Doctoral Dissertation

Research on Low Enrollment of Community-based Health Insurance Scheme: A Case Study of Rural Households in Savannakhet Province, Lao People's Democratic Republic

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Summary

In low-income countries, the poor are often more vulnerable than any other group to health risks and insufficient access to health care services. Numerous efforts have been made to resolve this vulnerability. Over the decades, the governments of developing countries have considered community-based health insurance (CBHI) as a powerful tool enabling the poor to equal access to affordable health services based on their needs. The commonly crucial characteristics of the CBHI scheme are its risk-pooling system at the community level and voluntary membership.

In practice, many developing countries have faced significant obstacles in implementing the CBHI scheme, including low enrollment rates, adverse selection, poor quality of health care, and high drop-out rates. Importantly, the problem of low enrollment rates especially links to the financial sustainability and low acceptance of the scheme. Although multidimensional factors are affecting the low enrollment rates, the present study focuses on the demand perspective of the targeted population for the CBHI scheme. This study selects the CBHI scheme in Lao People's Democratic Republic (Lao PDR) whose enrollment rate is as low as 3.7% by 2014 as a case in point. Does the low enrollment of the CBHI scheme in the Lao PDR crucially imply low demand of potential enrollees for the CBHI scheme? In order to clarify the research argument above, this dissertation carries out analysis based on three research objectives as follows:

1. **To evaluate the impacts of the CBHI scheme on household welfare**, we employ the method of inverse probability of treatment weight (IPTW) to correct imbalances in pre-intervention covariates between treated and untreated samples.
2. **To observe the association of households' likelihood of purchasing the CBHI scheme with their own risk preferences**, an incentive compatible

lottery choice field experiment is carried out to first assess their risk preferences. Each respondent confronts with a sheet of 35 decision rows, which decomposed into two series of gains and one series of losses. The respondent is asked to indicate a preference for either option A or option B in each row. Option A is a safe choice, and option B has a higher expected payoff and variance. Then, probit regressions are applied to examine the associations between their CBHI participation and their risk preferences by controlling their demographic and economic backgrounds.

3. **To measure willingness-to-pay (WTP) for the CBHI scheme improvement**, a randomized conjoint field experiment is conducted to elicit stated preference data. Each respondent ranks five randomly formed choice tasks. In each choice task, the respondent ranks three policy alternatives: two hypothetical CBHI scheme and the CBHI status quo scheme. The hypothetical CBHI scheme is defined by seven attributes: *monthly premium*; *insurance coverage for medical consultations*, *hospitalizations*, *traffic accidents*, *pharmaceuticals*, *transportation*; and *one-year prepaid discount*.

This study collects data of 580 self-employed households from eight rural villages in Savannakhet Province of the Lao PDR. The sample represents 46% of the eligible population in the selected villages, comprised of 210 (36%), 72 (13%), and 298 (51%) of active members, ex-members, and non-members, respectively. The survey is carried out from September 13-27, 2016. The household representatives are asked a series of questions on socio-economic indicators in the 12 months preceding the survey and two field experiments.

Empirical findings from this study suggest that:

1. The CBHI scheme has significant impacts on rice yield per capita and cow holdings among enrolled households. Such findings possibly reflect the fast recovery of illness and less reliance on coping responses resulting from the improved health status of enrolled households.

2. The findings show that the probability of a household's decision to enroll in the CBHI scheme is associated with the risk aversion towards probability prospects. This result provides some support that there seems to be the adverse selection in the current CBHI scheme.

3. The average WTP is estimated at least as large as 10.9% of the per capita income of those who live in rural areas. Notably, the presence of round-trip transportation insurance coverage significantly increases the WTP.

On the basis of the results of this research, it can be concluded that the CBHI scheme contributes to the agricultural production, policy practitioners should put great endeavors to scale up the enrollment rate. However, the problem of the CBHI scheme in the Lao PDR is not only low uptake, but there seems to be adverse selection. The adverse selection can somehow be mitigated by maximizing enrollment.

Although the WTP analysis demonstrates that there is strong demand for the CBHI scheme, but the majority of self-employed households fail to enroll. It can be interpreted that the current scheme design might not well meet people's preferences though premium is affordable. People might lack sufficient knowledge about the CBHI scheme and its risk-pooling system. Possibly, they might lack trust on the scheme operation. As suggested by Carrin (2003), the trust can be, to some extent, increased as long as people recognize that their preferences are addressed in the scheme design. To increase the enrollment rate, first and foremost, local authorities and stakeholders should give priority to the

CBHI scheme promotion campaign and improve the insurance coverage that meet their preferences, especially addressing transportation factor.

Acknowledgements

Three years of PhD research has been a period of intense learning for me. In the absence of the valuable contribution of many people, writing this dissertation would not have been possible. So, I would like to express my deepest gratitude to those who have supported and assisted me so much throughout this research as follows:

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Abbreviations

AMCE	average marginal component effect
ATT	average treatment on the treated
CBHI	community-based health insurance
CEM	Coarsened Exact Matching
CRRA	constant relative risk aversion
CVM	contingent valuation method
DCEs	discrete choice experiments
EUT	Expected Utility Theory
GDP	Gross Domestic Product
HDI	Human Development Index
HEFs	Health Equity Funds
IPD	inpatient department
IPTW	Inverse Probability of Treatment Weight
IV	instrumental variables
LAK	Lao Kip
Lao PDR	Lao People's Democratic Republic
LMICs	low- and middle-income countries
MOH	Ministry of Health
NHI	National Health Insurance
OOPs	out-of-pocket expenditures
OPD	outpatient department
PhD	Doctor of Philosophy
PSM	Propensity Score Matching

PT	Prospect Theory
RDD	regression discontinuity designs
RP	revealed preference
SASS	State Authority Social Security
SATT	sample average treatment effect on the treated
SP	stated preference
SSO	Social Security Organization
VF	village fund
WHO	World Health Organization
WTP	willingness-to-pay

Chapter 1

Introduction

1.1 Research motivation

In low-income countries, the poor often suffer from high rates of illness due to the low standards of living [1]. The poor are the most vulnerable group, especially for high exposure to risks and low access to sufficient health care services. Additionally, ill health reduces work productivity, which leads to lost income. To reduce the vulnerability, community-based health insurance (CBHI) scheme is considered one of the most powerful mechanisms to reduce both the health risks and financial risks caused by catastrophic health care expenditures for informally employed people, who are mainly lower-income people.

The CBHI scheme is a risk-pooling system that has received increasing attention as a powerful tool for health system improvement, particularly regarding financial protection and health equity, in low- and middle-income countries (LMICs) [2]. The scheme enrollment is on a voluntary basis, and the pooling of health risk and prepayment typically occur at the community level. Under the risk-pooling system, individuals' financial burden is spread across all scheme members making health care more affordable for the poor. Therefore, beneficiaries are protected against catastrophic costs of illness while ensuring their right to equal access to health services based on their needs.

Although this scheme intends to reduce reliance on direct out-of-pocket expenditures (OOPs) and to facilitate a targeted population's utilization of health services, in practice, the implementation of this scheme is slow and laborious, especially in low-income countries. According to an extensive body of empirical work, the four common problems of the CBHI scheme implementation are low enrollment rates , for instance, [3, 4], adverse selection [5–8], poor quality of health care [9], and high drop-out rates [10–12]. The low enrollment rates of the targeted populations are not only a primary challenge facing the financial sustainability of the scheme but also an indicator of low acceptance of the scheme [13]. Particularly, the literature often reports disappointing enrollment percentages, with the percentage of the eligible population covered by the scheme varying between 1% and 10% [4, 14–16] for most cases and, rarely, between 21% and 46% [17, 18].

In Lao People's Democratic Republic (Lao PDR), the health risk is expected to be an increasing threat to the poor, especially in remote areas [19] where the majority of the population remains dependent on agricultural activities for subsistence and the infrastructure is inadequate. Therefore, the government is concerned with strengthening the health system, health financing schemes, in particular, to ensure health equity for all groups in the population.

To improve the health system, the government launched four health financing schemes targeting specific groups in the population, including State Authority Social Security (SASS) for government workers, Social Security Organization (SSO) for salaried private and state-owned enterprises employees, Health Equity Funds (HEFs) for the extreme poor, and Community-Based Health Insurance (CBHI) for non-poor workers in the informal sector [20]. Among the four schemes, only the CBHI scheme is based on voluntary membership and decentralized implementation and has the very low enrollment rates compared to the target.

Therefore, the CBHI scheme in the Lao PDR is an appropriate case study to examine the determinants of low enrollment and potential improvements for three main reasons: 1. the scheme is voluntary, 2. the targeted population is mainly the poor in rural areas with limited infrastructure and geographic constraints, and 3. the scheme has made extremely slow progress towards the given target. This paper argues that the low enrollment of the CBHI scheme in the Lao PDR does not necessarily imply low demand of the targeted population. This study aims to test the validity of the following hypotheses:

1. The CBHI scheme has impacts on household welfare.
2. Individual risk preferences take part in explaining the likelihood of participation in the CBHI scheme.
3. There is potential demand for the CBHI scheme enrollment.

This study is expected to contribute complementary evidence to the health financing literature, especially low enrollment issue, using different country-specific setting. The following section discusses more details about the case study of the CBHI scheme in the Lao PDR.

1.2 Social health protection system in the Lao PDR

As in most developing countries, the social health protection system has become an instrument for sustainable poverty alleviation of the Lao government because the system protects vulnerable groups from the financial risk of ill health by the risk-pooling system. At present, four formal protection schemes have been implemented. In 1993, the government launched the SASS scheme for all civil servants and their dependents. The monthly contribution was initially 6% of employees' basic salary and the remaining amount contributed by the government. However, the revision of the scheme in 2006 featured that the monthly contribution rate was 8% of employees' basic salary and 8.5% of employers' payroll. For private sector employees and their families, the SSO scheme was officially introduced in 1999. The scheme was mandatory for all enterprises and organizations with ten or more workers. The employers and employees contributed equally 4.5% of the basic salary [21]. Both schemes mentioned above have been implemented under which mandatory membership is required. In 2002, in collaboration with donors, the CBHI scheme was established aiming at providing better access to affordable health services for the self-employed people. The monthly contribution was a flat amount according to household size and residence area (rural/urban residence). In addition to the CBHI scheme, the government launched another form of health protection schemes in 2004, known as the HEFs, in order to ensure that the extreme poor would not be left behind. The scheme primarily targets those whose income was below a poverty line of the Lao PDR. The scheme shall receive 100% of revenue sources from the government, donors, and/or international organizations.

The population coverage of the social health protection system regardless of any specific scheme is presented in Figure 1.1. Though the coverage has been increasing over time the rate is slightly low. As of 2014, 27.1% of the population was covered by the four schemes of the health financing system. However, there is heterogeneous variation when the coverage is decomposed by scheme as shown in Figure 1.2. While the coverage of the SASS and HEFs schemes, which targeted nearly 26% of the Lao population, achieved approximately 85% of their target, that of the SSO and CBHI schemes made little progress, with only 6.4% of the targeted group enrolled. Especially, the CBHI scheme is still in early stages of operation though the scheme has been established over a decade. By 2014 only 3.7% of the targeted population have participated in the CBHI scheme. Therefore, the failure of the CBHI scheme is conducive to detail overview in the following section.

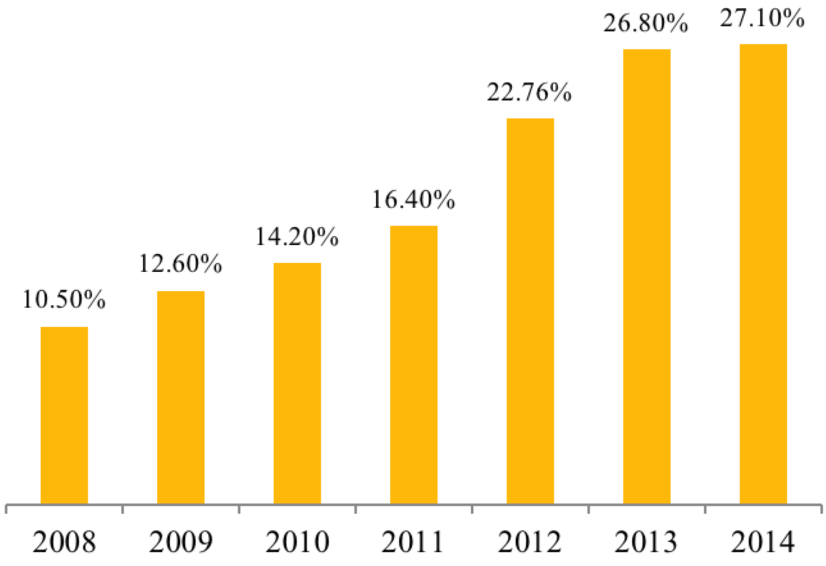


FIGURE 1.1: Social health protection coverage
Source: Central National Health Insurance Bureau, Ministry of Health

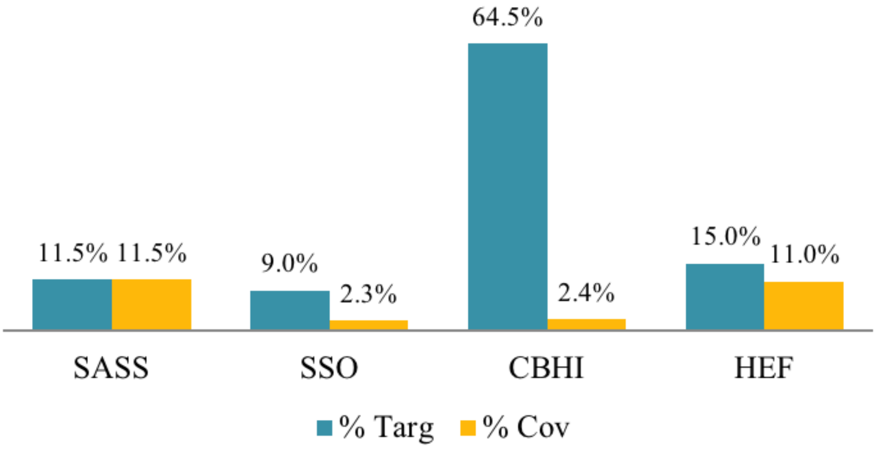


FIGURE 1.2: Coverage and target by scheme, 2014
Source: Central National Health Insurance Bureau, Ministry of Health

1.3 CBHI scheme in the Lao PDR

In 2002, the Ministry of Health (MOH) introduced the CBHI scheme as a pilot project in five areas (Sisathanak and Hatsiphong Districts of Vientiane Capital, Nambak District of Luangprabang Province, Champassak Province, and Vientiane Province) with technical assistance from the World Health Organization (WHO) and financial support from the United Nations Human Security Fund. The CBHI scheme targets on households who engage in the informal sector and are not insured by any other social protection schemes, which has the segment over 60% of the Lao population.

Since the household is the unit of enrollment, the premiums vary depending on household size and urban or rural residence as presented in Table 1.1. The premium rates have not been updated since 2005 [22]. Currently, the health care benefit package of the CBHI scheme covers outpatient department (OPD) and inpatient department (IPD) services, including primary health care, specialist services, diagnostic tests, and prescribed pharmaceuticals that are available in hospitals. However, the CBHI scheme does not cover long IPD stays, road accidents, non-prescribed pharmaceuticals, some specialist services and care outside the country.

TABLE 1.1: Monthly CBHI premium per household

	Urban residence (LAK)	Rural residence (LAK)
Single person	14,000	12,000
Household 2-4 persons	24,000	20,000
Household 5-7 persons	30,000	25,000
Household 8+ persons	33,000	28,000
Monks, nuns, dormitory students	5,000	5,000

Source: Regulation of Minister of Health No 723/MOH, dated 13 April 2015

The window period of service access upon enrollment is one month for OPD, three months for IPD and surgical emergency, six months for deliveries and obstetric surgery. With the gatekeeping system, the CBHI members have first to seek services at contracting facilities, such as dispensaries and district hospitals, and only referral patients are sent to provincial or regional hospitals [23]. Since 2012, 50% of the scheme's revenue has come from the premium collection, and the other 50% has come from government subsidization [24].

As of September 2015, the scheme was available in 50 of the 148 districts in 17 of the 18 provinces, which is equivalent to 2,271 of the 8,507 villages. The total number of beneficiaries was reported as 33,795 households (179,534 people). It is equivalent to 2.8 percent of the total population. The statistics points out that, after a decade of implementation, the CBHI scheme in the Lao PDR continues to encounter with the similar problem that most developing countries launching the CBHI scheme have experienced, that is the phenomenon of chronically low enrollment of targeted population.

1.4 Dissertation outline

This PhD consists of six chapters. Chapters 3, 4, and 5 form the main body of the dissertation. The main contents of each chapter are as follows:

Chapter 1 gives information on the motivation for the research on the CBHI scheme. The chapter lists the common problems facing the CBHI scheme implementation in developing countries, of which the issue of low enrollment rates is highlighted. Then, the overview on the CBHI scheme in the Lao PDR is presented.

Chapter 2 presents how the household survey is carried out. Criteria for selecting representative districts, representative villages, and sample households are discussed to ensure heterogeneous views of respondents.

Chapter 3 tests the first PhD research hypothesis (*the CBHI scheme has impacts on household welfare*). It provides empirical evidence on how the CBHI scheme is beneficial for enrolled households. In this chapter, the impacts of the CBHI scheme on household welfare are evaluated, focusing on intertemporal impacts on rice production and livestock holdings, by employing the inverse probability of treatment weighting technique to mitigate the imbalances of selected covariates between comparison groups.

Chapter 4 tests the validity of the third PhD research hypothesis (*Individual risk preferences take part in explaining the likelihood of participation in the CBHI scheme*). By adopting an incentive compatible lottery choice experiment, individual risk preference parameters are observed. It focuses on the correlation between behavioral predictors and the likelihood of the CBHI scheme uptake using probit regression.

Chapter 5 addresses the second PhD research hypothesis (*there is potential demand for the CBHI scheme enrollment*). It provides a closer look at the potential demand and affordability of the targeted population. The chapter shows how to elicit stated preference (SP) data for hypothetical CBHI scheme and estimate the demand distribution using the SP data from the randomized conjoint experiment.

Chapter 6 provides a summary of the key empirical findings of the dissertation in Chapters 3, 4, and 5. Then, policy implication is discussed.

Chapter 2

Study area and data collection

2.1 The Lao PDR

The fieldwork of this dissertation was carried out in the Lao PDR. It is a landlocked country, located in the South-East Asia and shares borders with China, Myanmar, Thailand, Cambodia, and Vietnam. The country is divided into 17 provinces and one capital city, with the estimated population at 6,492,228 people in 2015 and the population density of 27 people per square kilometer. The annual population growth rate was 6.5% in 2015. Lao population is relatively a young population with 32% is under 15 years old, while only 4.2% over 65 years old. The large proportion of the Lao population still resides in rural areas though declining from 73% in 2005 to 67% in 2015 (Lao Population and Housing Census, 2015).

With the gross domestic product (GDP) per capita of 2,159USD in 2015, the Lao PDR is classified as a lower middle-income country [25]. Based on the Human Development Report 2015, the country ranked 138th out of 188 countries on the Human Development Index (HDI), which was higher than Vietnam (115th) but well lower than Cambodia (143th) and Myanmar (145th). The share of the population that is below the poverty line declined from 48% in 1992 to 23% in 2012 [26]. Regarding health status, the underlying health indicators in 2015 are summarized in Table 2.1. It is evident that the Lao PDR is still not yet on track to achieving the targets by 2015.

Table 2.1: Key health indicators in the Lao PDR

	2015 achievement	2015 target
Life expectancy at birth (years)	66.54	70
Infant mortality rate (per 1,000 live births)	57	45
Under-five mortality rate (per 1,000 live births)	86	70
Maternal mortality rate (per 100,000 live births)	206	260
Malaria incidence (per 1,000)	4.92	0.6
Death rate associated with malaria (per 100,000)	0.3	0.2

Source: United Nations in Lao PDR (2017), Hayes, G. (2015), the World Bank, World Development Indicators (2018).

Table 2.2 reports the health expenditure in the Lao PDR. As of 2015, total expenditure on health was about 2.8% of GDP. The share translates to about 53USD per capita on the average. However, from the share, external resources took up 17%. The government expenditure on health was about 1% of GDP. As a result of the very low government expenditure on health, the shortfall is made up by private expenditure, about 45.4% of which is OOPs. This means that the health funding in the Lao PDR relies significantly on OOPs resource. With the OOPs, there can be a high incidence for households of suffering catastrophic expenditures at the time of service use. Therefore, many households are reluctant or cannot even pay for primary health care services.

Table 2.2: Health expernditures in the Lao PDR

	2011	2012	2013	2014	2015
Current health expenditure (% of GDP)	2.7	2.3	2.7	2.6	2.8
Current health expenditure per capita (current USD)	27.5	33.0	44.1	46.4	53
External health expenditure (% of current health expenditure)	27.6	27.0	19.0	16.8	17
Out-of-pocket expenditure (% of current health expenditure)	52.6	48.6	48.7	50.9	45.4
Out-of-pocket expenditure per capita (current USD)	14.5	16.0	21.5	23.6	24.0
Government health expenditure (% of GDP)	0.4	0.5	0.8	0.8	1.0
Government health expenditure (% of current health expenditure)	18.9	21.0	30.0	30.0	35.2

Source: The World Bank, World Development Indicators (2018).

2.2 Savannakhet Province

FIGURE 2.1: Map of Savannakhet Province in the Lao PDR

This research collects data from rural households in Savannakhet Province, which is located in the central part of the Lao PDR (see Figure 2.1). It is the province with the largest land area covering 21,774 square kilometers and also the largest population making up 14.9% of the total population in the country, with 77.8% of which live in remote villages (equivalent to 754,469 individuals). This means that there seem to be the large percent of the people engaged in the informal economy, which is the targeted sector of the CBHI scheme.

According to the Center National Health Insurance (NHI) Bureau report in 2015, Savannakhet Province had had the largest CBHI enrollment rate of all the provinces. There had also been significant fluctuation in enrollment and/or dropout rates since 2013 (see Figure 2.2). Figure 2.3 compares the enrollment rates of the CBHI scheme with other social health protection schemes. It is evident that the CBHI uptake rate declined greatly from 7.58% in 2013 to 6.31 in 2015 of the province population. So, the case study of the CBHI scheme in Savannakhet Province is worth to study.

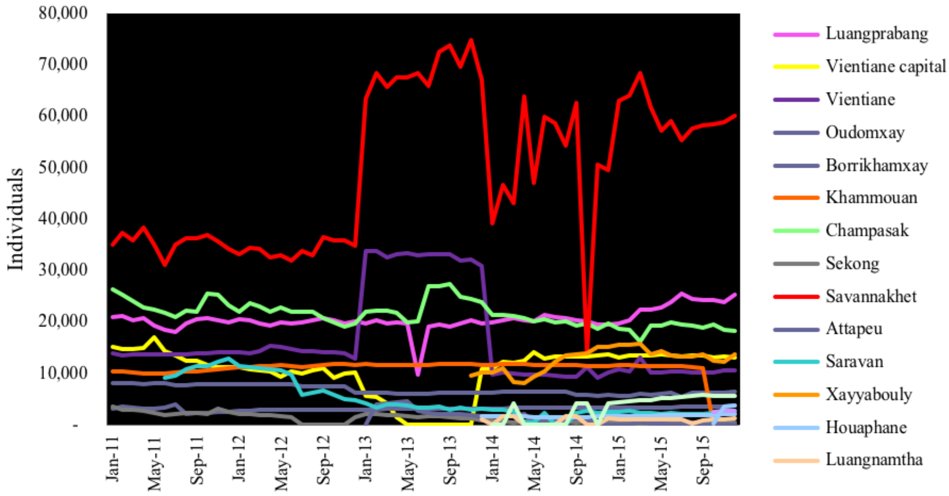


FIGURE 2.2: CBHI members by province (persons)
Source: Graphed by author

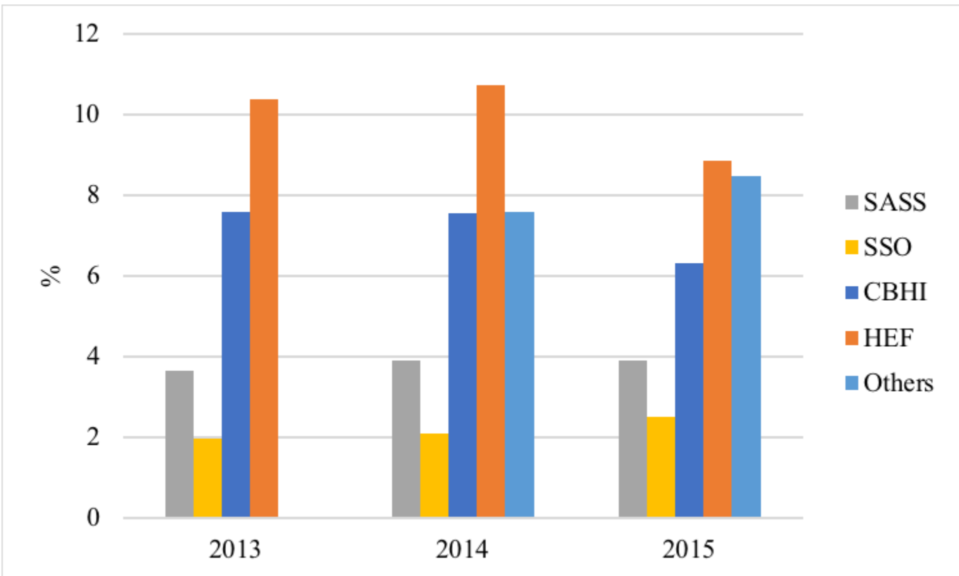


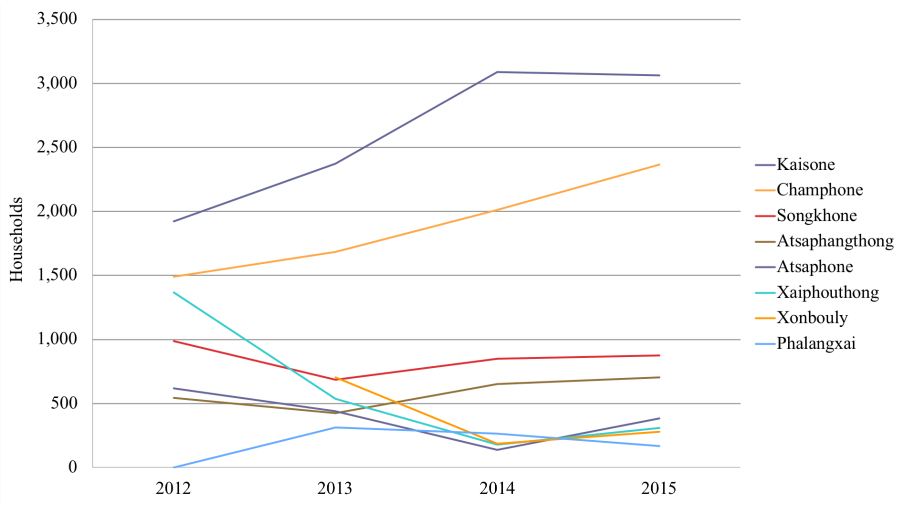
FIGURE 2.3: Social health protection coverage in Savannakhet Province
Source: Savannakhet Provincial National Health Insurance Bureau

2.3 Data sampling

The household survey is carried out in two districts of Savannakhet Province from September 13-27, 2016 and included 580 self-employed households randomly drawn from eight villages. Samples are recruited by a three-stage sampling technique according to the following reasons:

- Savannakhet Province is divided into 15 districts. Since 2014, eight of the districts reported increasing uptake rate of the CBHI scheme, while the remaining districts have faced a decreasing uptake rate over time. Note that neither the province capital district is included in our selection because its infrastructure differs from that of the other districts nor Nong District (one of the poorest districts in the Lao PDR) because it is covered by the HEFs scheme.

- To ensure that the results account for the views of heterogeneous respondents, we intentionally select two representative districts with increasing and decreasing uptake rates of CBHI members. Accordingly, we choose Champhone and Xaibouly Districts, which have the largest CBHI members among increasing and decreasing, for this study [1] (see Figure 2.4).



