-side factors include demographic and socioeconomic characteristics (age, categorized into age groups [2]; gender (female = 1, male = 0); educational attainment [3]; marital status (married = 1, unmarried/widowed/divorced = 0); urban/rural residence (see below for the definition); health insurance coverage and other relevant individual attributes. Demand-side factor data is taken from CHARLS survey.

Supply-side factors capture regional healthcare and economic conditions (gross regional product per capita, number of hospital beds per 1,000 population, number of healthcare institutions per 1,000 population, and number of medical personnel per 1,000 population). The supply-side data are collected from the National Bureau of Statistics (NBS) based on provinces and years, which are aligned with wave years in the survey.

[1] Self-reported health status is a categorical variable that is defined 1 as "excellent", 2 as "very good", 3 as "good", 4 as "fair", 5 as "poor" in the data, so smaller values indicate better health.

[2] Age group is a categorical variable consisting of 4 groups (45-55, 56-65, 66-75, 76+ years).

[3] Education status is defined as highest education in the survey. It is a categorical variable including 0 "no formal education", 1 "Elementary/Middle school education", 2 "High school/Vocational/two-three year college education" and 3 "Tertiary education".

Urban and rural areas are defined by the location of residential areas and categorized based on the National Bureau of Statistics (NBS) place of residence [4]. Urban areas include the main city zone (主城区), the combination zone between urban and rural areas (城乡结合区), the town center (镇中心区), the ZhenXiang area (镇乡结合区), and the special area (特殊区). Rural areas include township central (乡中心) and village (村).

According to the Chinese official statistical framework, an urban area consists of city and town districts. The main city zone (主城区) and the combination zone between urban and rural areas (城乡结合区) are part of city districts where residents and municipal governments are concentrated. The town center (镇中心区), the ZhenXiang area (镇乡结合区), and the special area (特殊区) are part of the town districts where seats of county governments and other designated towns (e.g., Special Economic Zones of China) are concentrated. In contrast, rural areas are regions outside urban areas. The township center (乡中心) is the local form of rural government above the village level. Villages (村) constitute the most fundamental unit of rural settlement in China. Based on these spatial connections, the territory is systematically categorized into urban and rural areas.

China's health insurance system comprises multiple schemes, largely determined by employment status and household registration. The main public programs include Urban Employee Basic Medical Insurance (UEBMI) for employed urban residents, Urban Resident Basic Medical Insurance (URBMI) for unemployed urban residents, and the New Cooperative Medical Scheme (NCMS) for rural residents. To address disparities between urban and rural coverage, the Urban and Rural Resident Basic Medical Insurance (URRBMI) was later introduced. In addition to these public schemes, private insurance options are also available. Further details of insurance types are explained in the next Chapter.

[4] https://www.stats.gov.cn/zs/tjws/tjbz/202301/t20230101_1903381.html

3.3 Methods and Results

I employed a combination of pooled Ordinary Least Squares (OLS), individual fixed effects (FE) models, and a difference-in-differences (DiD) specification with an event study design to examine geographical differences and the impact of mobility on healthcare utilization. Stata 18.5 MP is used for the estimation.

3.3.1 Descriptive statistics

Summary statistics are provided in Table 3.1. The dataset examines health service access, inequalities in healthcare costs, and the effects of socioeconomic status on health outcomes, particularly in rural and urban populations. The base sample consists of 93,101 observations. However, for some variables, I have missing observations either due to no response from respondents or because the question was not asked in later waves. (For instance, as previously mentioned, the questions of blood measurement are asked only during the first three waves.) The average age is around 61 years old, and around 52% of the sample is women. Most respondents are married, are rural residents, and have a lower education level. The systolic average in the table is the average of systolic blood pressure readings measured during the interview and at the end of the interview for the purpose of getting a more realistic measurement.

As for the supply-side, medical personnel and hospital beds per 1000 persons are 8 and 4, respectively, with a low standard deviation, while GDP per capita varies significantly due to high GDP per capita areas, such as Beijing, Shanghai, and Tianjin. Across different provinces, the mean GDP per capita is around 51726 CNY, which is approximately 8302 USD [5].

[5] Average 2015 USD -CNY exchange rate (1 USD = 6.23 CNY) from https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=CN

Table 3.1: Summary Statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Outcome variable					
Healthcare utilization					
Outpatients visit probability	92297	0.196	0.397	0.000	1.000
Number of Outpatient visits	93071	0.435	1.456	0.000	37.000
Total Outpatient cost (CNY)	93101	85.606	1200.367	0.000	130000
Inpatient visit probability	92441	0.144	0.351	0.000	1.000
Number of Inpatient visits	92411	0.233	0.950	0.000	150.000
Total Inpatient cost (CNY)	81714	706.333	8809.065	0.000	1400000
Subjective measure of health					
Self-reported health status	.	.	.	.	.
Excellent	89695	0.078	0.268	0.000	1.000
Very good	89695	0.122	0.327	0.000	1.000
Good	89695	0.385	0.487	0.000	1.000
Fair	89695	0.291	0.454	0.000	1.000
Poor	89695	0.124	0.329	0.000	1.000
Objective measure of health					
Hypertension probability	89208	0.297	0.457	0.000	1.000
Diabetes probability	91035	0.088	0.283	0.000	1.000
Systolic average (Hgmm)	40583	129.38	20.278	91.000	213.500
Control variables					
Age group	.	.	.	.	.
45-55	93101	0.343	0.475	0.000	1.000
56-65	93101	0.345	0.475	0.000	1.000
66-75	93101	0.225	0.418	0.000	1.000
76+	93101	0.087	0.282	0.000	1.000
Age	93101	60.803	9.645	45.000	85.000
Female	93095	0.519	0.500	0.000	1.000
Urban	86537	0.292	0.455	0.000	1.000
Education status					
No formal education	92834	0.430	0.495	0.000	1.000
Elementary/Middle	92834	0.440	0.496	0.000	1.000
High school/Vocational	92834	0.121	0.326	0.000	1.000
Tertiary education	92834	0.009	0.092	0.000	1.000
Married	93057	0.865	0.342	0.000	1.000
Insurance type					
No Insurance	88554	0.042	0.201	0.000	1.000
Urban Employee	88554	0.134	0.340	0.000	1.000
Urban Resident	88554	0.046	0.210	0.000	1.000
New Cooperative	88554	0.581	0.493	0.000	1.000

Continued on next page

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Urban and Rural Resident	88554	0.174	0.379	0.000	1.000
Other Insurance	88554	0.022	0.148	0.000	1.000
Wave					
1	93101	0.184	0.388	0.000	1.000
2	93101	0.194	0.395	0.000	1.000
3	93101	0.213	0.409	0.000	1.000
4	93101	0.207	0.405	0.000	1.000
5	93101	0.202	0.402	0.000	1.000
Supply-side variables					
GDP per capita in CNY	80182	51726.639	22374.773	16024	164158
Medical personnel per 1000 persons	80182	7.983	1.498	4.660	15.902
Hospital beds per 1000 persons	80182	4.001	1.022	1.949	6.787
Health institution per 1000 persons	80182	7.466	2.305	2.012	12.016

Notes: Values are reported exactly as provided.

Source: Author's own calculations.

Outpatient visits occur with greater frequency and probability than inpatient visits, though the cost of inpatient care substantially exceeds that of outpatient care. Most individuals in the sample self-report their health as ”good” or ”fair.” The prevalence of hypertension is higher than that of diabetes.

In Figure 3.1, the self-reported health status difference relative to GDP per capita in provinces is presented. I observe that higher GDP per capita provinces show better self-reported health status. For example, Beijing and Shanghai have the highest GDP per capita among the provinces and show much better than average health status.

Figure 3.1: Health status and GDP per capita by provinces.

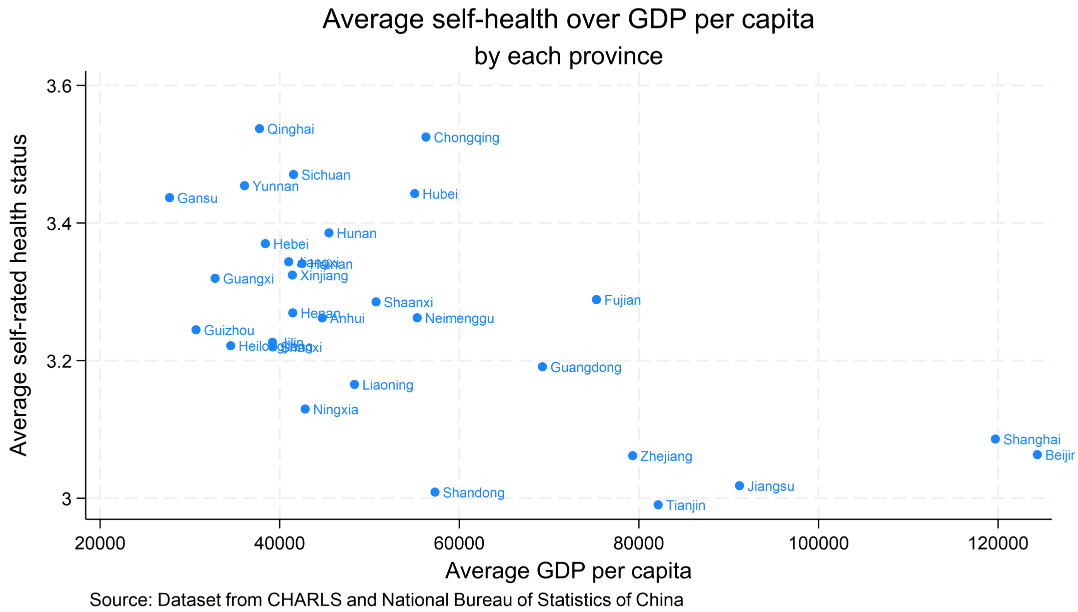


Figure 3.2 illustrates the relationship between provincial GDP per capita and the probability of outpatient visits. As seen in the figure, a mild positive association is indicated that some high-income provinces such as Shanghai, Guangdong, Fujian exhibit high outpatient utilization, while others like Beijing, Zhejiang, Tianjin, Jiangsu show only moderate use. Several middle-income provinces (e.g., Sichuan, Ningxia) also report high outpatient probabilities, whereas poorer provinces such as Guizhou display notably lower utilization.

Figure 3.3 shows the probability of inpatient visits across provinces. In contrast to outpatient care, wealthier provinces (e.g., Beijing, Shanghai, Jiangsu) exhibit relatively low inpatient utilization, while several lower- and middle-income provinces (e.g., Sichuan, Qinghai, Gansu) demonstrate higher rates.

Figure 3.2: Outpatient visit probability and GDP per capita by provinces

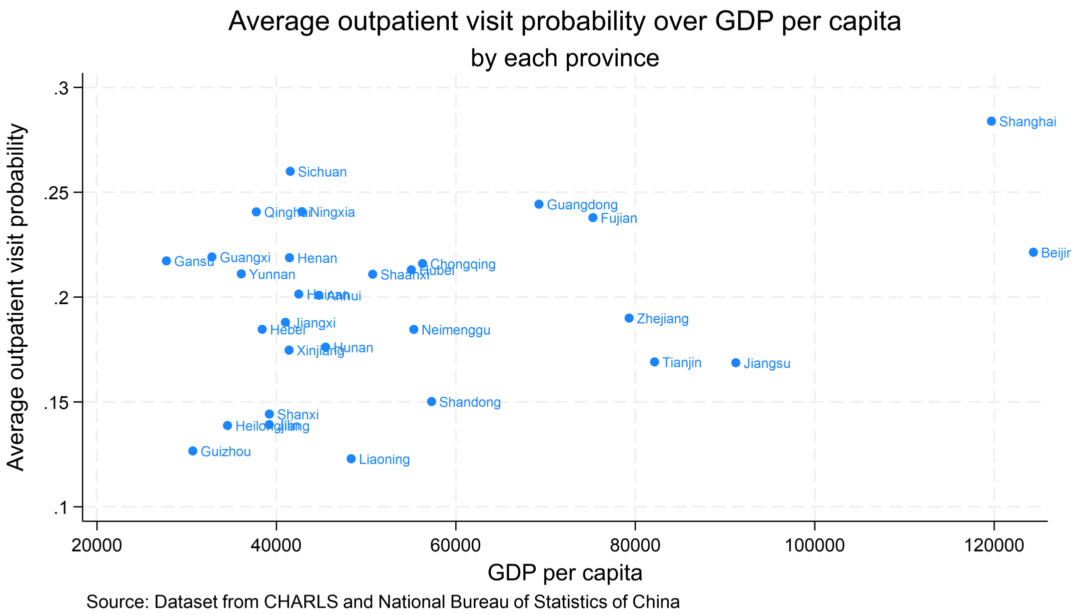
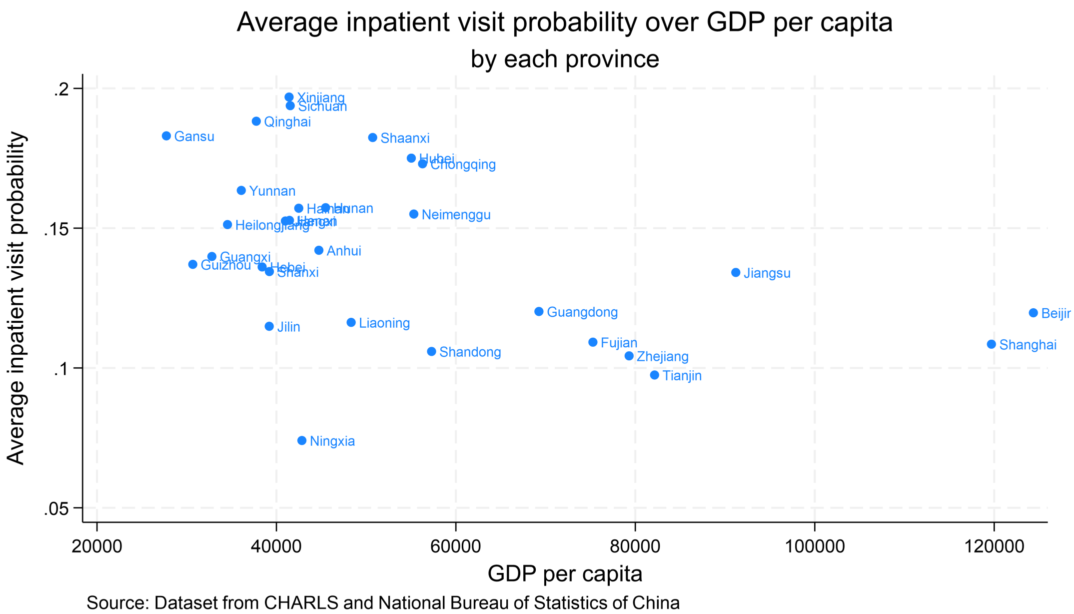


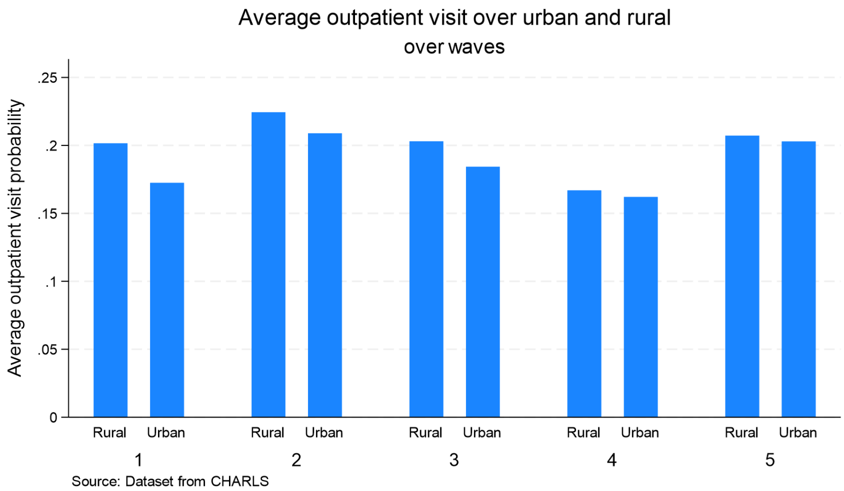
Figure 3.3: Inpatient visit probability and GDP per capita by provinces



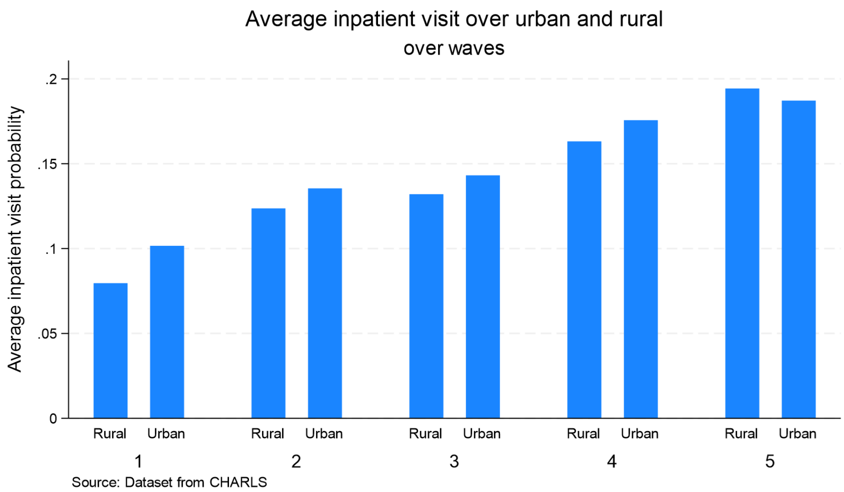
In the data, I further observe that there is a certain difference in healthcare utilization between urban and rural people. Figure 3.4a presents average outpatient visit probabilities by urban and rural residence across survey waves. In the first two waves, rural residents exhibit higher outpatient utilization compared to their urban counterparts. By the third wave, the gap narrows considerably, and in the fifth wave, the two groups converge to similar levels. This pattern suggests that rural residents initially relied more heavily on outpatient care, but over time, urban access improved, and disparities are narrowing. In Figure 3.4b , unlike outpatient care, inpatient utilization has been consistently higher among urban residents across the first four waves. Both rural and urban groups, however, show a steady upward trend in hospitalization probabilities. By the final wave, rural residents surpass urban levels.

Figure 3.4: The comparison between urban and rural areas for outpatient and inpatient visit probability

(a) 4/a



(b) 4/b



3.3.2 Pooled OLS Estimation and Results

I first estimate a pooled OLS model as a baseline specification. The empirical model for pooled OLS is provided as follows, where Y_{it} is the outcome variable for the individual i at time t. X_{it} refers to demographic and socioeconomic characteristics (age, gender, marital status, education, etc.) of an individual. I use standard errors clustered on the province level.

$$Y_{it} = \alpha_i + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_n X_{n,it} + \epsilon_{it} \tag{3.1}$$

According to Table 3.2, log GDP per capita is negatively associated with the self-rated health measure (-0.287***), indicating that individuals in wealthier regions tend to rate their health better. Log GDP per capita is positively associated with the self-reported prevalence of diabetes (0.0229*).