- As our focus is households in remote areas, to ensure that the experiment can plausibly be conducted in these areas, we purposively designate only type II villages

[1] However, the CBHI coverage in Champhone and Xaibouly Districts accounted for only 0.21% and 0.1% of the province population in 2015, respectively.

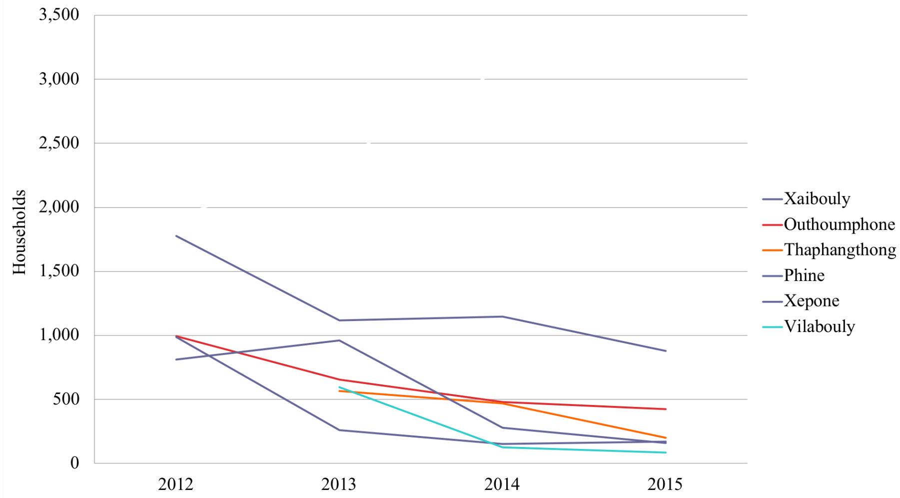


FIGURE 2.4: CBHI enrollment rates in districts, Savanakhet Province (households)
Source: Savannakhet Provincial National Health Insurance Bureau

with a homogeneous infrastructure surveillance of **"1 1 0 1 1 1 0"** [2] . Finally, we identify three villages in Champhone District and six villages in Xaibouly District. However, one village in Xaibouly District is removed due to accessibility constraints.

- All informal-sector households [3] , which are the targets of the CBHI scheme, are eligible for this study. However, in practice, we purposely omit monks because interviews with them are implausible. The eligible population is stratified into three groups: CBHI active members, non-members, and ex-members. Member respondents are randomly drawn from a list of currently active CBHI members in each village, whereas ex-members are randomly selected from a list of those who dropped out before August 2016. Non-members are randomly selected from a list of households in each village excluding households that work in formal sectors (employed households), member households and dropout households. There are 580

[2]Lao Statistics Bureau classifies villages into three types: Village type I indicates an urban village with road access, electricity, water supply, regular market, and administrative office; Village type II is a rural village with road access; and Village type III is a rural village without road access. **"1 1 0 1 1 1 0"** condition indicates road access (yes), electricity (yes), health care facility (no), clean water (yes), village drug kits (yes), primary school (yes), and regular market (no).

[3]Household is defined as a group of people in a housing unit living together as a family and sharing the same kitchen.

stratified random samples, representing 46% of the eligible population. Our samples comprise 210 (36%), 72 (13%), and 298 (51%) active members, ex-members, and non-members, respectively.

As is customary, we visit the chief of each village a few days beforehand to inform the objectives and experimental procedure. Once the list of random respondents is recruited, a day prior to the experiment the village chief announces the names of assigned household members to join with the family book and CBHI member card (if his/her household was enrolled in the CBHI scheme) at the given location (usually at temples). For ease, every six respondents are appointed at one-hour intervals from 8 a.m. to 5 p.m.

2.4 Data collection and field experiments

In the local context, the household head or spouse is the key decision maker over the allocation of economic resources within the household. Therefore, we exclusively identify either the household head or spouse as the representative of the household to our survey. Their preferences may be crucially relevant to the decision making of the entire household. To identify the household characteristics, each subject is asked a series of questions on socio-economic indicators prior to the experimental session, including their demographic details, household assets, microfinance history, CBHI experience, income and expenditure sources, and self-reported illness history in the 12 months preceding the survey [4]. In addition to the questionnaire-based interview, two field experiments are conducted for the sample of 580 households as follows:

[4]Eight investigators are employed and trained based on the content of the questionnaire. The questionnaire is pretested prior to the main survey.

2.4.1 Randomized conjoint field experiment

To test the verification of the second null hypothesis, we conduct the randomized conjoint field experiment in which the hypothetical CBHI scheme is defined by seven selected attributes: *monthly premium*; *insurance coverage for medical consultations*, *hospitalizations*, *traffic accidents*, *pharmaceuticals*, *transportation*; and *one-year prepaid discount*. Each respondent is asked to rank five randomly formed choice tasks. In each choice task, the respondent ranks three policy alternatives: two hypothetical policies and the CBHI status quo scheme. Once the respondent completes the ranking for five choice tasks, he/she participates in the risk field experiment.

2.4.2 Risk field experiment

For the risk experiment, each respondent confronts with a sheet of 35 decision rows, which decomposed into two series of gains and one series of losses. The respondent is asked to indicate a preference for either option A or option B in each row. Option A is a safe choice, and option B has a higher expected payoff and variance.

2.5 Descriptive characteristics of the samples

Descriptive characteristics of the participants can be found in Table 2.3. There are slightly higher proportions of women than men participated in our survey, the participants have a mean age of 44.66 years. Of the respondents, 66% completed primary school, 19% secondary school, 13% upper school, and 2% higher education. The average household size is 5.92. The average annual household income is 15.26mill.LAK (median income: 9.31mill.LAK). The average annual per capita income is 2.81mill.LAK, with a right-skewed distribution and standard deviation of 4.53mill.LAK. Moreover, 61% of households have an income level below the poverty line [5].

Table 2.3: Descriptive summary

	Mean	S.D.	Min	Max
Respondent characteristics				
Gender (1=male)	0.42	0.49		
Age (years)	44.66	14	16	91
Education (%)				
Primary	66			
Secondary	19			
High school	13			
Higher education	3			
Household characteristics				
Household size	5.92	2.16	2	14
Annual income (mil.LAK)	15.26	22.45	0.5	300
Annual per capita income (mil.LAK)	2.81	4.53	0,07	66.63
Poverty (1=poor)	0.61	0.49		

[5] According to the Prime Minister Office (2009), a household is non-poor if its per capita income is over 180,000LAK per month (national poverty line in rural areas). 1USD is equivalent to 8,200LAK in September 2016.

Chapter 3

Impacts of CBHI scheme on household welfare

3.1 Introduction

By reason of irregular occupation and income level, informally employed individuals are often not counted in any payroll-based health insurance schemes and continue to suffer from the high cost of seeking health care. Over two decades, the CBHI scheme has been implemented as an attempt to provide financial protection and health equity for those people in developing countries [28]. To ensure that the specific health insurance scheme leads to development outcomes, the impacts of the action for people in the informal sector is evaluated by extensive literature. For instance, Spaan (2012) concluded in a systematic review on the impact of health insurance in Africa and Asia that the intervention significantly improved financial protection and enhanced service utilization, but weak evidence on social inclusion, quality of care, and community empowerment were found. Further, a report reviewed by Acharya et al. (2013) on the impact of health insurance schemes for the informal sector in low- and middle-income countries found contradictory results of no strong evidence on utilization, financial protection, and health status. It is noticed that most of the previous studies primarily examined the impacts of specific health insurance on immediate outcomes of financial protection and health service utilization [31–34]. However, existing evidence of such immediate benefits from developing countries is rather divergent and inconsistent.

Beyond the direct effects, the potential benefits of health insurance might be found on indirect outcomes resulting from less OOPs, fast recovery of illness, or improved health status. In developing countries, people living in rural areas often depend on labor-intensive agriculture for subsistence and livelihoods, inevitably health status and agriculture production are correlated in multiple ways. Good health is an asset for agriculture production as they can work more [35], whereas poor health reduces the capacity to work of the sick individual and the level of output, accordingly [36]. Moreover, when rural dwellers encounter ill-health, which leads to higher OOPs and income loss, the common coping responses in the absence of sufficient cash savings are selling livestock, assets, or borrowing to finance health care treatment [37, 38]. Accordingly, a basic impact pathway diagram of the CBHI scheme and agriculture production is developed in Figure 3.1.

Few studies examine these hypotheses empirically. Parmar et al. (2012) evaluated whether the CBHI scheme protects household assets in rural Burkina Faso. The assets are defined by the monetary value of goods and livestock owned by the households. Parmar et al. (2011) found that the scheme participation leads to increasing household assets. Another interesting study is the work of Yilma et al. (2015) that assessed the impact of the CBHI scheme on household consumption, income, indebtedness, and livestock holdings in Ethiopia. The findings showed that the CBHI scheme reduced reliance on coping response, especially borrowing, but no evidence on livestock holdings was found. Due to the limited work on the indirect benefits of the CBHI scheme, more empirical evidence is needed, in particular, impacts on agriculture production.

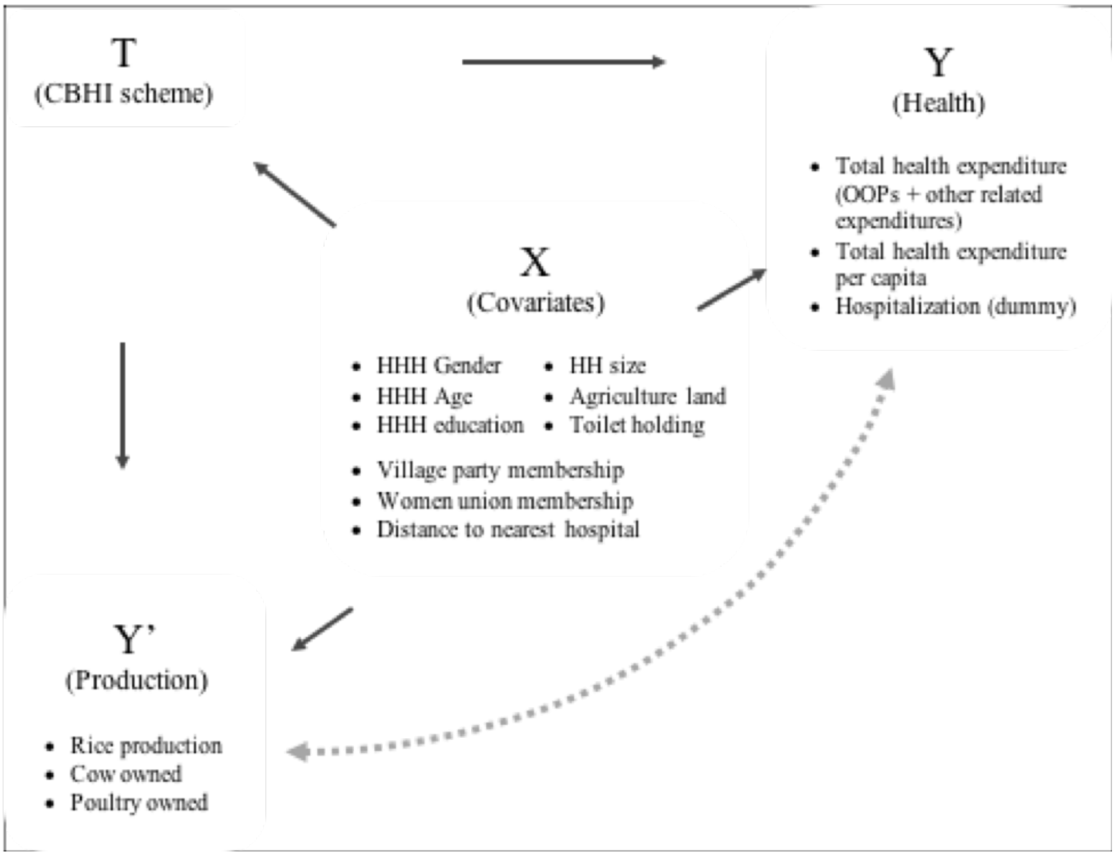


Figure 3.1: Framework for CBHI scheme and agriculture production linkages

The impacts of the CBHI scheme on the measured outcomes of informal-sector households in rural villages of the Lao PDR is an appropriate case in point to test the hypotheses. Like many other developing countries, in order to promote health equity for self-employed people, the government of the Lao PDR has launched the CBHI scheme since 2002.

In the Lao PDR, the majority of self-employed people resides in remote villages. They mainly depend upon labor-intensive rice production and livestock raising for subsistence. Especially, livestock is the most common form of non-cash saving for the poorest quantile making up about 77% [39]. It is also reported that cow is the second income source of rural people in Lao PDR [40]. Therefore, we hypothesize that the CBHI scheme increases rice yield and the number of livestock holdings of rural households. Thus, the objectives of this study are to investigate the impacts of the CBHI scheme on the rice production and livestock holdings among rural households in Savannakhet Province of the Lao PDR. Based on subsample analysis, two additional research questions are examined:

1. Do the impacts vary in the presence and absence of CBHI ex-members?
2. Are the impacts divergent in the presence and absence of households engaged in the village fund?

To accomplish the research objectives, the following methodology is adopted to estimate the causal effects from the study sample.

3.2 Methodology

To test the null hypothesis and answer two additional research questions, the samples are managed in the following categories:

- Full sample: we pool CBHI members, non-members, and ex-members (as untreated subjects) regardless if subjects simultaneously engaged in the village fund (hereinafter referred to as "VF subjects")[1].
- Subsample 1: To observe the results in the absence of the CBHI ex-members, subsample 1 is equivalent to the full sample minus the ex-members.
- Subsample 2: Similarly, subsample 2 equals the full sample subtracting the VF subjects.
- Subsample 3: This category is especially the focus of our efforts as both the ex-members and VF subjects are removed.

[1] The village fund program is available in all eight selected villages of our study, the program targets the similar group of the population with the CBHI scheme. The unit of enrollment is household. However, the program is implemented by different organizations.

Table 3.1 shows the description and measurement of the treatments, potential covariates, and outcome variables employed in this study. To address the impact variation associated with household size, we observe both aggregate and per capita outcomes. Summary statistics of the full sample and subsamples of treated and untreated households are presented in Table 3.2. The mean different test shows that the comparison groups have consistently significant differences on certain pre-intervention characteristics, especially household head age and education, household size, toilet availability in the household, engagement in village party and women union, and average distance from the village to the district hospital. These differences in baseline characteristics would lead to difference in selected outcomes even in the absence of the CBHI scheme enrollment. In particular, the differences are significant for aggregate expenditures, expenditures on education, food, other goods, rice yield, number of cows and poultry holdings. However, the imbalance of baseline characteristics is solved by the IPTW technique as shown in Table 3.3.

Table 3.1: Variable description and measurements

Variable	Type	Measurement
Treatment		
CBHI member	Dummy	1 if households are currently the members of CBHI scheme, 0 otherwise
Potential covariates		
Household head		
Gender	Dummy	Gender of the household head. 1 if male, 0 otherwise
Age	Continuous	Age of household head in years
Household		
Size	Continuous	Number of individuals living in the same household
Land	Continuous	Agricultural land holding size in square meters
Toilet	Dummy	Toilet availability in the household. 1 if have, 0 otherwise
Village party[a]	Dummy	Any member in the household is member of village party. 1 if yes, 0 otherwise
Women union	Dummy	Any member in the household is member of women union. 1 if yes, 0 otherwise
Village		
Distance	Discrete	Average distance from the village to the district hospital in kilometers
Outcomes variables[b]		
Income	Continuous	Total income in 1,000LAK
Income per capita	Continuous	Total income per capita in 1,000LAK
Expenditure	Continuous	Total expenditure in 1,000LAK
Expenditure per capita	Continuous	Total expenditure per capita in 1,000LAK
Health	Continuous	Health expenditure in 1,000LAK (including transportation, stay, and food expenditures during health treatment)
Health per capita	Continuous	Health expenditure per capita in 1,000LAK
Education	Continuous	Education expenditure in 1,000LAK
Food	Continuous	Food expenditure in 1,000LAK
Food per capita	Continuous	Food expenditure per capita in 1,000LAK
Transportation	Continuous	Transportation expenditure in 1,000LAK (on a regular basis)
Transportation per capita	Continuous	Transportation expenditure per capita in 1,000LAK
Energy	Continuous	Energy expenditure in 1,000LAK (including electricity, gas, wood, charcoal, oil, etc.)
Energy per capita	Continuous	Energy expenditure per capita in 1,000LAK
Water	Continuous	Water expenditure in 1,000LAK
Water per capita	Continuous	Water expenditure per capita in 1,000LAK
Telephone	Continuous	Telephone expenditure in 1,000LAK
Telephone per capita	Continuous	Telephone expenditure per capita in 1,000LAK
Maintenance	Continuous	Maintenance expenditure in 1,000LAK (including money paid for fixing agricultural assets, houses, vehicles, etc.)
Maintenance per capita	Continuous	Maintenance expenditure per capita in 1,000LAK
Other expenditures	Continuous	Other expenditures in 1,000LAK (including investment, livestock purchasing, association fee, donations, rent, clothes, cosmetics, etc.)
Other expenditures per capita	Continuous	Other expenditures per capita in 1,000LAK
Hospitalization	Dummy	Any member in the household hospitalized. 1 if yes, 0 otherwise
Rice	Continuous	Paddy rice yield in kilograms
Rice per capita	Continuous	Paddy rice yield per capita in kilograms
Cow	Continuous	Number of cow owned
Poultry	Continuous	Number of poultry owned

[a] Village party and women union are the local government authorities.

[b] The various income and expenditure categories, hospitalization, and rice yield are data in the last 12 months preceding the survey.

Table 3.2: Summary statistics

	Full sample							Subsample 1							Subsample 2							Subsample 3						
	Treated		Control		Mean difference			Treated		Control		Mean difference			Treated		Control		Mean difference			Treated		Control		Mean difference		
	n	Mean	n	Mean	Diff	S.E.		n	Mean	n	Mean	Diff	S.E.		n	Mean	n	Mean	Diff	S.E.		n	Mean	n	Mean	Diff	S.E.	
Potential covariates																												
Gender	210	0.84	369	0.85	-0.013	0.03		210	0.84	297	0.85	-0.01	0.03		141	0.82	267	0.87	-0.05	0.04	*	141	0.82	224	0.87	-0.05	0.04	*
Age	210	51.4	369	49.42	1.98	1.16	**	210	51.4	297	48.91	2.49	1.2	**	141	50.9	267	50.48	0.42	1.43		141	50.9	224	50.21	0.69	1.47	
Education	210	5.06	369	4.13	0.93	0.33	***	210	5.06	297	3.91	1.14	0.34	***	141	5.55	267	4.16	1.39	0.4	***	141	5.55	224	3.92	1.64	0.4	***
Size	210	6.37	370	5.67	0.7	0.18	***	210	6.37	298	5.62	0.75	0.2	***	141	6.2	268	5.69	0.51	0.22	**	141	6.2	225	5.68	0.52	0.23	**
Toilet	210	0.86	370	0.71	0.16	0.04	***	210	0.86	298	0.67	0.19	0.04	***	141	0.92	268	0.72	0.21	0.04	***	141	0.92	225	0.69	0.23	0.04	***
Land	210	17.87	370	17.77	0.01	1.90		210	17.87	298	1.85	-0.63	2.07		141	18.1	268	17.46	0.63	2.48		141	18.1	225	18.19	0.09	2.64	
Village party	210	0.1	370	0.04	0.06	0.02	***	210	0.1	298	0.04	0.06	0.02	***	141	0.1	268	0.04	0.05	0.03	**	141	0.1	225	0.04	0.05	0.03	**
Women union	210	0.3	370	0.21	0.09	0.04	***	210	0.3	298	0.19	0.1	0.04	***	141	0.32	268	0.20	0.12	0.04	***	141	0.32	225	0.18	0.14	0.05	***
Distance	210	14.79	370	16.36	-1.57	0.46	***	210	14.79	298	16.75	-1.97	0.48	***	141	14.37	268	16.54	-2.17	0.55	***	141	14.37	225	16.93	-2.56	0.56	***
Outcome variables																												
Income	210	16,573.91	370	14,511.02	2,062.89	1,939.84		210	16,573.91	298	14,898.23	1,675.68	2,126.44		141	16,343.73	268	14,133.89	2,209.84	2,136.43		141	16,343.73	225	14,277.19	2,066.54	2,289.77	
Income per capita	210	2,819.08	370	2,805.86	13.22	392.10		210	2,819.08	298	2,903.63	(84.55)	428.45		141	2,921.72	268	2,740.92	180.80	474.99		141	2,921.72	225	2,782.83	138.89	508.82	
Expenditure	210	7,264.51	370	5,660.55	1,603.96	642.99	**	210	7,264.51	298	5,538.19	1,726.32	697.02	***	141	7,003.81	268	5,140.14	1,863.66	528.11	***	141	7,003.81	225	4,866.60	2,137.20	533.48	***
Expenditure per capita	210	1,253.74	370	1,082.22	171.52	119.49	*	210	1,253.74	298	1,065.98	187.76	127.53	*	141	1,265.16	268	992.22	272.94	116.72	***	141	1,265.16	225	944.23	320.93	117.56	***
Health	210	413.27	370	390.88	22.39	68.92		210	413.27	298	391.70	21.57	74.61		141	302.75	268	360.21	(57.46)	82.95		141	302.75	225	372.34	(69.59)	89.50	
Health per capita	210	69.17	370	71.96	(2.79)	11.87		210	69.17	298	73.79	(4.61)	12.97		141	54.99	268	66.60	(11.60)	14.82		141	54.99	225	69.12	(14.13)	15.98	
Education	210	1,124.26	370	800.03	324.24	188.08	**	210	1,124.26	298	722.78	401.48	184.57	**	141	1,156.60	268	704.93	451.67	212.48	**	141	1,156.60	225	588.35	568.25	188.75	***
Food	210	1,139.46	370	851.92	287.54	142.44	**	210	1,139.46	298	795.55	343.91	150.83	**	141	1,035.62	268	797.22	238.40	132.76	**	141	1,035.62	225	705.00	330.63	128.96	***
Food per capita	210	194.41	370	158.18	36.23	23.49	*	210	194.41	298	150.70	43.71	24.54	**	141	184.97	268	153.54	31.43	26.42		141	184.97	225	139.96	45.01	26.11	**
Transportation	210	846.98	370	860.49	(13.51)	168.38		210	846.98	298	875.21	(28.23)	185.49	***	141	812.27	268	771.99	40.28	147.55		141	812.27	225	759.12	53.15	158.21	
Transportation per capita	210	146.57	370	172.36	(25.79)	33.86		210	146.57	297	177.76	(31.20)	37.27	**	141	146.58	268	156.13	(9.55)	35.94		141	146.58	225	155.87	(9.29)	38.69	
Energy	210	662.87	370	498.27	164.60	73.60	**	210	662.87	298	497.68	165.20	81.42	**	141	639.56	268	459.41	180.15	65.36	***	141	639.56	225	453.86	185.70	70.20	***
Energy per capita	210	115.23	370	94.91	20.32	13.03	*	210	115.23	298	95.33	19.90	14.35	*	141	114.22	268	88.65	25.57	12.69	**	141	114.22	225	87.97	26.24	13.61	**
Water	210	352.38	370	300.69	51.69	44.69		210	352.38	298	294.91	57.47	48.22		141	343.00	268	276.81	66.19	36.57	**	141	343.00	225	247.52	95.48	36.96	***
Water per capita	210	60.05	370	57.32	2.73	8.09		210	60.05	298	56.67	3.38	8.65		141	59.55	268	55.11	4.44	7.66		141	59.55	225	49.43	10.12	7.68	*
Telephone	210	452.33	370	385.24	67.10	45.36	*	210	452.33	297	373.17	79.17	47.33	**	141	422.06	268	367.27	54.79	45.96		141	422.06	225	351.20	70.86	45.24	*
Telephone per capita	210	76.79	370	74.75	2.03	9.09		210	76.79	297	73.40	3.39	9.22		141	75.05	268	71.01	4.04	9.63		141	75.05	225	67.79	7.26	9.13	
Maintenance	210	353.62	370	320.48	33.14	186.14		210	353.62	298	347.82	5.80	207.15		141	330.14	268	174.22	155.92	39.71	***	141	330.14	225	168.44	161.70	41.85	***
Maintenance per capita	210	58.43	370	57.23	1.20	30.71		210	58.43	298	62.42	(4.00)	34.16		141	57.90	268	32.14	25.76	7.56	***	141	57.90	225	31.22	26.69	7.91	***
Other expenditures	210	1,919.32	370	1,256.99	662.34	201.05	***	210	1,919.32	297	1,244.80	674.53	220.07	***	141	1,961.82	268	1,228.08	733.73	263.96	***	141	1,961.82	225	1,220.77	741.04	284.87	***
Other expenditures per capita	210	348.09	370	247.73	100.36	44.85	**	210	348.09	297	246.81	101.29	48.76	**	141	372.43	268	235.16	137.27	59.49	**	141	372.43	225	235.59	136.85	64.43	**
Hospitalization	210	0.28	370	0.23	0.05	0.04		210	0.28	298	0.23	0.05	0.04		141	0.26	268	0.20	0.06	0.04	*	141	0.26	225	0.21	0.04	0.05	
Rice	210	4,004.20	370	3,036.34	967.85	242.46	***	210	4,004.20	298	2,970.02	1,034.18	262.45	***	141	3,572.32	268	3,033.41	538.91	233.60	**	141	3,572.32	225	2,979.67	592.65	243.69	***
Rice per capita	210	667.87	370	572.09	95.79	40.51	***	210	667.87	298	569.87	98.01	43.76	**	141	646.95	268	559.63	87.31	46.13	**	141	646.95	225	556.51	90.44	48.98	**
Cow	210	4.11	370	2.76	1.35	0.36	***	210	4.11	298	2.78	1.33	0.38	***	141	5.02	268	2.78	2.24	0.45	***	141	5.02	225	2.92	2.11	0.48	***
Poultry	210	15.43	370	11.97	3.46	1.23	***	210	15.43	298	11.19	4.25	1.27	***	141	15.29	268	12.23	3.06	1.54	**	141	15.29	225	11.42	3.87	1.55	***

3.2.1 Estimation model

For the cross-sectional observational study, the marginal causal effect of the intervention can be evaluated by three main approaches including instrumental variables (IV), regression discontinuity designs (RDD), and propensity score method [41]. Among the three approaches, propensity score method is gaining widespread use in the non-experiment evaluation literature due to data unavailability [42]. The propensity score is the probability of treatment assignment conditional on observed baseline covariates [43]. There are four techniques that the propensity score is used, the most common technique is to match treated and untreated individuals on the propensity score, so-called propensity score matching (PSM) [44]. The more recent technique is called inverse probability of treatment weight (IPTW), which subjects are weighted based on the estimated propensity score. The basic idea of this technique is similar to sampling weight so that samples are representative of a specific population [45]. Joffe et al. (2004) illustrated how weighting by the inverse probability of treatment can construct an artificial population in which baseline covariates are not systematically correlated with treatment assignment. One advantage of the IPTW technique is that we can directly check and ensure the balance of the baseline covariates between treated and untreated groups [47]. Unlike PSM, IPTW maximizes data available. Austin (2010) showed empirical evidence that IPTW outperforms the other three propensity score techniques. Additionally, Austin (2013) suggested that the IPTW technique performs better precision than the PSM technique. In spite of the rapidly increasing application of IPTW in recent years, especially in the field of health economics [50–52], it is still scarce in the health insurance setting.

The CBHI scheme in Lao PDR was established for particularly self-employed households of which the screening of the beneficiaries is on a voluntary basis. Due to the self-selection bias associated with non-experimental data, to compare the outcomes between treated households (CBHI enrolled households) and untreated households (non-CBHI households) will result in biased estimates of the scheme's effect. Therefore, in the absence of experimental data, we employ the IPTW technique to evaluate the impact of the CBHI scheme on hospitalization, income, various expenditure categories, rice yield, and livestock holdings of enrolled households in rural Lao PDR. Following Joffe et al. (2004), the IPTW technique follows four steps to estimate the average treatment on the treated (ATT) as follows:

1. To examine whether the impact of the CBHI scheme is prone to be confounded, we regress single potential covariates on the treatment dummy as the following equation (Linden & Adams, 2012):

$$X = \beta_0 + \beta_1 T \tag{3.1}$$

   where X is each covariate. T is treatment. β_1 is not significantly different from zero if X is considered balanced between treated and untreated groups.