Older individuals (56+ years) report poorer self-reported health status compared to younger individuals. Age is positively associated with hypertension, diabetes, and systolic blood pressure. Older females have higher hypertension prevalence than their male counterparts (positive and significant coefficients). Marital status is negatively associated with systolic blood pressure (-2.547), indicating married individuals may have lower blood pressure.

As for urban and rural residences, urban residents have reported better health. However, urban people have a higher risk of hypertension (0.0364) and diabetes (0.0392). There is a positive association between urban residence and systolic blood pressure (1.067), though the effect size is relatively small. Individuals in later waves (years) report better self-rated health. Higher education is associated with better self-rated health; however, it has no strong effect on hypertension.

Self-rated health is influenced by income, age, gender, education, and urbanization. Objective health outcomes (hypertension, diabetes, blood pressure) worsen with age, and urbanization differences. Marital status and education play minor but notable roles in some health outcomes

Table 3.3 presents regression results examining factors associated with outpatient care and inpatient care utilization using three dependent variables for each; outpatient/inpatient visit probability (binary indicator for whether an individual visited a healthcare facility), outpatient/inpatient visit count (number of visits), and log of outpatient/inpatient cost (cost of outpatient/inpatient care in log form).

Older age groups (56+) have higher outpatient visit probabilities and visit counts. Females are more likely to visit outpatient care and have higher visit counts. Younger women (45–55) use more outpatient services than men, still this aligns with age that women aged 56–65, 66–75, and 76+ are more likely than men of the same age groups to utilize outpatient care, with the gender gap narrowing down at older ages. Later waves show increasing outpatient and inpatient costs, suggesting a rising trend in healthcare expenses over time. Tertiary education significantly increases outpatient visit probabilities (0.0420) but not visit count. Poorer self-rated health is associated with more outpatient and inpatient visits and higher costs.

Compared with the uninsured, all insurance schemes are associated with significantly higher probabilities of outpatient and inpatient visits. However, important differences emerge across types of coverage. Urban Employee Insurance exhibits the strongest effects, with beneficiaries not only more likely to seek care but also to have more visits and substantially higher expenditures, particularly for inpatient services. This suggests both improved access and greater treatment intensity under the more generous employee-based scheme.

Urban Resident Insurance and the New Cooperative Medical Scheme (NCMS) also expand access, as indicated by higher probabilities of both outpatient and

Table 3.2: Association of health indicators with the explanatory variables: OLS regression results.

	Subjective	**Objective health measurements**		
VARIABLES	(1) Self-health	(2) Diagnosed Hypertension	(3) Diagnosed Diabetes	(4) Systolic average
Log GDP per capita	−0.287***	0.0148	0.0229*	−0.572
	(0.0562)	(0.0324)	(0.0120)	(1.108)
Age Group (baseline: 45–55)				
56–65	0.140***	0.0881***	0.0322***	3.292***
	(0.0189)	(0.00656)	(0.00386)	(0.412)
66–75	0.288***	0.163***	0.0484***	6.736***
	(0.0254)	(0.0109)	(0.00793)	(0.586)
76+	0.331***	0.181***	0.0368***	9.530***
	(0.0291)	(0.0164)	(0.00925)	(0.889)
Female	0.165***	−0.0119	0.0110**	−3.786***
	(0.0181)	(0.00929)	(0.00446)	(0.467)
56–65#female	−0.00923	0.0350***	0.0114**	2.590***
	(0.0183)	(0.00964)	(0.00537)	(0.553)
66–75#female	−0.0602**	0.0699***	0.0212*	6.152***
	(0.0251)	(0.0187)	(0.0110)	(0.654)
76+#female	−0.0956**	0.0683***	0.0105	7.826***
	(0.0361)	(0.0228)	(0.0117)	(1.174)
Married	−0.0517***	−0.0177	0.00961*	−2.547***
	(0.0178)	(0.0118)	(0.00554)	(0.600)
Urban	−0.117***	0.0364***	0.0392***	1.067*
	(0.0196)	(0.00799)	(0.00428)	(0.592)
Wave (baseline: Wave 1)				
Wave 2	0.00266	0.00770	0.00279	0.402
	(0.0182)	(0.00610)	(0.00273)	(0.616)
Wave 3	0.00679	0.0550***	0.0173***	−1.968***
	(0.0258)	(0.00917)	(0.00485)	(0.496)
Wave 4	−0.353***	0.0990***	0.0486***	
	(0.0404)	(0.0174)	(0.00881)	
Wave 5	−0.379***	0.00731	0.0185*	
	(0.0461)	(0.0198)	(0.0100)	
Education Status (baseline: No education)				
Elementary/Middle school	−0.0787***	0.00746	0.0116***	−0.342
	(0.0134)	(0.00782)	(0.00411)	(0.347)
High school/Vocational	−0.199***	0.0150	0.0245***	−0.797*
	(0.0217)	(0.0125)	(0.00688)	(0.450)
Tertiary	−0.347***	0.0252	0.0443	−3.897*
	(0.0970)	(0.0515)	(0.0288)	(2.167)
Constant	6.424***	0.00903	−0.241*	135.3***
	(0.578)	(0.334)	(0.125)	(11.25)
Observations	74,829	73,794	75,431	34,353
R-squared	0.084	0.045	0.020	0.062

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: Author's own calculations.

inpatient utilization, but their effects on expenditures are limited. For rural residents covered under NCMS, hospitalization is more common than among the uninsured, yet associated costs do not rise significantly, reflecting reimbursement ceilings and more limited benefit packages. The merged Urban and Rural Resident Insurance (URRBMI) shows a similar pattern: improved access to care, especially inpatient services, but little increase in cost intensity.

Other forms of insurance, which are likely to include commercial or supplementary coverage, are associated with both greater utilization and higher expenditures, similar to the Urban Employee scheme. These findings indicate that while insurance expansion in China has successfully reduced access barriers across all schemes, inequities remain in the depth of financial protection and quality of care. Beneficiaries of the more generous Urban Employee and commercial plans receive more intensive and costly services, whereas those covered by resident- and rural-based schemes experience increased access without comparable improvements in treatment intensity or spending.

Table 3.3: Association of healthcare utilization with explanatory variables: OLS regression results.

	Outpatient care			**Inpatient care**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
VARIABLES	Outpatient visit probability	Outpatient visit count	Log of outpatient cost	Inpatient visit probability	Inpatient visit count	Log of inpatient cost
Log GDP per capita	0.0182	0.0332	0.309**	-0.0268**	-0.0601***	0.494***
	(0.0196)	(0.0587)	(0.148)	(0.00982)	(0.0157)	(0.143)
Age Group (baseline: 45-55)						
56-65	0.0136**	0.0573***	0.0219	0.0292***	0.0569***	-0.0852
	(0.00513)	(0.0158)	(0.0716)	(0.00327)	(0.00798)	(0.116)
66-75	0.0303***	0.0963***	0.0140	0.0705***	0.136***	-0.206*
	(0.00691)	(0.0227)	(0.0940)	(0.00670)	(0.0174)	(0.122)
76+	0.0167**	0.0276	0.0115	0.112***	0.233***	-0.0173
	(0.00771)	(0.0316)	(0.138)	(0.00940)	(0.0253)	(0.136)
Female	0.0558***	0.136***	0.0935	-0.00162	-0.00799	-0.164
	(0.00459)	(0.0131)	(0.0625)	(0.00494)	(0.00907)	(0.142)
56-65#female	-0.0227***	-0.0425	-0.0261	-0.00722*	-0.0182**	0.107
	(0.00614)	(0.0277)	(0.0954)	(0.00377)	(0.00873)	(0.166)
66-75#female	-0.0360***	-0.0966***	-0.200	-0.00630	-0.0181	0.155
	(0.00900)	(0.0286)	(0.128)	(0.00505)	(0.0160)	(0.136)
76+#female	-0.0360***	-0.0533*	-0.176	-0.00897	-0.0454	-0.0110
	(0.0101)	(0.0309)	(0.202)	(0.0116)	(0.0283)	(0.169)

Continued on the next page

VARIABLES	Outpatient care			Inpatient care		
	(1)	(2)	(3)	(4)	(5)	(6)
	Outpatient visit probability	Outpatient visit count	Log of outpatient cost	Inpatient visit probability	Inpatient visit count	Log of inpatient cost
Married	-0.00912	-0.0388	0.0745	-0.00363	-0.00567	0.0560
	(0.00650)	(0.0275)	(0.0671)	(0.00478)	(0.0125)	(0.0813)
Urban	-0.00982**	-0.0250*	0.258***	0.0159***	0.0237**	0.133
	(0.00366)	(0.0137)	(0.0734)	(0.00338)	(0.00893)	(0.0847)
Wave (baseline: Wave 1)						
2	0.0216**	0.0838***	0.400***	0.0460***	0.0859***	0.216**
	(0.00794)	(0.0259)	(0.0675)	(0.00463)	(0.00848)	(0.0983)
3	0.00416	0.0184	0.582***	0.0601***	0.106***	0.252**
	(0.00796)	(0.0283)	(0.0883)	(0.00422)	(0.00652)	(0.104)
4	-0.00735	0.0203	0.833***	0.123***	0.227***	0.489***
	(0.0115)	(0.0356)	(0.107)	(0.00749)	(0.0118)	(0.134)
5	0.0377**	0.120**		0.146***	0.265***	
	(0.0147)	(0.0476)		(0.00795)	(0.0120)	
Education Status (baseline: No education)						
Elementary/Middle school	0.00579	-0.0119	0.160***	0.000813	-0.00840	0.172***
	(0.00538)	(0.0198)	(0.0476)	(0.00403)	(0.00842)	(0.0601)
High school/Vocational	0.0181**	0.0148	0.275***	0.00151	-0.0192	0.202**
	(0.00782)	(0.0322)	(0.0863)	(0.00824)	(0.0180)	(0.0973)
Tertiary	0.0420*	0.00464	0.194	-0.0291*	-0.00552	0.274
	(0.0221)	(0.0805)	(0.356)	(0.0167)	(0.0430)	(0.314)
Self-Health (baseline: Excellent)						

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VARIABLES	Outpatient care			Inpatient care		
	(1)	(2)	(3)	(4)	(5)	(6)
	Outpatient visit probability	Outpatient visit count	Log of outpatient cost	Inpatient visit probability	Inpatient visit count	Log of inpatient cost
Very good	0.0261***	0.0655***	0.158	0.0264***	0.0473***	0.318
	(0.00437)	(0.0148)	(0.174)	(0.00371)	(0.00621)	(0.240)
Good	0.0930***	0.201***	0.174	0.0654***	0.100***	0.309*
	(0.00727)	(0.0220)	(0.173)	(0.00462)	(0.00767)	(0.170)
Fair	0.178***	0.460***	0.409**	0.152***	0.271***	0.462***
	(0.00888)	(0.0298)	(0.168)	(0.00697)	(0.0124)	(0.161)
Poor	0.267***	0.777***	0.776***	0.249***	0.490***	0.721***
	(0.0111)	(0.0433)	(0.178)	(0.00785)	(0.0202)	(0.172)
Insurance type (baseline: No insurance)						
Urban Employee	0.0652***	0.124***	0.373**	0.0744***	0.122***	0.581***
	(0.0109)	(0.0369)	(0.179)	(0.00881)	(0.0189)	(0.132)
Urban Resident	0.0451***	0.0412	0.0614	0.0504***	0.0871***	0.119
	(0.00782)	(0.0285)	(0.209)	(0.00934)	(0.0229)	(0.112)
New Cooperative	0.0474***	0.0645**	-0.182	0.0426***	0.0639***	-0.161
	(0.00597)	(0.0295)	(0.149)	(0.00622)	(0.0123)	(0.137)
Urban and Rural Resident	0.0412***	0.0708**	-0.0288	0.0391***	0.0758***	0.0699
	(0.00695)	(0.0298)	(0.222)	(0.00780)	(0.0161)	(0.162)
Other Insurance	0.0570***	0.138***	0.333*	0.0537***	0.100***	0.432**
	(0.0144)	(0.0437)	(0.190)	(0.0109)	(0.0244)	(0.157)
Constant	-0.206	-0.401	1.470	0.172	0.422**	3.010**
	(0.207)	(0.612)	(1.468)	(0.105)	(0.167)	(1.465)

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VARIABLES	Outpatient care			Inpatient care		
	(1)	(2)	(3)	(4)	(5)	(6)
	Outpatient visit probability	Outpatient visit count	Log of outpatient cost	Inpatient visit probability	Inpatient visit count	Log of inpatient cost
Observations	71,926	72,011	4,946	71,978	71,958	2,075
R-squared	0.042	0.027	0.114	0.065	0.055	0.139

Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: Author's own calculations.

Clear disparities emerge across both urban–rural residence and regional income levels. Rural residents are more likely to use outpatient services, while urban residents have a higher probability of inpatient admission. Without controls in Table 3.4, the rural advantage in outpatient use is about 1.3 percentage points, and the urban advantage in inpatient use about 1.1 percentage points. After adjusting for demographics and socioeconomic factors in Table 3.3, the outpatient gap narrows slightly, whereas the inpatient gap widens to 1.6 percentage points. Urban residents substitute away from outpatient visits, which are costlier in cities, and instead access hospitals even for outpatient needs. In contrast, rural residents depend primarily on local clinics, resulting in lower costs but fewer hospitalizations.

A distinct GDP gradient is also observed. In richer areas, the probability of inpatient visits is significantly lower (–4.5 percentage points without controls; –2.7 with controls), while outpatient utilization remains largely unaffected. However, conditional on use, both outpatient and inpatient costs rise sharply with GDP per capita, indicating that wealthier regions experience fewer but more resource-intensive treatment episodes. This pattern suggests that richer regions experience fewer hospitalizations, likely reflecting better underlying health or greater access to preventive care—yet when treatment occurs, it is considerably more costly.

Table 3.4: Association of healthcare use indicators without the explanatory variables: OLS regression result

VARIABLES	(1) Outpatient visit probability	(2) Inpatient visit probability	(3) Outpatient visit probability	(4) Inpatient visit probability
Log GDP per capita			−0.00400	−0.0447***
			(0.0212)	(0.0115)
Wave (baseline: Wave 1)				
2	0.0251***	0.0429***	0.0270***	0.0534***
	(0.00702)	(0.00462)	(0.00800)	(0.00471)
3	0.00421	0.0515***	0.00668	0.0659***
	(0.00696)	(0.00322)	(0.00826)	(0.00432)
4	−0.0294***	0.0838***	−0.0257**	0.109***
	(0.00714)	(0.00565)	(0.0125)	(0.00780)
5	0.0129	0.107***	0.0160	0.138***
	(0.00843)	(0.00590)	(0.0161)	(0.00867)
Urban	−0.0127	0.0112*		
	(0.00869)	(0.00617)		
Constant	0.199***	0.0823***	0.236	0.551***
	(0.0128)	(0.00619)	(0.222)	(0.122)
Observations	76,795	76,864	79,769	79,865
R-squared	0.002	0.010	0.002	0.012

Robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: Author's own calculations.

Including supply-side variables in Table 3.5 indicates that utilization is not shaped by demand alone. Hospital capacity reduces reliance on outpatient care and may raise inpatient use, while the GDP effect on inpatient visits is the same as in Tables 3.3 and 3.4 with a slight difference. Yet, greater provider or institutional density does not guarantee higher utilization, highlighting the importance of system design, financial protection, and patient behavior. Unlike Finkelstein et al. (2016), where utilization responds strongly to supply shifts, my results suggest that self-reported health status is a stronger driver of service use.

Table 3.5: Adding supply-side factors to the association of healthcare use indicators with the explanatory variables: OLS regression result

VARIABLES	**(1)** Outpatient visit probability	**(2)** Inpatient visit probability
Log GDP per capita	0.000981	-0.0190*
	(0.0173)	(0.0109)
Medical personnel per1000	0.00473	-0.00282
	(0.00682)	(0.00431)
Hospital bed per1000	-0.0262**	0.0121
	(0.0110)	(0.00914)
Health institutions per10000	-0.00242	0.000941
	(0.00327)	(0.00181)
Age Group (baseline: 45–55)		
56-65	0.0132**	0.0294***
	(0.00512)	(0.00326)
66-75	0.0295***	0.0708***
	(0.00685)	(0.00677)
76+	0.0163**	0.112***
	(0.00795)	(0.00934)
Female	0.0559***	-0.00166
	(0.00440)	(0.00488)
56-65#female	-0.0229***	-0.00711*
	(0.00614)	(0.00385)
66-75#female	-0.0357***	-0.00639
	(0.00894)	(0.00515)
76+#female	-0.0362***	-0.00888
	(0.00981)	(0.0117)
Married	-0.00875	-0.00381
	(0.00663)	(0.00475)
Urban	-0.00816**	0.0153***
	(0.00384)	(0.00322)
Wave (baseline: Wave 1)		
2	0.0379***	0.0390***
	(0.00921)	(0.00608)
3	0.0333**	0.0475***
	(0.0126)	(0.00829)
4	0.0431**	0.101***
	(0.0205)	(0.0129)
5	0.0972***	0.120***
	(0.0245)	(0.0141)
Education Status (baseline: No education)		
Elementary/Middle school	0.00702	0.000387
	(0.00510)	(0.00387)

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VARIABLES	(1) Outpatient visit probability	(2) Inpatient visit probability
High school/Vocational	0.0187**	0.00143
	(0.00862)	(0.00792)
Tertiary	0.0430*	-0.0291
	(0.0220)	(0.0175)
Self-Health (baseline: Excellent)		
Very good	0.0255***	0.0266***
	(0.00410)	(0.00393)
Good	0.0924***	0.0656***
	(0.00701)	(0.00465)
Fair	0.178***	0.152***
	(0.00888)	(0.00690)
Poor	0.267***	0.249***
	(0.0111)	(0.00763)
Insurance type (baseline: No insurance)		
Urban Employee	0.0653***	0.0743***
	(0.0106)	(0.00895)
Urban Resident	0.0478***	0.0491***
	(0.00710)	(0.00895)
New Cooperative	0.0470***	0.0427***
	(0.00552)	(0.00598)
Urban and Rural Resident	0.0405***	0.0395***
	(0.00679)	(0.00758)
Other Insurance	0.0569***	0.0538***
	(0.0140)	(0.0110)
Constant	0.0313	0.0693
	(0.180)	(0.114)
Observations	71,926	71,978
R-squared	0.044	0.066

Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: Author's own calculations.