2. Then, these potential covariates are used to estimate the propensity score. Let the probability that a household would enroll in the CBHI scheme given the observed baseline covariates as $p(x) \equiv Pr(T = 1 \mid \mathbf{X})$, the score can be estimated as follows:

$$logit\{Pr(T = 1 \mid \mathbf{X})\} = \mathbf{X}\beta \tag{3.2}$$

   $\mathbf{X}$ is a vector of the observed baseline covariates.

As our interest is the impact of the CBHI scheme on the enrolled households, based on the estimated propensity score, $\hat{p}(x)$, the inverse probability of treatment weight for ATT estimation is defined as follows (Austin & Stuart, 2015):

$$w_i = T_i + (1 - T_i) \frac{\hat{p}(x)_i}{(1 - \hat{p}(x)_i)} \tag{3.3}$$

where w_i is the weight of household i. Note that, for treated households ($T_i = 1$), $w_i = 1$ and untreated households ($T_i = 0$), $w_i = \frac{\hat{p}(x)_i}{(1-\hat{p}(x)_i)}$. This weight sets the treated households as the reference population.

3. We repeat the first step over with weight to construct an artificial population in which single potential covariates are independent of the treatment assignment.

4. Finally, ATT is estimated using the weighting technique (Lunceford & Davidian, 2004; Austin & Stuart, 2017).

$$ATT_{IPTW} = \frac{1}{N_1} \sum_{i=1}^{N_1} w_i Y_i - \frac{1}{N_0} \sum_{i=1}^{N_0} w_i Y_i \tag{3.4}$$

where Y_i is the outcome of household i. N_1 and N_0 are the number of CBHI households and non-CBHI households, respectively.

3.3 Results

3.3.1 Estimation results

To estimate ATT that is not confounded, we need to eliminate the covariate imbalances as summarized in Table 3.2 by propensity score weighting. Table 3.3 shows the results

Table 3.3: Covariate weighting

Covariates	Unweighted				Weighted			
	Full sample (580)	Subsample 1 (508)	Subsample 2 (409)	Subsample 3 (366)	Full sample (580)	Subsample 1 (508)	Subsample 2 (40)	Subsample 3 (366)
Gender	-0.0979	-0.105	-0.405	-0.419	-0.0127	-0.0001	0.0555	0.136
	(0.238)	(0.249)	(0.283)	(0.295)	(0.256)	(0.279)	(0.317)	(0.347)
Age	1.982 *	2.492 **	0.418	0.686	-0.396	-0.610	-0.593	-0.781
	(1.158)	(1.197)	(1.431)	(1.466)	(1.220)	(1.308)	(1.498)	(1.583)
Education	0.927 ***	1.145 ***	1.388 ***	1.638 ***	-0.0825	-0.0881	-0.265	-0.436
	(0.333)	(0.342)	(0.398)	(0.405)	(0.406)	(0.488)	(0.511)	(0.644)
Size	0.704 ***	0.754 ***	0.512 **	0.523 **	0.0105	-0.0176	-0.0362	-0.0427
	(0.184)	(0.195)	(0.221)	(0.231)	(0.214)	(0.240)	(0.261)	(0.293)
Land	96.108	-635.833	628.894	-96.206	1,040	1,322	772.8	1,309
	(1,904.94)	(2,067.75	(2,479.48)	(2,637.02)	(1,863)	(1,962)	(3,066)	(3,059)
Toilet	0.958 ***	1.133 ***	1.543 ***	1.675 ***	0.0160	0.0363	-0.00139	-0.00206
	(0.230)	(0.235)	(0.342)	(0.345)	(0.240)	(0.251)	(0.355)	(0.367)
Village party	0.0595 ***	0.0631 ***	0.0545 **	0.0548 **	0.0173	0.0298	0.0179	0.0331
	(0.021)	(0.022)	(0.025)	(0.027)	(0.0305)	(0.0311)	(0.0366)	(0.0352)
Women union	0.0871 **	0.101 ***	0.118 ***	0.137 ***	-0.0138	-0.0106	-0.0197	-0.0241
	(0.037)	(0.038)	(0.044)	(0.045)	(0.0446)	(0.0495)	(0.0570)	(0.0640)
Distance	-1.571 ***	-1.966 ***	-2.172 ***	-2.56 ***	0.0872	0.162	0.0389	0.0995
	(0.463)	(0.479)	(0.547)	(0.564)	(0.396)	(0.418)	(0.424)	(0.437)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

of step 1 and step 3 as mentioned in the estimation model section. The four left-hand-side columns right after the covariates column are unweighted estimates, and the four right-hand-side columns are estimates weighted by the propensity score between treated and untreated households. As shown, the unweighted estimates report the statistically significant imbalances of many baseline covariates. The enrolled households are more likely to have a more educated household head, larger household members, more toilets at home, more engaged in the village party and women union, and enrolled households tend to live in the villages that are relatively close to the district hospital. However, once the weight is used, the imbalances are all removed. We now ensure that the ATT estimates are less confounding by the selected covariates.

Table 3.4: ATT estimates based on the IPTW method

	Full sample (580)				Subsample 1 (508)[a] [Full - Ex]				Subsample 2 (409) [Full - VF]				Subsample 3 (366) [Full - EX - VF]			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Income	597.7	560.0	1,130	1,447	-566.4	-712.2	421.5	709.6	-1,023	-895.4	699.4	354.9	-2,545	-2,417	362.2	-198.4
	(1,774)	(1,823)	(1,670)	(1,656)	(2,169)	(2,275)	(1,901)	(1,911)	(2,467)	(2,473)	(1,914)	(2,201)	(3,162)	(3,253)	(2,103)	(2,583)
Income per capita	-15.38	-31.44	140.5	157.8	-228.6	-276.4	35.58	31.90	-296.4	-278.2	103.0	-3.596	-620.3	-620.2	35.06	-135.5
	(359.4)	(371.0)	(312.8)	(327.1)	(458.0)	(481.1)	(355.1)	(386.8)	(556.1)	(558.2)	(404.8)	(486.7)	(729.5)	(751.4)	(445.4)	(580.5)
Expenditure	948.0*	907.3	893.8	1,004*	1,128*	979.9	876.4	1,082*	788.9	710.5	984.3*	934.5	**1,136***	**1,051***	**1,186****	**1,161***
	(544.6)	(558.1)	(600.4)	(542.1)	(586.0)	(629.1)	(687.6)	(590.0)	(586.4)	(585.9)	(574.3)	(575.1)	**(622.7)**	**(632.7)**	**(587.6)**	**(599.9)**
Expenditure per capita	156.8	147.1	165.2	173.3*	191.9*	160.7	172.1	190.7*	145.5	129.3	194.3	180.0	204.8	181.1	232.1*	215.6*
	(101.0)	(103.1)	(107.5)	(99.83)	(107.5)	(114.7)	(118.3)	(106.6)	(125.4)	(125.5)	(120.7)	(122.1)	(132.1)	(135.1)	(120.5)	(126.7)
Health	-13.15	-22.73	-28.11	-35.73	-21.02	-37.91	-43.01	-61.76	-95.08	-115.0	-118.1	-129.9	-112.5	-143.1	-152.7	-175.9
	(74.12)	(76.10)	(78.11)	(80.40)	(87.45)	(90.62)	(92.78)	(98.47)	(84.36)	(92.62)	(93.88)	(99.06)	(101.2)	(114.3)	(115.3)	(126.2)
Health per capita	-2.067	-3.753	-4.060	-5.804	-3.966	-6.869	-7.262	-10.81	-12.35	-16.33	-16.56	-18.53	-15.09	-20.78	-22.34	-26.19
	(12.09)	(12.41)	(12.72)	(13.14)	(14.41)	(14.91)	(15.22)	(16.24)	(14.54)	(15.78)	(16.07)	(16.93)	(17.28)	(19.33)	(19.51)	(21.35)
Education	142.1	156.7	181.0	156.5	227.1	219.3	252.3	177.2	206.8	191.9	273.2	255.2	341.6	329.5	386.3*	316.2
	(204.7)	(202.6)	(205.1)	(201.8)	(205.4)	(206.3)	(203.6)	(213.3)	(253.8)	(253.0)	(250.8)	(238.9)	(241.5)	(239.7)	(232.4)	(240.7)
Food	101.0	107.4	103.4	115.2	205.8	201.6	150.5	226.1	22.78	16.39	119.8	71.08	181.4	194.4	237.0	230.3
	(163.1)	(164.4)	(191.7)	(167.9)	(175.7)	(180.4)	(234.9)	(182.4)	(164.4)	(164.7)	(155.9)	(163.5)	(157.1)	(155.4)	(155.0)	(153.9)
Food per capita	19.91	20.06	24.47	23.55	35.15	32.44	32.20	40.02	-1.053	0.448	17.32	8.675	23.45	24.73	33.53	32.01
	(25.84)	(26.07)	(27.70)	(26.25)	(26.63)	(27.54)	(31.62)	(27.16)	(32.76)	(31.20)	(30.37)	(31.88)	(31.16)	(30.99)	(31.07)	(31.10)
Transportation	-35.67	-45.38	-72.74	-26.02	-40.27	-63.82	-112.0	-32.03	-60.58	-82.92	-62.93	-51.37	-50.39	-72.27	-58.46	-38.65
	(124.5)	(129.6)	(138.8)	(119.6)	(150.9)	(162.8)	(172.1)	(141.9)	(153.5)	(155.9)	(133.8)	(141.9)	(197.7)	(204.2)	(153.3)	(168.6)
Transportation per capita	-13.98	-16.63	-16.73	-11.83	-16.73	-22.75	-23.18	-14.55	-20.52	-25.02	-15.30	-18.30	-23.34	-29.18	-16.39	-20.18
	(24.62)	(25.82)	(24.90)	(23.44)	(30.81)	(33.36)	(30.16)	(28.23)	(35.52)	(36.13)	(27.76)	(32.58)	(46.63)	(48.55)	(31.62)	(39.56)
Energy	107.3	95.86	77.24	99.63	78.78	58.78	35.67	70.91	117.3	112.1	71.87	110.2	102.0	94.53	51.79	99.36
	(77.05)	(80.43)	(94.80)	(80.63)	(92.63)	(99.52)	(121.2)	(99.04)	(75.51)	(75.74)	(109.0)	(78.33)	(81.91)	(83.58)	(124.6)	(82.97)
Energy per capita	19.80	17.73	18.29	19.48	15.45	11.79	13.27	15.22	19.91	18.47	17.93	19.97	16.38	14.00	15.44	17.30
	(13.14)	(13.57)	(14.01)	(13.26)	(15.47)	(16.43)	(16.66)	(15.73)	(15.07)	(15.16)	(15.71)	(14.69)	(17.23)	(17.65)	(17.05)	(15.95)

Robust standard errors in parentheses

*** p¡0.01, ** p¡0.05, * p¡0.1

[a] Subsample 1: Full sample - Ex-members

Subsample 2: Full sample - Subjects engaged in village fund

Subsample 3: Full sample - Ex-members -Subjects engaged in village fund

	Full sample (580)				**Subsample 1 (508)**[a] [Full - Ex]				**Subsample 2 (409)** [Full - VF]				**Subsample 3 (366)** [Full - EX - VF]			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Water	25.96	25.57	35.01	36.64	47.55	43.22	52.88	59.93	14.80	6.263	54.29	34.05	43.97	41.08	86.06**	71.23*
	(37.67)	(38.22)	(41.40)	(37.38)	(38.99)	(41.38)	(45.93)	(39.41)	(39.09)	(38.89)	(38.51)	(38.53)	(39.25)	(39.58)	(39.21)	(38.93)
Water per capita	3.839	3.685	5.531	5.906	6.741	5.866	7.630	9.168	-0.796	-2.563	5.502	2.659	4.102	3.069	10.73	9.196
	(6.519)	(6.599)	(7.049)	(6.452)	(6.781)	(7.202)	(7.876)	(6.834)	(7.575)	(7.560)	(7.554)	(7.501)	(7.667)	(7.880)	(7.804)	(7.614)
Telephone	47.07	44.38	50.93	51.81	67.46	59.89	61.94	68.30	2.393	-1.198	21.44	13.14	28.24	24.83	35.25	32.01
	(46.01)	(46.28)	(45.97)	(45.51)	(49.88)	(50.44)	(50.09)	(48.85)	(48.43)	(48.98)	(46.83)	(46.72)	(53.57)	(54.27)	(49.69)	(49.40)
Telephone per capita	5.645	5.016	6.866	6.607	8.762	7.187	8.542	9.325	-0.0944	-0.952	3.485	2.048	4.327	3.539	5.933	5.635
	(8.087)	(8.135)	(7.917)	(7.950)	(8.520)	(8.579)	(8.313)	(8.244)	(9.226)	(9.338)	(8.717)	(8.854)	(9.801)	(9.798)	(8.835)	(8.952)
Mainteanance	46.52	37.53	3.307	45.80	45.72	17.46	-31.24	26.09	**118.7****	**113.7****	**117.7****	**108.7****	**136.5*****	**129.2****	**116.4****	**107.3****
	(115.5)	(123.6)	(148.5)	(113.3)	(124.6)	(148.4)	(183.6)	(129.8)	**(49.54)**	**(49.67)**	**(49.35)**	**(49.33)**	**(51.14)**	**(52.21)**	**(52.09)**	**(52.30)**
Maintenane per capita	7.395	5.706	0.525	7.289	7.133	2.119	-5.528	3.909	**22.20****	**20.85****	**21.80****	**20.29****	**25.44*****	**23.68****	**21.57****	**20.21****
	(18.13)	(19.48)	(23.79)	(17.67)	(19.76)	(23.80)	(29.78)	(20.56)	**(8.942)**	**(8.965)**	**(8.680)**	**(8.815)**	**(9.127)**	**(9.259)**	**(8.974)**	**(9.239)**
Other expenditures	**525.8****	**507.3****	**541.8*****	**558.7*****	**515.3****	**480.7***	**507.0****	**545.0****	461.8	469.3	506.9*	523.3*	465.6	452.5	484.2	518.6*
	(215.0)	**(221.3)**	**(208.6)**	**(209.2)**	**(235.1)**	**(251.7)**	**(223.9)**	**(223.2)**	(308.8)	(306.5)	(287.2)	(292.0)	(338.7)	(351.9)	(303.9)	(311.4)
Other expenditures per capita	**103.7****	**100.3****	**110.9****	**110.2****	**104.3****	**97.73***	**107.9****	**110.3****	107.4	107.6	120.9*	120.2*	105.5	102.0	115.7*	117.1
	(48.04)	**(49.11)**	**(46.26)**	**(47.04)**	**(51.43)**	**(54.29)**	**(48.03)**	**(49.22)**	(71.12)	(70.84)	(66.51)	(68.29)	(76.50)	(78.90)	(68.81)	(71.60)
Hospitalization	0.0477	0.0454	0.0326	0.0424	0.0459	0.0435	0.0349	0.0497	0.0584	0.0647	0.0548	0.0629	0.0252	0.0359	0.0317	0.0406
	(0.0398)	(0.0398)	(0.0403)	(0.0397)	(0.0429)	(0.0428)	(0.0431)	(0.0421)	(0.0484)	(0.0469)	(0.0475)	(0.0469)	(0.0543)	(0.0517)	(0.0507)	(0.0503)
Rice	**637.5****	**640.0****	**633.3****	**666.4****	**641.5****	**660.5****	**629.9****	**684.9****	220.7	161.3	213.7	282.0	272.9	212.8	260.1	360.4
	(284.4)	**(285.4)**	**(278.5)**	**(281.2)**	**(305.0)**	**(303.1)**	**(289.0)**	**(295.5)**	(273.5)	(269.0)	(260.4)	(259.7)	(305.6)	(296.8)	(272.2)	(274.6)
Rice per capita	**108.7*****	**107.6*****	**110.5*****	**109.5*****	**110.0****	**110.2****	**108.9****	**110.1****	**92.76***	77.21	**89.93***	**95.53****	**99.89***	82.42	**93.24***	**103.7****
	(41.34)	**(41.59)**	**(41.00)**	**(41.36)**	**(44.05)**	**(44.12)**	**(42.65)**	**(43.83)**	**(49.75)**	(48.29)	**(47.98)**	**(48.38)**	**(53.91)**	(51.95)	**(50.03)**	**(51.30)**
Cow	**1.104*****	**1.095*****	**0.999****	**1.148*****	**1.153*****	**1.078****	**0.882***	**1.139****	**1.966*****	**1.996*****	**1.830*****	**2.030*****	**1.973*****	**1.937*****	**1.627*****	**1.976*****
	(0.398)	**(0.399)**	**(0.414)**	**(0.403)**	**(0.434)**	**(0.446)**	**(0.467)**	**(0.451)**	**(0.500)**	**(0.501)**	**(0.521)**	**(0.501)**	**(0.539)**	**(0.548)**	**(0.569)**	**(0.544)**
Poultry	1.928	2.010	1.799	2.020	**2.571***	**2.565***	**2.459***	**2.667***	1.051	1.176	0.983	1.113	1.807	2.076	1.788	1.862
	(1.390)	(1.383)	(1.388)	(1.385)	**(1.470)**	**(1.449)**	**(1.446)**	**(1.454)**	(1.787)	(1.755)	(1.766)	(1.759)	(1.927)	(1.851)	(1.840)	(1.865)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[a] Subsample 1: Full sample - Ex-members

Subsample 2: Full sample - Subjects engaged in village fund

Subsample 3: Full sample - Ex-members -Subjects engaged in village fund

The estimates of ATT for the full sample and subsamples are reported in Table 3.4 [2]. Subsample 3 is the center of our interest because both CBHI ex-members and VF subjects are excluded. As a sensitivity analysis, we report the estimates from four models with different covariate combinations. The same models are applied across the four categories of samples to allow the ATT estimates to be compared.

For direct outcomes, we find no evidence of the CBHI scheme impact on health expenditures and hospitalization. The estimates show consistent signs as expected but fail to reject the null hypothesis. Such findings are consistent regardless of the presence of the VF subjects but no ex-members in subsample 1, including ex-members but no VF subjects in subsample 2, and the absence of both CBHI ex-members and VF subjects in subsample 3.

For indirect outcomes, however, the results show positive impacts of the scheme on rice production per capita in the full sample and all subsamples. Although the significance level fades away in model 2 of subsample 2 and 3, which VF subjects are not included, it might be caused by fewer baseline covariates controlled. To be more precise, the rice yields per capita increase on average over 80 kg per year. The effect is slightly magnified and the significance level increases significantly when VF subjects are pooled in the samples. As the fact that rice production is the function of not only labor supply but also capital.

Further, we also find strong and robust evidence that the scheme significantly increases the number of cow holdings. The impacts are somewhat similar irrespective of whether CBHI ex-members are present or not. The enrolled households own almost two heads of cow more than non-CBHI households. More interestingly, the effect is stronger in

[2] See Appendix A for covariate balancing and Appendix B for propensity score distributions of the selected models.

the absence of VF subjects than the presence of VF subjects in the samples. The findings support our hypotheses that the CBHI scheme leads to an increase in agriculture production and livestock holdings of CBHI enrolled households in rural Lao PDR.

3.3.2 Robustness confirmation

To reinforce our findings, the robustness of the IPTW estimates is checked with an alternative measurement method, coarsened exact matching (CEM), which is a causal inference without balancing check [53]. The SATT estimates based on the CEM method is presented in Appendix C. The findings show a consistent sign and significance level, only the degree of effects slightly varies. Overall, the estimates by the CEM method provides supporting evidence for the robustness perspective.

Furthermore, the heterogeneous effects on ATT show that the impacts of CBHI scheme on cow holdings are robust for the 50th and 75th quantiles, but no longer for the 25th quantile of household head age with relatively young household head. In turn, the CBHI scheme increases the number of poultries of the 25th quantile but does not for the 50th and 75th quantiles of household head age. From the perspective of household size quantiles, the CBHI scheme consistently increases the rice, rice per capita, and cow holdings across all quantiles. Similar to household head age quantiles, the CBHI scheme has significant impacts on the poultry holdings of the 25th quantile but does not for other quantiles. As cow is more valuable livestock than poultries, the households with more experienced household head and more family members prefer to invest in cow to poultries as a form of non-cash savings (See Appendix D).

3.4 Conclusion

In this paper, we evaluate the impacts of the CBHI scheme on household welfare, focusing on indirect impacts on rice production and livestock holdings. We use household surveys in rural villages of Savannakhet Province of the Lao PDR, to test the null hypothesis. Based on the fact that the CBHI is a voluntary-based scheme, self-selection bias may exist. To this end, we employ the method of the IPTW to mitigate imbalances in pre-intervention covariates between treated and untreated samples. Our analysis suggests that the CBHI scheme has neither direct impacts on health expenditure nor hospitalization. In contrast, we find that there are substantial indirect impacts of participation in the CBHI scheme on rice yield per capita and cow holdings. Such findings possibly reflect the fast recovery of illness, the improved health status of household members, or lower incidence of catastrophic health care expenditure among enrolled households.

Further, the lack of significant evidence on direct benefits of the scheme might be a reason explained why the current CBHI scheme had received less popularity from informally employed households. To encourage more enrollment, it is important to understand the preferences of potential enrollees towards the hypothetical CBHI scheme. Besides, supply-side improvement, such as quality of service and geographic access, is also critical to scale-up the scheme.

It is worth noting some limitations of this study. First, to observe the direct impacts we fail to capture the frequency of health care seeking and the frequency of hospitalization. Second, we use quantity instead of a monetary value of livestock holdings in the analysis.

Chapter 4

Risk preferences and CBHI scheme uptake

4.1 Introduction

Although the CBHI scheme has an apparent objective to reduce health and financial risks for the poor, the progress of its actual implementation is very slow, especially in low-income countries. As suggested in the literature, apart from exogenous variables risk preferences are of fundamental importance for individual heterogeneity [54] and are found to have a significant role in most important settings. The empirical correlation between risk preferences and economic behaviors under uncertainty is well-documented in a growing number of studies, such as those on migration [55, 56], higher education enrollment [57, 58], occupational decisions [59–63], and technology adoption [64, 65]. In the research on risky health-related behaviors, several studies have shown that risk preferences are likely to shape the likelihood that a subject engaged in cigarette smoking, drinking alcohol, becoming obese, seat belt non-use while driving, and failing to have insurance [66–68].

Since the primary purpose of health insurance is to reduce financial and health risks, the more risk-averse individuals are more likely to purchase insurance. Some studies investigated the links between risk preferences and the likelihood of insurance uptake. For instance, Lammers and Warmerdam (2010) use standard lottery questions with hypothetical rewards to measure the constant relative risk aversion (CRRA) of individuals, which is a measure under Expected Utility Theory (EUT). Furthermore, Pierre and Jusot (2017) apply a self-reported questionnaire with 11-point scales to measure self-perceived risks. Both studies find that the likelihood of health insurance uptake is significantly related to individual risk preference variations. However, both Lammers and Warmerdam (2010) and Pierre and Jusot (2017) elicit individual risk preferences with no monetary incentives. Glaeser et al. (2000) suggests that self-reported attitudes do not always indicate the subjects' real attitudes.

To measure more realistic risk preferences, some studies conducted experiments with real money at stake. The study of Alkenbrack and Lindelow (2015) is particularly relevant to this paper as it examines the correlation between individual risk aversion and the CBHI enrollment in urban and semi-urban Lao PDR. Risk preferences are measured based on the EUT assumption. Household heads encounter five repeated gambles in which they choose a hand that they think having money. The stake is increasingly heterogeneous starting from risk free until the all or nothing risk. Another closely related preceding work to the present study is that of Ito and Kono (2010), which assesses the reasons why the uptake of the Yeshasvini microinsurance scheme in India remains so low by focusing on the risk preference parameters of Prospect Theory (PT). The experiment is designed so that there are equal probabilities of obtaining either a better or worse outcome (the risk aversion for probability prospects cannot be observed). The risk parameters are defined as categorical dummies based on switching points that respondents make accordingly. Despite different theories of prior assumptions, no clear evidence results from the two studies on the relationship between risk preferences and health insurance adoption decisions. Overall, the existing evidence regarding whether individual risk preferences predict individual decisions to buy insurance is rather mixed.

Therefore, this study aims to examine the association of households' risk preferences on their decisions to participate in the CBHI scheme in rural villages of Savannakhet Province of the Lao PDR with three main contributions to the literature. First, we conduct a field experiment to elicit the parameters of risk preferences with real money rewards. Second, we measure not only the parameters of risk aversion for gains and loss aversion but also risk aversion for subjective probability prospects (which is omitted in the literature). Third, unlike many preceding studies, experimental data allows us to test the validity of either the EUT or PT assumption simultaneously without a prior assumption.

To attain the objective, we employ the risk elicitation experiment technique of Tanaka et al. (2010). The experiment is designed in a way that is more realistic with varying probabilities of winning better or worse outcomes. Despite an increasing application of this technique in a variety of contexts [64, 71, 72], there are still scarce applications in the health insurance setting, especially with respect to the voluntary CBHI scheme.

We select the CBHI scheme in the Lao PDR as a case study because of its chronically low enrollment. According to Sydavong and Goto (2018), evidence shows that the CBHI scheme has indirect positive impacts on the rice production and cow holdings of enrolled households in rural villages of the Lao PDR. Thus, to promote greater enrollment, it is necessary to analyze several dimensions of factors that lead to an increased likelihood of the scheme's uptake, including both exogenous and behavioral determinants.

4.2 Methodology

4.2.1 Measurement of risk parameters

Tanaka et al. (2010) incorporated prospect theory [1] as an alternative theoretical framework to EUT in the experiment. PT presumes that individuals behave in a risk-averse manner for gains but are risk-seeking for losses. The real power of this methodology is evident in ways that, unlike EUT in which the risk preference depends solely on the gains, the risk preferences of PT are based on the gains, the losses and probability prospects. Therefore, researchers can simultaneously elicit three parameters concerning risk preferences: risk aversion, subjective probability weighting and loss aversion [74]. More importantly, EUT, which is treated as a special case of PT, can be examined in the same experiment. That is, the methodology of Tanaka et al. (2010) enables researchers to test the null hypothesis of the EUT statistically. In PT, risk attitudes are jointly defined by two functions, including a value function of outcomes that explains the attitude towards outcomes (or the subject's valuation of money) and a subjective probability weighting function describing the subject's attitude towards probabilities. Decision making under risk can be viewed as a preference for either prospects or gambles. A utility function according to Tanaka et al. (2010) has the form as follows:

$$U\left(x, p; y, q\right) = \begin{cases} v\left(y\right) + \pi\left(p\right)\left(v\left(x\right) - v\left(y\right)\right) & , x > y > 0 \text{ or } \; x < y < 0 \\ v\left(y\right) + \pi\left(p\right) v\left(x\right) + \pi\left(q\right) v\left(y\right) & , x < 0 < y \end{cases}$$

[1] In prospect theory, each probability p_i for receiving the separate outcome x_i is transformed to the probability weighting function $p(p_i)$.

where $v(x) = \begin{cases} x^{\sigma} & , \text{for } \; x > 0 \\ \\ -\lambda\left(-x^{\sigma}\right) & , \text{for } \; x < 0 \end{cases}$

and $\pi(p) = \frac{1}{exp\left[ln\left(\frac{1}{p}\right)\right]^{\alpha}}$

$U(x, p; y, q)$ denotes for the expected value of binary prospects. x and y are the outcomes with the corresponding probabilities p and q, respectively. $v(x)$ is the power value function defined by the outcomes. If the outcome is zero, $v(0) = 0$. $\pi(p)$ is the weighting function defined by the probabilities. If the probabilities are zero and one, $\pi(0) = 0$ and $\pi(1) = 1$, respectively. σ captures the concavity of the value function, which is known as risk aversion [2]. λ illustrates the curvature of below zero compared to that of above zero, which is also stated as the degree of loss aversion (losses are weighed more heavily than gains). Notice that the higher the λ, the more loss aversion that exists [3]. α is the parameter to identify the shape of the probability weighting function [4]. Note that for the special case where $\pi(p) = p$ for all p, resulting from $\alpha = 1$, and $\lambda = 1$, the prospect value function would transform to the traditional EUT [5]. Due to the advantages above, the utility function of PT is employed in place of the EUT and probability weighting $\pi(p)$ is employed in place of p. The loss aversion parameter λ is jointly constructed based on the utility curvature σ and switching point in series 3. Since series 3 of the experiment is designed given equal probability between option A and B, the probability weighting function is ignored.