3.3.3 Using movers to understand urban-rural differences

To make an attempt on disentangling demand- and supply-side influences, I implement a mover-based identification strategy. To identify the causal relationship between location of residence and healthcare utilization, I employ a panel-data fixed effects model in a difference-in-differences (DiD) approach:

$$Y_{it} = \alpha_i + \delta_1 Post_{it} \times Treated_{1,i} + \delta_2 Post_{it} \times Treated_{2,i} + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_n X_{n,it} + \lambda_t + \epsilon_{it} \quad (3.2)$$

The main treatment variable is movement between urban and rural areas over the five survey waves. Movement is defined as a change in an individual's urban/rural status between waves, categorized into two groups: urban-to-rural movers ($Treated_1$) and rural-to-urban movers ($Treated_2$), with non-movers serving as the control group. The variable $Post_{it}$ is a binary indicator equal to 1 if individual i has moved by time t. The model includes individual fixed effects (α_i) and time fixed effects (λ_t), with the interaction terms $Post_{it} * Treated_{1,i}$ and $Post_{it} * Treated_{2,i}$ capturing the respective treatment effects.

Because inter-city and inter-province moves were rare and data were limited, location is defined by urban–rural status. For waves 1 and 2, where direct questions on residence were unavailable, urban–rural classification was inferred that wave 2 status was assigned from wave 3 with a question asking location on previous wave, and wave 1 from wave 2, assuming no moves between waves 1 and 2. Thus, mobility is measured across waves 2–3, 3–4, and 4–5. Since clear urban–rural changes occurred between waves 3 and 4, this interval was selected as the treatment period for the fixed-effects (FE) DiD analysis.

The first estimation examines the effect of urban-to-rural and rural-to-urban migration on outpatient visits and inpatient visits, controlling for GDP per capita, wave effects, and health status using a fixed effects (FE) model with DiD specification (See Table 6). As provided in Table 6, both direction migrations do not significantly impact outpatient and inpatient visits. Mobility alone does not predict healthcare use once we account for fixed effects (individual unobserved characteristics) and other controls. This suggests migrants may not adapt quickly to local systems, or that barriers remain in both directions. Across survey waves, both outpatient and inpatient utilization increased, reflecting rising demand for healthcare over time, possibly due to aging, chronic disease prevalence, and insurance reforms. Self-rated health is a robust predictor that those perceiving worse health are much more likely to use both outpatient and inpatient care.

Mobility between urban and rural areas does not independently drive healthcare use once fixed effects are accounted for, whereas economic context, worsening self-health, and broader temporal trends are the main forces behind rising outpatient and inpatient utilization. Even though not statistically significant, the signs of mobility suggest that moving between regions might slightly increase outpatient care while lowering inpatient care. This is consistent with a substitution effect that migrants may rely more on outpatient visits and less on hospitalizations.

Table 3.6: Outpatient and Inpatient Fixed-effect model in DiD with mobility

	(1)	(2)
VARIABLES	Outpatient visit probability	Inpatient visit probability
Post urban-to-rural move	0.0140	-0.0113
	(0.0114)	(0.0107)
Post rural-to-urban move	0.00111	-0.0126
	(0.00953)	(0.0132)
Log GDP per capita	-0.0806	0.0976***
	(0.0504)	(0.0284)
Wave (baseline: Wave 1)		
2	0.0435***	0.0296***
	(0.0105)	(0.00811)
3	0.0356**	0.0310***
	(0.0144)	(0.00955)
4	0.0419	0.0667***
	(0.0261)	(0.0173)
5	0.0883***	0.0833***
	(0.0297)	(0.0199)
Self-Health (baseline: Excellent)		
Very good	0.00828	0.0231***
	(0.00507)	(0.00430)
Good	0.0432***	0.0420***
	(0.00535)	(0.00372)
Fair	0.0907***	0.0917***
	(0.00686)	(0.00514)
Poor	0.143***	0.146***
	(0.00918)	(0.00616)
Constant	0.959*	-1.015***
	(0.527)	(0.296)
Observations	77,756	77,844
R-squared	0.011	0.033
Number of ID	19,831	19,838

Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: Author's own calculations.

Event study

I estimate a two-way fixed effects event-study model to compare the change in healthcare utilization for treated and untreated groups before and after the treatment. The baseline model is given below, where Y_{it} denotes the healthcare utilization for an individual i at time t. The movement occurs between wave 3 and wave 4, I define event time such that wave 3 is the baseline period ($k = 0$). Specifically, event-time indicators D_{it}^{k} equal 1 if individual i is observed in the period t, exactly k periods relative to wave 3, and 0 otherwise. The regression model is given by

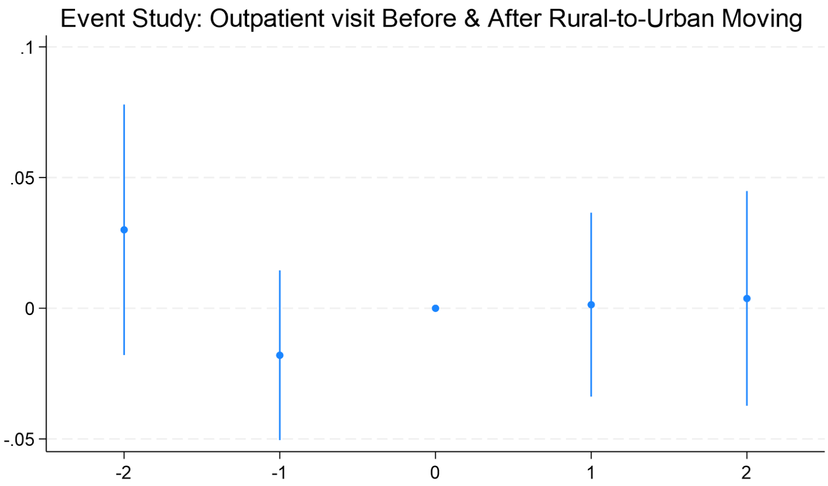
$$Y_{it} = \alpha_i + \lambda_t + \sum_{k \neq -0} \left(\beta_k^{RU} D_{it}^{k} + \beta_k^{UR} D_{it}^{k} \right) + \gamma' X_{it} + \varepsilon_{it} \tag{3.3}$$

where α_i refers to individual fixed effects, λ_t are time fixed effects, and X_{it} refers to control variables in the model. The coefficients β_k^{g} trace the dynamic effects of migration for group $g \in \{RU, UR\}$, capturing deviations in healthcare utilization at event time k relative to the baseline wave 3. Pre-event coefficients ($k < 0$) serve as a test of parallel trends, while post-event coefficients ($k > 0$) capture the adjustment in healthcare utilization following migration.

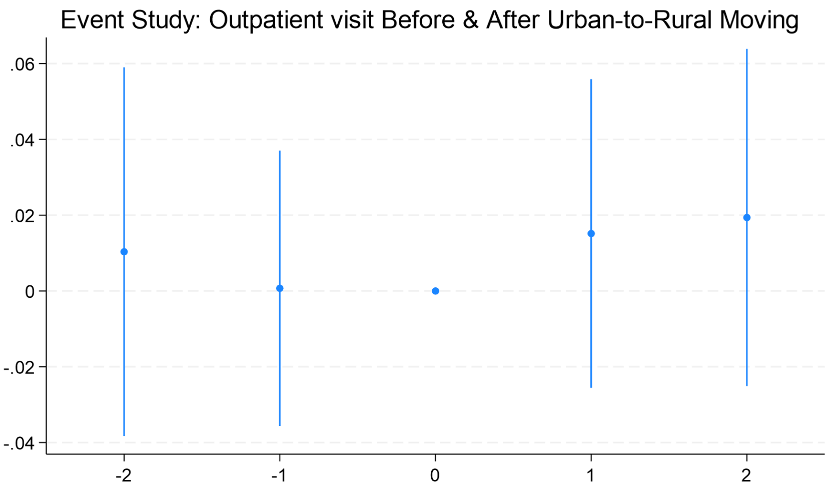
Figure 3.5 presents event-study estimates of outpatient visit probabilities before and after migration. For rural-to-urban migrants, coefficients remain close to zero throughout the pre- and post-move periods, with confidence intervals overlapping zero at all points. This indicates that moving from rural to urban areas does not significantly increase outpatient utilization, despite the expectation of greater healthcare availability in urban regions (Figure 3.5a). Similarly, for urban-to-rural migrants, coefficients are consistently small and statistically insignificant, showing no systematic decline in outpatient use following relocation (Figure 3.5b). Overall, the event-study evidence reinforces the fixed-effects results, highlighting that mobility itself does not generate measurable shifts in outpatient care use. These findings point to structural barriers—such as hukou restrictions, limited portability of health insurance, and entrenched care-seeking habits—that may prevent migrants from altering their healthcare utilization patterns even after relocation.

Figure 3.5: Outpatient visit event study results before and after rural-to-urban and urban-to-rural mobility

(a) 5/a



(b) 5/b

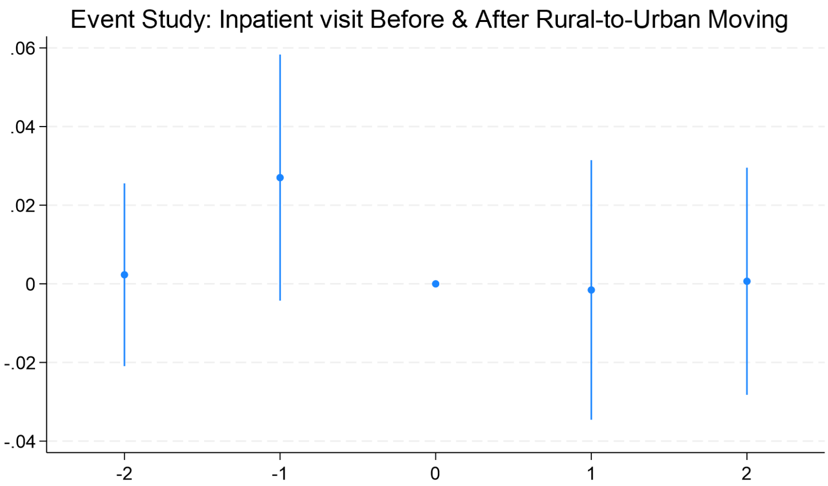


Source: Author's own calculations.

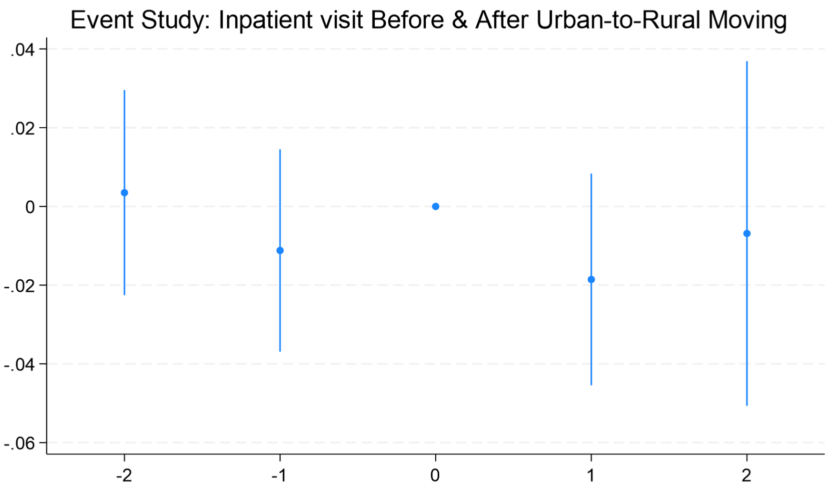
Figure 3.6 presents event–study estimates of inpatient visits before and after migration. For both rural–to–urban and urban–to–rural movers, the coefficients around the migration date remain small and statistically insignificant (Figure 3.6a and 3.6b). The positive, though statistically imprecise, coefficients indicate that movers may have somewhat higher hospitalization needs relative to non-movers prior to migration, but the act of migrating does not appear to generate additional inpatient demand. These findings indicate that household mobility does not significantly alter the likelihood of inpatient care use, consistent with earlier fixed–effects results.

Figure 3.6: Inpatient visit event study results before and after rural-to-urban and urban-to-rural mobility

(a) 6/a



(b) 6/b



Source: Author's own calculations.

3.4 Conclusion and Discussion

The results underscore the importance of considering both demand- and supply-side factors in explaining healthcare utilization. On the demand side, socioeconomic status, insurance type, gender, and age all shape access to care. Wealthier provinces experience lower hospitalization probabilities but higher costs per admission, insurance expands access unevenly across schemes, and gender–age interactions reveal that older women utilize more compared to men, yet the gap is narrowing. On the supply side, the findings indicate that infrastructure capacity also influences utilization patterns. Greater availability of hospital beds is associated with fewer outpatient visits, suggesting a substitution toward inpatient care in settings with stronger hospital capacity. At the same time, the number of medical personnel and health institutions shows no significant effect, indicating that system capacity alone does not automatically translate into greater service use. These patterns suggest that demand-side factors dominate over supply availability in shaping healthcare use.

Extending the analysis to migration, I incorporate mobility indicators for rural-to-urban and urban-to-rural moves in difference-in-differences and event study settings. The coefficients on migration are generally small and statistically insignificant, indicating that relocation itself does not systematically alter healthcare utilization. Neither post-urban-to-rural nor post-rural-to-urban moves are associated with changes in outpatient or inpatient visit probabilities once individual characteristics are controlled for. By contrast, provincial economic context plays a role that higher GDP per capita is positively associated with inpatient utilization, though not with outpatient visits, suggesting that wealthier provinces rely more heavily on hospital-based care. Strong time effects are also evident, with both outpatient and inpatient visit probabilities rising steadily across survey waves. Finally, self-rated health emerges as a powerful predictor of healthcare use. Compared with individuals reporting excellent health, those with poorer self-assessed health are substantially more likely to seek both outpatient and inpatient services. These findings suggest that while mobility per se does not change healthcare use, economic environment, temporal shifts, and individual health needs remain central determinants of service utilization.

There are several limitations associated with this research. The reliance on self-reported health status data may lead to inaccuracies in measuring one's health status in real time. Additionally, the exact location of an individual and tracking of an individual's movement between cities and provinces are limited in the survey. Furthermore, there is less variation observed in the movements. In addition to this, data inconsistencies across all five wave limits the ability to draw causal inferences from the findings. Future research could address these limitations by employing objective location-based data.

These findings carry some policy implications. The absence of large utilization shifts following migration suggests that institutional barriers — including hukou restrictions and the limited portability of health insurance — constrain migrants' ability to adapt to local healthcare supply conditions. Addressing these barriers through greater insurance portability, more equitable reimbursement rules, and targeted investment in primary care would help ensure that mobility translates into meaningful access gains. In addition, strengthening community-based care in urban areas could reduce reliance on hospital-based services and promote more efficient use of resources.

In conclusion, while China's health reforms have expanded access and reduced some disparities, the persistence of institutional frictions and structural imbalances continues to shape healthcare utilization. Future reforms should focus on integrating insurance systems, enhancing portability, and balancing investment between outpatient and inpatient services to promote equity and efficiency in healthcare use across populations.

Chapter 4

The Impact of Change in Health Insurance on Utilization of Healthcare Services in China: Evidence from the China Health and Retirement Longitudinal Study (CHARLS)

Abstract: In 2016, the government initiated a major reform to merge fragmented rural and urban resident schemes into a single program, namely the New Cooperative Medical Scheme (NCMS) and the Urban Resident Basic Medical Insurance (URBMI) into the unified Urban and Rural Resident Basic Medical Insurance (URRBMI). This paper evaluates the effects of the integration on healthcare utilization and rural–urban disparities using panel data from five waves (2011–2020) of the China Health and Retirement Longitudinal Study (CHARLS). The analysis combines pooled OLS regressions, an intention-to-treat (ITT) difference-in-differences framework, and event study models, exploiting Urban Employee Basic Medical Insurance (UEBMI) participants as a control group and NCMS participants in the pre-reform period as the treatment group. Results show no strong differences in utilization between NCMS and urban participants prior to integration, but uninsured individuals were clearly disadvantaged. During the transition period, NCMS participants experienced a temporary decline in outpatient and inpatient use relative to controls, consistent with short-term administrative fric-

tions. By the post-integration period, however, these disparities narrowed, with NCMS participants comparable to UEBMI in both outpatient and inpatient utilization. The findings indicate that the integration contributed to reducing rural–urban disparities in healthcare utilization but has yet to deliver substantial improvements in financial protection.

Key words: Health insurance, healthcare utilization, URRBMI, NCMS, UEBMI, China

4.1 Introduction

China's healthcare system has made remarkable progress over the past few decades, achieving near-universal health insurance coverage that now reaches approximately 95% of its population. This achievement reflects substantial policy innovation and expansion of health insurance schemes designed to provide broader access to medical services. However, despite this progress, significant challenges remain that undermine both the effectiveness of health insurance and the sustainability of the system. In particular, the rapid aging of China's population, persistent urban-rural disparities, rising financial burdens, and the growing prevalence of chronic diseases threaten the long-term viability and equity of healthcare provision.

China is experiencing one of the most rapid demographic shifts in the world. In 2019, nearly 254 million people—approximately 18% of the total population—were over 60 years old. By 2040, this number is projected to rise to 402 million, or 28% of the population (WHO, 2019) [1]. Such rapid aging, combined with a rising prevalence of chronic diseases, places immense pressure on the healthcare system. For policymakers, the financial sustainability of health insurance funds is an urgent concern, as growing demand for long-term and high-cost care strains available resources.

[1]https://www.who.int/china/health-topics/ageing

Alongside demographic pressures, structural inequalities exacerbate health disparities. China's healthcare system has evolved through multiple stages and schemes, including the New Cooperative Medical Scheme (NCMS) for rural residents and the Urban Resident Basic Medical Insurance (URBMI) for urban residents. However, these schemes historically operated separately and were divided along hukou (household registration) lines (H. Chen et al., 2022).

The hukou system has entrenched disparities between urban and rural populations. Research shows that rural hukou holders have substantially higher unmet long-term care needs (Y. Zhu & Österle, 2017) and higher depression rates (Guo et al., 2017). Urban hukou holders, by contrast, generally enjoy better well-being and access to healthcare (Q. Song & Smith, 2019). These differences are strongly linked to socioeconomic status, with income emerging as the dominant factor in healthcare access.

Regional disparities further illustrate this inequality. Health insurance exhibits strong pro-rich tendencies to wealthier provinces, such as Zhejiang, provide significantly better access and outcomes compared to poorer regions like Gansu (Y. Wang et al., 2012). Migrant workers also face structural disadvantages; those with access to urban health insurance report better health outcomes compared to those limited to rural coverage (Fu et al., 2021). Taken together, these findings underscore the urgent need for integration and reform of the hukou-based system to reduce long-term inequalities.