[2]If $\sigma < 1$, $\sigma = 1$, or $0 < \sigma < 1$, the subject is considered to be risk-seeking, risk-neutral, or risk-averse, respectively.

[3]The theory expects the results of loss neutrality ($\lambda = 1$) or loss aversion ($\lambda > 1$), but not loss seeking ($\lambda < 1$).

[4]The function would be linear if $\alpha = 1$, but it would be S-shaped and inverted S-shaped if $\alpha > 1$ and $0 < \alpha < 1$, respectively. The inverted-S shape of the probability weighting function favors risk-seeking and risk-averse preferences for small-probability and moderate- or high-probability prospects of losses, respectively (Tversky & Kahneman, 1992). As stated in the study of Gonzalez and Wu (1999), probabilities below 30% are treated as small-probabilities.

[5]The risk attitude towards gains would be entirely explained by the value function in the case that the probability weighting function for gains is linear. The risk attitude for gains is wholly defined by the probability weighting function for gains if the value function is linear for gains.

4.2.2 Field experiment

As Weber et al. (2002) found that the degree of risk taking of individuals is highly domain-specific, in the present study, it is crucial to assume invariant risk preferences of individuals over time and across decision contexts. Indeed, observing risk preferences of all household members is far beyond our limits due to the experimental complexity and budgetary constraints. Thus, we again assume that the risk preferences of the respondents are an applicable proxy for the entire household's preferences. Additionally, we assume that the probability weighting in the scope of this study is interpreted as the probability of financial losses due to health care seeking [6]. This study is based on the risk elicitation experiment of Tanaka et al. (2010) that uses a set of two-outcome prospects with monetary outcomes [7]. The lottery choice experiment is implemented to elicit the parameters of risk aversion, probability weighting and loss aversion of rural dwellers in Savannakhet Province. Our team paid significant effort to collect the high-quality data. Accordingly, a paper-based method is used in place of a computer-based experiment for better comprehension of the subjects. Before getting started the experiment, an investigator distributes a sample sheet and explains the instructions to every single subject separately as follows:

- The subjects can either choose option A or option B in all cases. However, those who start off by choosing option A can switch over to option B at some point, but no double switches are allowed over each series [8]. In contrast, the subject who selects option B in the beginning cannot switch in reverse to option A, given that it is a logically coherent decision

[6]We thank Professor Shinji KANEKO for his insightful comment on this assumption.

[7]The value of stakes is tailored to be consistent with the income level of rural people in Lao PDR.

[8]Due to the assumption of subjects' rationality, monotonic switching is enforced in this experiment.

- After all subjects complete the given 35 decision rows, each respondent draws one of 35 numbered balls from a box to determine a decision row at random and does the same from another box of 10 numbered balls to decide the real monetary reward. The mechanism is that each subject earns the actual money [9] based jointly on the outcome of the lots and the choices that the respondent makes.

Table 4.1 displays the full set of pairwise lottery choices used in the experiment and the expected payoff difference in the rightmost column [10]. According to Tanaka et al. (2010), the experiment is categorized into 3 series of gains and losses. The choices are ranked in order of increasing payoffs. Each subject is confronted with a series of 35 paired choices, as shown in Table 1, but not the expected payoff difference. Subjects are asked to indicate a preference for either option A or option B in each decision row sequentially. Option A is relatively a safe choice, whereas option B has a higher expected payoff and variance. Note, however, that a higher prize can be earned at the cost of a lower probability for both options. The probability of gambles remains unchanged across series. Only the amount at stake in option B varies in each decision row of series 1 and 2 in which the probability of winning the higher prize in option A is relatively superior to that of option B. For instance, option A has a 3/10 chance to win 20,000LAK and a 7/10 chance to win 5,000LAK with certainty across series 1, whereas option B has relatively higher stakes but a higher variance of probability that ranged between 2,500LAK and 850,000LAK. Theoretically, only those who are very risk-seeking would

[9]The average payoff of the experiment is 22,000LAK, or about 70% of a single day's wage of an unskilled worker. 1USD ≈ 8,200LAK in September 2016.

[10]The expected payoff difference means the maximum amount of money that the subject is willing to give up in exchange for the allocation with certainty. Note that the subjects in the experiment were not given the payoff difference column. Prior to conducting the experiment, all subjects were asked whether they still wanted to be involved in the experiment in which they might face the possibility of a financial loss of their own money (but not a large amount). Fortunately, all participants were willing to take part in the experimental session.

Table 4.1: Risk experiment sheet

	Option A		Option B		Expected payoff difference
			Series 1		
Probability	**3/10**	**7/10**	**1/10**	**9/10**	
1	20,000	5,000	34,000	2,500	3,850
2	20,000	5,000	37,500	2,500	3,500
3	20,000	5,000	41,500	2,500	3,100
4	20,000	5,000	46,500	2,500	2,600
5	20,000	5,000	53,000	2,500	1,950
6	20,000	5,000	62,500	2,500	1,000
7	20,000	5,000	75,000	2,500	-250
8	20,000	5,000	92,500	2,500	-2,000
9	20,000	5,000	110,000	2,500	-3,750
10	20,000	5,000	150,000	2,500	-7,750
11	20,000	5,000	200,000	2,500	-12,750
12	20,000	5,000	300,000	2,500	-22,750
13	20,000	5,000	500,000	2,500	-42,750
14	20,000	5,000	850,000	2,500	-77,750
			Series 2		
	9/10	**1/10**	**7/10**	**3/10**	
1	20,000	15,000	27,000	2,500	-150
2	20,000	15,000	28,000	2,500	-850
3	20,000	15,000	29,000	2,500	-1,550
4	20,000	15,000	30,000	2,500	-2,250
5	20,000	15,000	31,000	2,500	-2,950
6	20,000	15,000	32,500	2,500	-4,000
7	20,000	15,000	34,000	2,500	-5,050
8	20,000	15,000	36,000	2,500	-6,450
9	20,000	15,000	38,500	2,500	-8,200
10	20,000	15,000	41,500	2,500	-10,300
11	20,000	15,000	45,000	2,500	-12,750
12	20,000	15,000	50,000	2,500	-16,250
13	20,000	15,000	55,000	2,500	-19,750
14	20,000	15,000	65,000	2,500	-26,750
			Series 3		
	5/10	**5/10**	**5/10**	**5/10**	
1	12,500	-2,000	15,000	-10,500	3,000
2	2,000	-2,000	15,000	-10,500	-2,250
3	500	-2,000	15,000	-10,500	-3,000
4	500	-2,000	15,000	-8,000	-4,250
5	500	-4,000	15,000	-8,000	-5,250
6	500	-4,000	15,000	-7,000	-5,750
7	500	-4,000	15,000	-5,500	-6,500

choose option B from the beginning, or vice versa. Unlike the first two series, the value of both options systematically varies in series 3.

The range of risk parameters is defined such that the subjects make the switching points following the models in Tanaka et al. (2010). The model is constructed by the manner in which the choices in series 1 and 2 of each subject are incorporated to measure the risk aversion parameters (σ and α), and only the parameter of curvature utility function (σ) is then combined with the subject's choice in series 3 to determine the intervals of loss aversion (λ). However, Tanaka et al. (2010) provide the tables of the approximate values of σ and α, and the experimental data in the present study refers to the point values in those tables [11].

4.2.3 Estimation model of CBHI enrollment

In this study, we estimate the likelihood of CBHI scheme adoption decisions by combining household demographic information and experimental data. In the empirical approximation, we primarily run the probit regression with risk parameters and then consider the extension of including household's demographics and characteristics to examine the sensitivity of the estimates. The distance to the district hospital is added in the regression as a general control for the village's infrastructure. In practice, the following model is estimated as follows:

[11] See Nguyen et al. (2010) for the sample of the risk parameter measurement.

$$CBHI_i = \beta_0 + \boldsymbol{\beta_1}'\mathbf{RP_i} + \boldsymbol{\beta_2}'\mathbf{SES_i} + \varepsilon_i \tag{4.1}$$

where $CBHI_i$ takes value of 1 if respondent i (representing the household) is a member of the CBHI scheme and 0 otherwise [12]. $\mathbf{RP_i}$ is the vector of risk parameters and $\mathbf{SES_i}$ is the vector of socio-economic variables (household head gender, household head age, household head education, household size, agriculture area, and distance from the village to district hospital). ε_i is the error term.

Because only an interval of λ is measured by the experiment, following Liu and Huang (2013), the midpoint of the interval is used as the point estimate in the regression. For the elicited λ with a single bound, either lower or upper, resulting from selecting all option A or option B, we treat the observed bound as the point estimate.

4.2.4 Summary statistics

The questionnaire-based interview and risk experiment are conducted for the sample of 580 households. Figure 4.1 reports the distribution of switching points. Like the results of Tanaka et al. (2010), our samples make few switches from option A to option B across all three series, thus suggesting a considerable amount of heterogeneous distribution of risk preferences. Only 27.2%, 22.6%, and 35% of subjects make switching points in series 1, 2, and 3, respectively. A significant portion of the respondents prefers option B from the first decision row in all series. Across this lottery choice experiment, the total reward is approximately 22,247AK earning per respondent, and ranges from -10,500LAK to 500,000LAK. Figure 4.1.Distribution of switching points.

[12] Note that non-members and ex-members are not distinguished.

Series 2 \ Series 1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Never	Total
1	175	22	7	3	4	4	4	3	4	3	3	3	7	5	55	302
2	32	11	2	1		3	1				1	1			5	57
3	6	2	1						1						1	11
4	4					1			1						1	7
5	2								1							3
6	4			1			1									6
7	1							1							1	3
8								1			1					2
9								2	1			2			1	6
10	3	2				1	1	1	2				1	1		12
11					1				1	1					1	4
12										3	3	2				8
13					2										1	3
14	1									1			1	2	4	9
Never	26	8				1		1	3		3	3	1	3	98	147
Total	254	45	10	5	7	10	7	9	14	8	11	11	10	11	168	580

Series 3

1	2	3	4	5	6	7	Never	Total
291	137	49	9	4	2	2	86	580

Choices compatible with EUT.

FIGURE 4.1: Distribution of switching points

Compared to the risk preferences of Vietnamese villagers in Tanaka et al. (2010), the experimental data suggests that the majority of self-employed individuals in the Lao PDR tend to be less risk-averse in gains and less loss-averse. However, the mean value of the risk-aversion in small-probability prospects in losses is close to that of the Vietnamese villagers.

Table 4.2 gives the summary of the generated risk parameters and controlled variables of the pool samples and subsamples conditioned to the CBHI. The mean difference tests are performed to examine whether significantly systematic variations of behavioral predictors and other characteristic confounders exist across subgroups. Interestingly, many of the mean tests indicate significantly systematic distributions of the observed variables across subsamples. For instance, the heads of member households are likely to be elderly and better educated. The test still presents substantial differences with

Table 4.2: Descriptive statistics

Variables	Full sample	Subsample				Mean difference test		
		M	EN	N	E	M-EN	M-N	M-E
	580	210	370	298	72			
σ (risk aversion for gains	0.88	0.9	0.86	0.89	0.75	0.04	0.01	0.15**
	(0.58)	(0.57)	(0.59)	(0.58)	(0.60)			
α (risk aversion for	0.71	0.74	0.69	0.69	0.7	0.05	0.05*	0.05
probability prospects)	(0.34)	(0.34)	(0.33)	(0.33)	(0.33)			
λ (loss aversion)[a]	2.28	2.21	2.33	2.31	2.43	n.a	n.a	n.a
Household head gender (1=male)	0.85	0.84	0.85	0.85	0.85	-0.013	-0.001	-0.009
	(0.36)	(0.37)	(0.36)	(0.36)	(0.36)			
Household head age	50.14	51.4	49.42	48.91	51.53	1.98*	2.92**	-0.12
	(13.42)	(12.44)	(13.92)	(13.84)	(14.12)			
Household head education	4.47	5.06	4.13	3.91	5.03	0.93***	1.16***	0.03
	(3.87)	(3.63)	(3.97)	(3.91)	(4.12)			
Household size	5.92	6.37	5.67	5.62	5.88	0.7***	0.75***	0.50**
	(2.16)	(2.29)	(2.03)	(2.07)	(1.87)			
Agriculture area (m2)	17,809	17,871	17.774	18,506	14,745	96.11	-635.8	3,125.50
	(22,029)	(20,651)	(22,802)	(24,438)	(13,867)			
Distance to district hospital (km)	15.79	14.79	16.36	16.75	14.72	-1.97***	-1.57***	0.06
	(5.40)	(4.11)	(5.95)	(6.03)	(5.33)			

Standard errors are reported in parentheses.

M, N, E, and EN are CBHI currently active members, non-members, ex-mebers, and ex- and non-members, respectively.

[a] Last 12 months reported (2015 price base).

respect to household sizes and distance to the nearest hospital among subsamples.

With no functional form assumption and no controlling for other socio-economic confounders, the mean test exhibits an undifferentiated risk aversion in gains among CBHI members and non-members. However, the degree of risk aversion for gains is statistically different between members and ex-members. In other words, the ex-members are more risk-averse than the members. In addition, the degree of risk aversion towards subjective probability aspects in losses is considerably heterogeneous among members and non-members. Especially, non-members are relatively more risk-seeking for moderate- and high-probabilities of losses than members. There is further discussion on the consistency when functional form of regression is set up and other confounders are controlled in the following section.

4.2.5 Results

According to the measured risk parameters, the validity of the EUT hypothesis is tested. The null hypothesis of $\alpha = \lambda = 1$, with the condition that the prospect value function would transform to the conventional EUT, is rejected at 1% confidence interval, thus showing strong evidence that the means of the observed and are significantly different from one. The result suggests that a substantial number of samples behave in a coherent pattern with the PT.

We next examine the linkages between households' decisions to enroll in the CBHI scheme and their risk preferences. In addition to the full sample, we estimate separate models for the two subsamples. Subsample 1 is our interest in which the CBHI ex-members are removed from the regression. However, for a comprehensive insight into any significant differences between CBHI members and ex-members, we intentionally include subsample 4 in the analysis. As a sensitivity confirmation, we report the results from four different specifications for all models.

The hypothesis that risk-averse subjects are more likely to engage in the CBHI scheme is confirmed with two main findings in this study. The regression results are summarized in Table 4.3. The specification (1) presents the benchmark results. Among the three elicited risk parameters of PT (risk aversion for gains, risk aversion for probability prospects, and loss aversion), the risk aversion for probability prospects appears to be the strongest behavioral predictor. The estimates are positive and significant at 5% level in the full sample, but at 10% level in subsample 1. The results are robust, even upon considering the demographic and economic confounders. The findings imply that subjects who are less risk-seeking in moderate- or high-probabilities of losses are more likely to favor the CBHI scheme. Furthermore, weak evidence on the correlation between the loss aversion and the CBHI scheme uptake likelihood is found in subsample 1 when household heads' education, household size, agriculture land, and distance to the district hospital are controlled in the regression. More specifically, there is a growing probability to engage in the CBHI scheme since subjects are more loss-averse.

Additionally, the association between many demographic variables and the likelihood of scheme enrollment is statistically significant and has expected signs throughout all specifications. Like the common findings in previous literature [33, 77], households with educated and older household heads and larger sizes are associated with an increased probability for the CBHI scheme uptake decision.

Table 4.3: Risk preferences and the CBHI scheme uptake

Variables	**Full sample [580]** [M + N + EX]				**Subsample 1 [508][a]** [M + N]				**Subsample 4 [282]** [M + EX]			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
σ (risk aversion for gains	0.12	0.11	0.09	0.09	0.07	0.06	0.03	0.03	0.303 **	0.305 **	0.311 **	0.313 **
	(0.23)	(0.26)	(0.36)	(0.36)	(0.5)	(0.54)	(0.79)	(0.8)	(0.15)	(0.15)	(0.15)	(0.15)
α (risk aversion for probability	0.33 **	0.33 **	0.35 **	0.35 **	0.33 *	0.32 *	0.33 *	0.33 *	0.32	0.32	0.33	0.34
prospects)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.06)	(0.24)	(0.24)	(0.25)	(0.25)
λ (loss aversion)	0.02	0.02	0.02	0.02	0.02	0.02	0.03 *	0.03 *	0.01	0.01	0.01	0.01
	(0.32)	(0.3)	(0.13)	(0.13)	(0.3)	(0.27)	(0.07)	(0.07)	(0.02)	(0.02)	(0.02)	(0.02)
Household head gender		-0.02	-0.06	-0.06		0.008	-0.01	-0.01		-0.06	-0.11	-0.11
(1=male)		(0.92)	(0.71)	(0.71)		(0.99)	(0.96)	(0.96)		(0.23)	(0.25)	(0.25)
Household head age		0.01	0.004	0.01		0.008 *	0.01	0.01		-0.002	-0.006	-0.006
		(0.12)	(0.29)	(0.3)		(0.05)	(0.1)	(0.1)		(0.01)	(0.01)	(0.01)
Household head education			0.04 ***	0.04 ***			0.05 ***	0.05 ***			0.002	0.0005
			(0.005)	(0.001)			(0.001)	(0.001)			(0.002)	(0.002)
Household size			0.11 ***	0.11 ***			0.12 ***	0.12 ***			0.08 *	0.08 *
			(0.00)	(0.00)			(0.00)	(0.00)			(0.04)	(0.04)
Agriculture area (m^2)				0.0000009				-0.0000004				-0.00009
				(0.000003)				(0.000003)				(0.00005)
Distance to district			-0.04 ***	-0.04 ***			-0.05 ***	-0.05 ***			-0.0002	-0.006
hospital (km)			(0.00)	(0.00)			(0.00)	(0.00)			(0.0019)	(0.0019)
Constant	-0.73 ***	-0.02 ***	-1.11 ***	-1.12 ***	-0.56 ***	-0.97 ***	-1.04 ***	-1.04 ***	0.15	0.3	0.04	0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.26)	(0.49)	(0.57)	(0.57)

The numbers in parentheses are standard deviations. [a] Subsample 1: sample includes CBHI members and non-members. Subsample 4: sample includes CBHI members and ex-members.

4.2.6 Conclusion

It is well known that health insurance reduces the risks of unexpected catastrophic health expenditures. Thus, individuals with either high risk aversion or loss aversion are expected to favor the insurance. Although there have already been many studies examining the links between individual-specific risk preferences and their decisions to buy health insurance, evidence varies by country, health insurance setting, and the method used to measure risk preferences. Especially with respect to the risk preference measurement, some studies employ self-reported questionnaires or lottery choice experiments with hypothetical rewards [78, 79], which do not always reflect the real attitudes of subjects. Conversely, some other studies conduct risk experiments with real money at stake, but the experimental design forces the researchers to establish prior assumptions on the theory of decision-making under uncertainty for the subjects, especially under either EUT [33] or PT [77]. Unlike the previous literature, this study employs the risk elicitation experiment technique of Tanaka et al. (2010), in which the validity of the EUT and PT assumptions can be tested simultaneously. We then relate the measured risk parameters to examine the association between individual risk preferences and the probability of opting for the CBHI scheme in rural villages of Savannakhet Province, Lao PDR.

The findings suggest that a substantial number of samples illustrate risk preferences that support the hypothesis of PT. Subjects are likely to be risk-averse over gains and risk-seeking over losses. For empirical analysis, the results suggest robust evidence that individuals who are less risk-seeking for moderate- or high-probabilities of losses tend to participate in the CBHI scheme. However, once the ex-members are excluded from the regression, we find additional significant but weak evidence on the association between loss aversion and the scheme uptake decisions. Furthermore, we find that high risk aversion for gains is affiliated with the CBHI scheme dropout. Despite high risk aversion, why did ex-members drop out of the scheme? Further study on the stated preferences for their expected CBHI scheme merits future study, especially to determine whether the benefit package of the current CBHI scheme is a reason leading to the dropout. The significant correlation of the behavioral predictors with the likelihood of CBHI scheme enrollment shows that the decision to engage in the CBHI scheme for rural households in Lao PDR is not completely rational in exogenous predictors.

Chapter 5

Potential demand for CBHI scheme improvement

5.1 Introduction

The low popularity of the CBHI scheme among targeted populations is a major concern for governments in low-income countries. To design appropriate measures to encourage enrollment, policy practitioners need to return to the factors that might influence the targeted population's demand for health insurance. The evidence from observational studies on determinants of CBHI membership can be summarized as follows: premium unaffordability, limited health care facilities, long distance to health care facility, insufficient information, poor quality of health services (including pharmaceuticals out of stock), and inappropriate benefit packages are the significant bottlenecks leading to low enrollment rates [12, 80–85]. These studies suggested that among the four problems, health care quality and benefit package are the two problems to prioritize improvements to promote CBHI enrollment. Yet, the following questions remain: how are benefit packages designed to meet the preferences of potential enrollees? How much is potential enrollees' average willingness-to-pay (WTP) for health insurance?

In general, WTP can be estimated by two approaches: revealed preference (RP), which is based on actual behavior towards actual policy, and stated preference (SP), which is based on hypothetical behavior towards hypothetical policy [86]. However, SP is more applicable to the study of potential policy improvement. There are two methods for collecting SP: the contingent valuation method (CVM) and discrete choice experiments (DCEs). More specifically, the CVM is the direct method in which respondents are directly asked about their WTP for a hypothetical policy. This method has been widely applied in the field of health economics [87–90]. A recent systematic review of the application of the CVM to measure WTP for health insurance in LMICs concluded that the average WTP for health insurance of rural households is less than 2% of GDP per capita [91]. Nonetheless, the CVM can only observe the value of a policy as a whole bundle.

By contrast, the DCEs is an attribute-driven experimental method in which a hypothetical policy is described by a set of attributes, including pecuniary and non-pecuniary attributes. Therefore, DCEs can measure the value of each attribute of the policy and produce findings that are more informative for policy interventions [92]. Due to this obvious advantage, DCEs have received dramatically more attention in the literature, particularly the health economics literature that addresses health-related policy concerns [93]. In LMICs, a number of studies utilized DCEs to either quantify individual preferences or measure individuals' average WTP for a health insurance intervention, such as micro health insurance in the health care system in Liberia [94] and Malawi [95], social health insurance in Ethiopia [96], community-based health insurance in Cambodia [18], and social health insurance in Bulgaria [97]. The selection of attributes (and attribute levels) for DCEs in these studies was rather diverse across settings. However, the attributes that were often considered included the health insurance premium, availability of medicines, a transportation-related attribute [1], enrollment unit, copayment, wait time, and reputation of the health care staff. From the health system perspective,

[1] Including coverage for transportation cost to health care facilities and distance to health care facilities.

these attributes are all prerequisites for effective improvement; however, in practice, the policy interventions are very costly and have many limitations, especially budget constraints. Thus, to prioritize and design appropriate improvement measures considering the preferences of potential enrollees, it is important to identify the causal effect of a given attribute in isolation on their choice probabilities. Although DCEs can elicit the effect of changes in individual attributes of a policy on the WTP distribution, they cannot identify causal effects of individual policy attributes on choice outcomes, unless a whole set of intervention.

To address the above limitation of DCEs, Hainmueller et al. (2014) developed a new design of the conjoint experiment (a type of DCE) in which attribute levels and attribute positions are randomly assigned, and alternatives are randomly paired. The full randomization design ensures that the observable and unobservable confounding variables of respondents are approximately equally distributed across treatment assignments (choice tasks) such that the estimated effects can be interpreted as causality [98]. In addition, this methodology enables researchers to estimate the nonparametric causal effect of each policy attribute on observable choice outcomes [99]. An increasing number of studies have applied this approach to estimate the average marginal component effect (AMCE) in a variety of contexts. For instance, Hainmueller and Hopskins (2015) explored which immigrant attributes affect Americans' attitudes towards immigrants. Bechtel and Scheve (2013), Gampfer et al. (2014), and Bernauer and Gampfer (2015) used the same approach to examine public support for different types of climate policies.

An outstanding empirical example of the application of this approach is the study of Hninn et al. (2017), which was the first study to introduce the theoretical framework on welfare implications using the conjoint experiment of Hainmueller et al. (2014). The above paper incorporated the nonparametric point-identification welfare analysis of Bhattacharya (2015) [2] with the observed data from conjoint experiment approach of Hainmueller et al. (2014). Unlike conventional welfare analyses of DCEs [3], the approach of Hninn et al. (2017) was based on a rational choice model with no assumption of functional form on preference distribution needed. With only weak assumptions regarding the preference distribution, the authors showed that the marginal WTP distribution can be nonparametrically measured, which is more advanced in that it addresses the likely misspecification bias in choice making. The first empirical this methodology was to evaluate a water quality improvement intervention in Inlay Lake, Myanmar [4].

To provide more informative potential solutions to the phenomenon of low enrollment in the CBHI scheme with a focus on improving the benefit package, the present study employs the identification analysis of Hninn et al. (2017). Thus far, no studies have applied this approach in the health system context with a focus on improving health financing policy. To ensure effective benefit package design, it is important to evaluate how potential enrollees' CBHI scheme preferences can be enhanced via a set of attributes and how much they are willing to pay for a CBHI scheme improvement.

[2] The work cited above evaluates the welfare effects from price changes of a discrete good using individual-level data.

[3] Choices made in DCEs are analyzed using random utility theory with assumed specification for the choice probabilities. Therefore, the results of welfare analysis are potentially based on the parametric assumption [104].

[4] The water quality improvement intervention is defined by a set of attributes, *toilet*, *garbage*, *waste water*, *fertilizer*, *period*, *organization*, and *payment*, for the floating settlement on Inlay Lake, Myanmar. The findings show that the estimated average WTP for water quality improvement among people living on Inlay Lake is up to 5.9% of the average annual income per capita, and toilet provision is a pronounced attribute impacting the welfare effect.

5.2 Methodology

5.2.1 Design

In designing the experiment, we need to consider some appropriate potential attributes, particularly attributes that are highly correlated with common CBHI scheme-related problems in either LMICs or the Lao setting. For this study, we consider a literature review and local CBHI staff's point of view as appropriate sources for attribute selection.

In this study, the hypothetical CBHI benefit package is described according to seven attributes: *monthly premium*; *insurance coverage for medical consultations*, *hospitalizations*, *traffic accidents*, *pharmaceuticals*, *transportation*; and *one-year prepaid discount.*

The attributes of insurance coverage for pharmaceuticals [94, 96] and transportation [18, 95, 97] are selected based on a literature review. The attribute of transportation is particularly relevant to the Lao context, where transportation infrastructure remains a challenging issue in many parts of the country, especially in remote areas. Lack of access to sufficient transportation and excessive OOPs for transportation could hinder people from obtaining health care even when care is readily available. However, the significance of this component is uncertain based on the existing literature. Therefore, this study assumes that transportation might be a significant determinant in explaining why self-employed people are reluctant to participate the CBHI scheme in the Lao PDR.

The attributes of insurance coverage for traffic accidents and prepaid discount are obtained from interviews with local CBHI staff. The lack of coverage for medical treatment fees due to traffic accidents has long been a complaint of many active members and even dropouts. Meanwhile, premium collectors at the community level have also faced difficulties in collecting monthly premiums; they state that offering annual collection at a discounted rate might be more appropriate for rural enrollees who earn income on a seasonal basis.

Although the CBHI status quo scheme covers hospitalization and medical consultation fees, we intentionally include these attributes in the experiment to observe their trade-off with other hypothetical attributes.

Table 5.1 presents the attributes and levels applied in our experiment [5]. Note that the reference category of premiums shown in Table 5.1 refers to the current premiums for those residing in rural areas.

To minimize bias as a result of the communication process, the survey is carried out in two parts: a household survey and an experiment. First, five investigators conduct questionnaire-based interviews to gather households' demographic information and self-reported reasons for not enrolling. Second, respondents who complete the first session proceed to the experiment session with a different investigator. Before progressing to the second session, three investigators explain the scenario, the rules of experiment, and show pictures used in the experiment to respondents in a face-to-face manner.

Each respondent is asked to rank five randomly formed choice tasks [6]. In each choice task, participants compare three policy alternatives, two hypothetical policies and the CBHI status quo scheme, and rank the policies based on which scheme will maximize their benefit [7]. To ensure that our experiment setup is understandable for respondents, we conduct a pretest of 20 random samples (equivalent to 200 observations) of individuals

[5] Total number of attributes and levels provide a total of $4 \times 2^3 \times 3^2 = 575$ possible scenarios, excluding the status quo scenario. These scenarios can be combined as a pair in $575 \times 574 = 330,050$ possible ways. For simplicity and holding the condition of uncorrelated attributes, we randomly select 575 pairs and form 115 choice sets. Each respondent is presented with a choice set of five choice tasks; thus, the causal effects are estimated using 115 choice sets in total.

[6] We allow the respondents to see all five choice tasks at once.

[7] In this experiment, "1", "2" and "3" indicates most, average and less preferred policies, respectively. To avoid bias resulting from attribute position order effect, the position order is randomized. For simplicity, a respondent receives identical attribute order across the five choice tasks. See Appendix E for conjoint experiment sheet.

Table 5.1: Attributes and levels

No.	Attribute	No.	Levels	Description
1	Premium	1	10,000 LAK (1 member)	Premium per household per month in Lao currency (LAK). It is
			18,000 LAK (2-4 members)	2,000 LAK cheaper than current premium which varies
			23,000 LAK (5-7 members)	across household size.
			26,000 LAK (8+ members)	
		2	12,000 LAK (1 member)	Premium per household per month in Lao currency (LAK). It is
			20,000 LAK (2-4 members)	the current premium which varies across household size.
			25,000 LAK (5-7 members)	
			28,000 LAK (8+ members)	
		3	14,000 LAK (1 member)	Premium per household per month in Lao currency (LAK). It is
			22,000 LAK (2-4 members)	2,000 LAK higher than current premium which varies
			27,000 LAK (5-7 members)	across household size.
			30,000 LAK (8+ members)	
		4	16,000 LAK (1 member)	Premium per household per month in Lao currency (LAK). It is
			24,000 LAK (2-4 members)	4,000 LAK higher than current premium which varies
			29,000 LAK (5-7 members)	across household size.
			32,000 LAK (8+ members)	
2	Medical consultations	5	No	Insurance does not cover for medical consultation and diagnostic test fee.
		6	Yes	Insurance covers for medical consultation and diagnostic test fee.
3	Hospitalizations	7	No	Insurance does not cover for hospitalization fee due to medical treatment or surgery.
		8	Yes	Insurance covers for hospitalization fee due to medical treatment or surgery.
4	Traffic accidents	9	No	Insurance does not cover for medical treatment fee due to traffic accident.
		10	Yes	Insurance covers for medical treatment fee due to traffic accident.
5	Pharmaceuticals	11	Partly	Insurance covers for pharmaceuticals fee identified on the essential medicines list of Ministry of Health
		12	Fully	Insurance covers for all pharmaceuticals fee associated with treatment.
6	Transportation	13	No	Insurance does not cover for patients travel cost to referral hospitals out of the district.
		14	One way	Insurance covers for one-way patients travel cost to referral hospitals out of the district.
		15	One round	Insurance covers for one-round patients travel cost to referral hospitals out of the district.
7	Prepaid discount	16	No	No discount for one-year premium prepayment.
		17	5%	5% discount for one-year premium prepayment.
		18	10%	10% discount for one-year premium prepayment.

Note: The bold levels are status quo of CBHI scheme.

with different CBHI statuses (members, ex-members, and non-members) [8]. The pretest confirms that the selected attributes and the variation in premium levels are appropriate

[8]Members, ex-members and non-members are defined as households that are currently enrolled, dropped out of and never enrolled in the CBHI scheme, respectively. Note that 20 households are excluded from the main survey.

and that the design of the experiment is understandable. It further confirms that only the number of choice tasks is tiring; however, the tasks are manageable because we utilize pictures. Thus, the bias associated with the illiteracy effect can be overcome.

5.2.2 Analysis

5.2.2.1 Estimation of choice probabilities

This paper applies the full randomization design of the conjoint analysis of Hainmueller et al. (2014). In this approach, respondents are presented with a set of choice tasks with several alternatives. Each alternative is randomly formed by a set of selected attributes and individual attribute levels.

For our experiment, we generate two hypothetical CBHI alternatives, each of which is described by the premium and a set of non-pecuniary attributes: insurance coverage of medical consultations, hospitalizations, traffic accidents, pharmaceuticals, and transportation as well as a prepaid discount. Respondents are then asked to rank the alternatives based on their preferences.

In this study, we intentionally include the CBHI status quo scheme as an alternative; thus, each choice task has three alternatives: two hypothetical CBHI alternatives and the current CBHI scheme. For this reason, two types of results can be observed simultaneously: internal choice probability (when an alternative is preferred to another alternative) and external choice probability (when an alternative is preferred to the status quo).

To view this more formally under Hninn et al.'s (2017) framework, let $\mathbf{K} = \{1, ..., k\}$ be a set of choice tasks of CBHI alternatives, C_{ijk} insurance premium, $\mathbf{A}_{ijk} = \{A_{jk1}, ..., A_{jkL}\}$

a set of non-pecuniary attributes for individual i in alternative j^{th} of choice task k^{th}, and L the number of attributes. Thus, CBHI alternatives are defined by C_{ijk} and $\mathbf{A}_{ijk}$.

In each of $\mathbf{K}$ choice tasks, individual i makes choices between J (=2) hypothetical CBHI alternatives and the CBHI status quo scheme. Y_{ijk} is individual choice outcome; if individual i prefers alternative j^{th} in choice task k^{th} over the status quo (or over the other alternative for internal choice probabilities), Y_{ijk}=1 and 0 otherwise.

There are two main assumptions needed for this approach. First, the independence assumption ensures that the round of the choice task and order of alternatives do not influence the individual choice outcome. Thus, Y_{ijk}, C_{ijk}, and $\mathbf{A}_{ijk}$ can be referred to as Y_{ij}, C_{ij}, and $\mathbf{A}_{ij}$. Second, the randomization assumption allows us to define the AMCE identification of changes in the level of attribute l from a_0 to a_1 by the following equation:

$$\hat{\pi}_l(a_1, a_0) = \bar{Y}_{ij|C_{ij}=c, A_{ijl}=a_1} - \bar{Y}_{ij|C_{ij}=c, A_{ijl}=a_0} \tag{5.1}$$

where c, a_1 and a_0 are the given levels of premium (C_{ij}) and attribute l (A_{ijl}) for the hypothetical CBHI alternative. $\bar{Y}_{ij|C_{ij}=c, A_{ijl}=a_1}$ and $\bar{Y}_{ij|C_{ij}=c, A_{ijl}=a_0}$ are the conditional averages of the observed choice outcome.

According to the aforesaid identification, the AMCE can then be estimated with our conjoint experiment data by the following linear model:

$$E[Y_{ij}] = \beta_0 + \beta_c I_{ijc} + \sum_{l=1}^{6} \beta_l \mathbf{I}_{ijl} \tag{5.2}$$

where $E[Y_{ij}]$ is an expected binary choice indicator of respondent i for CBHI alternative j^{th}. I_{ijc} and $\mathbf{I}_{ijl}$ denote the vectors of dummy for premium levels and attribute l^{th} levels.

β_c and β_l are vectors of the estimates of the AMCE. As the experiment allows each respondent to rank three alternatives in several choice tasks, Eq (5.2) is estimated by the cluster robust standard errors estimation method accounting for within-respondent correlations between preferences.

5.2.2.2 Component effect on WTP distribution

For the WTP analysis, we mimic the methodology of Hninn et al. (2017). Only four assumptions of utility function: monotonicity, continuity, boundary, and rationality are sufficient to identify the marginal WTP distribution as follows, respectively:

$$\hat{F}(c) = 1 - \bar{Y}_{ij|C_{ij}=c} \tag{5.3}$$

where $\hat{F}(c)$ is the identification result of marginal WTP distribution or the share of those having a WTP value of c or lower.

However, the boundary assumption only assumes the lower bound of WTP at zero and does not assume the upper bound. This assumption means that the levels of non-pecuniary attributes in the alternatives are better off relative to the CBHI status quo scheme. Therefore, only the lower bounds of average marginal WTP from conjoint data can be identified using the following equations:

$$\underline{\hat{\mu}} = \sum_{i=0}^{n} c_i[\hat{F}(c_{i+1}) - \hat{F}(c_i)] \tag{5.4}$$

where c_i is the lower premium in i^{th} threshold. n is the number of threshold levels.

Based on the CBHI status quo scheme, in which premium varies across household size, hypothetical premium levels in this study also vary accordingly. For simplicity, we define the premium levels as:

$$p_1 = \begin{cases} 10,000 \text{ LAK} & \text{1 member} \\ 18,000 \text{ LAK} & \text{2-4 members} \\ 23,000 \text{ LAK} & \text{5-7 members} \\ 26,000 \text{ LAK} & \text{8+ members} \end{cases}, \quad p_2 = \begin{cases} 12,000 \text{ LAK} & \text{1 member} \\ 20,000 \text{ LAK} & \text{2-4 members} \\ 25,000 \text{ LAK} & \text{5-7 members} \\ 28,000 \text{ LAK} & \text{8+ members} \end{cases}$$

$$p_3 = \begin{cases} 14,000 \text{ LAK} & \text{1 member} \\ 22,000 \text{ LAK} & \text{2-4 members} \\ 27,000 \text{ LAK} & \text{5-7 members} \\ 30,000 \text{ LAK} & \text{8+ members} \end{cases}, \quad p_4 = \begin{cases} 16,000 \text{ LAK} & \text{1 member} \\ 24,000 \text{ LAK} & \text{2-4 members} \\ 29,000 \text{ LAK} & \text{5-7 members} \\ 32,000 \text{ LAK} & \text{8+ members} \end{cases}$$

From Eq (5.3), the probability intervals of the marginal WTP distribution are rewritten as:

$$\begin{aligned} \hat{F}(p_1) &= 1 - \bar{Y}_{ij|C_{ij}=p_1} \\ \hat{F}(p_2) - \hat{F}(p_1) &= \bar{Y}_{ij|C_{ij}=p_1} - \bar{Y}_{ij|C_{ij}=p_2} \\ \hat{F}(p_3) - \hat{F}(p_2) &= \bar{Y}_{ij|C_{ij}=p_2} - \bar{Y}_{ij|C_{ij}=p_3} \\ \hat{F}(p_4) - \hat{F}(p_3) &= \bar{Y}_{ij|C_{ij}=p_3} - \bar{Y}_{ij|C_{ij}=p_4} \\ 1 - \hat{F}(p_4) &= \bar{Y}_{ij|C_{ij}=p_4} \end{aligned} \tag{5.5}$$

Again, the boundary assumption enables us to identify five threshold premium levels, as follows: $[0, p_1]$; $[p_1, p_2]$; $[p_2, p_3]$; $[p_3, p_4]$; and $[p_4, \infty)$. Thus, the lower bound of the average marginal WTP in Eq (5.4) is measured as follows:

$$\underline{\hat{\mu}} = \begin{pmatrix} 10,000s_1 & 12,000s_1 & 14,000s_1 & 16,000s_1 \\ 18,000s_{2\text{-}4} & 20,000s_{2\text{-}4} & 22,000s_{2\text{-}4} & 24,000s_{2\text{-}4} \\ 23,000s_{5\text{-}7} & 25,000s_{5\text{-}7} & 27,000s_{5\text{-}7} & 29,000s_{5\text{-}7} \\ 26,000s_{8+} & 28,000s_{8+} & 30,000s_{8+} & 32,000s_{8+} \end{pmatrix} \begin{pmatrix} \hat{F}(p_2) - \hat{F}(p_1) \\ \hat{F}(p_3) - \hat{F}(p_2) \\ \hat{F}(p_4) - \hat{F}(p_3) \\ 1 - \hat{F}(p_4) \end{pmatrix} \tag{5.6}$$

where s_1, $s_{2\text{-}4}$, $s_{5\text{-}7}$, and s_{8+} are the percentages of households that have 1 member, 2-4 members, 5-7 members, and 8 or more members, respectively.

5.3 Results

5.3.1 Component effect on choice probabilities

Figure 5.1 shows the results of the AMCE on internal and external choice probabilities from estimating Eq (5.2). The dots indicate point estimates of AMCE for each attribute level on the respondents' choice probability to join the CBHI scheme compared against its baseline level, and error bars illustrate 95% confidence intervals. The solid dots along the vertical axis are the reference categories of each attribute.

Overall, the findings show that the signs, magnitudes and significance levels of the estimates are particularly close between the two results, suggesting that the respondents'

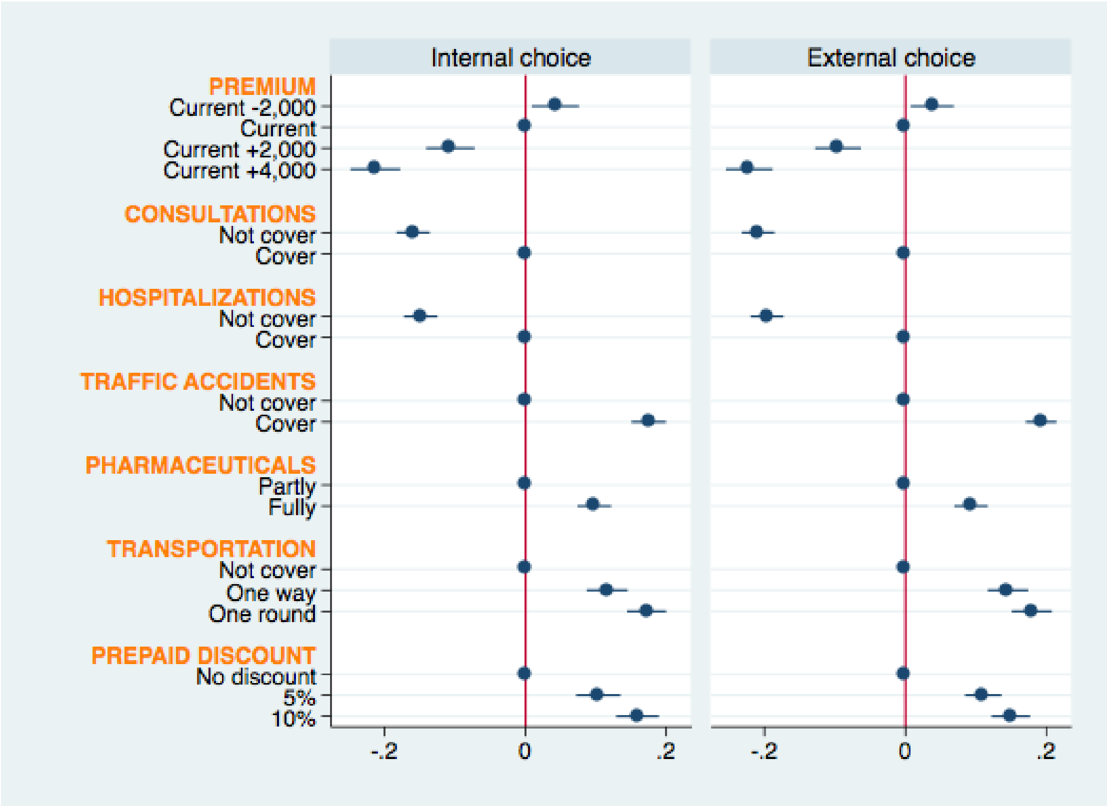


Figure 5.1: Average marginal component effect on choice probabilities

preferences are robust. All estimated coefficients are statistically significant at 99% confidence interval except for the current premium, which is significant at 95% confidence interval. Premium clearly stands out as the great burden affecting the choice probabilities; the roughly monotonic effects of premium support the monotonicity assumption. The preferences are more sensitive to a higher premium than a lower premium. Particularly, when the 4,000LAK higher premium is presented, the probability of joining the CBHI scheme decreases by about 21 percentage points compared to the probability given the current premium.

As stated in the experiment design section, we intentionally include the attributes of consultations and hospitalizations insurance coverage (which have been covered in the CBHI status quo scheme) in the experiment to examine their causal effects in comparison with the hypothetical attributes. The results of internal choice probabilities indicate that the effects of removing either consultation or hospitalization insurance coverage from the CBHI benefit package are roughly less than the effects of including either traffic accidents or round-trip transportation insurance coverage but, on the other hand, are larger for that of external choice probabilities. Among the effects of the hypothetical attributes (traffic accidents, pharmaceuticals, transportation, and prepaid discount), the causal effects of both traffic accidents and round-trip transportation are outstandingly large. This finding can be interpreted as showing that the CBHI scheme with insurance coverage for either traffic accidents or round-trip transportation would be more popular among the targeted population.

For the external choice probabilities, we can further explore the distribution of respondents' WTP across the given ranges of the premium for the CBHI scheme improvements compared to the status quo. The results of Eq (5.5) are reported in the following section.

5.3.2 WTP distribution

To estimate the lower bound of the average WTP, we conduct subsample analysis in which all levels of non-pecuniary attributes meet the boundary assumption. To ensure that the hypothetical alternatives will improve the CBHI status quo scheme, we exclude the alternatives with inferior levels of medical consultations and hospitalizations attributes relative to the CBHI status quo. By so doing, the number of observations reduces from 5,800 to 1,437. According to the four levels of premium in the conjoint experiment and the boundary assumption, the estimated WTP is distributed into five intervals.

Fig 5.2 shows the marginal share of the respondents whose WTP value lies below the upper bound of a certain interval. Error bars display 95% confidence intervals. The findings show that the estimated marginal WTP are all significant at 1% level, except that of the second interval, which is negative but insignificant. Only 6.74% of the respondents expressed that they are willing to pay only if the premium is not more than p_1. Interestingly, the respondents whose WTP value is greater than p_4 is considerably higher than other bins with a share of 64.61%. Based on Equation 6, the lower bound of the average WTP is measured at 25,579LAK, which is equivalent to 10.9% of the monthly per capita income of households in the area (or 3.29% of the monthly median income).

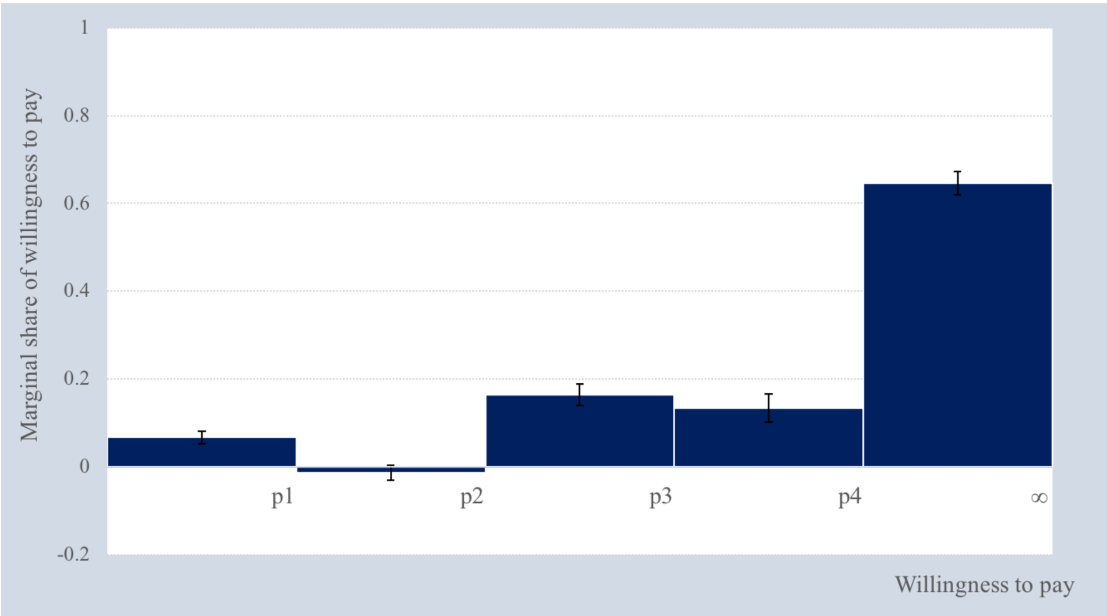


FIGURE 5.2: Marginal share of willingness to pay

According to the estimated marginal share of WTP, we measure the approval rate of the respondents for each interval of CBHI premium as shown in Fig 5.3. Error bars display 95% confidence intervals. Results show that 93.26% of the respondents will enroll the CBHI scheme if the premium is between p_2 and p_3. While Fig 5.3 provides information on the distribution of the approval rate averaged across the possible levels of all attributes, the following section reports the distribution of the approval rate when individual attributes change from baseline level to new level.

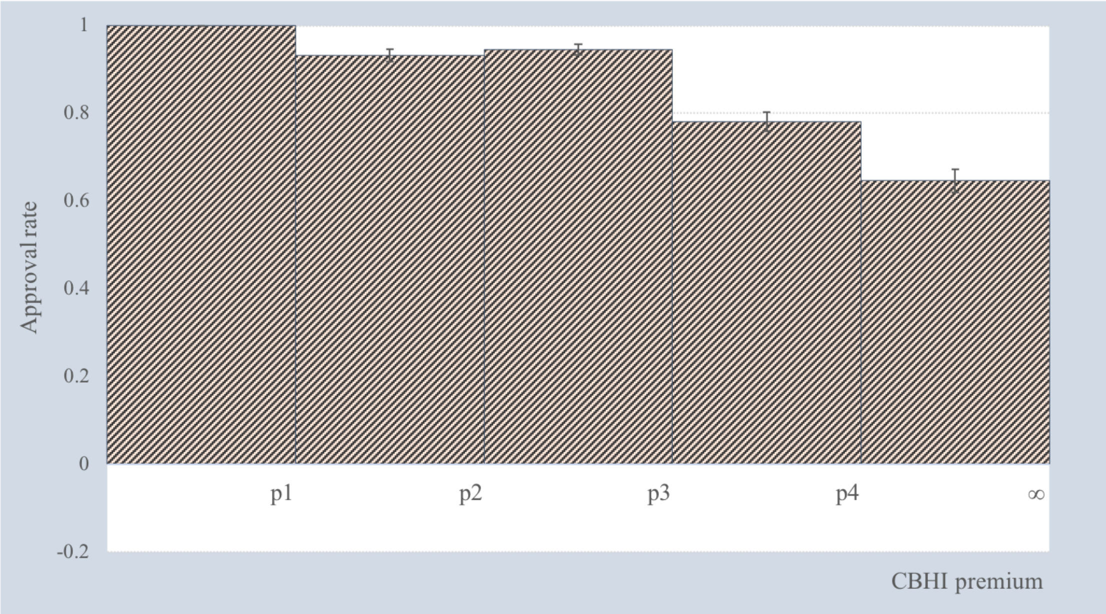


FIGURE 5.3: Approval rate for CBHI scheme improvement

As only hypothetical attributes are of interest, Table 5.2 shows the changes from the baseline level to a new level for each hypothetical attribute. The distribution of the approval rate by attribute is presented in Fig 5.2, and error bars show 95% confidence intervals. It is pronounced that the approval rate of the upper bins is significantly affected by the level changes across all hypothetical attributes. Especially, the change in levels of attributes increases the share of those whose WTP value is greater than p_4.

TABLE 5.2: Attributes change from baseline level to new level

	Baseline level (a_0)	**New level** (a_1)
(a)	Not cover traffic accidents	Cover traffic accidents
(b)	Partly cover pharmaceuticals	Fully cover pharmaceuticals
(c)	Not cover transportation	Cover one-way transportation
(d)	Not cover transportation	Cover round-trip transportation
(e)	No prepaid discount	5% prepaid discount
(f)	No prepaid discount	10% prepaid discount

Strikingly, compared to no insurance coverage for transportation, addressing the insurance coverage for round-trip transportation significantly increases the approval rate for

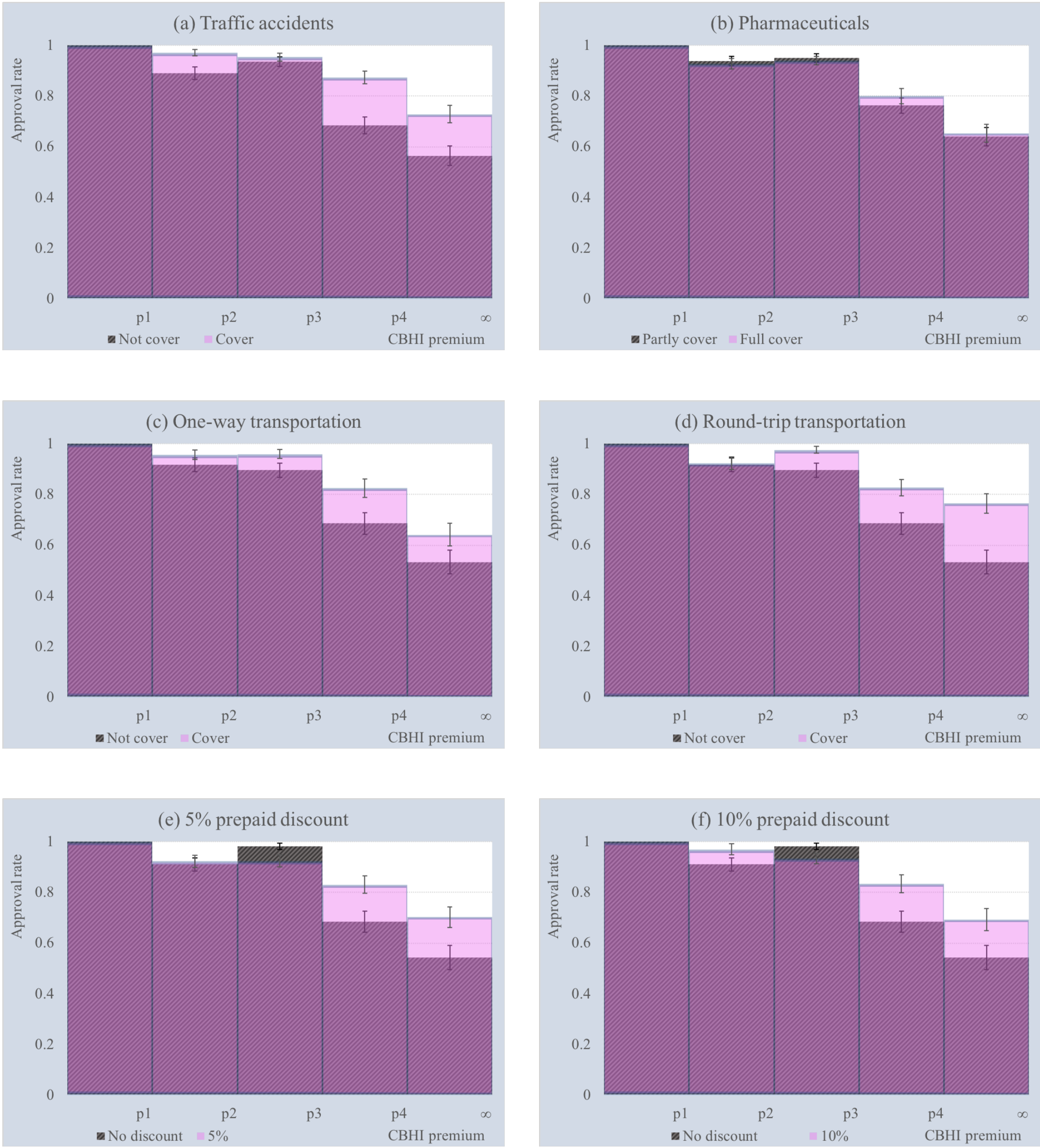


FIGURE 5.4: Approval rate by attribute

the CBHI scheme with the price more than p_4 by 23.14 percentage points. Due to the randomization, the effect of an attribute-level is independent of others. Therefore, the exclusion of negative levels of medical consultations and hospitalizations would not lead to significant variation in WTP results between full sample and subsample. To confirm this point, the estimated approval rate of full sample is reported in Appendix F. From the aggregate perspective, the approval rate of the full sample is slightly lower than the subsample. It is because the inferior hypothetical alternatives are included in the experiment, so more respondents prefer status quo to the alternatives. However, from the individual attribute perspective, we found robust evidence between full sample and subsample that the coverage for traffic accidents and round-trip transportation significantly increase the approval rate of bin 4 and 5, respectively.