By addressing these challenges, this paper examines the impact of integrating the New Cooperative Medical Scheme (NCMS) and the Urban Resident Basic Medical Insurance (URBMI) into the unified Urban and Rural Resident Basic Medical Insurance (URRBMI). Specifically, this study focuses on how this integration affects healthcare utilization, health outcomes, and the role of insurance in reducing disparities. Thus, the main research questions are as follows:

1. How did the integration of China's health insurance schemes affect healthcare utilization and health outcomes?

2. To what extent did the reform reduce rural–urban disparities in healthcare access and utilization?

3. Did the transition from separate rural and urban schemes to the unified URRBMI create short-term disruptions in utilization during the implementation period?

From these research questions, I propose the following hypotheses:

- **H1:** Health insurance integration increases healthcare access and utilization for rural residents, thereby reducing rural–urban disparities.

- **H2:** Health insurance integration lowers health spending for rural residents.

This study contributes to the literature by providing the longitudinal evidence, using nationally representative panel data and event-study methods, on how the integration of China's health insurance schemes affected healthcare utilization and rural–urban disparities. Methodologically, this study adds to the current literature by applying a difference-in-differences and event-study design, providing robust causal evidence on the effects of China's insurance integration. From a policy perspective, this study demonstrates that while insurance integration narrowed rural–urban disparities in healthcare utilization, it has not yet delivered substantial reductions in financial burden, highlighting the need for complementary reforms.

The structure of the this paper as follows. In the next sub-sections, institutional backgrounds on health insurance, and existing literature are included. In Section 2, data, and variables are provided. Section 3 discusses the methodology and result. The paper concludes with discussion in Section 4.

4.1.1 Institutional background

There are three main health insurance schemes and one newly introduced health insurance scheme in China. Those are Urban Employee Basic Medical Insurance (UEBMI), Urban Resident Basic Medical Insurance (URBMI), New Cooperative Medical Scheme (NCMS), and Urban and Rural Resident Basic Medical Insurance (URRBMI).

Urban Employee Basic Medical Insurance (UEBMI) was started in 1998. This is a mandatory insurance scheme for urban employees and retirees in both public and private sectors. It replaced earlier systems like the Government Health Insurance (GHI) and Labor Health Insurance (LHI). Funding is primarily through payroll deductions, with employers contributing 6% and employees 2% of wages. This scheme offers comprehensive coverage with higher reimbursement rates, ensuring urban workers have access to necessary medical services.

Compared to UEBMI, Urban Resident Basic Medical Insurance (URBMI) is a voluntary health insurance for people who are unemployed but live in urban areas. Introduced in 2007, the URBMI targeted urban residents who are not eligible for UEBMI, such as children, students, non-working and self-employed urban residents, elderly employees in informal sectors, and immigrants from rural areas. Similar to the NCMS, it was a voluntary, government-subsidized scheme with individual contributions. By 2010, it had achieved nationwide coverage. The URBMI provided basic medical coverage, but often with higher co-payment rates and lower reimbursement compared to UEBMI.

The New Rural Cooperative Medical Scheme (NCMS) is a voluntary health insurance for rural residents who were not covered by UEBMI. This insurance is mainly funded by central and local governments, with participants contributing a nominal amount. By 2008, over 91% of the eligible rural population had enrolled. The main purpose of NCMS is to reduce the financial burden of healthcare for rural communities, though it often had lower pooling funds and reimbursement rates compared to urban schemes.

Urban and Rural Resident Basic Medical Insurance (URRBMI) is a new type of health insurance scheme for those who live in either rural or urban areas. This insurance was introduced in 2016 by the government to lower the disparity between the benefits of rural and urban citizens' insurance. In 2016, to address disparities between urban and rural healthcare access, China integrated the NCMS and URBMI into the URRBMI. This unified scheme aims to standardize benefits and reduce inequities, offering a more extensive risk pool and improved fund allocation. A summary of the insurance types affected by the reform is given in Table 4.1. The comparison between each insurance is provided in Table 4.2 [2] [3].

Table 4.1: The affected insurance types by the reform.

Before the integration	**After the integration**
UEBMI (Urban Employee Basic Medical Insurance)	**UEBMI** (Urban Employee Basic Medical Insurance)
URBMI (Urban Resident Basic Medical Insurance)	**URRBMI** (Urban and Rural Resident Basic Medical Insurance)
NCMS (New Cooperative Medical Scheme)	

[2] https://english.www.gov.cn/policies/latest_releases/2016/01/12/content_281475270798428.htm

[3] https://www.commonwealthfund.org/international-health-policy-center/countries/china

Table 4.2: Comparison of Health Insurance Schemes in China

Insurance Type	**UEBMI (Urban Employee Basic Medical Insurance)**	**URBMI (Urban Resident Basic Medical Insurance)**	**NCMS (New Cooperative Medical Scheme)**	**URRBMI (Urban and Rural Resident Basic Medical Insurance)**
	Permanent	Integrating into URRBMI	Integrating into URRBMI	New unified insurance type
Introduction year	1998	2007	2003	2016
Mandatory/Voluntary	Mandatory	Voluntary	Voluntary	Voluntary
Premiums	Employer/employee payroll	$<1\%$ of disposable income	~200 CNY/year	CNY 350/year
Eligibility	Urban employees (including retirees)	Urban non-employed	Rural residents	Unified: rural and urban non-employed (merged URBMI and NCMS)
Coverage (2018/2022)	316.8m (2018)	897.4m (2018)		983 million (2022)
Financing	Payroll + minimal gov't fund	Pooling fund (Individual (minimal) + local government fund)	Government subsidies + individual	Public funding + premiums
Key Issues	Limited to the employed	Fragmented; urban focus	Rural focus, low benefits	Improved integration, but disparities remain

Source: Table 1 is compiled based on different sources (Y. Cao et al., 2023; X. Liu et al., 2016; J. Zhang et al., 2024; K. Zhu et al., 2017)

4.1.2 Literature review on Health insurance integration in China

Studies on the impact of the integration into new insurance schemes on health outcomes and healthcare utilization have been studied extensively recently. Various research uses various types of data in this. Current studies address inequality between urban and rural, socioeconomic, and gender. From pension to insurance integration, economic factors are critical to health outcomes. The results of the integration of newly introduced health insurance on health outcomes and healthcare utilization are mixed.

A. Zhang et al. (2017)'s study shows that health insurance increases healthcare utilization. Specifically, Urban Employee Basic Medical Insurance (UEBMI) and Urban Resident Basic Medical Insurance (URBMI) improve inpatient service utilization (G. Fan et al., 2020). Studies of Yang et al. (2016) and Huang and Wu (2020) highlight positive outcomes, such as reduced hospitalization costs and increased utilization of inpatient services. With health insurance integration (Huang & Wu, 2020) and reforms (X. Chen et al., 2022) significantly improved access to inpatient and outpatient care. Ren et al. (2022) also highlights that integration of URRBMI improves outpatient access. Integration was positively associated with self-rated health and negatively associated with depression among middle-aged and elderly rural adults (Ye & Wang, 2023). Integration of health insurance increases outpatient and inpatient visits for rural residents and improves the impact of inpatient visits on health equity, but does not necessarily improve the impact of outpatient care (J. Li et al., 2019). In X. Fan et al. (2021) study, integrated health insurance increased inpatient care utilization, but did not decrease outpatient care visits.

On the other hand, issues like high out-of-pocket expenditure and inefficiencies persist. Insurance helped narrow disparities but could not fully offset gaps rooted in socioeconomic factors, rural-urban divides, and childhood circumstances (Mitra et al., 2020; Smith et al., 2014; Yan et al., 2020). Insurance mitigated financial strain and allowed better management of health-related work declines, but its influence varied by gender and location (Mitra et al., 2020). There are disparities in healthcare utilization between different health insurance schemes. For example, UEBMI provides the best healthcare services with high reimbursement (Z. Wang et al., 2018), URRBMI does not fully eliminates these disparities (Z. Wang et al., 2019).

Healthcare utilization improvements were often more pronounced in rural or economically disadvantaged populations. Regional disparities still persist even after the integration of the new insurance (Ren et al., 2022). Inequalities in healthcare service usage still persist (G. Fan et al., 2020). While integration helped reduce the outpatient care, disparities in inpatient care even widened after the integration. While health insurance reduced financial barriers and facilitated better disease management (H. Chen et al., 2022; Smith et al., 2014; Yan et al., 2020), its direct impact on broader health outcomes (e.g., mortality, cognitive decline) was mixed due to persistent inequities. Huang and Wu (2020) study also finds limited effects of integration on health outcomes.

While prior studies have examined related questions, they have relied on heterogeneous methodological approaches and often lacked a rigorous causal identification strategy. In contrast, this paper applies causal inference techniques specifically Pooled OLS and a Difference-in-Difference (DiD) framework supplemented with an event-study design, to more robustly estimate the effects of the policy.

Existing research has also been constrained by relatively small samples and limited temporal coverage. To address these limitations, I construct a dataset with a broader scope and an extended study period. This allows for a more detailed examination of dynamic effects by distinguishing the pre-policy, transition, and post-policy periods.

Despite several papers exploring related themes, important gaps still remain in understanding how the policy affects health outcomes, healthcare utilization, and financial burden. This study contributes to the literature by addressing these gaps through a comprehensive dataset and a consistent causal framework.

4.2 Data and Variables

4.2.1 Data

The data used in this research are derived from the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative panel dataset spanning the period from 2011 to 2020. CHARLS collects detailed information on the demographic, social, and economic characteristics of individuals across various provinces in China. The dataset comprises five waves of surveys (Zhao et al. 2023o: 5) (Zhao et al., 2023) . For the purpose of this analysis, individuals aged below 45 years and above 85 years were excluded.

The dataset contains approximately 90,000 individuals from the survey between wave 1 and wave 5. Table 4.3 provides the summary statistics of pre-, transition, and post-reform periods.

Table 4.3: Summary statistics

Variable	**Pre (waves 1–3)**	**Transition (wave 4)**	**Post (wave 5)**
N (all participants)	55,028	19,232	18,841
Age, years – mean (SD)	59.751 (9.645)	61.68 (9.593)	62.982 (9.236)
Age group, n (%):			
45–55 years	37.6%	33.1%	25.6%
56–65 years	35.5%	31.8%	34.4%
66–75 years	19.3%	25.3%	29.2%
≥76 years	7.6%	9.8%	10.8%
Gender, n (%):			

Continued on next page

Table 4.3: Summary statistics (continued)

Variable	**Pre (waves 1–3)**	**Transition (wave 4)**	**Post (wave 5)**
Male	48.6%	47.6%	47.3%
Female	51.4%	52.4%	52.7%
Marital, n (%):			
Not married	12.8%	14.1%	15%
Married	87.2%	85.9%	85%
Education level, n (%):			
No formal education	43.4%	42.8%	42.2%
Elementary/Middle	43.6%	44.4%	44.7%
High school/Vocational	12.1%	12%	12.3%
Tertiary education	0.9%	0.8%	0.8%
Hukou, n (%):			
Agricultural hukou	76.8%	76.8%	74.4%
Non-agricultural hukou	22%	21.3%	15%
Unified residence	1.1%	1.9%	10.5%
Do not have hukou	0	0	0
Urban status, n (%):			
Rural – 0	76.2%	71.1%	63.2%
Urban – 1	23.8%	28.9%	36.8%
Insurance, n (%):			
No Insurance	4.6%	2.9%	4.6%
Urban Employee	12.7%	14.4%	14.2%
Urban Resident	4.8%	4.2%	4.4%
New Cooperative	74.1%	64.5%	9.0%
Urban and Rural	1.5%	12.1%	65.5%
Other Insurance	2.4%	1.9%	2.3%
Wave			
1	31.2%	0	0
2	32.8%	0	0
3	36%	0	0
4	0	100%	0
5	0	0	100%
Outcome Variable:			
Self-Health			
Excellent – 1	5.1%	11.7%	12%
Very good – 2	11.9%	12.6%	12.7%
Good – 3	31.5%	47.4%	50.5%
Fair – 4	35.6%	20.7%	18.1%
Poor – 5	15.9%	7.6%	6.7%

Continued on next page

Table 4.3: Summary statistics (continued)

Variable	**Pre (waves 1–3)**	**Transition (wave 4)**	**Post (wave 5)**
Healthcare Utilization, mean (SD)			
Probability of outpatient visit	0.203 (0.402)	0.165 (0.372)	0.206 (0.404)
Number of outpatient visit	0.452 (1.480)	0.364 (1.377)	0.458 (1.460)
Total cost of outpatient visit (RMB)	100.332 (1183.598)	127.337 (1719.726)	–
Total cost of outpatient visit (log)	5.727 (1.505)	6.242 (1.447)	–
Probability of inpatient visit	0.120 (0.325)	0.167 (0.373)	0.192 (0.394)
Number of inpatient visit	0.186 (0.648)	0.277 (1.373)	0.325 (1.133)
Total cost of inpatient visit (RMB)	630.719 (6317.412)	1561.141 (16007.908)	–
Total cost of inpatient visit (log)	9.082 (1.278)	9.439 (1.254)	–

Notes: Values are mean (SD) or n (%). Ns may vary by variable due to missing data. Insurance information was available for around 88,000 observations.

4.2.2 Variables

The primary variables of interest are healthcare utilization, health outcomes, health insurance, and urban–rural status, with demographic and socioeconomic characteristics as controls. The dataset and operational definitions (e.g., urban–rural status, insurance type) are consistent with those used in another manuscript I have prepared using the same data source in the previous chapter (See Chapter 3). The present analysis addresses a different research aim, focusing on the impact of health insurance reform, and therefore does not overlap in research questions or conclusions.

Healthcare Utilization and Health Outcomes

Healthcare utilization is considered one of the dependent variables in this study. It is measured by probability of outpatient and inpatient visits (dummy), number of visits if used (counts), and expenditures for outpatient and inpatient visits (continuous). This measurement is consistent with prior literature (Diehr et al., 1999; G. Fan et al., 2020; C. Li et al., 2019; Z. Wang et al., 2019). Self-reported health status of an individual is used to measure the health outcomes. Self-reported health is categorized as excellent, very good, good, fair, and poor.

Health Insurance

Health insurance status is grouped into six categories: UEBMI, URBMI, NCMS, URRBMI, other insurance, and no insurance. The analysis focuses specifically on URBMI, NCMS, and URRBMI, while UEBMI serves as a control.

Urban–Rural Status and Hukou

Urban–rural status is measured in two ways. First, it is defined by residential location (main city, combination zone, special zone, township center, or village). Second, I additionally incorporate hukou status, classified as agricultural hukou, non-agricultural hukou, unified hukou, and no hukou. Hukou reflects a stable institutional registration system tied to access to social benefits, including health insurance. The hukou system (household registration system) is a central institutional framework in China that has historically regulated population mobility and access to resources. Established in the 1950s, the hukou system classifies citizens according to both their place of registration and their registration type, typically urban or rural (Chan & Zhang, 1999). This dual structure has created a formal boundary between urban and rural populations, linking individuals' hukou status to their entitlement to public services such as education, healthcare, housing, and social welfare. As a result, rural residents migrating to cities often face institutional barriers to full integration, even when they contribute significantly to the urban labor force. Z. Liu (2005) and Wu and Treiman (2007) emphasize that the hukou system not only shapes migration patterns, but also reinforces disparities in income, education, healthcare access, and intergenerational mobility. Due to its strong correlation with insurance type, hukou is not included in later regression models (Pooled OLS and DiD) to avoid multicollinearity.

Demographic and Socioeconomic Controls

Age, gender, education level, and marital status are included as controls in the estimation. Education is grouped into four categories (No formal education, Elementary and Middle education, High school and Vocational education, and Higher education), and marital status is classified as married versus not married (including separated, widowed, and divorced).

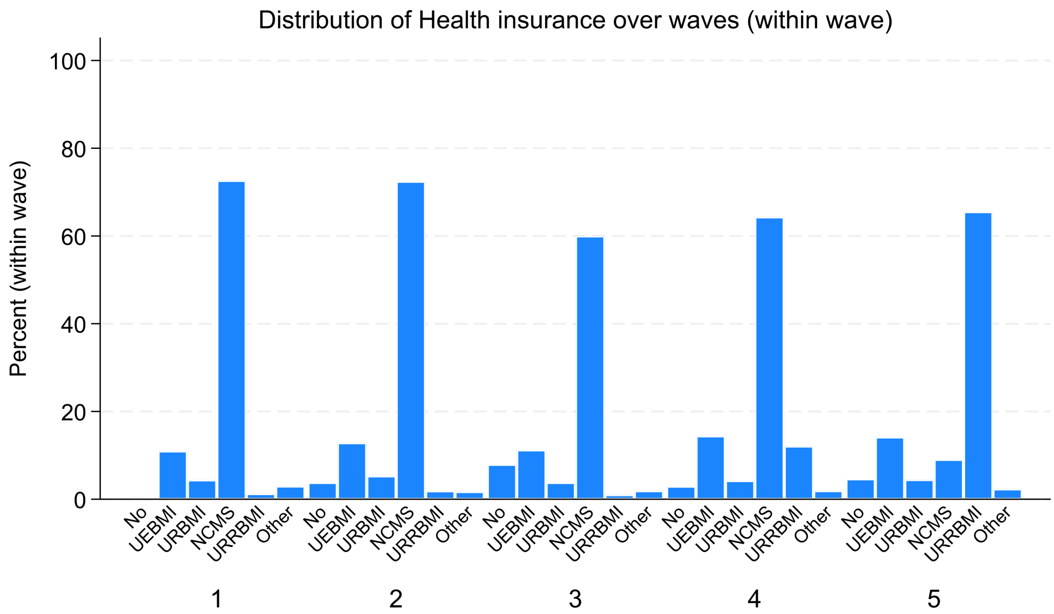
4.3 Methods and Results

4.3.1 Descriptive Statistics

Descriptive analyses are presented below, revealing significant temporal variations in health insurance coverage across waves. Figures further illustrate differential patterns between urban and rural populations, alongside distributions stratified by hukou status. Moreover, the analysis reveals notable differences in outpatient and inpatient service utilization between the pre- and post-reform periods of the health insurance system.

Figure 4.1 presents the distribution of health insurance coverage across the five survey waves. Prior to the reform period (waves 1–3), the majority of respondents were enrolled in either the New Cooperative Medical Scheme (NCMS) or the Urban Resident Basic Medical Insurance (URBMI), with relatively small shares in the Urban Employee Basic Medical Insurance (UEBMI), other insurance categories, or no insurance. Starting in wave 4, the Urban and Rural Resident Basic Medical Insurance (URRBMI) emerges as a major program, reflecting the policy integration of NCMS and URBMI into a unified scheme.

Figure 4.1: Health insurance distribution by wave



Source: Author's own calculations.