The empirical evidence of this study supports the findings of Abiiro et al. (2014) in rural Malawi and Ozawa et al. (2016) in northwest Cambodia. These two studies employed a DCEs approach to elicit SPs on CBHI enrollment and found that greater transportation insurance coverage significantly influences respondents' choice behavior. However, the findings of the present study are causally interpretable. The results indicate that transportation is a crucial component of CBHI scheme promotion in rural areas of Savannakhet Province.

Similar to our sample, a substantial number of people in distant areas of the Lao PDR are highly dependent on public transportation commuting to health care facilities. Until very recently, the limited public transportation services along with poor road conditions are the fundamental sources of excessive travel expenses. Hence, our findings provide useful insight for policy improvements to the CBHI scheme across the Lao PDR considering the transportation barrier. Especially, the implementation of a CBHI scheme with insurance coverage for round-trip transportation might not only attain greater popularity but also increase the willingness to pay among the targeted population in remote areas. Moreover, as a complement to redesigning the benefit package such that it fulfills the expectations of targeted enrollees per se, the development of transportation infrastructure is a supporting mechanism to ensure greater coverage of the CBHI scheme in the Lao PDR.

5.4 Conclusion

The goal of the CBHI scheme is to protect people against direct OOPs and enhance their access to primary health care services via enrollment promotion. However, in practice, the implementation of the scheme fails to reach satisfactory enrollment rates in many LMICs. In particular, an inappropriate benefit package is recognized as an essential drawback leading to the low popularity of the scheme. Similarly, the CBHI scheme enrollment rate is low in the Lao PDR. Therefore, this study identifies SPs and WTP distribution for CBHI scheme improvements via a set of hypothetical attributes, namely *premium*; *insurance coverage for medical consultations*, *hospitalizations*, *traffic accidents*, *pharmaceuticals*, *transportation*; and *prepaid discount*, in rural Lao PDR. We apply the full randomization design of the conjoint experiment of Hainmueller et al. (2014) to elicit SP data because the estimates are interpreted as causal inference and apply the nonparametric identification analysis of Hninn et al. (2017) to measure WTP distribution.

The findings show that the compositions of the benefit package have crucial impacts on respondents' probability of enrolling in the CBHI scheme. Remarkably, respondents value hypothetical alternative policy over the status quo. The lower bound of average WTP is estimated at 25,579LAK per month, which is at least as large as 10.9% of the per capita income in the area (or 3.29% of the median household income). The average WTP of this study is higher than the average WTP reported in the systematic review on WTP for health insurance in LMICs [91]. More importantly, the existence of round-trip transportation fee coverage significantly increases enrollment probabilities and WTP. In conclusion, low enrollment in the CBHI scheme in the Lao PDR does not necessarily indicate low demand of potential enrollees. The enrollment rate can increase by improving the benefit package and addressing transportation factor.

An important limitation of this study is that we fail to conduct group discussions of sample respondents to obtain the most relevant attributes of scheme enrollment, which merits future research.

Chapter 6

Conclusions

6.1 Summary of findings

This dissertation intends to analyze the potential ways to enhance enrollment of the CBHI scheme in the Lao PDR. The overarching research argument is to understand whether the low enrollment phenomenon of the CBHI scheme in the Lao PDR necessarily implies a low demand of the potential enrollees. To achieve the overall research argument, this dissertation sets up three hypotheses as follows:

1. The CBHI scheme has impacts on household welfare.
2. Individual risk preferences take part in explaining the likelihood of participation in the CBHI scheme.
3. There is potential demand for the CBHI scheme enrollment.

Chapter 3 seeks to test the validity of hypothesis 1 using the IPTW method. The results suggest that the CBHI scheme has intertemporal impacts on rice yield per capita and cow holdings among enrolled households. Chapter 4 seeks to test the hypothesis 2 using the risk experiment to quantify the risk preference parameters of individuals (risk aversion for gains, risk aversion for probability prospects, and loss aversion). Evidence indicates that individuals who are less risk-seeking for moderate- or high-probabilities of losses tend to get engaged in the CBHI scheme. Chapter 5 addresses the hypothesis

3 using the randomized conjoint experiment to elicit SP data. In the experiment, the hypothetical CBHI scheme is defined by seven attributes (*monthly premium*; *insurance coverage for medical consultations*, *hospitalizations*, *traffic accidents*, *pharmaceuticals*, *transportation*; and *one-year prepaid discount*). Results suggest that the average WTP is estimated at least as large as 10.9% of the per capita income in the survey area. Especially, among the selected attributes round-trip transportation attribute significant increases the WTP.

The findings in this dissertation can be concluded as follows:

1. The CBHI scheme improves rice yield and cow holdings of enrolled households.
2. Subjects who are less risk-seeking for moderate- or high probabilities of losses are likely to engage in CBH scheme.
3. Average WTP is at least as large as 11% of monthly per capita income in the rural area, showing strong demand for CBHI scheme improvement.

The above findings are conducive to further discussions and policy implications in the following section.

6.2 Discussions and policy implications

Taken together the findings in this dissertation, the evidences confirm that the current CBHI scheme is not so bad, the scheme has especially positive impacts on the agricultural production side. However, the problem of the CBHI scheme in the Lao PDR is not only low uptake, but there seems to be adverse selection. To mitigate adverse selection, one approach is to maximize enrollment.

According to WTP analysis, there appear to have strong demand for the CBHI scheme, but the majority of self-employed households fail to enroll. A number of reasons can be drawn. For instance, the design of the CBHI scheme might not well meet people's preferences though premium is affordable. People might lack understanding of the risk-pooling system and/or receive insufficient information about the CBHI scheme. Possibly, people might lack trust in the scheme operation, especially the health service provision. However, Carrin (2003) suggested that the trust can be, to some extent, enhanced as long as people recognize that their preferences do matter in the scheme design.

Therefore, to ensure an optimum enrollment, availability of information about the CBHI scheme is necessary for decision making of people, such as levels of premium, benefit package, the degree of financial protection, number of beneficiaries, the process of getting the services, information of health care providers. More importantly, local authorities and stakeholders should carry out the promotion campaign more frequently and continuously. To ensure that the benefit package will be attractive for the community, community's preferences should be reflected in the design process, especially the issue of transportation from home to health care providers.

In the meantime, the long-term success of the CBHI scheme would also be determined by the government's ability in strengthening health care infrastructure. There should be an improvement in terms of quality of services, especially the double standard performance of the health care providers towards insured and uninsured patients. This dissertation looks at the potential improvements of the CBHI scheme using data of self-employed households in rural villages of Savannakhet Province, the findings from this study may not translate to self-employed households of other provinces of the Lao PDR.

Bibliography

[1] C. G. Orach. Health equity: challenges in low income countries. *African Health Sciences*, (9 (Suppl 2)):S49–S51, 2009.

[2] J. Kutzin. *Health financing policy: a guide for decision-makers*. Copenhagen: World Health Organization, Regional Office for Europe, Division of Country Health Systems, 2008 (Health Financing Policy Paper 2008/1). URL http://www.euro.who.int/__data/assets/pdf_file/0004/78871/E91422.pdf.

[3] R. Basaza, B. Criel, and P. V. D. Stuyft. Community health insurance in Uganda: Why does enrolment remain low? A view from beneath. *Health Policy*, 87(2): 172–184, 2008. doi: 10.1016/j.healthpol.2007.12.008.

[4] I. O. Odeyemi. Community-based health insurance programmes and the National Health Insurance Scheme of Nigeria: challenges to uptake and integration. *International journal for equity in health*, 13(1):20, 2014. doi: 10.1186/1475-9276-13-20. URL http://www.equityhealthj.com/content/13/1/20.

[5] G. Carrin. *ommunity-Based Health Insurance Schemes in Developing Countries: Facts, Problems and Perspectives*. Discussion Paper no.1. World Health Organization, Department Health System Financing, Expenditure and resource Allocation (FER), Geneva, 2003. URL http://www.who.int/health_financing/documents/dp_e_01_3-community_based_health_insurance.pdf.

[6] H. Wang, L. Zhang, W.Yip, and W. Hsiao. Adverse selection in a voluntary Rural Mutual Health Care health insurance scheme in China. *Social Science and Medicine*, 63(5):1236–1245, 2006. doi: 10.1016/j.socscimed.2006.03.008.

[7] D. Parmar, S.Reinhold, A. Souares, G. Savadogo, and R. Sauerborn. Does community-based health insurance protect household assets? Evidence from rural Africa. *Health Services Research*, 47(2):819–839, 2012. doi: 10.1111/j.1475-6773.2011.01321.x.

[8] S. K. O. Duku, F. Asenso-Boadi, E. Nketiah-Amponsah, and D. K. Arhinful. Utilization of healthcare services and renewal of health insurance membership: evidence of adverse selection in Ghana. *Health Economics Review*, 6(1):43, 2016. doi: 10.1186/s13561-016-0122-6. URL http://healtheconomicsreview.springeropen.com/articles/10.1186/s13561-016-0122-6.

[9] C. Delavallade. Quality health care and willingness to pay for health insurance retention: A randomized experiment in Kolkata slums. *Health economics*, 26:619–638, 2017. doi: 10.1002/hec.3337.

[10] H. Dong, M. D. Allegri, D. Gnawali, A. Souares, and R. Sauerborn. Drop-out analysis of community-based health insurance membership at Nouna, Burkina Faso. *Health Policy*, 92:174–179, 2009. doi: 10.1016/j.healthpol.2009.03.013.

[11] A. D. Mebratie, R. Sparrow, Z. Yilma, G. Alemu, and A. S. Bedi. Dropping out of Ethiopia's community-based health insurance scheme. *Health Policy and Planning*, 30(10):1296–1306, 2015. doi: 10.1093/heapol/czu142.

[12] P. Panda, A. Chakraborty, W. Raza, and A. S. Bedi. Renewing membership in three communitybased health insurance schemes in rural India. *Health Policy and Planning*, 31:1433–1444, 2016. doi: 10.1093/heapol/czw090.

[13] D. Wiesmann and J. Jtting. The emerging movement of community based health insurance in sub-saharan africa: Experiences and lessons learned. *Africa Spectrum*, 35(2):193–210, 2000. URL http://www.jstor.org/stable/40174841.

[14] M. D. Allegri, M. Sanon, J. Bridges, and R. Sauerborn. Understanding consumers' preferences and decision to enrol in community-based health insurance in rural West Africa. *Health Policy*, 76:58–71, 2006. doi: 10.1016/j.healthpol.2005.04.010.

[15] W. Soors, N. Devadasan, V. Durairaj, and B. Criel. *Community health insurance and universal coverage: multiple paths, many rivers to cross (World Health Report 2010 Background Paper 48)*. Geneva:World Health Organization, 2010.

[16] S. Alkenbrack, B. Jacobs, and M. Lindelow. Achieving universal health coverage through voluntary insurance: what can we learn from the experience of Lao PDR? *BMC health services research*, 13:521, 2013. doi: 10.1016/S0140-6736(12)61340-3.

[17] P. Panda, A. Chakraborty, D. M. Dror, and A. S. Bedi. Enrolment in community-based health insurance schemes in rural Bihar and Uttar Pradesh, India. *Health Policy and Planning*, 29:960–974, 2014. doi: 10.1093/heapol/czt077.

[18] S. Ozawa, S. Grewal, and J. F. P. Bridges. Household size and the decision to purchase health insurance in Cambodia: Results of a discrete-choice experiment with scale adjustment. *Applied Health Economics and Health Policy*, 14(2):195–204, 2016. doi: 10.1007/s40258-016-0222-9.

[19] World Health Organization. *Health service delivery profile Lao PDR 2012*. 2012. URL http://www.wpro.who.int/health_services/health_service_delivery_profiles/en/.

[20] S. Ahmed, P. L. Annear, B. Phonvisay, C. Phommavong, V. D. O. Cruz, A. Hammerich, and B. Jacobs. Institutional design and organizational practice for universal coverage in lesser-developed countries: Challenges facing the Lao PDR. *Social Science and Medicine*, 96, 2013. doi: 10.1016/j.socscimed.2013.01.019. URL http://dx.doi.org/10.1016/j.socscimed.2013.01.019.

[21] I. Phetsiriseng. *The Lao Peoples Democratic Republic: Updating and Improving the Social Protection Index. Technical Assistance Consultant's Report, August 2012, Asian Development Bank*, 18:141–152, 2012. doi: 10.1016/j.socscimed.2013.11.016. URL https://www.adb.org/sites/default/files/project-document/76081/44152-012-reg-tacr-10.pdf.

[22] World Bank. *Community-based health insurance in Lao Peoples Democratic Republic: understanding enrollment and impacts.* Washington, DC:World Bank, 2010. URL http://documents.worldbank.org/curated/en/135411468278055896/Community-based-health-insurance-in-Lao-Peoples-Democratic-Republic\-understanding-enrollment-and-impacts.

[23] P. L. Annear, M. Bigdeli, and B. Jacobs. A functional model for monitoring equity and effectiveness in purchasing health insurance premiums for the poor: Evidence from Cambodia and the Lao PDR. *Health Policy*, 102(2-3):295–303, 2011. doi: 10.1016/j.healthpol.2011.03.005.

[24] Lao Government. *Decree on national health insurance.* Vientiane Capital: National Health Insurance Bureau, 2012. URL https://www.google.co.jp/url?sa=t&rct=j&q=&esrc=s&source=web&cd=2&cad=rja&uact=8&ved=0ahUKEwi767vZmOHXAhWJxrwKHUBbBQgQFggvMAE&url=http%3A%2F%2Fwww.social-protection.org%2Fgimi%2Fgess%2FRessourceDownload.action%3Fressource.ressourceId%3D43358&usg=AOvVaw3pJ2Zgq4IxCUhRe1e6KJG9.

[25] United Nations in Lao PDR. *Country analysis report: Lao PDR: Analysis to inform the Lao Peoples Democratic Republic-United Nations partnership framework (2017-2021).* Vientiane:United Nations in Lao PDR, 2015. URL http://www.la.

undp.org/content/dam/laopdr/docs/Reports%20and%20publications/2015/Country%20Analysis%20Report%20Lao%20PDR%202015.pdf.

[26] United Nations in Lao PDR. *From millennium development goals to sustainable development goals: Laying the base for 2030*. Vientiane:United Nations in Lao PDR, 2017. URL http://la.one.un.org/images/publications/MDG-SDG-Review-UN-in-Lao-PDR.pdf.

[27] G. Hayes. *Population situation analysis: Lao PDR*. Hamilton:United Nations Population Fund, 2015. URL http://lao.unfpa.org/sites/default/files/pub-pdf/PSA%20LAYOUT.pdf.

[28] I. Mathauer, B. Mathivet, and J. Kutzin. *Community based health insurance: how can it contribute to progress towards UHC? Health Financing Policy Brief no 3*, Geneva:World Health Organization. License: CC BY–NC–SA 3.0 IGO, 2017. URL http://www.who.int/iris/handle/10665/255629.

[29] E. Spaan, J. Mathijssen, N.Tromp, F. McBain, A. ten Have, and R. Baltussen. The impact of health insurance in Africa and Asia: a systematic review. *Bulletin of the World Health Organization*, 90(9):685–692, 2012. doi: 10.2471/BLT.12.102301. URL http://www.who.int/bulletin/volumes/90/9/12-102301.pdf.

[30] A. Acharya, S. Vellakkal, F. Taylor, E. Masset, A. Satija, M. Burke, and S. Ebrahim. The impact of health insurance schemes for the informal sector in low-and middle-income countries: A systematic review. *The World Bank Research Observer*, 28(2):236–266, 2013. doi: 10.1093/wbro/lks009.

[31] J. P. Jütting. Do community-based health insurance schemes improve poor people's access to health care? Evidence from rural senegal. *World Development*, 32 (2):273–288, 2004. doi: 10.1016/j.worlddev.2003.10.001.

[32] H. T. H. Nguyen, Y. Rajkotia, and H. Wang. The financial protection effect of Ghana National Health Insurance Scheme: evidence from a study in two rural districts. *International Journal for Equity in Health*, 10(1):4, 2011. doi: 10.1186/1475-9276-10-4. URL http://equityhealthj.biomedcentral.com/articles/10.1186/1475-9276-10-4.

[33] S. Alkenbrack and M. Lindelow. The impact of community-based health insurance on utilization and out-of-pocket expenditures in Lao People's Democratic Republic. *Health economics*, 24:379–399, 2015. doi: 10.1002/hec.

[34] W. A. Raza, E. V. Poel, A. S. d Bedi, and F. Rutten. Impact of community-based health insurance on access and financial protection: evidence from three randomized control trials in rural india. *Health Economics*, 25:675–687, 2016.

[35] K. Asenso-Okyere, C. Chiang, P. Thangata, and K. S. Andam. *The Interaction between Health and Farm Labor Productivity in Africa. Food Policy Report*, Washington D.C.:International Food Research Policy Institute (IFPRI), 2011.

[36] J. M. Antle and P. L. Pingali. Pesticides, productivity, and farmer health: A philippine case study. *American Journal of Agricultural Economics*, 76(3):418–30, 1994.

[37] R. Sauerborn, A. Adams, and M. Hien. Household strategies to cope with the economic costs of illness. *Social Science & Medicine*, 43(3):291–301, 1996.

[38] Z. Yilma, A. Mebratie, R. Sparrow, M. Dekker, G. Alemu, and A. S. Bedi. Impact of ethiopia's community-based health insurance on household economic welfare. *The World Bank economic review*, 2015.

[39] B. E. Coleman and J. Wynne-Williams. *Rural finance in the Lao Peoples Democratic Republic: demand, supply, and sustainability. Results of Household and Supplier Surveys.* Financial Reform and Strengthening Initiative. Manila:Asian Development Bank, 2006.

[40] A. Phonvisay, B. Vanhnalat, and P. Sinavong. *Pro-poor policy analysis on cattle productivity and industry in Lao PDR.* Final Draft Report. FAO Representative in Lao PDR, 2015.

[41] H. White and D. A Raitzer. *Impact evaluation of development interventions. A practical guide.* 2017.

[42] R. Pirracchio, M. Resche-Rigon, and S. Chevret. Evaluation of the propensity score methods for estimating marginal odds ratios in case of small sample size. *BMC Med Res Methodol*, 12:70, 2012. doi: 10.1186/1471-2288-12-70. URL http://www.ncbi.nlm.nih.gov/pubmed/22646911.

[43] P. R. Rosenbaum and D. B. Rubin. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55, 1983. doi: 10.2307/2335942. URL http://www.jstor.org/stable/2335942{%}5Cnhttp://about.jstor.org/terms.

[44] J. S. Haukoos and R. J. Lewis. The propensity score. *JAMA*, 314(15):1637–1638, 2015. doi: 10.1001/jama.2015.13480.

[45] S. L. Morgan and J. J. Todd. A diagnostic routine for the detection of consequential heterogeneity of causal effects. *Sociological Methodology*, 38(1):231–281, 2008. doi: 10.1111/j.1467-9531.2008.00204.x.

[46] M. M. Joffe, T. R. Ten Have, H. I. Feldman, and S. E. Kimmel. Model selection, confounder control, and marginal structural models: review and new applications. *The American Statistician*, 58(4):272–279, 2004.

[47] A. Linden and J. L. Adams. Combining the regression discontinuity design and propensity score-based weighting to improve causal inference in program evaluation. *Journal of Evaluation in Clinical Practice*, 18(2):317–325, 2012. doi: 10.1111/j.1365-2753.2011.01768.x.

[48] P. C. Austin. The performance of different propensity-score methods for estimating differences in proportions (risk differences or absolute risk reductions) in observational studies. *Statistics in Medicine*, 29(20):2137–2148, 2010. doi: 10.1002/sim.3854.

[49] P. C. Austin. The performance of different propensity score methods for estimating marginal hazard ratios. *Statistics in Medicine*, 32(16):2837–2849, 2013. doi: 10.1002/sim.5705.

[50] A. S. Vaughan, C. F. Kelley, N.Luisi, C. del Rio, P. S. Sullivan, and E. S. Rosenberg. An application of propensity score weighting to quantify the causal effect of rectal sexually transmitted infections on incident HIV among men who have sex with men. *BMC Medical Research Methodology*, 15(1):25, 2015. doi: 10.1186/s12874-015-0017-y. URL http://bmcmedresmethodol.biomedcentral.com/articles/10.1186/s12874-015-0017-y.

[51] I. Maeda, T. Morita, T. Yamaguchi, S. Inoue, M. Ikenaga, Y. Matsumoto, and . . . H. Kinoshita. Effect of continuous deep sedation on survival in patients with advanced cancer (J-Proval): A propensity score-weighted analysis of a prospective cohort study. *The Lancet Oncology*, 17(1):115–122, 2016. doi: 10.1016/

S1470-2045(15)00401-5. URL http://dx.doi.org/10.1016/S1470-2045(15)00401-5.

[52] P. B. Nielsen, F. Skjth, M. Sgaard, J. N. Kjldgaard, G. Y. H. Lip, and T. B. Larsen. Effectiveness and safety of reduced dose non-vitamin k antagonist oral anticoagulants and warfarin in patients with atrial fibrillation: propensity weighted nationwide cohort study. *Bmj*, page j510, 2017. doi: 10.1136/bmj.j510. URL http://www.bmj.com/lookup/doi/10.1136/bmj.j510.

[53] S. M. Iacus, G. King, and G. Porro. Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, 20(1):1–24, 2012. doi: 10.1093/pan/mpr013.

[54] C. Dave, C. C. Eckel, C. A. Johnson, and C. Rojas. Eliciting risk preferences: When is simple better? *Journal of Risk and Uncertainty*, 41(3):219–243, 2010. doi: 10.1007/s11166-010-9103-z.

[55] D. A. Jaeger, T. Dohmen, A. Falk, D. Huffman, U. Sunde, and H. Bonin. Direct evidence on risk attitudes and migration. *Review of Economics and Statistics*, 92(3):684–689, 2010. doi: 10.1162/REST_a_00020. URL http://www.mitpressjournals.org/doi/abs/10.1162/REST{_}a{_}00020.

[56] T. Bernauer and R. Gampfer. How robust is public support for unilateral climate policy? *Environmental Science and Policy*, 54:316–330, 2015. doi: 10.1016/j.envsci.2015.07.010. URL http://dx.doi.org/10.1016/j.envsci.2015.07.010.

[57] R. Breen, H. G. van de Werfhorst, and M. M. Jæger. Deciding under doubt : A theory of risk aversion , time discounting preferences , and educational decision-making. *European Sociological Review*, 30(2):258–270, 2014. doi: 10.1093/esr/jcu039.

[58] S. J. Heckman and C. P. Montalto. Consumer risk preferences and higher education enrollment decisions. *Journal of Consumer Affairs*, pages 1–31, 2016. doi: 10.1111/joca.12139.

[59] H. Bonin, T. Dohmen, A. Falk, D. Huffman, and U. Sunde. Cross-sectional earnings risk and occupational sorting: The role of risk attitudes. *Labour Economics*, 14(6):926–937, 2007. doi: 10.1016/j.labeco.2007.06.007.

[60] T. Ahn. Attitudes toward risk and self-employment of young workers. *Labour Economics*, 17(2):434–442, 2010. doi: 10.1016/j.labeco.2009.06.005. URL http://dx.doi.org/10.1016/j.labeco.2009.06.005.

[61] J. S. Cramer, J. Hartog, N. Jonker, and C. M. Van Praag. Low risk aversion encourages the choice for entrepreneurship: An empirical test of a truism. *Journal of Economic Behavior and Organization*, 48(1):29–36, 2002. doi: 10.1016/S0167-2681(01)00222-0.

[62] J. Ekelund, E. Johansson, M. R. Järvelin, and D. Lichtermann. Self-employment and risk aversion - evidence from psychological test data. *Labour Economics*, 12(5):649–659, 2005. doi: 10.1016/j.labeco.2004.02.009.

[63] C. Batista and J. Umblijs. Migration , risk attitudes , and entrepreneurship : evidence from a representative immigrant survey. *IZA Journal of Migration*, pages 1–25, 2014. doi: 10.1186/s40176-014-0017-4.

[64] E. M. Liu and J. Huang. Risk preferences and pesticide use by cotton farmers in China. *Journal of Development Economics*, 103(1):202–215, 2013. doi: 10.1016/j.jdeveco.2012.12.005. URL http://dx.doi.org/10.1016/j.jdeveco.2012.12.005.

[65] Y. Qiu, G. Colson, and C. Grebitus. Risk preferences and purchase of energy-efficient technologies in the residential sector. *Ecological Economics*, 107:216–229, 2014. doi: 10.1016/j.ecolecon.2014.09.002. URL http://dx.doi.org/10.1016/j.ecolecon.2014.09.002.

[66] C. Pfeifer. A note on smoking behavior and health risk taking. *Nordic Journal of Health Economics*, 2012.

[67] R. B. Barsky, F. T. Juster, and M. S. Kimballand M. D. Shapiro. Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics*, 112(2):537–579, 1997. doi: 10.1162/003355397555280. URL http://www.jstor.org/stable/2951245{%}5Cnhttp://www.jstor.org/stable/pdfplus/2951245.pdf.

[68] L. R. Anderson and J. M. Mellor. Predicting health behaviors with an experimental measure of risk preference. *Journal of Health Economics*, 27(5):1260–1274, 2008. doi: 10.1016/j.jhealeco.2008.05.011.

[69] E. L. Glaeser, D. I. Laibson, J. A. Scheinkman, and C. L. Soutter. Measuring trust. *The Quarterly Journal of Economics*, 115(3):811–846, 2000. URL http://www.jstor.org/stable/2586897.

[70] T. Tanaka, C. F. Camerer, and Q. Nguyen. Risk and time preferences: Experimental and household survey data from Vietnam. *American Economic Review*, 100(1):557–571, 2010. doi: 10.1257/aer.100.1.557.

[71] Q. Nguyen and P. Leung. How nurture can shape preferences: an experimental study on risk preferences of Vietnamese fishers. *Environment and Development Economics*, 15:609–631, 2010. doi: 10.1017/s1355770x10000203.

[72] S. Liebenehm and H. Waibel. Simultaneous estimation of risk and time preferences among small-scale cattle farmers in West Africa. *American Journal of Agricultural Economics*, 96(5):1420–1438, 2014. doi: 10.1093/ajae/aau056.

[73] T. Sydavong and D. Goto. Does community-based health insurance have potential impacts on direct and indirect outcomes? evidence from rural villages, savannakhet province, lao pdr. *Journal of International Development and Cooperation*, 25(2), 2019.

[74] A. Tversky and D. Kahneman. Advances in Prospect-Theory - cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4):297–323, 1992. doi: Doi10.1007/Bf00122574.

[75] R. Gonzalez and G. Wu. On the shape of the probability weighting function. *Cognitive Psychology*, 166:129–166, 1999.

[76] E. U. Weber, A. E. Blais, and N. E. Betz. A Domain-specific Risk-attitude Scale: Measuring Risk Perceptions and Risk Behaviors. *Journal of Behavioral Decision Making J. Behav. Dec. Making*, 15(August):263–290, 2002. doi: 10.1002/bdm.414.

[77] S. Ito and H. Kono. Why is the take-up of microinsurance so low? Evidence from a health insurance scheme in India. *Developing Economies*, 48(1):74–101, 2010. doi: 10.1111/j.1746-1049.2010.00099.x.