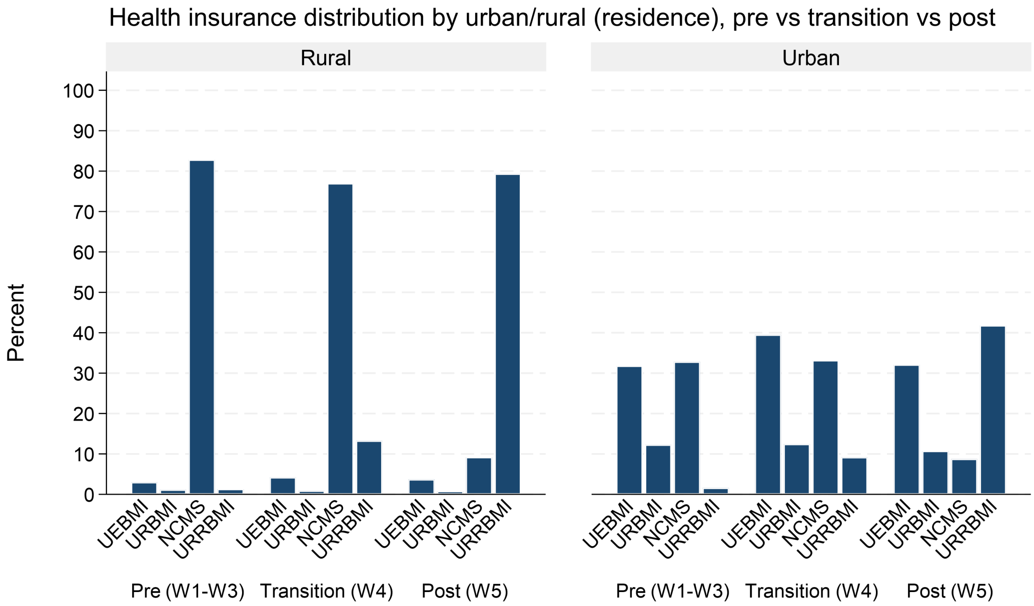
As expected, the share of respondents in URRBMI rises sharply in waves 4 and 5, while participation in NCMS declines substantially. However, the two schemes, NCMS and URBMI, do not disappear entirely from the data after the reform. A small proportion of respondents continue to report coverage under NCMS or URBMI in wave 4 and 5, which may reflect administrative lag in implementation, local variation in policy rollout, or reporting inconsistencies. Likewise, a small number of individuals report URRBMI even before wave 4, which likely corresponds to pilot programs or early adopters prior to the full integration.

Overall, the figure captures the transition from fragmented insurance schemes (NCMS and URBMI) toward a unified URRBMI system, while also illustrating that institutional reforms may take time to fully eliminate earlier schemes in practice.

Figure 4.2 presents the distribution of health insurance schemes by urban–rural residence, distinguishing pre-integration (W1–W3), the transition period (W4), and post-integration (W5). The integration of NCMS and URBMI into URRBMI was announced in 2016, meaning Wave 4 (2018) reflects a transition period. During this time, both the old and new schemes coexisted, and thus insurance distributions changed little compared to previous waves. For this reason, Wave 4 is treated as a transitional phase in the graph separately, with substantive post-integration changes more clearly observed in Wave 5.

Prior to 2016, during the Wave 1-3, the rural coverage was dominated by NCMS pre-reform (80%), with URRBMI nearly absent. Post-reform by Wave 5, URRBMI expands to about 80% of rural coverage as NCMS declines markedly. Urban residents, in contrast, exhibited a more fragmented distribution, with substantial shares in URBMI, UEBMI, and NCMS prior to integration. UEBMI remains stable while URRBMI grows substantially in the post-reform period. Small shares of URBMI/NCMS persist after the reform. During the transition period in Wave 4, NCMS still dominated among rural residents, along with a small share of increasing URRBMI, while in urban areas, there is a slight increase in the share of URRBMI, while others remain stable.

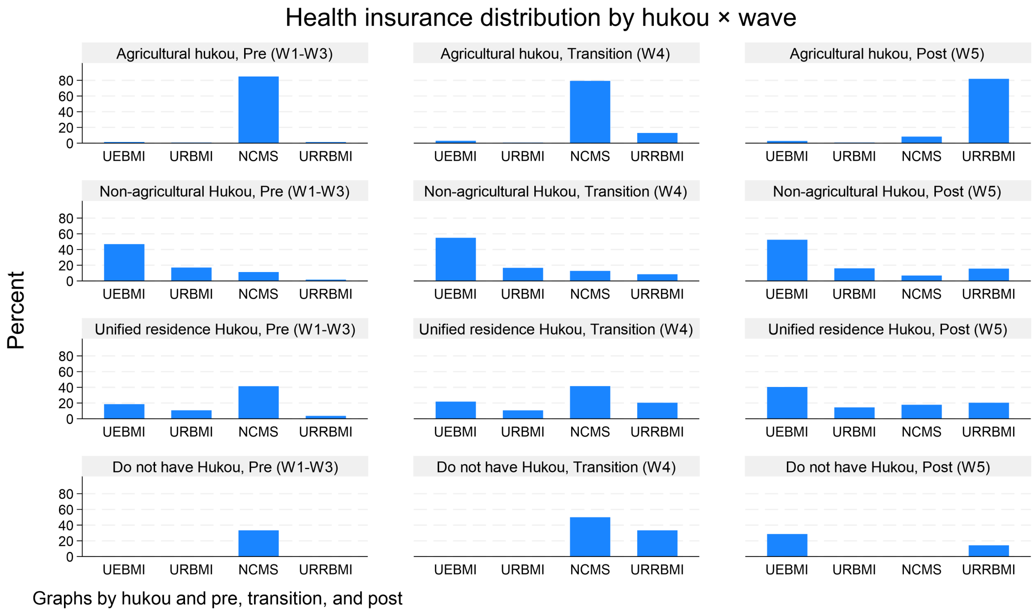
Figure 4.2: Health Insurance distribution by urban and rural (residence), pre vs transition vs post



Notes: "Other insurance" and "No insurance" categories (5% combined) are omitted for clarity. Thus, the sum is not exactly 100%. Appendix includes the full distribution with "No" and "Other" for further detail (see Figure A.2). Source: Author's own calculations.

Across waves and hukou status in Figure 4.3, the graphs clearly show how China's health insurance reform shifted coverage patterns by hukou type. For agricultural hukou, the pre-reform period (W1–W3) is dominated by NCMS, with little presence of other schemes. By the transition wave (W4), URRBMI starts to appear, and by the post-reform wave (W5), NCMS shrinks while URRBMI grows, reflecting the merger of schemes. Among non-agricultural hukou, UEBMI is consistently the largest program across all waves, but URBMI declines over time as URRBMI takes its place. For those with a unified residence hukou (a reclassified group emerging under reform), coverage is more mixed, but again, URRBMI becomes increasingly important post-reform. Even people who lack hukou relied heavily on NCMS before reform, but over time, they also moved into URRBMI. In short, the wave-by-wave breakdown reveals that the reform did not happen instantaneously that coverage gradually shifted from fragmented schemes (NCMS, URBMI) toward a unified URRBMI, with UEBMI remaining dominant for formal urban workers.

Figure 4.3: Health Insurance distribution by urban and rural (hukou), pre vs transition vs post



Source: Author's own calculations.

The two graphs (Figure 4.4 and Figure 4.5) highlight distinct patterns in outpatient and inpatient utilization across insurance schemes before and after the reform. Outpatient visits show relatively small differences between schemes, with all groups clustered around similar levels pre-reform, a temporary dip during the transition, and a rebound post-reform. This suggests that outpatient services were broadly accessible even under fragmented programs, and the reform mainly stabilized rather than dramatically altered usage. In contrast, inpatient visits reveal sharper disparities. Prior to reform, UEBMI members consistently exhibited higher hospitalization rates, reflecting the scheme's stronger financing and more generous inpatient coverage, while NCMS participants had much lower utilization. Following the consolidation of NCMS and URBMI into URRBMI, inpatient visits rose across the board, particularly for rural and informal populations, narrowing the gap with UEBMI. Taken together, the results indicate that the reform had its greatest equalizing effect in access to inpatient care, where the original benefit differences between UEBMI and NCMS were most pronounced.

Figure 4.4: Mean outpatient visit by health insurance types over waves (pre vs transition vs post)

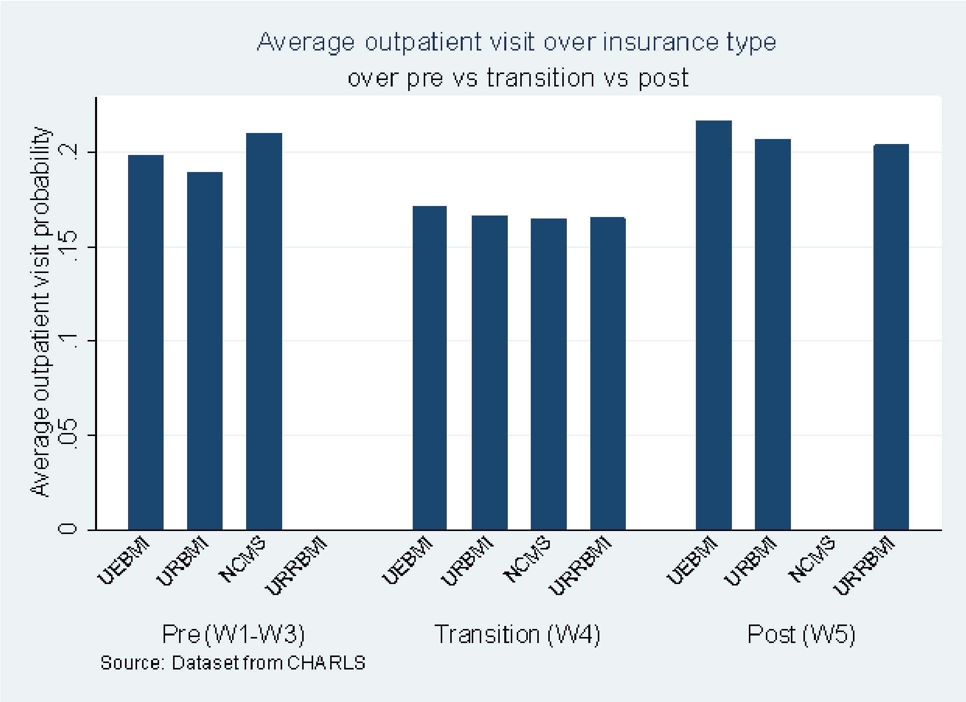
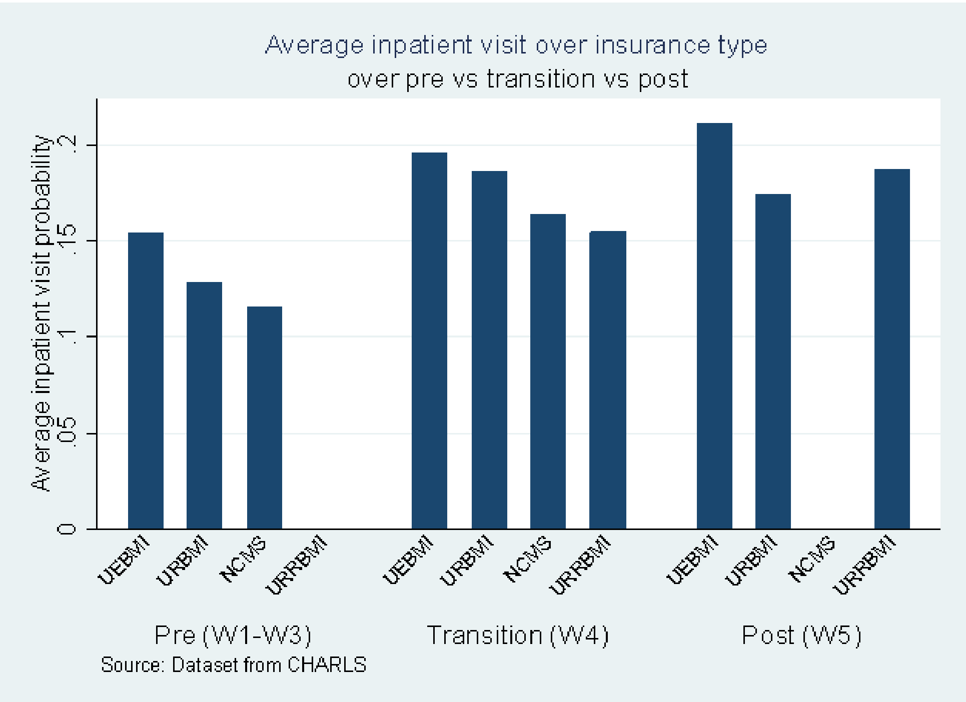


Figure 4.5: Mean inpatient visit by health insurance types over waves (pre vs transition vs post)



4.3.2 Methodology and Results Before the Integration

The descriptive patterns highlight the substantial restructuring of health insurance following the integration of NCMS and URBMI into URRBMI, with especially pronounced changes among rural residents. To formally evaluate whether these structural changes translated into improvements in healthcare access and health outcomes, I proceed in two steps. First, I estimate pooled OLS models using the pre-integration sample (Waves 1–3) to establish baseline associations between insurance type and key outcomes, including self-reported health status, and the probability of outpatient and inpatient visits. In these regressions, hukou status is excluded to avoid collinearity, as health insurance type already captures institutional differences in access. Second, I turn to a Difference-in-Differences (DiD) framework with an event study, comparing outcomes before and after integration (Waves 1–5) between groups differentially exposed to the reform. The specification of the Pooled OLS model is provided as follows:

$$Y_{it} = \alpha + \beta_1 Insurance_{it} + \gamma X_{it} + \delta_t + \epsilon_{it} \tag{4.1}$$

where Y_{it} is the outcome of interest in an individual i in wave t. $Insurance_{it}$ is a categorical variable indicating the type of insurance. X_{it} includes demographic and socioeconomic controls (age, gender, education, marital status, etc.), δ_t captures wave fixed effects, and ϵ_{it} is the error term in the equation. The purpose of using the pooled OLS for estimation is to get an initial view of how insurance types are correlated with health outcomes and healthcare utilization before integration.

The result of Pooled OLS estimation is reported in Table 4.4 for Waves 1-3 (pre-integration). The results confirm well-known demographic patterns that older individuals report worse health and use more healthcare, while higher education is associated with better health. Importantly, when comparing insurance types, no significant differences emerge between NCMS and URBMI in terms of self-reported health or healthcare utilization, while those with UEBMI show better health status and are more likely to utilize outpatient and inpatient care. In contrast, those without insurance consistently show lower utilization rates. These findings highlight that before integration, disparities between NCMS and urban schemes were not strongly reflected in utilization probabilities, but the urban-employed were advantaged and uninsured were clearly disadvantaged.

4.3.3 Methodology and Results on the Effect of Integration

The reform of interest—the integration of URBMI and NCMS into URRBMI—occurs between wave 3 and wave 4. To estimate the policy's impact, I implement an intention-to-treat (ITT) two-way fixed-effects DiD with individual and wave fixed effects. With an intention-to-treat (ITT) design, I define treatment based on pre-reform affiliation, not on post-reform switching. I report the average post-reform effect ($Treated * Post$) and an event-study that traces dynamic effects relative to wave 3. Covariates include age group, gender, urban and rural location, and self-reported health status. Standard errors are clustered at the individual level.

I construct the analysis sample as follows. Let i denote individuals and $t \in \{1,2,3,4,5\}$ represent survey waves. Individuals enrolled in the New Cooperative Medical Scheme (NCMS) during the in-pre-reform wave ($t = 3$) are classified as the treated group ($Treated_i = 1$), since their insurance coverage was directly affected by the integration reform. Specifically, NCMS participants in Wave 3 constitute the primary treatment population, as they were absorbed into the Urban and Rural Resident Basic Medical Insurance (URRBMI) scheme. In contrast, individuals covered by Urban Employee Basic Medical Insurance (UEBMI) in any pre-reform wave are assigned to the control group ($Treated_i = 0$), given that their insurance status was unaffected by the reform.

Table 4.4: Pooled OLS Result Before Integration

VARIABLES	(1) Self-reported health status	(2) Probability of outpatients visit	(3) Probability of inpatients visit
Self-reported health status (baseline: Excellent)			
Very good		0.0165**	0.0139***
		(0.00723)	(0.00510)
Good		0.0829***	0.0478***
		(0.00671)	(0.00476)
Fair		0.148***	0.0931***
		(0.00682)	(0.00494)
Poor		0.251***	0.203***
		(0.00834)	(0.00668)
Age Group (baseline: 45–55 years)			
56–65 years	0.126***	0.000607	0.0214***
	(0.0139)	(0.00449)	(0.00341)
66–75 years	0.247***	0.0202***	0.0548***
	(0.0170)	(0.00567)	(0.00466)
≥76 years	0.199***	0.00496	0.0803***
	(0.0277)	(0.00913)	(0.00830)
Female	0.148***	0.0414***	-0.00103
	(0.0130)	(0.00402)	(0.00320)
Married	-0.0620***	-0.00860	-0.00133
	(0.0199)	(0.00650)	(0.00542)
Education level (baseline: No Education)			
Elementary/Middle	-0.0797***	0.00221	0.00115
	(0.0141)	(0.00448)	(0.00355)
High school/Vocational	-0.183***	0.00945	-0.00570
	(0.0235)	(0.00709)	(0.00568)
Higher education	-0.403***	0.0283	-0.0546***
	(0.0773)	(0.0242)	(0.0169)
Wave (baseline: Wave 1)			
Wave 2	-0.0527***	0.0257***	0.0397***
	(0.0103)	(0.00487)	(0.00367)
Wave 3	-0.0864***	0.00953**	0.0498***
	(0.0111)	(0.00483)	(0.00373)
Urban residence	-0.103***	-0.0122**	0.0206***
	(0.0170)	(0.00533)	(0.00437)
Insurance type (baseline: NCMS)			
No insurance	-0.0257	-0.0498***	-0.0385***
	(0.0264)	(0.00862)	(0.00689)
UEBMI	-0.0756***	0.0155**	0.0342***
	(0.0225)	(0.00728)	(0.00615)
URBMI	0.0264	-0.0128	0.00481
	(0.0296)	(0.00987)	(0.00825)
URRBMI	-0.0337	-0.000692	0.00254
	(0.0401)	(0.0160)	(0.0126)
Other	-0.131***	0.0159	0.00502
	(0.0369)	(0.0138)	(0.0113)
Constant	3.474***	0.0567***	-0.0248***
	(0.0259)	(0.0103)	(0.00802)
Observations	43,532	43,419	43,490
R-squared	0.030	0.039	0.049

Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Author's own calculations.