[78] J. Lammers and S. Warmerdam. Adverse selection in voluntary micro health insurance in nigeria. *AIID Research Series*.

[79] A. Pierre and F. Jusot. The likely effects of employer-mandated complementary health insurance on health coverage in france. *Health Policy*, 121:141–152, 2017. doi: 10.1016/j.healthpol.2016.12.004.

[80] V. Govender, M. F. Chersich, B. Harris, O. Alaba, J. E. Ataguba, N. Nxumalo, and . . . J. Goudge. Moving towards universal coverage in South Africa? Lessons from a voluntary government insurnace scheme. *Global Health Action*, 6(1), 2013. doi: 10.3402/gha.v6i0.19253.

[81] J. Macha, A. Kuwawenaruwa, S. Makawia, G. Mtei, and J. Borghi. Determinants of community health fund membership in Tanzania: a mixed methods analysis. *BMC Health Services Research*, 14(1):538, 2014. doi: 10.1186/s12913-014-0538-9. URL http://bmchealthservres.biomedcentral.com/articles/10.1186/s12913-014-0538-9.

[82] E. F. Adebayo, O. A. Uthman, C. S. Wiysonge, E. A. Stern, K. T. Lamont, and J. E. Ataguba. A systematic review of factors that affect uptake of community-based health insurance in low-income and middle-income countries. *BMC health services research*, 15(1):543, 2015. doi: 10.1186/s12913-015-1179-3. URL http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=4673712{&}tool=pmcentrez{&}rendertype=abstract.

[83] D. M. Dror, S. A. Shahed Hossain, A. Majumdar, T. L. P. Koehlmoos, D. John, and P. K. Panda. What factors affect voluntary uptake of community-based health insurance schemes in low- and middle-income countries? A systematic review and meta-analysis. *PLoS ONE*, 11(8):1–31, 2016. doi: 10.1371/journal.pone.0160479.

[84] A. P. Fenny, A. Kusi, D. K. Arhinful, and F. AN. Asante. Factors contributing to low uptake and renewal of health insurance: a qualitative study in Ghana. *Global Health Research and Policy*, 1(1):18, 2016. doi: 10.1186/s41256-016-0018-3. URL http://ghrp.biomedcentral.com/articles/10.1186/s41256-016-0018-3.

[85] S. G. Workneh, G. A. Biks, and S. A. Woreta. Community-based health insurance and communities' scheme requirement compliance in Thehuldere district, North-east Ethiopia: Cross-sectional community-based study. *ClinicoEconomics and Outcomes Research*, 9:353–359, 2017. doi: 10.2147/CEOR.S136508.

[86] T. Kjær. A review of the discrete choice experiment - with emphasis on its application in health care. *Health Economics Papers*, pages 1–139, 2005.

[87] S. Ahmed, M. E. Hoque, A. R. Sarker, M. Sultana, Z. Islam, R. Gazi, and J. A. M. Khan. Willingness-to-pay for community-based health insurance among informal workers in urban bangladesh. *PLoS ONE*, 11(2):1–16, 2016. doi: 10.1371/journal.pone.0148211.

[88] R. Babatunde, O. Oyedejiand A. Omoniwa, and A. Adenuga. Willingness-to-pay for community based health insurance by farming households: A case study of hygeia community health plan in Kwara State, Nigeria. *Trakia Journal of Science*, 14(3):281–286, 2016. doi: 10.15547/tjs.2016.03.014. URL http://tru.uni-sz.bg/tsj/Vol.14,N3,2016/R.O.Babatunde.pdf.

[89] S. Nosratnejad, A. Rashidian, and A. A. Sari. Willingness to pay for complementary health care insurance in iran. *Iran J Public Health*, 46(9):1247–1255, 2017.

[90] M. G. Ory. Willingness to Pay for social health insurance in central Vietnam. *Frontiers in Public Health*, 2017. doi: 10.3389/fpubh.2017.00089.

[91] S. Nosratnejad, A. Rashidian, and D. M. Dror. Systematic review of willingness to pay for health insurance in low and middle income countries. *PLoS ONE*, 11 (6):1–14, 2016. doi: 10.1371/journal.pone.0157470.

[92] N. Hanley, S. Mourato, and R. E. Wright. Choice Modelling Approaches: A Superior Alternative for Environmental Valuatioin? *Journal of Economic Surveys*, 15(3):435–462, 2002. doi: 10.1111/1467-6419.00145. URL http://doi.wiley.com/10.1111/1467-6419.00145.

[93] M. D. Clark, D. Determann, S. Petrou, D. Moro, and E. W. de Bekker-Grob. Discrete Choice Experiments in Health Economics: A Review of the Literature. *PharmacoEconomics*, 32(9):883–902, 2014. doi: 10.1007/s40273-014-0170-x.

[94] M. E. Kruk, P. C. Rockers, S. Tornorlah Varpilah, and R. MacAuley. Population preferences for health care in Liberia: Insights for rebuilding a health system. *Health Services Research*, 46(6 PART 2):2057–2078, 2011. doi: 10.1111/j.1475-6773.2011.01266.x.

[95] G. A. Abiiro, A. Torbica, K. Kwalamasa, and M. D. Allegri. Eliciting community preferences for complementary micro health insurance: A discrete choice experiment in rural Malawi. *Social Science and Medicine*, 120:160–168, 2014. doi: 10.1016/j.socscimed.2014.09.021. URL http://dx.doi.org/10.1016/j.socscimed.2014.09.021.

[96] A. Obse, M. Ryan, S. Heidenreich, C. Normand, and D. Hailemariam. Eliciting preferences for social health insurance in Ethiopia: A discrete choice experiment. *Health Policy and Planning*, 31(10):1423–1432, 2016. doi: 10.1093/heapol/czw084.

[97] T. van de Schoot, M. Pavlova, E. Atanasova, and W. Groot. Preferences of Bulgarian consumers for quality, access and price attributes of healthcare servicesresult of a discrete choice experiment. *International Journal of Health Planning and Management*, 32(1):e47–e71, 2017. doi: 10.1002/hpm.2325.

[98] M. M. Bechtel and K. F. Scheve. Mass support for global climate agreements depends on institutional design. *Proceedings of the National Academy of Sciences*, 110(34):13763–13768, 2013. doi: 10.1073/pnas.1306374110. URL http://www.pnas.org/lookup/doi/10.1073/pnas.1306374110.

[99] S. T. Hninn, S. Kaneko, K. Kawata, and Y. Yoshida. A nonparametric welfare analysis on water quality improvement of the floating people on Inlay Lake via a randomized conjiont field experiment. *IDEC DP2 Series*, 6(2), 2017.

[100] J. Hainmueller and D. J. Hopkins. The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes toward Immigrants. *American Journal of Political Science*, 59(3):529–548, 2015. doi: 10.1111/ajps.12138.

[101] R. Gampfer, T. Bernauer, and A. Kachi. Obtaining public support for North-South climate funding: Evidence from conjoint experiments in donor countries. *Global Environmental Change*, 29:118–126, 2014. doi: 10.1016/j.gloenvcha.2014.08.006. URL http://dx.doi.org/10.1016/j.gloenvcha.2014.08.006.

[102] D. Bhattacharya. Nonparametric welfare analysis for discrete choice. *Econometrica*, 83(2):617–649, 2015. doi: 10.3982/ECTA12574. URL https://www.econometricsociety.org/doi/10.3982/ECTA12574.

[103] J. Hainmueller, D. J. Hopkins, and T. Yamamoto. Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments. *Political Analysis*, 31:1–30, 2014. doi: 10.1093/pan/mpt024.

[104] E. Lancsar and J. Louviere. Conducting Discrete Choice Experiments to Inform Health Care Decision Making : A User ' s Guide , Experiments to Inform Healthcare A User ' s Guide. 26(December 2015):661–677, 2008. doi: 10.2165/00019053-200826080-00004.

Appendix A

Covariate balancing for ATT estimation

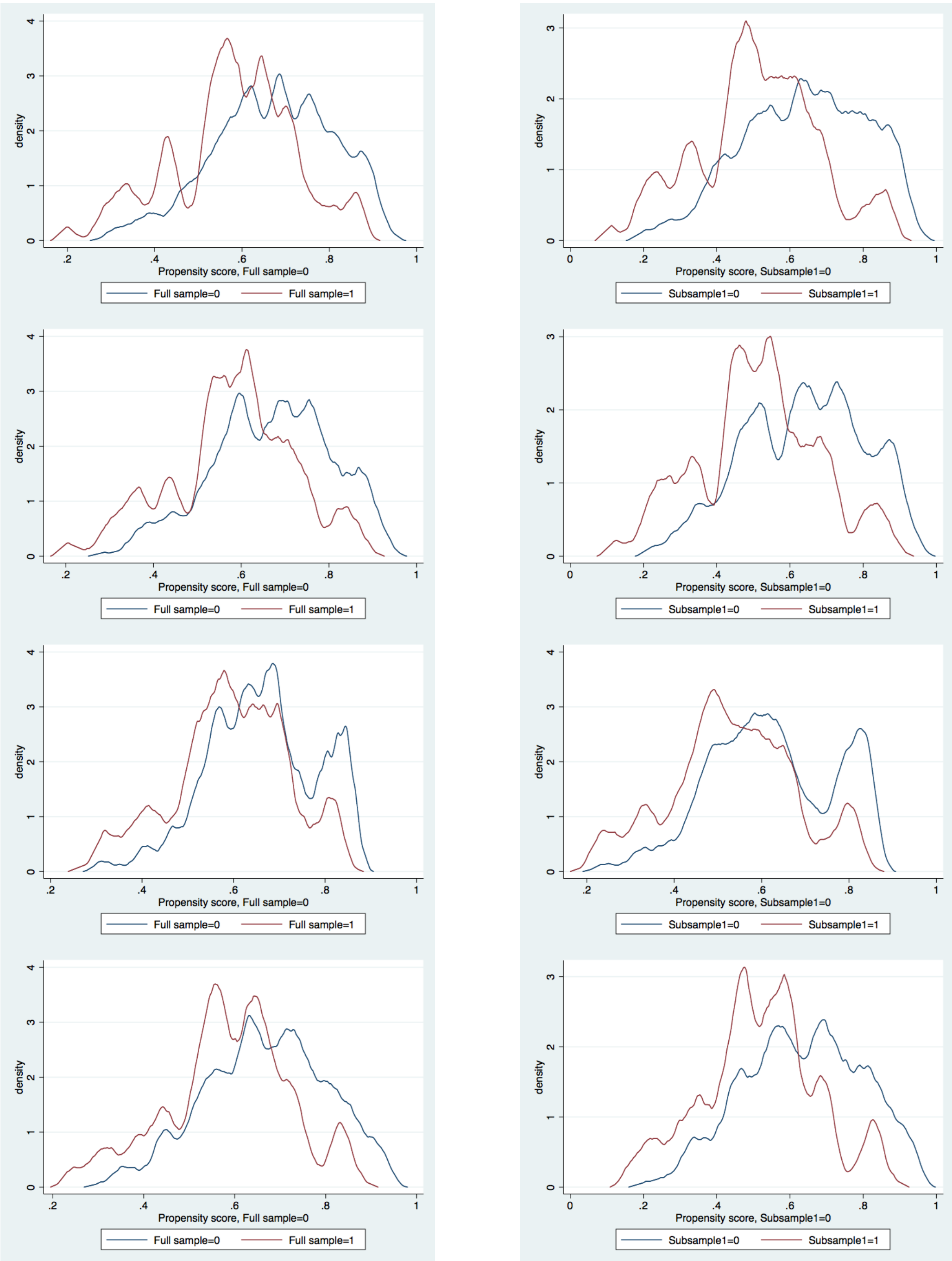
Covariates	(1)				(2)				(3)				(4)			
	Standardized differences		Variance ratio		Standardized differences		Variance ratio		Standardized differences		Variance ratio		Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
Full sample																
Gender	-0.035	-0.003	1.072	1.006					-0.035	0.003	1.072	0.995	-0.035	0.004	1.072	0.992
Age	0.150	-0.032	0.799	0.815					0.150	-0.006	0.799	0.851	0.150	-0.028	0.799	0.828
Education	0.244	-0.016	0.833	0.667	0.244	-0.005	0.833	0.689								
Size	0.322	0.004	1.274	1.135	0.322	0.008	1.274	1.133	0.322	-0.011	1.274	1.116	0.322	0.009	1.274	1.150
Land	0.004	0.054	0.818	0.952												
Toilet	0.388	0.007	0.573	0.985	0.388	0.012	0.573	0.976	0.388	0.007	0.573	0.986	0.388	0.009	0.573	0.981
Village party	0.233	0.056	2.313	1.173	0.233	0.053	2.313	1.161	0.233	0.018	2.313	1.049	0.233	0.044	2.313	1.130
Women union	0.200	-0.031	1.263	0.973	0.200	-0.029	1.263	0.975	0.200	0.003	1.263	1.003	0.200	-0.022	1.263	0.981
Distance	-0.309	0.022	0.477	0.677	-0.309	0.017	0.477	0.667					-0.309	0.028	0.477	0.685
Subsample 1																
Gender	-0.038	0.002	1.077	0.996					-0.038	-0.002	1.077	1.003	-0.038	0.003	1.077	0.995
Age	0.189	-0.046	0.808	0.849					0.189	-0.015	0.808	0.867	0.189	-0.047	0.808	0.856
Education	0.303	-0.013	0.859	0.633	0.303	0.006	0.859	0.663								
Size	0.341	-0.007	1.228	1.064	0.341	0.003	1.228	1.065	0.341	-0.016	1.228	1.049	0.341	0.006	1.228	1.102
Land	-0.029	0.067	0.712	0.953												
Toilet	0.472	0.018	0.536	0.964	0.472	0.025	0.536	0.950	0.472	0.012	0.536	0.976	0.472	0.020	0.536	0.960
Village party	0.251	0.099	2.527	1.344	0.251	0.095	2.527	1.327	0.251	0.037	2.527	1.110	0.251	0.066	2.527	1.207
Women union	0.233	-0.024	1.326	0.979	0.233	-0.022	1.326	0.981	0.233	-0.001	1.326	0.999	0.233	-0.031	1.326	0.973
Distance	-0.383	0.037	0.465	0.705	-0.383	0.025	0.465	0.680					-0.383	0.041	0.465	0.707
Subsample 2																
Gender	-0.146	0.024	1.325	0.963					-0.146	0.006	1.325	0.991	-0.146	0.008	1.325	0.987
Age	0.031	-0.057	0.815	0.870					0.031	-0.011	0.815	0.909	0.031	-0.044	0.815	0.877
Education	0.368	-0.054	0.857	0.633	0.368	-0.035	0.857	0.645								
Size	0.235	-0.013	1.084	0.978	0.235	-0.002	1.084	1.016	0.235	-0.019	1.084	0.933	0.235	-0.005	1.084	0.988
Land	0.026	0.037	1.031	0.798												
Toilet	0.555	0.004	0.354	0.989	0.555	0.011	0.354	0.966	0.555	0.000	0.354	0.999	0.555	0.013	0.354	0.962
Village party	0.211	0.061	2.091	1.191	0.211	0.045	2.091	1.135	0.211	0.013	2.091	1.035	0.211	0.027	2.091	1.078
Women union	0.268	-0.042	1.351	0.970	0.268	-0.035	1.351	0.974	0.268	0.012	1.351	1.010	0.268	0.001	1.351	1.000
Distance	-0.440	0.009	0.425	0.800	-0.440	0.012	0.425	0.809					-0.440	0.000	0.425	0.801
Subsample 3																
Gender	-0.151	0.056	1.338	0.917					-0.151	0.018	1.338	0.971	-0.151	0.023	1.338	0.964
Age	0.051	-0.066	0.826	0.918					0.051	-0.017	0.826	0.924	0.051	-0.058	0.826	0.905
Education	0.438	-0.083	0.886	0.570	0.438	-0.037	0.886	0.599								
Size	0.237	-0.014	1.044	0.933	0.237	0.006	1.044	0.964	0.237	-0.020	1.044	0.884	0.237	-0.004	1.044	0.954
Land	-0.004	0.055	0.938	0.838												
Toilet	0.618	0.007	0.336	0.978	0.618	0.020	0.336	0.939	0.618	-0.001	0.336	1.003	0.618	0.021	0.336	0.937
Village party	0.212	0.112	2.102	1.408	0.212	0.093	2.102	1.320	0.212	0.021	2.102	1.058	0.212	0.045	2.102	1.135
Women union	0.317	-0.047	1.457	0.967	0.317	-0.032	1.457	0.977	0.317	0.007	1.457	1.006	0.317	-0.006	1.457	0.995
Distance	-0.513	0.020	0.411	0.822	-0.513	0.011	0.411	0.809					-0.513	0.005	0.411	0.808

Appendix B

Distribution of propensity score

Full sample | Subsample 1

(1) (2) (3) (4)



Subsample 2 | Subsample 3

(1)

(2)

(3)

(4)

Appendix C

SATT estimates based on CEM method

	Full sample (580)				**Subsample 1 (508)**[a]				**Subsample 2 (409)**				**Subsample 3 (366)**			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Income	-3,923	-1,558	1,015	-724.0	-3,949	-5,144	-64.43	-64.43	-1,496	-1,953	415.9	415.9	-3,503	-2,228	456.9	456.9
	(3,100)	-2,793	(1,850)	(2,040)	(3,889)	(3,691)	(2,101)	(2,101)	(3,634)	(2,928)	(2,316)	(2,316)	(4,589)	(3,147)	(2,392)	(2,392)
Income per capita	-988.3	-568.6	1.652	-417.1	-993.3	-1,185	-110.8	-110.8	-544.6	-480.9	-67.14	-67.14	-836.6	-559.2	-134.3	-134.3
	(674.1)	-624.2	(364.8)	(444.7)	(901.6)	(802.7)	(404.0)	(404.0)	(848.6)	(668.1)	(520.1)	(520.1)	(1,075)	(719.6)	(537.5)	(537.5)
Expenditure	422.5	716.3	968.0	612.7	899.4	408.6	812.2	812.2	723.4	567.5	1,205*	1,205*	1,043	808.1	1,597**	1,597**
	(785.0)	-649.8	(654.9)	(726.6)	(788.1)	(985.4)	(846.1)	(846.1)	(844.2)	(682.6)	(647.6)	(647.6)	(900.7)	(706.0)	(623.6)	(623.6)
Expenditure per capita	14.72	68.27	139.0	40.05	99.44	18.52	124.8	124.8	59.52	107.8	201.3	201.3	149.8	143.6	228.5	228.5
	(154.6)	-130.2	(122.5)	(145.0)	(172.0)	(185.3)	(143.9)	(143.9)	(199.3)	(143.5)	(141.2)	(141.2)	(199.3)	(147.8)	(142.5)	(142.5)
Health	-30.38	13.86	-22.25	-44.79	32.28	-4.242	-20.01	-20.01	-127.4	-109.4	-134.5	-134.5	-137.3	-131.8	-149.8	-149.8
	(89.93)	-80.1	(74.70)	(81.27)	(99.52)	(92.63)	(84.43)	(84.43)	(120.5)	(99.39)	(89.57)	(89.57)	(124.4)	(111.5)	(112.3)	(112.3)
Health per capita	-2.732	1.822	-3.697	-6.507	2.546	-1.332	-5.547	-5.547	-16.77	-15.43	-17.69	-17.69	-15.80	-19.43	-24.37	-24.37
	(15.05)	-13.05	(12.48)	(13.81)	(16.69)	(15.72)	(14.27)	(14.27)	(20.24)	(16.92)	(15.56)	(15.56)	(21.05)	(18.85)	(19.33)	(19.33)
Education	305.8	134.3	108.6	-234.8	383.8	311.5	273.2	273.2	482.4*	183.1	398.2	398.2	623.9**	298.7	469.0*	469.0*
	(246.8)	-226.9	(253.1)	(464.8)	(271.8)	(229.7)	(215.8)	(215.8)	(263.1)	(273.7)	(263.7)	(263.7)	(266.1)	(265.3)	(246.2)	(246.2)
Food	54.43	93.23	187.8	307.7**	113.1	218.9	-50.24	-50.24	69.29	99.92	234.5	234.5	155.9	198.5	239.2	239.2
	(218.5)	-182.2	(188.0)	(149.1)	(144.6)	(158.5)	(390.6)	(390.6)	(171.3)	(153.8)	(155.2)	(155.2)	(171.8)	(153.5)	(165.8)	(165.8)
Food per capita	10.24	11.7	32.32	42.04	8.147	24.87	1.813	1.813	-8.398	13.77	33.08	33.08	11.16	26.66	24.11	24.11
	(32.72)	-30.44	(28.29)	(27.08)	(26.26)	(28.53)	(47.43)	(47.43)	(35.60)	(29.89)	(29.79)	(29.79)	(33.78)	(30.56)	(36.77)	(36.77)
Transportation	-190.2	-51.06	-73.24	-22.22	-46.76	-179.6	-103.1	-103.1	-260.9	-189.7	-91.67	-91.67	-187.5	-179.1	-15.19	-15.19
	(217.1)	-175.2	(145.1)	(130.7)	(240.8)	(277.2)	(188.4)	(188.4)	(257.2)	(197.4)	(161.9)	(161.9)	(279.1)	(212.4)	(156.0)	(156.0)
Transportation per capita	-60.06	-29.6	-25.42	-21.71	-35.72	-54.15	-30.51	-30.51	-74.93	-42.47	-30.07	-30.07	-50.47	-44.42	-23.31	-23.31
	(47.43)	-39.89	(29.16)	(29.18)	(59.24)	(57.79)	(35.80)	(35.80)	(63.65)	(43.00)	(38.47)	(38.47)	(66.64)	(47.10)	(39.17)	(39.17)
Energy	38.88	115.2	101.8	95.31	100.3	22.33	126.0	126.0	21.29	-9.260	45.06	45.06	-2.665	-15.67	200.2***	200.2***
	(97.12)	-78.03	(86.70)	(81.75)	(101.4)	(111.6)	(88.79)	(88.79)	(115.8)	(163.5)	(126.1)	(126.1)	(162.8)	(165.6)	(74.50)	(74.50)
Energy per capita	0.761	14.04	17.43	10.71	9.852	-1.652	19.96	19.96	-1.107	6.108	11.61	11.61	2.032	4.410	27.43*	27.43*
	(18.85)	-15.97	(14.82)	(14.98)	(21.92)	(21.45)	(15.94)	(15.94)	(23.87)	(21.47)	(18.41)	(18.41)	(26.87)	(22.12)	(16.13)	(16.13)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[a] Subsample 1: Full sample - Ex-members

Subsample 2: Full sample - Subjects engaged in village fund

Subsample 3: Full sample - Ex-members -Subjects engaged in village fund

	Full sample (580)				**Subsample 1 (508)**[a]				**Subsample 2 (409)**				**Subsample 3 (366)**			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Water	1.434	-4.609	28.46	-21.05	47.56	1.291	20.80	20.80	37.00	30.06	33.38	33.38	51.89	57.36	74.16*	74.16*
	(49.18)	-42.51	(43.31)	(47.51)	(44.63)	(63.44)	(53.84)	(53.84)	(43.21)	(39.40)	(39.76)	(39.76)	(46.24)	(40.55)	(41.17)	(41.17)
Water per capita	-2.594	-1.567	2.030	-7.908	4.932	-2.783	1.250	1.250	-0.130	-0.619	0.835	0.835	1.853	4.040	7.231	7.231
	(8.594)	-7.426	(7.863)	(8.300)	(8.370)	(11.03)	(9.408)	(9.408)	(8.871)	(8.462)	(8.466)	(8.466)	(9.412)	(8.822)	(8.712)	(8.712)
Telephone	10.62	32.03	43.24	-7.393	-4.914	-11.83	53.20	53.20	-30.84	19.62	21.94	21.94	18.59	29.42	53.53	53.53
	(56.95)	-47.91	(47.79)	(50.88)	(47.92)	(55.48)	(49.82)	(49.82)	(62.96)	(48.34)	(54.85)	(54.85)	(51.10)	(50.56)	(49.00)	(49.00)
Telephone per capita	-5.076	-1.309	4.709	-5.285	-8.944	-8.890	4.020	4.020	-12.09	2.407	3.061	3.061	-0.154	4.022	4.224	4.224
	(11.14)	-9.694	(8.710)	(9.027)	(10.84)	(11.38)	(9.070)	(9.070)	(14.33)	(9.400)	(10.33)	(10.33)	(9.644)	(9.580)	(9.906)	(9.906)
Mainteanance	-12.98	57.22	23.64	105.9	77.29*	-132.8	-87.89	-87.89	**119.4****	**117.6****	**127.9****	**127.9****	**157.1*****	**116.3****	**98.06***	**98.06***
	(180.8)	-126.6	(159.2)	(105.5)	(46.11)	(293.1)	(224.3)	(224.3)	**(60.32)**	**(49.30)**	**(53.79)**	**(53.79)**	**(56.86)**	**(51.37)**	**(54.71)**	**(54.71)**
Maintenane per capita	-5.253	7.066	1.709	15.31	13.30	-23.44	-15.92	-15.92	17.16	**21.49****	**22.14****	**22.14****	**25.30****	**21.30****	16.73	16.73
	(28.77)	-19.76	(25.54)	(15.51)	(9.471)	(48.23)	(36.71)	(36.71)	(12.73)	**(8.775)**	**(9.345)**	**(9.345)**	**(10.67)**	**(9.054)**	(10.33)	(10.33)
Other expenditures	242.1	321.9	569.0***	431.0	188.2	176.5	597.5***	597.5***	413.2	425.5	569.9*	569.9*	363.0	434.3	627.9*	627.9*
	(345.9)	-330.2	(219.1)	(262.9)	(495.1)	(409.4)	(229.8)	(229.8)	(474.9)	(372.8)	(322.0)	(322.0)	(583.7)	(394.2)	(329.1)	(329.1)
Other expenditures per capita	41.81	54.63	106.0**	77.41	40.17	38.56	109.6**	109.6**	86.27	90.37	119.4	119.4	74.15	89.26	121.1	121.1
	(77.76)	-72.5	(51.74)	(61.51)	(104.8)	(85.94)	(53.38)	(53.38)	(107.1)	(84.89)	(76.73)	(76.73)	(127.8)	(88.81)	(78.33)	(78.33)
Hospitalization	0.0294	0.049	0.0232	0.0228	0.0379	0.0559	0.0666	0.0666	0.0350	0.0746	0.0440	0.0440	0.0231	0.0476	0.0690	0.0690
	(0.0501)	-0.0435	(0.0418)	(0.0454)	(0.0618)	(0.0497)	(0.0425)	(0.0425)	(0.0557)	(0.0479)	(0.0506)	(0.0506)	(0.0603)	(0.0504)	(0.0517)	(0.0517)
Rice	**761.2****	**677.5****	**662.4****	**668.0****	**710.6****	**666.3****	**555.9****	**555.9****	**603.9****	173.7	369.5	369.5	556.5*	219.1	489.6*	489.6*
	(299.0)	**-292.1**	**(303.9)**	**(317.9)**	**(351.4)**	**(315.4)**	**(260.3)**	**(260.3)**	**(305.5)**	(295.1)	(300.1)	(300.1)	(333.4)	(304.3)	(294.4)	(294.4)
Rice per capita	**115.5****	**94.97****	**105.8****	**93.73***	**112.6***	**108.9****	**88.57***	**88.57***	**121.4****	75.22	**98.31***	**98.31***	**108.7***	75.28	**101.0***	**101.0***
	(51.60)	**-46.03**	**(45.96)**	**(49.71)**	**(58.14)**	**(51.64)**	**(47.08)**	**(47.08)**	**(57.83)**	(52.13)	**(53.43)**	**(53.43)**	**(65.36)**	(54.28)	**(58.06)**	**(58.06)**
Cow	**1.510*****	**1.047****	**0.988***	**0.905***	**1.364*****	**1.102****	**1.002****	**1.002****	**2.955*****	**1.883*****	**1.895*****	**1.895*****	**2.739*****	**1.681****	**1.854*****	**1.854*****
	(0.441)	**-0.47**	**(0.527)**	**(0.500)**	**(0.464)**	**(0.512)**	**(0.448)**	**(0.448)**	**(0.528)**	**(0.632)**	**(0.611)**	**(0.611)**	**(0.559)**	**(0.658)**	**(0.544)**	**(0.544)**
Poultry	1.639	2.136	1.655	2.331	1.566	1.686	2.454*	2.454*	0.174	0.420	0.893	0.893	0.906	1.219	2.143	2.143
	(1.644)	-1.432	(1.545)	(1.497)	(1.902)	(1.738)	(1.432)	(1.432)	(2.026)	(1.881)	(1.924)	(1.924)	(2.402)	(1.867)	(1.870)	(1.870)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[a] Subsample 1: Full sample - Ex-members