I define the post-treatment period as the years following the 2016 integration. However, due to little change in Wave 4, I treat Waves 1–3 as pre-treatment, Wave 4 as transitional, and Wave 5 as post-treatment period. To capture staggered take-up, I further create two post indicators: $Post_1 = 1$ for Wave 4 ($t = 4$) and $Post_2 = 1$ for Wave 5 ($t = 5$). This distinction reflects the observed data pattern, with limited transitions in Wave 4 and substantially greater consolidation by Wave 5, consistent with administrative lags in changing insurance enrollment that largely resolved by the later wave. I then estimate treatment effects separately for outpatient and inpatient visits using a Difference-in-Differences (DiD) framework. Baseline Difference-in-Differences (DiD) model specification can be expressed as follows:

$$Y_{it} = \beta_0 + \beta_1 Post_1 + \beta_2 Post_2 + \beta_3 Treat_1 + \beta_4 (Post_1 * Treat_1) \\ + \beta_5 (Post_2 * Treat_1) + \gamma X_{it} + \epsilon_{it} \quad (4.2)$$

where Y_{it} is the outcome specifically healthcare utilization for an individual i at time t; $Post_1$ and $Post_2$ capture the transitional and post-integration periods; $Treat_1$ is an indicator for individuals affected by insurance integration; $Post_t * Treat_1$ is the interaction term capturing the integration's impact; X_{it} refers to control variables; ϵ_{it} is error term.

Table 4.5 presents the DiD estimates comparing NCMS participants to UEBMI participants. In Wave 4 (transition), NCMS enrollees exhibited significantly lower outpatient and inpatient utilization relative to controls, consistent with administrative frictions in the early phase of integration. By Wave 5, these differences appear to narrow, as overall outpatient and inpatient use rises and NCMS participants show levels closer to those of UEBMI. This pattern supports Hypothesis 1, suggesting that integration improved access and reduced rural–urban disparities. While utilization rose, the results on expenditures (Cols 4, 8) do not show clear reductions, providing limited support for Hypothesis 2. Specifications with and without self-reported health status yield consistent results; I emphasize the models without self-health as our baseline, since health status may itself be influenced by insurance.

Table 4.5: Baseline DiD Regression Result

	Outpatient care				Inpatient care			
VARIABLES	(1) Probability of OP visit (no self-health)	(2) Probability of OP visit	(3) Number of OP visits	(4) Total OP cost (log)	(5) Probability of IP visit (no self-health)	(6) Probability of IP visit	(7) Number of IP visits	(8) Total IP cost (log)
Post1 (t=4)	-0.0212***	-0.00379	0.0196	0.184	0.0511***	0.0678***	0.119***	0.296*
	(0.00553)	(0.00567)	(0.0218)	(0.141)	(0.00537)	(0.00548)	(0.0121)	(0.161)
Post2 (t=5)	0.0124**	0.0256***	0.0869***		0.0675***	0.0820***	0.154***	
	(0.00612)	(0.00642)	(0.0228)		(0.00579)	(0.00602)	(0.0131)	
Treated#Post1	-0.0128*	-0.0144**	-0.0453*	0.0585	-0.0178***	-0.0175***	-0.0200	-0.225
	(0.00656)	(0.00661)	(0.0250)	(0.155)	(0.00634)	(0.00636)	(0.0140)	(0.187)
Treated#Post2	-0.00224	-0.00176	-0.00365		0.00466	0.00458	0.0139	
	(0.00712)	(0.00733)	(0.0266)		(0.00676)	(0.00692)	(0.0152)	
Wave (baseline: wave 3)								
Wave 1	-0.00878*	-0.00716	-0.0351**	-0.732***	-0.0613***	-0.0593***	-0.101***	-0.329**
	(0.00467)	(0.00472)	(0.0167)	(0.0935)	(0.00374)	(0.00377)	(0.00770)	(0.143)
Wave 2	0.0180***	0.0192***	0.0609***	-0.231***	-0.0156***	-0.0136***	-0.0201***	0.157
	(0.00416)	(0.00421)	(0.0157)	(0.0762)	(0.00339)	(0.00344)	(0.00665)	(0.117)
Age Group (baseline: 45–55 years)								
56-65 years	0.00714	0.00858	0.0566**	-0.0354	-0.0117**	-0.00969*	-0.0137	-0.566***
	(0.00627)	(0.00637)	(0.0229)	(0.151)	(0.00534)	(0.00536)	(0.0113)	(0.213)
66-75 years	0.0165*	0.0194*	0.0575	-0.0263	9.19e-05	0.00273	0.0293	-0.218

Continued on next page

	Outpatient care				Inpatient care			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.0100)	(0.0101)	(0.0383)	(0.228)	(0.00884)	(0.00887)	(0.0186)	(0.298)
≥76 years	-0.000121	-0.00279	-0.0270	-0.304	0.0405***	0.0421***	0.107***	-0.0528
	(0.0151)	(0.0153)	(0.0543)	(0.354)	(0.0139)	(0.0140)	(0.0288)	(0.426)
Self-reported health status (baseline: Excellent)								
Very good		0.00453	0.0116	0.278		0.0239***	0.0488***	-0.188
		(0.00550)	(0.0164)	(0.431)		(0.00459)	(0.00754)	(0.611)
Good		0.0402***	0.0866***	0.328		0.0442***	0.0721***	0.0443
		(0.00534)	(0.0157)	(0.423)		(0.00448)	(0.00754)	(0.598)
Fair		0.0889***	0.234***	0.307		0.0946***	0.175***	0.244
		(0.00608)	(0.0190)	(0.419)		(0.00514)	(0.0102)	(0.596)
Poor		0.139***	0.423***	0.476		0.147***	0.294***	0.267
		(0.00806)	(0.0305)	(0.425)		(0.00710)	(0.0156)	(0.598)
Urban residence	-0.00811	-0.00923	-0.0159	0.0249	-0.00322	-0.00505	-0.0116	0.204
	(0.00628)	(0.00646)	(0.0239)	(0.222)	(0.00580)	(0.00590)	(0.0117)	(0.219)
Constant	0.194***	0.127***	0.233***	5.665***	0.135***	0.0601***	0.0613***	9.105***
	(0.00575)	(0.00773)	(0.0273)	(0.437)	(0.00501)	(0.00658)	(0.0135)	(0.651)
Observations	86,001	83,015	83,292	5,628	86,092	83,096	83,075	2,360
R-squared	0.003	0.010	0.007	0.082	0.023	0.032	0.027	0.083
Number of ID	22,846	22,346	22,378	4,375	22,847	22,347	22,347	1,996

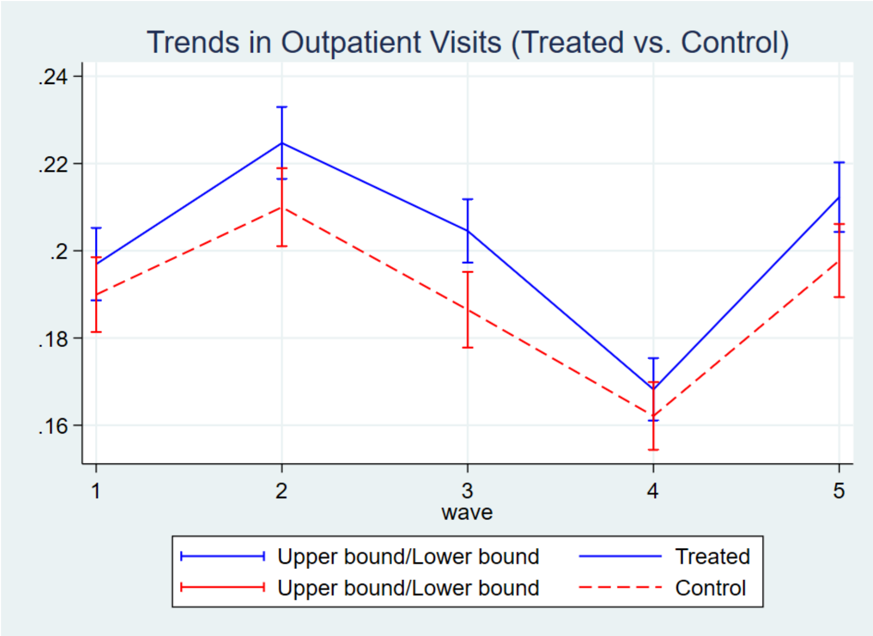
Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author's own calculations.

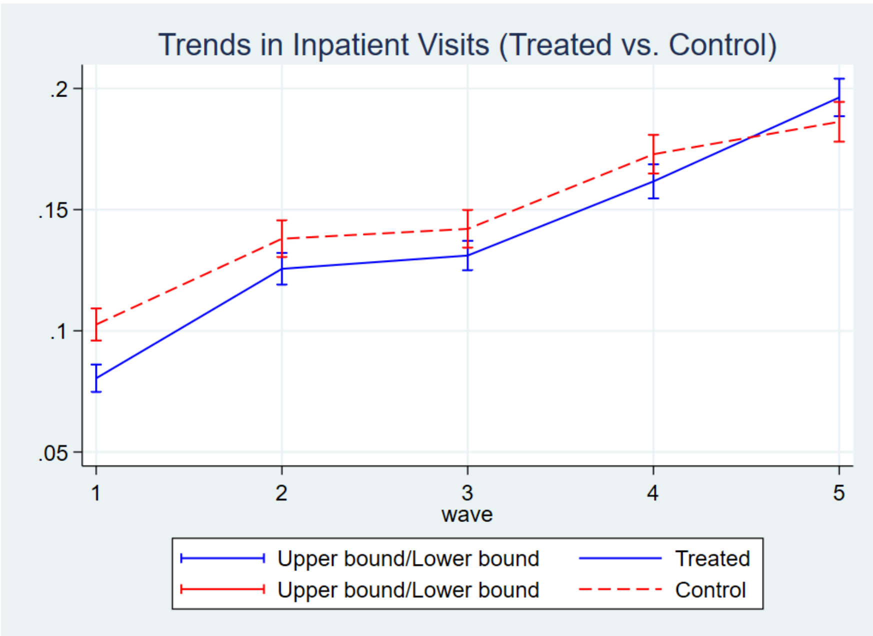
Figures 4.6a , and 4.6b plot average outpatient and inpatient visit probabilities for NCMS (treated) and UEBMI (control) participants across waves, with 95% confidence intervals. In both outcomes, the pre-integration trends are similar, supporting the parallel trends assumption. During the transition period (Wave 4), NCMS participants exhibit a sharper decline in outpatient visits and remain behind in inpatient use, consistent with the negative DiD estimates for the transition in Table 4.5 and temporary administrative disruptions. By Wave 5, the NCMS group's utilization levels are broadly comparable to those of UEBMI, as indicated by overlapping confidence intervals. This suggests that while the integration may have introduced short-term instability, access later appears to have become more even across groups, with potential gains for rural residents. These findings support Hypothesis 1 (increased utilization post-integration for rural residents), though evidence for Hypothesis 2 (reduced financial burden) remains limited.

Figure 4.6: Trends in Outpatient and Inpatient visit

(a) 6/a



(b) 6/b



Source: Author's own calculations.

Event-Study Design

To examine how health insurance integration affects healthcare utilization over time, I estimate an event-study model centered around the wave in which China implemented the reform. With event-study approach, I am able to observe whether outpatient and inpatient visit probability changes after integration and how these changes unfold relative to the implementation wave. Figure 4.7 presents the resulting coefficients for outpatient visits (left panel) and inpatient visits (right panel) between NCMS (treated) and UEBMI (control) relative to the pre-integration baseline (Wave 3), with 95% confidence intervals.

Model Specification

$$Y_{it} = \sum_{k \neq -1} \beta_k \, \mathbf{1}\{\text{EventTime}_{it} = k\} + \alpha_i + \lambda_t + X_{it} + \epsilon_{it} \tag{4.3}$$

In the equation, Y_{it} denotes the probability of outpatient (or inpatient) visits for individual i and wave t. $EventTime_{it}$ refers to wave relative to China's health insurance integration. Event time $k = 0$ corresponds to the year of integration, negative value represents the wave before integration (e.g., $k = -2, -1$), and positive value represents wave after integration (e.g., $k = 1, 2$). The indicator $1EventTime_{it} = k$ is equal to 1 if individual i from integration in wave t. α_i and λ_t are individual and wave fixed effects. ϵ_{it} represents the error term and X_{it} refers to controls. β_k denotes the difference in visit probability in every wave t relative the wave of integration.

In Figure 4.7, left panel Figure 4.7a presents the estimated dynamic effects of health insurance integration on the probability of outpatient visits for the treated group relative to the control group. The pre-integration estimates at event times -2 and -1 are small, negative, and statistically insignificant. This pattern indicates the absence of differential pre-trends between treatment and control groups and supports the identifying assumption that both groups would have followed similar trajectories in the absence of integration.

The effect at event time 0 is normalized to zero, as it serves as the omitted reference period. In the transition period immediately following the reform (event time +1), the treated group experiences a roughly two–percentage-point decline in outpatient visit probability relative to the pre-integration baseline. Although the confidence interval marginally overlaps zero, the point estimate suggests a short-run adjustment or temporary disruption in service utilization during the early stages of integration. By the post-integration period (event time +2), the estimate moves back toward zero and becomes statistically indistinguishable from the baseline, indicating that any initial adjustment effects dissipate over time.

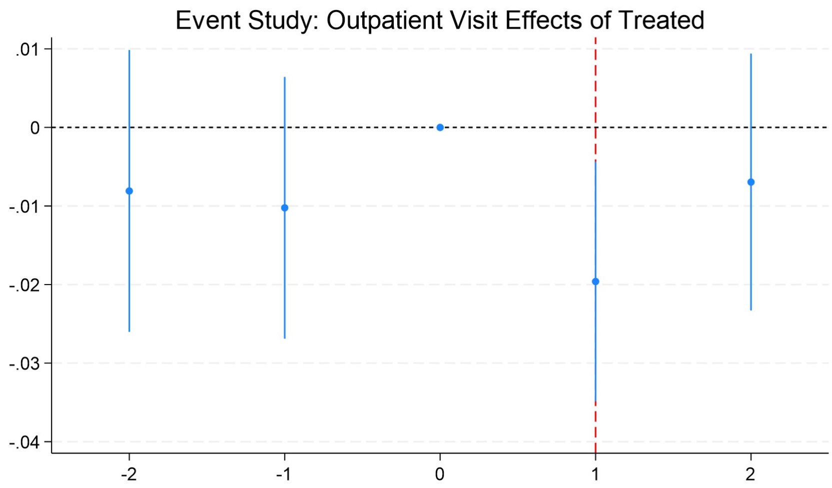
In Figure 4.7, right panel Figure 4.7b visualizes the estimated effects for the probability of inpatient visits. The estimated coefficients at event times –2 and –1 are close to zero and statistically insignificant as well. Although the point at –1 is slightly positive (around 0.005), its confidence interval overlaps with zero. In the first period following the reform (event time +1), the coefficient becomes noticeably negative (around –0.015 to –0.02), suggesting a short-run decline in inpatient visits among the treated group relative to the baseline. Although the confidence interval is wide and crosses zero, the point estimate implies a potential temporary adjustment effect—possibly reflecting administrative transitions, changes in reimbursement processes, or shifts in patient behavior during the rollout of the integration. By event time +2, the estimate moves upward toward a small positive value. Its confidence interval spans both positive and negative values, indicating no statistically meaningful effect. This reversion suggests that any transitional decline in inpatient use dissipates relatively quickly, and the reform does not produce sustained changes in the likelihood of inpatient admission.

As a result, inpatient event-study pattern aligns with the outpatient results as there is no pre-existing differences, a temporary short-run dip around the reform period, and no persistent long-term effect. All in all, event-study suggests that health insurance integration does not lead to sustained increases in outpatient and inpatient use among treated individuals. Instead, the reform appears to generate only a small, short-lived reduction in both outpatient and inpatient visits during the transition period, which is consistent with temporary administrative or behavioral frictions rather than structural changes in access.

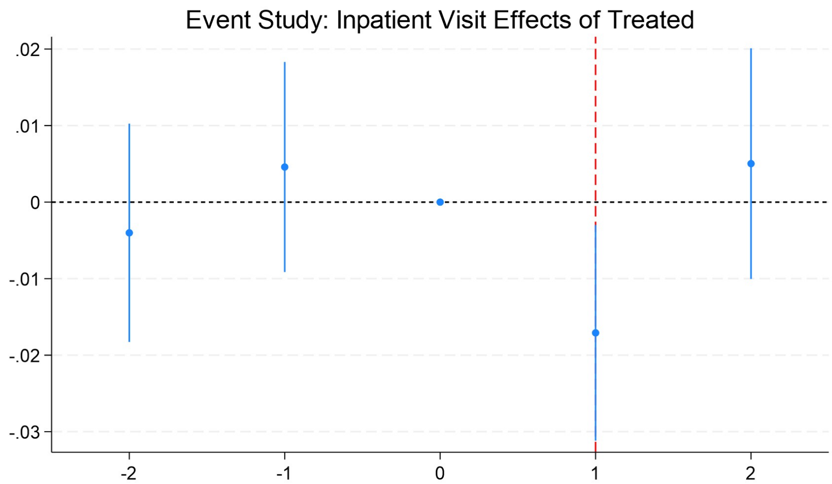
I focus my discussion on the event-study estimates for the probability of outpatient and inpatient visit as this outcome most directly reflects changes. For completeness, I also report the event-study results for the number of outpatient and inpatient visits; however, because these estimates follow patterns similar to those for the probability outcome and do not alter the substantive interpretation, I do not discuss them in detail. Figure 4.8 reports this result.

Figure 4.7: Event-study estimates of dynamic impact of health insurance integration on outpatient and inpatient visit probability.

(a) 7/a



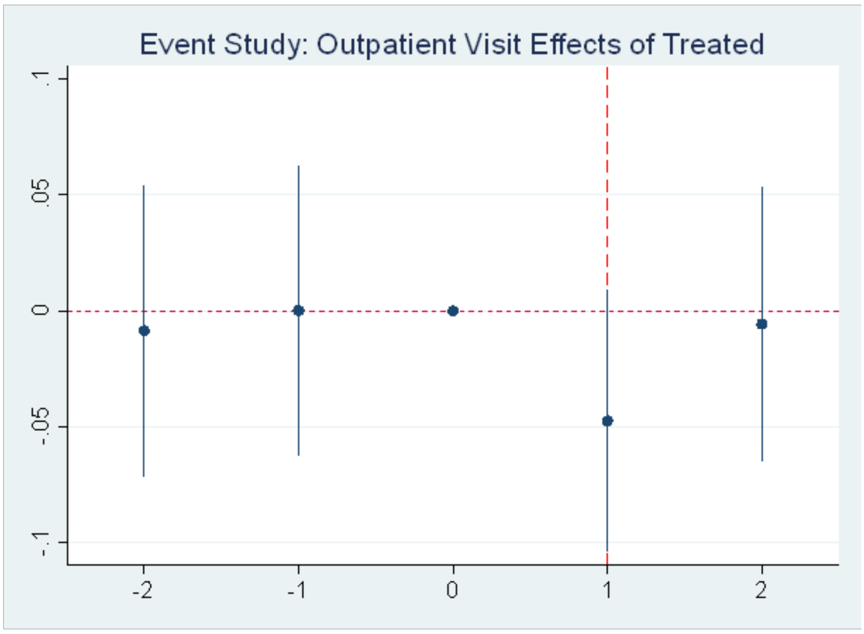
(b) 7/b



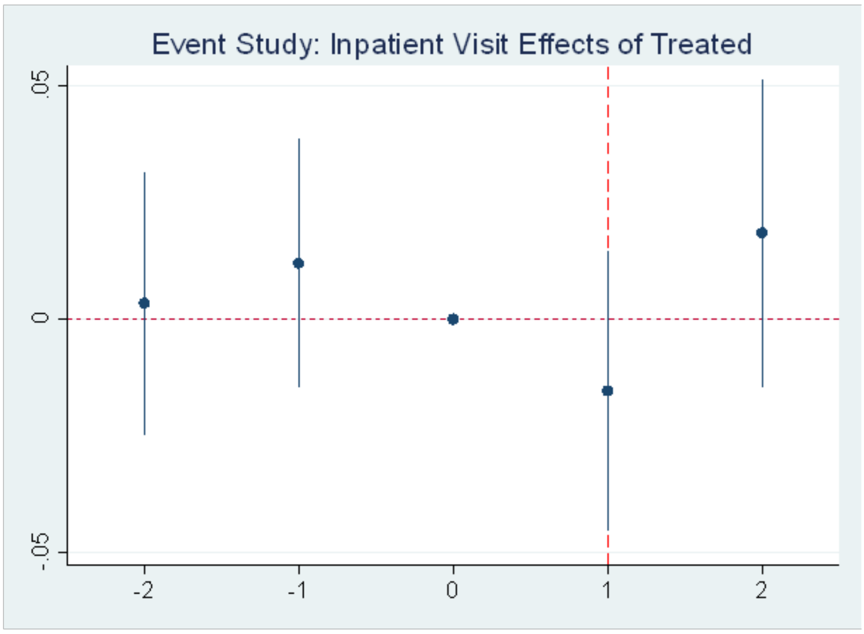
Notes: The figure plots coefficients from an event-study specification in which event time 0 corresponds to the wave in which the treatment group experienced health insurance integration. The markers represent point estimates and the vertical bars show 95% confidence intervals. The red dashed line marks the timing of the reform. Estimates are measured relative to the treatment group in the integration wave. Standard errors are clustered at the individual level. Source: Author's own calculations.

Figure 4.8: Event-study estimates of dynamic impact of health insurance integration on number of outpatient and inpatient visits.

(a) 8/a



(b) 8/b



Source: Author's own calculations.

4.4 Conclusion and Discussion

This study examined the effect of China's health insurance integration—specifically the merger of NCMS and URBMI into URRBMI—on healthcare utilization and health outcomes, with a focus on rural–urban disparities. Using data from CHARLS (2011–2020), the analysis proceeded in three steps: pooled OLS regressions on pre-integration waves, difference-in-differences (DiD) models around the reform, and event study designs to validate dynamic effects and parallel trends.

The pooled OLS results for Waves 1–3 provided a descriptive benchmark. Consistent with demographic expectations, older individuals reported worse health and higher inpatient use, while higher education was associated with better health outcomes. Crucially, before integration, differences in healthcare utilization between NCMS and URBMI participants were not statistically significant, suggesting that disparities were not strongly visible in utilization probabilities, though uninsured individuals exhibited clear disadvantages. These findings highlight the need to assess whether structural reforms altered utilization and outcomes over time (Research Question 1).

The DiD results revealed a distinct transition dynamic. During Wave 4 (transition), NCMS participants were significantly less likely than UEBMI controls to access both outpatient and inpatient care, consistent with short-term disruptions during the reform rollout (Research Question 3). By Wave 5 (post-integration), however, these differences decreased that outpatient and inpatient utilization increased overall, and NCMS participants had converged with UEBMI controls. These findings directly address Research Question 2 by showing that integration did affect healthcare utilization, with rural NCMS participants ultimately comparable to urban controls. However, results on expenditures were more mixed which shows outpatient costs did not fall, and inpatient costs rose slightly, providing limited support for reductions in financial burden.

The event study results reinforce these conclusions. First, pre-treatment estimates were small and insignificant, supporting the parallel trends assumption underlying DiD. Second, in Wave 4, NCMS participants experienced a temporary decline in utilization relative to UEBMI, replicating the negative interaction effects found in DiD. Finally, by Wave 5, treatment effects were statistically indistinguishable from zero, indicating that rural participants had regained parity with their urban counterparts. The event study thus confirms the narrative of transitional frictions followed by convergence, in line with the descriptive insurance distribution patterns shown earlier.

After the analysis, Hypothesis 1 is supported. After the integration, both outpatient and inpatient use increased, and the treated group (NCMS) showed utilization levels more aligned with the control group. Specifically, rural NCMS participants initially lagged but achieved parity with urban UEBMI participants by Wave 5, indicating that the integration improved in reducing rural–urban disparities in utilization. As for Hypothesis 2, while integration expanded access, there is little evidence that expenditures declined; inpatient costs even rose. This suggests that financial equalization lags behind utilization equalization. Thus, it needs further in-depth analysis for Hypothesis 2.

Taken together, these results indicate that the integration of health insurance schemes in China contributed to narrowing rural-urban differences in access to healthcare, though with temporary disruptions during the rollout. However, the reform has not yet delivered clear evidence of reduced financial burdens, raising concerns about the depth of coverage. This suggests that equalizing coverage does not automatically ensure stronger financial protection. Policymakers should thus view integration as a foundation that needs to be complemented with measures aimed at enhancing benefit depth and controlling medical costs.

Chapter 5

Conclusion

This thesis examines three interrelated aspects of household decision-making, budget allocation, and healthcare systems in China and Indonesia, with a particular focus on the distribution of resources, the determinants of healthcare utilization, and the impact of structural reforms. Considering together, the studies highlight the importance of both intra-household dynamics and institutional arrangements in shaping welfare outcomes, with implications for human capital development, health equity, and policy design.

The first study investigated the role of women's bargaining power in household budget allocation, emphasizing spending on food, bad goods, education, and health—domains critical for child human capital formation. Women's education and employment emerge as the main factors for women's bargaining power. Specifically, having higher education and being employed increases the possibility of having better bargaining power in the household. The results also show that stronger female bargaining power is associated with a reduction in spending on bad goods. In contrast, in education and health spending, households with greater women's bargaining power allocate less budget compared with households with no women's bargaining power. However, urban household allocate more to education and less to bad goods. These findings underscore the welfare gains of empowering women within households and highlight complementarities in spousal cooperation.

The second study analyzed healthcare utilization patterns, emphasizing the interplay between demand- and supply-side factors. Socioeconomic status, insurance type, gender, and age emerge as dominant determinants of healthcare use, while supply-side factors such as hospital infrastructure play a more limited role. Urban and rural disparities are visible, and wealthier areas show better self-reported health and better results. Migration between urban and rural areas does not independently affect healthcare utilization once individual characteristics are controlled for, but institutional barriers—particularly hukou restrictions and limited insurance portability—constrain migrants' ability to adapt to local healthcare contexts. These findings emphasize that demand-side inequalities remain central to explaining healthcare access.

The third study assessed the impact of China's health insurance integration, specifically the merger of NCMS and URBMI into URRBMI, on healthcare utilization and health outcomes. Using multiple empirical strategies, the analysis reveals transitional disruptions in access during the reform rollout but eventual comparability between rural and urban participants. While integration contributed to reducing rural–urban disparities in utilization, evidence of reduced financial burden is limited, with inpatient costs rising slightly. The results suggest that integration equalized access but not financial protection.

Collectively, the three studies advance understanding of how household agency, socioeconomic determinants, and institutional reforms interact to shape welfare outcomes in China and Indonesia. The first study contributes to the literature on intra-household bargaining by demonstrating the welfare-enhancing potential of women's empowerment. The second enriches health economics by showing that demand-side factors dominate over supply-side availability in determining utilization, and that institutional frictions undermine the benefits of migration. The third contributes to policy evaluation by documenting both the improvement and limitations of health insurance integration, highlighting the difference between equalizing access and ensuring financial security.

Several limitations should be acknowledged. Across studies, reliance on self-reported measures—whether of decision-making power, health status, or household expenditures—raises concerns about measurement accuracy. Endogeneity and omitted variable bias may also affect causal interpretation. Moreover, while reforms such as insurance integration were evaluated using quasi-experimental methods, the generalizability of the of findings may be constrained by institutional and cultural specifics. These caveats point to the need for future research incorporating standardized outcome measures, objective data sources, and natural experiments that strengthen causal inference.

The findings carry important implications for policy. Strengthening women's bargaining position—through education, employment opportunities, and legal protections—may enhance household investment in human capital. In healthcare, addressing institutional barriers such as insurance portability and hukou restrictions is critical for ensuring equitable access, particularly for mobile populations. Finally, while health insurance integration represents a milestone in China's health reform, it needs to be complemented with deeper benefit packages, cost containment, and primary care investment to ensure both equity and efficiency.

Future research should explore inter-generational effects of women's empowerment in Indonesia and other countries, examine causal mechanisms of healthcare access using richer datasets, and track the long-term effects of insurance integration. Comparative studies across institutional contexts could shed light on the generalizability of these dynamics beyond China.

The originality of this thesis lies in its multi-level approach, connecting intra-household bargaining processes with broader determinants, and evaluating its association with child-related household expenditures. Further, institutional determinants of healthcare utilization and reform are studied. While much of the existing literature addresses these themes, this thesis demonstrates how micro-level dynamics of agency in Indonesia and combined with macro-level structures of access and equity in China, are examined. By combining evidence from household resource allocation, healthcare utilization, and mobility between urban and rural, and insurance integration, the thesis offers a comprehensive perspective on welfare outcomes in China and Indonesia.

The significance of the research is twofold. First, it deepens empirical understanding by showing how bargaining power and institutional design jointly associate with investment in human capital. Second, it offers concrete policy insights: empowering women, reforming insurance systems, and addressing structural inequities are complementary strategies for enhancing both individual welfare and social development. In this way, the thesis makes an original contribution not only to academic perspectives in economics and development studies but also to ongoing policy discussions on gender equality, healthcare reform, and inclusive growth.

Overall, this thesis demonstrates that both micro-level dynamics within households and macro-level institutional reforms are crucial in shaping welfare outcomes. Women's empowerment, socioeconomic inequalities, and systemic reforms are not isolated forces but interconnected drivers of development. By combining analyses of intra-household decision-making, healthcare demand and supply, and policy integration, this work underscores the need for a multidimensional approach to improving human capital and health equity. The findings provide a foundation for policies that not only expand access but also promote efficient, equitable, and sustainable welfare outcomes for future generations.

Appendix A

Appendix

Figure A.2: Health insurance distribution by urban/rural (residence), pre vs transition vs post

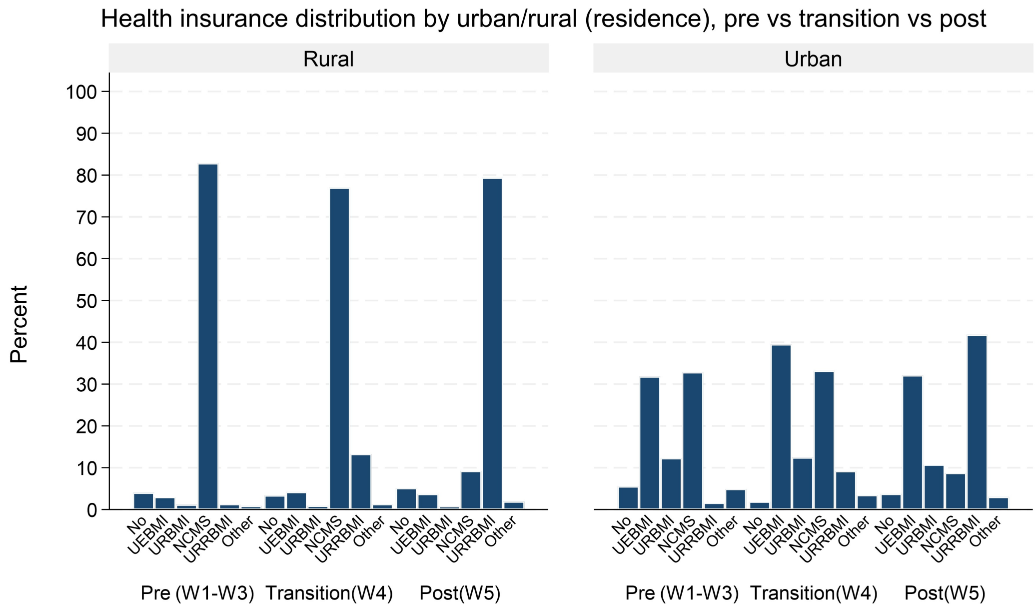


Figure A.1: Flowchart for data collection

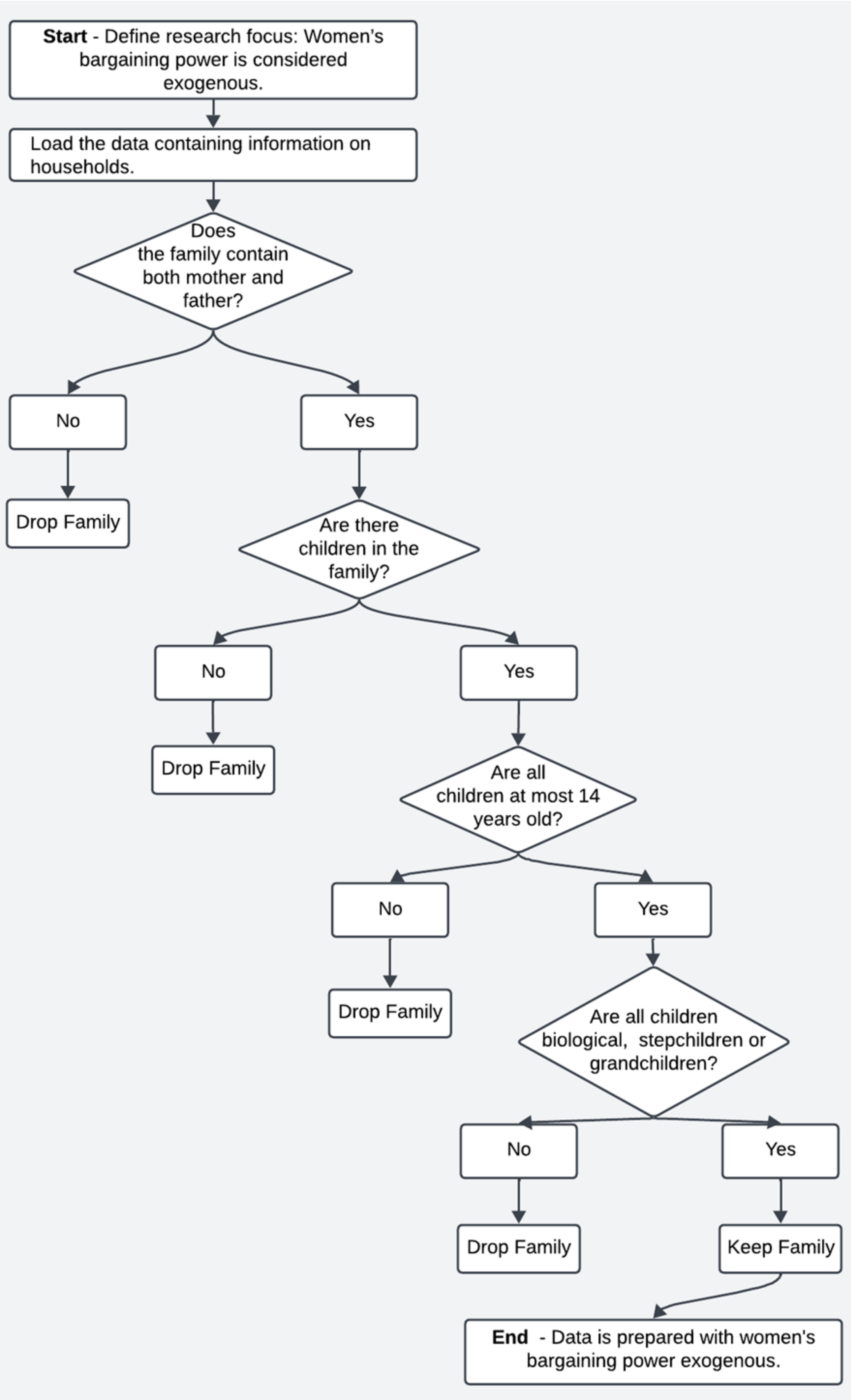


Table A.1: Multinomial logistic regression parameter estimates for women's bargaining power in food spending

VARIABLES	(1) Bargaining power No	(2) Bargaining power Partial (less)	(3) Bargaining power Partial (joint)
	(WBP in Food = 0)	(WBP in Food = 1)	(WBP in Food = 2)
Wife Age	-0.0035	0.0340**	0.0003
	(0.0079)	(0.0155)	(0.0075)
Wife's education level (baseline: no education)			
Elementary, Junior high	-0.7326***	-0.9313***	-0.2905
	(0.1673)	(0.2832)	(0.1914)
Senior high	-1.2473***	-0.7488**	-0.3411*
	(0.1898)	(0.3351)	(0.2053)
Higher education	-1.3033***	-0.1435	-0.0845
	(0.2322)	(0.3716)	(0.2245)
Wife works	-0.2762***	-0.0238	0.0969
	(0.0737)	(0.1414)	(0.0648)
Husband age	-0.0064	0.0001	-0.0184***
	(0.0073)	(0.0145)	(0.0070)
Husband's education level (baseline: no education)			
Elementary, Junior high	0.0096	-0.0061	-0.2532
	(0.2139)	(0.3783)	(0.2139)
Senior high	-0.2001	-0.0045	-0.3706*
	(0.2280)	(0.4159)	(0.2243)
Higher education	-0.2246	0.0517	-0.2528
	(0.2594)	(0.4514)	(0.2422)
Husband works	-0.1061	0.0458	0.0312
	(0.1134)	(0.2204)	(0.1121)
Income group (baseline: 0–5M)			
5M–10M	-0.0622	-0.1294	-0.0975
	(0.0820)	(0.1726)	(0.0756)
10M–15M	-0.0522	0.0482	-0.1242
	(0.1101)	(0.2121)	(0.1002)
15M+	-0.1240	0.0558	-0.2460**
	(0.1436)	(0.2510)	(0.1252)
Child number	0.0083	-0.1820*	-0.0160
	(0.0441)	(0.0932)	(0.0411)
Urban	-0.1186	-0.1749	-0.1100*
	(0.0726)	(0.1479)	(0.0666)
Constant	0.0362	-3.3562***	0.0054
	(0.3262)	(0.6198)	(0.3255)
Observations	7,748	7,748	7,748

Note: The baseline category of WBP is "full bargaining power".
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' own calculation.