Subsample 2: Full sample - Subjects engaged in village fund

Subsample 3: Full sample - Ex-members -Subjects engaged in village fund

Appendix D

Heterogeneous effects on ATT

TABLE D.1: ATT by household head age quantile

25th quantile

	Full sample (153)				**Subsample 1 (137)**				**Subsample 2 (103)**				**Subsample 3 (93)**			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Rice	**916.1****	**930.8****	**986.8****	**943.7****	**915.6****	**1,028*****	**916.9****	**906.8****	**1,065***	**1,091****	**978.3***	**956.9***	**1,043***	**1,159****	851.4	842.0
	(401.4)	**(389.8)**	**(391.2)**	**(401.6)**	**(405.7)**	**(385.8)**	**(397.6)**	**(405.4)**	**(572.7)**	**(546.0)**	**(535.5)**	**(545.3)**	**(563.9)**	**(542.6)**	(546.9)	(540.2)
Rice per capita	**206.3****	**201.8****	**227.9****	**210.9****	**209.9****	**232.7****	**215.2****	**199.1****	**289.1****	**302.2****	**286.3****	**250.7***	**268.8***	**308.1****	**262.6****	215.0
	(99.34)	**(95.73)**	**(96.60)**	**(97.74)**	**(102.3)**	**(96.71)**	**(97.37)**	**(100.4)**	**(144.8)**	**(134.9)**	**(128.2)**	**(139.7)**	**(149.6)**	**(137.5)**	**(128.6)**	(144.1)
Cow	1.166	1.019	1.216*	1.187	1.041	0.837	1.170	1.038	**2.429****	**2.137****	**2.475*****	**2.370****	**2.341****	**1.985***	**2.335****	**2.190****
	(0.743)	(0.739)	(0.718)	(0.732)	(0.816)	(0.809)	(0.769)	(0.803)	**(1.001)**	**(0.960)**	**(0.927)**	**(1.010)**	**(1.067)**	**(1.026)**	**(0.968)**	**(1.088)**
Poultry	**5.959*****	**5.781****	**5.261****	**5.864*****	**6.061*****	**5.985*****	**5.013****	**6.017*****	**9.968*****	**9.593*****	**8.096*****	**9.600*****	**10.19*****	**9.964*****	**8.260****	**9.816*****
	(2.292)	**(2.291)**	**(2.421)**	**(2.265)**	**(2.258)**	**(2.256)**	**(2.525)**	**(2.255)**	**(2.871)**	**(2.867)**	**(3.122)**	**(2.808)**	**(2.865)**	**(2.867)**	**(3.209)**	**(2.843)**

50th quantile

	Full sample (304)				**Subsample 1 (270)**				**Subsample 2 (214)**				**Subsample 3 (193)**			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Rice	421.8	501.3	493.9	439.3	556.7*	682.2**	551.4*	518.7	241.1	299.9	311.7	301.4	615.1	685.1*	444.5	513.8
	(321.6)	(319.0)	(312.9)	(322.3)	(332.4)	(327.4)	(329.1)	(342.6)	(393.3)	(381.7)	(346.5)	(366.4)	(381.5)	(369.2)	(358.9)	(375.4)
Rice per capita	**98.35***	**113.3***	**102.3***	93.38	109.2*	**134.1****	**105.3***	95.75	114.7	**124.7***	109.1	108.0	**141.9***	**158.2****	119.0	121.9
	(58.54)	**(58.29)**	**(58.49)**	(59.40)	(62.15)	**(61.28)**	**(61.63)**	(63.59)	(77.39)	**(74.79)**	(72.13)	(74.77)	**(82.61)**	**(78.92)**	(74.31)	(78.82)
Cow	**1.060****	**1.012***	**1.117****	**1.119****	**1.084***	**0.995***	**1.089***	**1.097****	**1.918*****	**1.861*****	**2.086*****	**2.093*****	**1.902****	**1.820****	**1.918*****	**1.951*****
	(0.527)	**(0.527)**	**(0.527)**	**(0.523)**	**(0.573)**	**(0.574)**	**(0.560)**	**(0.557)**	**(0.682)**	**(0.683)**	**(0.675)**	**(0.666)**	**(0.767)**	**(0.767)**	**(0.723)**	**(0.719)**
Poultry	1.938	2.516	2.420	2.519	2.589	2.965	3.025	3.246	2.180	2.891	3.405	3.486	3.226	3.867	4.040	4.289
	(2.011)	(2.018)	(1.983)	(1.988)	(2.075)	(2.086)	(2.076)	(2.052)	(2.816)	(2.824)	(2.563)	(2.616)	(2.961)	(2.952)	(2.677)	(2.693)

75th quantile

	Full sample (443)				**Subsample 1 (388)**				**Subsample 2 (308)**				**Subsample 3 (274)**			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Rice	**686.8****	**681.4****	**664.6****	**685.8****	**705.3****	**757.0****	**670.1****	**724.2****	345.7	293.6	292.8	356.0	400.2	388.4	336.2	464.0
	(309.2)	**(311.1)**	**(304.4)**	**(309.2)**	**(329.0)**	**(326.1)**	**(319.8)**	**(327.0)**	(298.8)	(290.5)	(281.0)	(284.3)	(351.3)	(318.1)	(301.5)	(307.0)
Rice per capita	**108.1****	**109.7****	**107.7****	**105.2****	**105.7****	**117.7****	**103.7****	**103.6****	**100.9***	87.64	90.11	**95.39***	103.2	95.10	89.61	**104.1***
	(47.83)	**(47.90)**	**(47.66)**	**(48.16)**	**(51.79)**	**(51.01)**	**(50.29)**	**(51.78)**	**(58.63)**	(55.93)	(55.68)	**(56.66)**	(67.01)	(61.43)	(59.30)	**(61.60)**
Cow	**1.035****	**0.989****	**0.967****	**1.052****	**1.109****	**0.959****	**0.888***	**1.083****	**1.743*****	**1.743*****	**1.636*****	**1.772*****	**1.714*****	**1.626*****	**1.428****	**1.734*****
	(0.429)	**(0.433)**	**(0.450)**	**(0.434)**	**(0.467)**	**(0.484)**	**(0.501)**	**(0.471)**	**(0.543)**	**(0.548)**	**(0.574)**	**(0.544)**	**(0.607)**	**(0.613)**	**(0.635)**	**(0.589)**
Poultry	2.333	2.649	1.909	2.313	3.004*	3.229*	2.517	2.975*	2.487	2.971	1.951	2.310	3.132	3.685*	2.581	3.033
	(1.625)	(1.613)	(1.651)	(1.619)	(1.736)	(1.695)	(1.761)	(1.725)	(2.156)	(2.071)	(2.126)	(2.088)	(2.405)	(2.237)	(2.296)	(2.279)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Subsample 1: Full sample - Ex-members
Subsample 2: Full sample - Subjects engaged in village fund
Subsample 3: Full sample - Ex-members -Subjects engaged in village fund

Table D.2: ATT by household size quantile

25th quantile

	Full sample (164)				Subsample 1 (144)				Subsample 2 (123)				Subsample 3 (110)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Rice	**958.0****	**934.9****	**953.6****	**932.3****	**967.6****	**953.9****	**931.4****	**937.0****	**1,621*****	**1,485*****	**1,573*****	**1,573*****	**1,512*****	**1,362*****	**1,455*****	**1,463*****
	(415.3)	**(402.3)**	**(410.9)**	**(413.3)**	**(431.0)**	**(416.6)**	**(424.2)**	**(426.5)**	**(505.0)**	**(489.7)**	**(490.9)**	**(495.5)**	**(531.8)**	**(510.2)**	**(506.7)**	**(512.4)**
Rice per capita	**243.7****	**235.0****	**240.8****	**234.1****	**244.1****	**238.1****	**234.7****	**233.4***	**442.4*****	**397.5*****	**416.9*****	**423.4*****	**414.7*****	**363.6*****	**386.7*****	**395.3*****
	(117.6)	**(113.6)**	**(115.9)**	**(117.3)**	**(122.3)**	**(117.9)**	**(119.2)**	**(121.4)**	**(141.2)**	**(133.3)**	**(137.0)**	**(138.2)**	**(147.9)**	**(138.3)**	**(141.1)**	**(142.8)**
Cow	**1.883****	**1.790****	**1.902*****	**1.853****	**2.044*****	**1.878*****	**1.953*****	**1.993*****	**3.706*****	**3.554*****	**3.554*****	**3.642*****	**3.523*****	**3.327*****	**3.348*****	**3.463*****
	(0.743)	**(0.714)**	**(0.722)**	**(0.725)**	**(0.745)**	**(0.728)**	**(0.741)**	**(0.724)**	**(0.987)**	**(0.966)**	**(0.962)**	**(0.964)**	**(1.045)**	**(1.022)**	**(0.998)**	**(1.000)**
Poultry	**5.095***	**5.326***	**5.595****	**5.254***	**5.224***	**5.501***	**5.823****	**5.447****	**6.445***	**6.373***	**6.688****	**6.543***	**6.737***	**6.777***	**7.053****	**6.968****
	(2.721)	**(2.728)**	**(2.656)**	**(2.689)**	**(2.829)**	**(2.810)**	**(2.722)**	**(2.766)**	**(3.530)**	**(3.581)**	**(3.361)**	**(3.384)**	**(3.756)**	**(3.747)**	**(3.489)**	**(3.519)**

50th quantile

	Full sample (377)				Subsample 1 (329)				Subsample 2 (270)				Subsample 3 (239)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Rice	**517.0****	**485.4****	**490.9****	**465.6***	**550.2****	**509.1***	**520.6****	**481.2***	**719.1****	**554.9***	**642.5****	**622.3****	**832.3****	**571.7***	**701.0****	**684.6****
	(245.6)	**(244.7)**	**(243.9)**	**(245.3)**	**(272.9)**	**(269.3)**	**(263.8)**	**(271.3)**	**(322.9)**	**(307.8)**	**(308.7)**	**(313.1)**	**(362.1)**	**(337.3)**	**(329.6)**	**(342.6)**
Rice per capita	**124.6****	**116.4****	**118.0****	**113.5****	**131.2****	**121.0****	**123.1****	**117.4****	**193.2*****	**155.8****	**173.5****	**172.0****	**212.6*****	**156.4****	**182.1****	**183.3****
	(54.17)	**(53.98)**	**(53.78)**	**(54.03)**	**(58.88)**	**(58.21)**	**(57.04)**	**(58.15)**	**(73.70)**	**(69.34)**	**(70.08)**	**(70.81)**	**(81.31)**	**(74.41)**	**(73.78)**	**(75.71)**
Cow	**0.801***	**0.749***	**0.685**	**0.767***	**1.090****	**0.944****	**0.760***	**0.963****	**1.940*****	**1.812*****	**1.670*****	**1.803*****	**2.100*****	**1.918*****	**1.569*****	**1.840*****
	(0.427)	**(0.426)**	**(0.423)**	**(0.416)**	**(0.441)**	**(0.451)**	**(0.441)**	**(0.422)**	**(0.563)**	**(0.556)**	**(0.555)**	**(0.543)**	**(0.590)**	**(0.594)**	**(0.581)**	**(0.561)**
Poultry	2.413	2.237	2.161	2.196	2.899	2.630	2.696	2.738	2.892	2.680	2.256	2.319	3.201	3.039	2.659	2.735
	(1.740)	(1.747)	(1.741)	(1.726)	(1.916)	(1.883)	(1.890)	(1.882)	(2.356)	(2.283)	(2.312)	(2.272)	(2.613)	(2.455)	(2.522)	(2.492)

75th quantile

	Full sample (442)				Subsample 1 (384)				Subsample 2 (312)				Subsample 3 (278)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Rice	**585.5****	**576.4****	**624.3****	**592.6****	**636.7****	**607.2****	**656.5****	**612.6****	**552.4***	**440.1**	**591.5****	**583.5***	**700.5****	**527.3**	**660.3****	**672.4****
	(276.3)	**(272.9)**	**(268.4)**	**(271.6)**	**(298.1)**	**(295.2)**	**(284.9)**	**(295.0)**	**(321.4)**	**(308.5)**	**(301.6)**	**(305.4)**	**(345.4)**	**(329.5)**	**(319.5)**	**(328.8)**
Rice per capita	**124.9****	**120.5****	**128.7****	**122.4****	**130.5****	**124.4****	**131.0****	**124.3****	**149.3****	**123.6****	**149.2****	**148.6****	**170.2****	**132.8****	**158.0****	**161.9****
	(51.95)	**(51.60)**	**(51.16)**	**(51.58)**	**(56.20)**	**(55.44)**	**(53.97)**	**(55.42)**	**(64.80)**	**(61.56)**	**(61.65)**	**(62.43)**	**(70.30)**	**(65.89)**	**(64.85)**	**(66.56)**
Cow	**0.865****	**0.854****	**0.767***	**0.901****	**1.255*****	**1.094****	**0.877****	**1.152*****	**1.956*****	**1.906*****	**1.762*****	**1.953*****	**2.238*****	**2.071*****	**1.666*****	**2.052*****
	(0.411)	**(0.408)**	**(0.414)**	**(0.405)**	**(0.423)**	**(0.432)**	**(0.442)**	**(0.414)**	**(0.530)**	**(0.524)**	**(0.538)**	**(0.518)**	**(0.540)**	**(0.550)**	**(0.570)**	**(0.530)**
Poultry	0.861	0.998	0.998	1.004	1.991	1.940	1.987	2.245	0.809	0.714	1.104	1.020	1.812	1.964	1.978	2.081
	(1.651)	(1.623)	(1.630)	(1.642)	(1.747)	(1.674)	(1.698)	(1.684)	(2.175)	(2.176)	(2.140)	(2.136)	(2.358)	(2.199)	(2.260)	(2.234)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Subsample 1: Full sample - Ex-members
Subsample 2: Full sample - Subjects engaged in village fund
Subsample 3: Full sample - Ex-members -Subjects engaged in village fund

Appendix E

Conjoint experiment sheet

(*Before the experiment, investigators have to read out loud the following information to each respondent and confirm the respondents understanding at the end of the message.*)

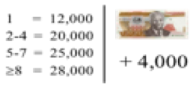
We aim to promote the improved health of self-employed households through CBHI enrollment expansion, which is a risk-pooling system, at the district level.

Below is a scenario presented before you rank the policies that you think will maximize the benefit of the policy intervention.

"*We would like to propose various policies for CBHI scheme improvement. We assume that the benefit packages in the hypothetical CBHI scheme cover out- and in-patient services. Under the CBHI scheme, health care would be first delivered by the contracting facilities (dispensaries and district hospitals) in your local area. Only referred patients are sent to provincial or regional hospitals. The premium can be paid monthly or annually. The window period of service access is three months upon enrollment. We further assume that if every district achieves greater than or equal to 500 CBHI members, the quality of health care will gradually improve because district hospitals can improve cost recovery.*"

In the experiment, you are presented with five different choice tasks. Each choice task has three options: two hypothetical CBHI schemes, A and B, and the CBHI status quo scheme. Each alternative is characterized by random levels of seven attributes, namely, *premium*; *insurance coverage for hospitalizations*, *medical consultations*, *traffic accidents*, *transportation*; and *prepaid discount*.

The levels of each attribute are demonstrated by the following images.

1.1		Premium per household per month is 2,000LAK cheaper than the current premium, i.g., 12,000 kip → 10,000 kip.
1.2		Current premium per household per month.
1.3		Premium per household per month is 2,000LAK more expensive than the current premium, i.g., 12,000 kip → 14,000 kip.
1.4		Premium per household per month is 4,000LAK more expensive than the current premium, i.g., 12,000 kip → 16,000 kip.
2.2		Cover the fee for technical examinations and disease diagnosis.
3.2		Cover the hospital bed costs if you stay overnight in the hospital (in which CBHI scheme has defined).
4.2		Cover charges of medical treatment due to traffic accident.
5.1		Cover only the pharmaceuticals that are mentioned in the essential medicines list defined the Ministry of Health for each level of hospital.
5.2		Cover all pharmaceutical charge used for the treatment.
6.2		Cover one-way travel cost of the patient to a hospital out of the district.
6.3		Cover round-ttrip travel cost of the patient to a hospital out of the district.
7.2		5% off for members who pay the CBHI premium fee 1 year in advance.
7.3		10% off for members who pay the CBHI premium fee 1 year in advance.

You are then asked to rank the three options in each choice task based on your preferences.

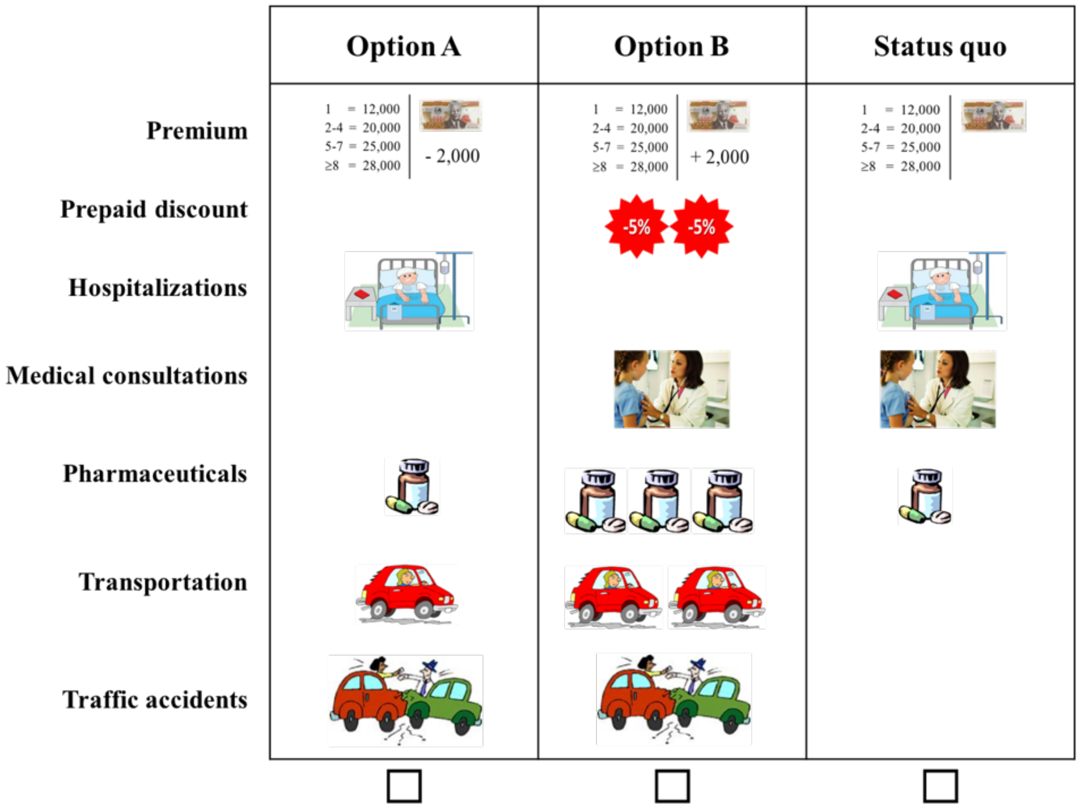
1. = most preferred

2. = average preferred

3. = less preferred

For example:

Choice task 1:



(The respondent has to rank four additional choice tasks with different combinations of seven attribute levels)

Appendix F

WTP distribution of full sample

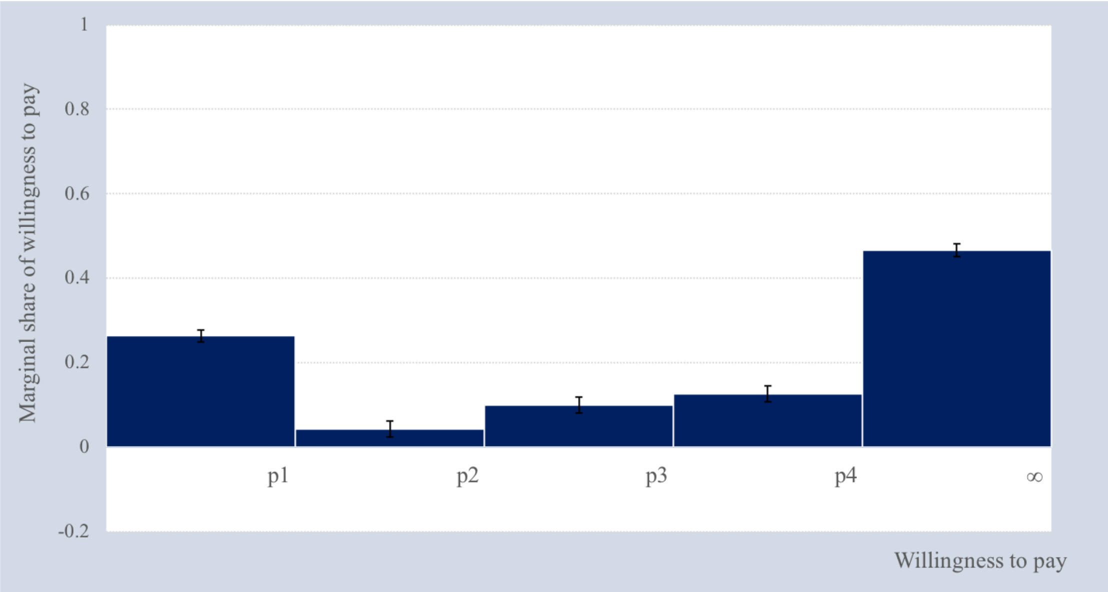


FIGURE F.1: Marginal share of willingness to pay (full sample)

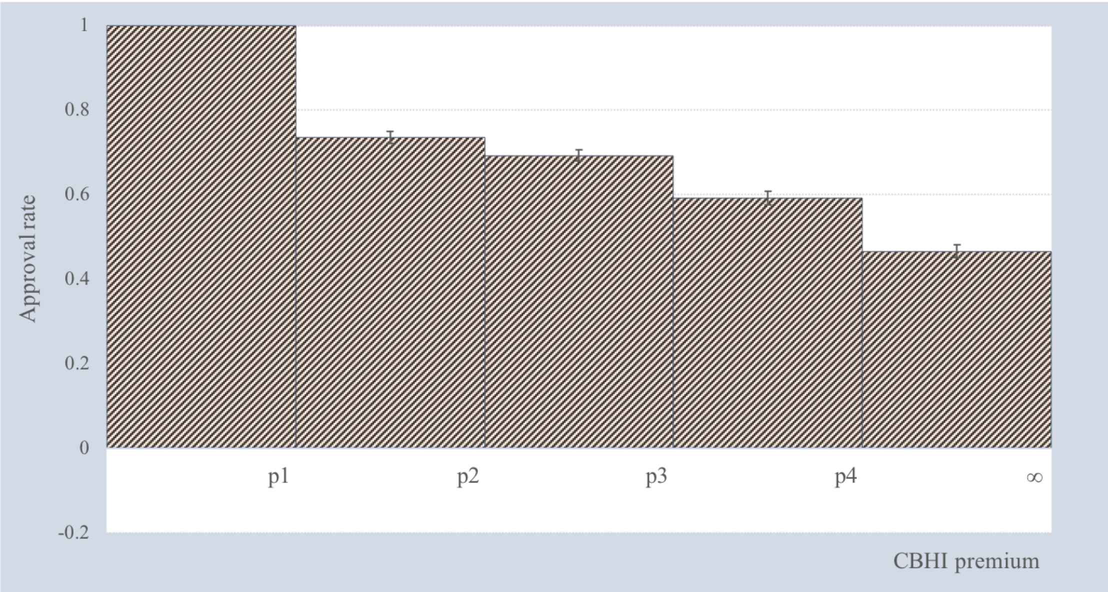


FIGURE F.2: Approval rate for CBHI scheme improvement (full sample)

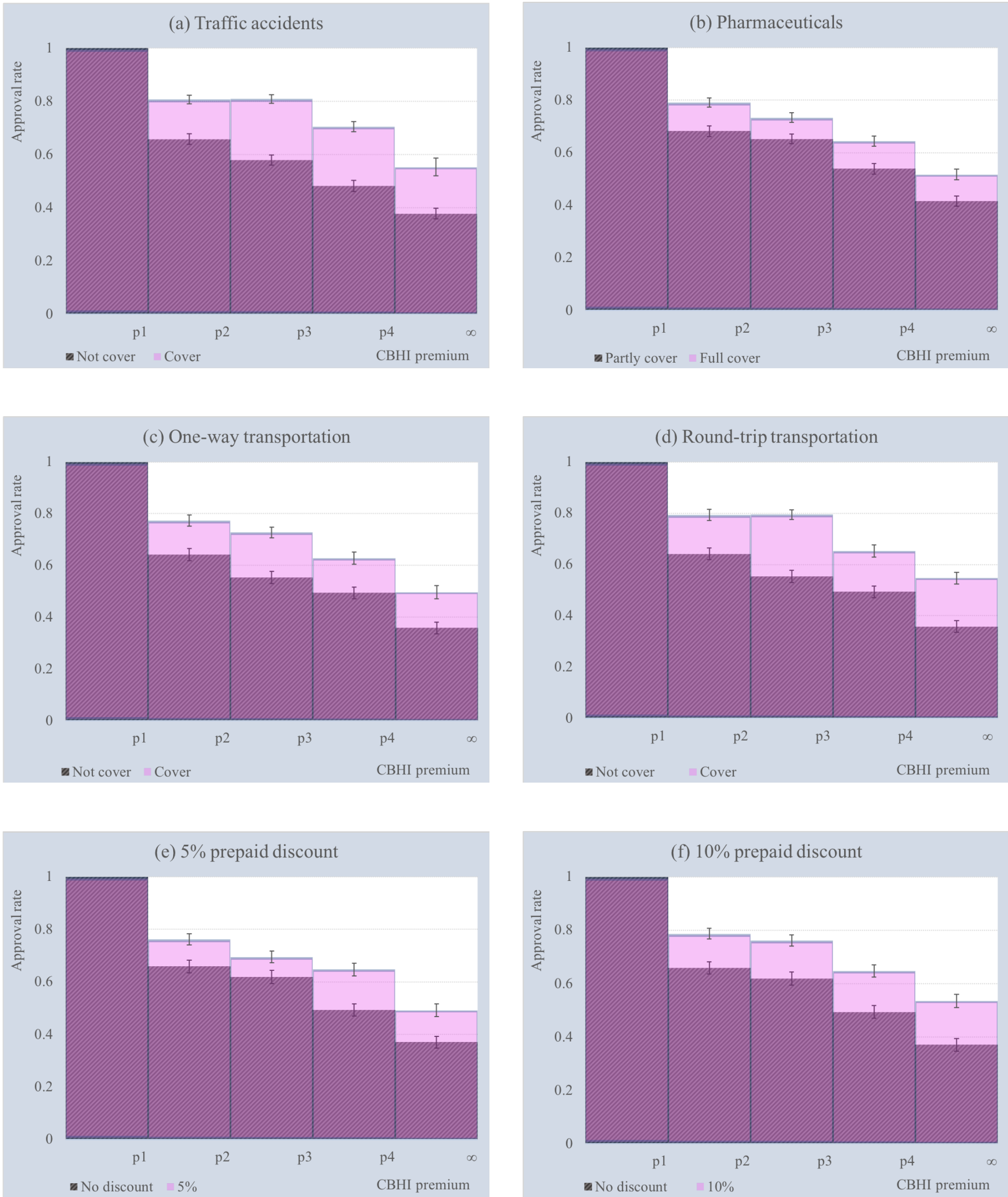


FIGURE F.3: Approval rate by attribute (full sample)