Table A.2: Multinomial logistic regression parameter estimates for women's bargaining power in education spending

VARIABLES	(1) Bargaining power No (WBP in Education = 0)	(2) Bargaining power Partial (less) (WBP in Education = 1)	(3) Bargaining power Partial (joint) (WBP in Education = 2)
Wife Age	0.0249***	0.0806***	0.0019
	(0.0085)	(0.0160)	(0.0064)
Wife's education level (baseline: no education)			
Elementary, Junior high	-0.1581	0.8362*	0.0506
	(0.1850)	(0.4281)	(0.1559)
Senior high	-0.3367	1.2871***	0.1971
	(0.2096)	(0.4647)	(0.1698)
Higher education	-0.5503**	1.1241**	0.4292**
	(0.2533)	(0.5116)	(0.1956)
Wife works	-0.2295***	-0.0697	-0.0193
	(0.0800)	(0.1445)	(0.0577)
Husband age	-0.0009	-0.0174	-0.0155***
	(0.0079)	(0.0151)	(0.0059)
Husband's education level (baseline: no education)			
Elementary, Junior high	0.3929*	0.7093	0.6470***
	(0.2201)	(0.4955)	(0.1798)
Senior high	0.8547***	0.7105	1.0578***
	(0.2366)	(0.5246)	(0.1901)
Higher education	1.4677***	1.5695***	1.6540***
	(0.2708)	(0.5534)	(0.2164)
Husband works	0.1623	0.3598	0.0826
	(0.1251)	(0.2273)	(0.0931)
Income group (baseline: 0–5M)			
5M–10M	0.0573	0.5926***	0.0277
	(0.0936)	(0.2008)	(0.0676)
10M–15M	-0.0647	0.7259***	-0.1022
	(0.1216)	(0.2310)	(0.0882)
15M+	-0.0708	0.6309**	-0.3091***
	(0.1475)	(0.2673)	(0.1092)
Child number	-0.0622	-0.1968**	-0.0709**
	(0.0481)	(0.0905)	(0.0352)
Urban	-0.0987	0.0091	-0.2397***
	(0.0819)	(0.1554)	(0.0593)
Constant	-1.7824***	-6.7971***	0.6415**
	(0.3569)	(0.7835)	(0.2773)
Observations	7,748	7,748	7,748

Note: The baseline category of WBP is "full bargaining power".
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' own calculation.

Table A.3: Multinomial logistic regression parameter estimates for women's bargaining power in health spending

VARIABLES	(1) Bargaining power No (WBP in Health = 0)	(2) Bargaining power Partial (less) (WBP in Health = 1)	(3) Bargaining power Partial (joint) (WBP in Health = 2)
Wife Age	0.0072	0.1220***	-0.0065
	(0.0095)	(0.0243)	(0.0061)
Wife's education level (baseline: no education)			
Elementary, Junior high	-0.0939	1.3978*	0.0620
	(0.2041)	(0.7552)	(0.1464)
Senior high	-0.1349	1.5933**	0.3142**
	(0.2344)	(0.8075)	(0.1600)
Higher education	0.1199	1.2563	0.5525***
	(0.2754)	(0.8898)	(0.1854)
Wife works	-0.1248	-0.0840	0.0652
	(0.0910)	(0.2201)	(0.0551)
Husband age	0.0152*	-0.0567**	-0.0128**
	(0.0089)	(0.0230)	(0.0057)
Husband's education level (baseline: no education)			
Elementary, Junior high	0.0908	0.4786	0.4224**
	(0.2417)	(0.7597)	(0.1726)
Senior high	0.4171	0.5445	0.7754***
	(0.2617)	(0.8012)	(0.1822)
Higher education	0.7076**	0.8663	1.1844***
	(0.2967)	(0.8554)	(0.2043)
Husband works	0.0102	0.0066	0.1835**
	(0.1342)	(0.2984)	(0.0885)
Income group (baseline: 0–5M)			
5M–10M	-0.1386	0.4693	-0.0163
	(0.1075)	(0.2947)	(0.0645)
10M–15M	-0.0378	0.6927**	-0.0569
	(0.1363)	(0.3400)	(0.0846)
15M+	-0.0143	0.7049*	-0.2132**
	(0.1640)	(0.3991)	(0.1049)
Child number	-0.0474	-0.4754***	-0.0652*
	(0.0546)	(0.1572)	(0.0336)
Urban	-0.0034	0.3554	-0.2272***
	(0.0939)	(0.2458)	(0.0565)
Constant	-2.0551***	-7.4341***	0.8546***
	(0.3962)	(1.2322)	(0.2642)
Observations	7,748	7,748	7,748

Note: The baseline category of WBP is "full bargaining power".
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' own calculation.

Table A.4: Summary of the Share of Health and Education Expenditure According to the Age of Children

Summary of Share of Health Expenditure

Age of children	Mean	Std. Dev.	Freq.
0	0.0507	0.1125	1,049
1	0.0446	0.1046	1,051
2	0.0305	0.0785	1,032
3	0.0300	0.0903	987
4	0.0237	0.0805	1,042
5	0.0211	0.0669	996
6	0.0146	0.0593	984
7	0.0134	0.0571	884
8	0.0095	0.0396	964
9	0.0094	0.0450	945
10	0.0106	0.0592	894
11	0.0089	0.0440	917
12	0.0087	0.0452	799
13	0.0084	0.0411	769
14	0.0053	0.0346	814
Total	0.0203	0.0712	14,127

Summary of Share of Education Expenditure

Age of children	Mean	Std. Dev.	Freq.
0	0	0	1,049
1	0	0	1,051
2	0.0000	0.0005	1,032
3	0.0020	0.0242	987
4	0.0332	0.0814	1,042
5	0.1029	0.1304	996
6	0.1232	0.1476	984
7	0.1917	0.1634	884
8	0.2328	0.1484	964
9	0.2316	0.1402	945
10	0.2291	0.1391	894
11	0.2364	0.1478	917
12	0.2379	0.1415	799
13	0.2908	0.1667	769
14	0.3093	0.1715	814
Total	0.1388	0.1649	14,127

Source: Authors' own calculation.

Table A.5: Effects of women's bargaining power on education and health spending shares using age-restricted samples (OLS regression results with multiple control variables)

VARIABLES	**(1)** **Share of education**	**(2)** **Share of health**
WBP in education = 1 (less partial)	-0.0259***	
	(0.0096)	
WBP in education = 2 (joint)	-0.0033	
	(0.0047)	
WBP in education = 3 (full)	-0.0127**	
	(0.0052)	
WBP in health = 1 (less partial)		-0.0148
		(0.0139)
WBP in health = 2 (joint)		-0.0086
		(0.0056)
WBP in health = 3 (full)		-0.0097*
		(0.0056)
Urban	0.0413***	-0.0013
	(0.0032)	(0.0025)
Family size	-0.0047***	-0.0007
	(0.0007)	(0.0006)
Husband works	-0.0073	-0.0085*
	(0.0055)	(0.0044)
Wife works	-0.0059*	-0.0056**
	(0.0032)	(0.0025)
Wife age	-0.0001	-0.0001
	(0.0002)	(0.0002)
Wife's insurance JKN		0.0036
		(0.0030)
Husband's insurance JKN		-0.0045
		(0.0030)
Log of total spending	0.0014	0.0299***
	(0.0032)	(0.0032)
Number of children	-0.0429***	-0.0172***
	(0.0019)	(0.0017)
Child age (baseline: age 0)		
1		-0.0109**
		(0.0049)
2		-0.0216***
		(0.0044)
3		-0.0206***
		(0.0047)
4		-0.0270***
		(0.0045)
5	-0.0226***	-0.0300***

Continued on next page

VARIABLES	(1) Share of education	(2) Share of health
	(0.0065)	(0.0044)
7	0.0694***	
	(0.0074)	
8	0.1138***	
	(0.0068)	
9	0.1120***	
	(0.0066)	
10	0.1088***	
	(0.0067)	
11	0.1164***	
	(0.0068)	
12	0.1200***	
	(0.0069)	
13	0.1708***	
	(0.0077)	
14	0.1907***	
	(0.0078)	
Female (child gender)	0.0135***	-0.0050**
	(0.0031)	(0.0024)
Child health status (baseline: very unhealthy)		
Somewhat unhealthy		-0.0248
		(0.0288)
Somewhat healthy		-0.0467
		(0.0286)
Very healthy		-0.0507*
		(0.0286)
Constant	0.2092***	-0.3101***
	(0.0505)	(0.0535)
Observations	8,073	5,219
R-squared	0.256	0.078

Note: The sample is restricted to children aged at least five years for education spending and at most five years for health spending.

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' own calculations.

Table A.6: Fractional Logit Regression Result for Robustness Check

VARIABLES	(1) Share of food	(2) Share of bad goods	(3) Share of education	(4) Share of health
WBP in food = 1 (less partial)	0.1601**	-0.2063**		
	(0.0654)	(0.0872)		
WBP in food = 2 (partial [joint])	0.0295	-0.0693		
	(0.0366)	(0.0486)		
WBP in food = 3 (full)	-0.0457	-0.0639*		
	(0.0301)	(0.0386)		
WBP in education = 1 (less partial)			-0.1325**	
			(0.0535)	
WBP in education = 2 (partial [joint])			-0.0011	
			(0.0275)	
WBP in education = 3 (full)			-0.0614**	
			(0.0308)	
WBP in health = 1 (less partial)				-0.4024
				(0.3251)
WBP in health = 2 (joint)				-0.2180*
				(0.1147)
WBP in health = 3 (full)				-0.1764
				(0.1234)
Urban	-0.0469**	-0.0916***	0.2415***	-0.0845
	(0.0203)	(0.0273)	(0.0197)	(0.0676)
Family size	0.0061	0.0208***	-0.0277***	-0.0459***
	(0.0044)	(0.0055)	(0.0045)	(0.0166)
Husband works	-0.0670*	-0.0628	-0.0323	-0.3065***
	(0.0356)	(0.0472)	(0.0316)	(0.1034)
Wife works	0.0696***	-0.1384***	-0.0402**	-0.1389**
	(0.0203)	(0.0276)	(0.0190)	(0.0673)
Wife age	-0.0035***	-0.0149***	-0.0029**	-0.0006
	(0.0012)	(0.0016)	(0.0014)	(0.0044)
Wife's insurance JKN				0.0507
				(0.0771)
Husband's insurance JKN				-0.1209
				(0.0773)
Log of total spending	-0.4746***	-0.2475***	-0.0875***	0.8574***
	(0.0174)	(0.0217)	(0.0186)	(0.0631)
Number of children			-0.2803***	-0.5534***
			(0.0122)	(0.0451)
Child age				
0			-17.2645***	
			(0.0576)	

Continued on next page

VARIABLES	(1) Share of food	(2) Share of bad goods	(3) Share of education	(4) Share of health
1			-17.3176***	-0.2390**
			(0.0575)	(0.1125)
2			-9.0219***	-0.5539***
			(1.0019)	(0.1142)
3			-4.2005***	-0.5567***
			(0.3940)	(0.1255)
4			-1.4248***	-0.7654***
			(0.0943)	(0.1350)
5			-0.1932***	-0.8868***
			(0.0631)	(0.1343)
6				-1.3197***
				(0.1611)
7			0.5374***	-1.5221***
			(0.0575)	(0.1639)
8			0.8227***	-1.8304***
			(0.0520)	(0.1612)
9			0.8475***	-1.7371***
			(0.0516)	(0.1882)
10			0.8184***	-1.7374***
			(0.0520)	(0.2147)
11			0.8557***	-1.8863***
			(0.0519)	(0.1978)
12			0.8775***	-1.7916***
			(0.0523)	(0.2197)
13			1.1356***	-1.9431***
			(0.0534)	(0.2076)
14			1.2586***	-2.4951***
			(0.0539)	(0.2634)
Female (child gender)			0.1018***	-0.1700***
			(0.0186)	(0.0629)
Child health status (Baseline: very unhealthy)				
somewhat unhealthy				-0.4244
				(0.3013)
somewhat healthy				-1.0257***
				(0.2971)
very healthy				-1.1794***
				(0.3004)
Constant	8.2776***	2.2408***	0.0783	-13.5677***
	(0.2710)	(0.3409)	(0.2925)	(1.0084)

Observations	7,782	7,782	12,564	11,933

Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Source: Authors' own calculations.

Table A.7: Two-part model, part 1: Probit (any spending) for robustness

VARIABLES	(1) Positive bad goods	(2) Positive education	(3) Positive health
WBP in food = 1 (less partial)	-0.1712*		
	(0.1002)		
WBP in food = 2 (partial [joint])	-0.1327**		
	(0.0574)		
WBP in food = 3 (full)	-0.1144**		
	(0.0476)		
WBP in education = 1 (less partial)		-0.0233	
		(0.1221)	
WBP in education = 2 (partial [joint])		0.0291	
		(0.0612)	
WBP in education = 3 (full)		-0.0408	
		(0.0668)	
WBP in health = 1 (less partial)			-0.2029
			(0.1680)
WBP in health = 2 (joint)			-0.0612
			(0.0564)
WBP in health = 3 (full)			-0.0502
			(0.0599)
Urban	-0.2417***	-0.0692*	-0.0651**
	(0.0320)	(0.0407)	(0.0322)
Family size	0.0463***	-0.0043	-0.0120
	(0.0075)	(0.0094)	(0.0073)
Husband works	-0.0371	-0.1819**	-0.0716
	(0.0520)	(0.0711)	(0.0514)
Wife works	-0.1215***	0.0120	-0.0763**
	(0.0315)	(0.0401)	(0.0317)
Wife age	-0.0102***	-0.0031	-0.0009
	(0.0018)	(0.0028)	(0.0019)
Wife's insurance JKN			-0.0135
			(0.0384)
Husband's insurance JKN			-0.0231
			(0.0385)
Log of total spending	0.1178***	0.4952***	0.4097***
	(0.0257)	(0.0390)	(0.0269)
Number of children		-0.2067***	-0.1611***

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VARIABLES	(1) Positive bad goods	(2) Positive education	(3) Positive health
		(0.0249)	(0.0216)
Child age			
1			-0.1617**
			(0.0629)
2		-3.4995***	-0.2463***
		(0.3249)	(0.0633)
3		-2.5608***	-0.3759***
		(0.1215)	(0.0654)
4		-1.0726***	-0.5221***
		(0.0642)	(0.0664)
5		0.0735	-0.5339***
		(0.0621)	(0.0667)
6			-0.7491***
			(0.0708)
7		0.4816***	-0.8177***
		(0.0682)	(0.0751)
8		1.4684***	-0.8529***
		(0.0902)	(0.0742)
9		1.7176***	-0.9698***
		(0.1064)	(0.0750)
10		1.8075***	-0.9170***
		(0.1130)	(0.0773)
11		1.6944***	-1.0257***
		(0.1080)	(0.0809)
12		1.6938***	-1.0165***
		(0.1131)	(0.0838)
13		1.5770***	-1.0257***
		(0.1074)	(0.0852)
14		1.2711***	-1.1552***
		(0.0897)	(0.0857)
Female (child gender)		0.2591***	-0.0223
		(0.0380)	(0.0281)
Child health status (Baseline: very unhealthy)			
somewhat unhealthy			-0.1740
			(0.2126)
somewhat healthy			-0.6137***
			(0.2104)
very healthy			-0.7850***
			(0.2111)
Constant	-0.7832**	-6.8923***	-5.5707***
	(0.3995)	(0.5972)	(0.4638)
Observations	7,782	10,683	11,933

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VARIABLES	(1) Positive bad goods	(2) Positive education	(3) Positive health

Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Source: Authors' own calculations.

Table A.8: Two-part model, part 2: OLS on log-transformed share among positives for robustness

VARIABLES	(1) Log share of bad goods	(2) Log share of education	(3) Log share of health
WBP in food = 1 (less partial)	-0.1403		
	(0.0925)		
WBP in food = 2 (partial [joint])	-0.0366		
	(0.0502)		
WBP in food = 3 (full)	-0.0088		
	(0.0398)		
WBP in education = 1 (less partial)		-0.2183***	
		(0.0636)	
WBP in education = 2 (partial [joint])		-0.0021	
		(0.0282)	
WBP in education = 3 (full)		-0.0578*	
		(0.0312)	
WBP in health = 1 (less partial)			-0.2068
			(0.3039)
WBP in health = 2 (joint)			-0.1431
			(0.1003)
WBP in health = 3 (full)			-0.1608
			(0.1082)
Urban	0.0045	0.3287***	0.0244
	(0.0280)	(0.0200)	(0.0561)
Family size	0.0093	-0.0275***	-0.0361***
	(0.0059)	(0.0044)	(0.0138)
Husband works	-0.0279	0.0216	-0.2279**
	(0.0468)	(0.0342)	(0.1028)
Wife works	-0.0911***	-0.0412**	-0.0447
	(0.0283)	(0.0193)	(0.0594)
Wife age	-0.0125***	-0.0019	-0.0002
	(0.0016)	(0.0013)	(0.0036)
Wife's insurance JKN			0.0799
			(0.0690)

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VARIABLES	(1) Log share of bad goods	(2) Log share of education	(3) Log share of health
Husband's insurance JKN			-0.0865
			(0.0693)
Log of total spending	-0.3801***	-0.2956***	0.1259**
	(0.0244)	(0.0192)	(0.0581)
Number of children		-0.2510***	-0.3260***
		(0.0130)	(0.0367)
Child age			
1			-0.1259
			(0.1011)
2		-2.5054***	-0.3797***
		(0.0457)	(0.0999)
3		-0.5872**	-0.1619
		(0.2570)	(0.1077)
4		-0.5066***	-0.1622
		(0.0802)	(0.1116)
5		-0.3595***	-0.3514***
		(0.0570)	(0.1190)
6			-0.5256***
			(0.1265)
7		0.3960***	-0.4319***
		(0.0491)	(0.1303)
8		0.4032***	-0.7655***
		(0.0479)	(0.1434)
9		0.4085***	-0.5396***
		(0.0471)	(0.1480)
10		0.3799***	-0.7802***
		(0.0473)	(0.1666)
11		0.3948***	-0.4930***
		(0.0482)	(0.1542)
12		0.4484***	-0.4537**
		(0.0486)	(0.1803)
13		0.7453***	-0.5715***
		(0.0503)	(0.1727)
14		0.9474***	-1.1143***
		(0.0499)	(0.1938)
Female (child gender)		0.0399**	-0.0731
		(0.0183)	(0.0526)
Child health status (Baseline: very unhealthy)			
somewhat unhealthy			-0.3147
			(0.2838)
somewhat healthy			-0.4260

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VARIABLES	(1) Log share of bad goods	(2) Log share of education	(3) Log share of health
			(0.2803)
very healthy			-0.3170
			(0.2826)
Constant	4.1873***	3.5826***	-2.6865***
	(0.3778)	(0.3014)	(0.9406)
Observations	5,696	7,147	2,150
R-squared	0.072	0.288	0.116

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' own calculations.

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