Potential Surplus Gains for Voluntary Community-based Health Insurance Improvement in Rural Lao PDR: A Randomized Conjoint Experiment

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Abstract

This study examines the causal effects of benefit package components of community-based health insurance (CBHI) on choice probabilities and potential surplus gains resulting from policy changes through mean of 580 households from two distinct districts. A randomized conjoint field experiment is employed to collect the rural household stated preference data. In the experimental design, each respondent ranks three options: two alternative schemes and the current one as status quo. The two alternative CBHIs' profiles on seven attributes are randomly assigned. The attributes include the insurance coverage of *medical consultation, hospitalization, traffic accident, drugs, transportation*, and *premium*, simultaneously. We find that premium is the solely negative component effect in the choice probabilities, while significant increase in preferences is from the presenting of traffic accident and transportation. The finding that current premium has no effect on the choice probabilities of ex-member respondents is highlighted, the main source of their preferences is, in turn, from 10% discount. More interestingly, substitutable interactions are found in most cases, only single pair of current premium and two-way transportation is found to be complementary which is associated with 23% of potential surplus gain.

Keywords: Community-based health insurance, Randomized conjoint experiment, Rural Lao PDR

1. Introduction

While the targets of rural development and poverty reduction become the central concern of the Lao government, in turn health security has played a significant role as building block to achieve the targets. However, the high out-of-pocket (OOP) expenditure for health care is burdensome for households leading to less utilization of health care and ultimately poor economic performance [1]. Therefore, in company with rural development per se the government addresses close attention on the promotion of universal health coverage, defined as "access to adequate health care for all at an affordable price" [2].

In an effort to increase health service utilization and, in the meantime, cut OOP expenditures down, several risk protection schemes have been operated. Apart from Civil Servants' Scheme (CSS) for government employees, Social Health Insurance (SHI) for private and state-owned enterprises, and Health Equity Funds (HEFs) for households living in extreme poverty, CBHI is one of four main risk protection schemes operating alongside targeting self-employed workforce which is mainly in remote underserved health care facility areas (see Table 1). CBHI scheme is the mechanism of pooling of risks and resources and the first decentralized scheme in Lao PDR empowering lower layers of government in health sector and local community on implementation. In this fashion, the benefit as the result of successful scheme operation will be seen not just in terms of mobilization of resources but also the improvement of health care services from local levels.

Schemes	**SASS (State Authority Social Security)**	**SSO (Social Security office)**	**CBHI (Community-based Health Insurance)**	**HEF (Health Equity Fund)**
System	Mandatory		Voluntary	Certified by local authority
Target population	Civil servants & dependents	Worker & dependents	Self-employed & informal economy people	Families identified as living in extreme poverty
Contribution	Employee 2% Employer 2%	2.2% deduction from SSO fund	Flat amount by family size , urban & rural residence	None
Benefit package	Out-patient services (OPS) & In-patient services (IPS)			OPS & IPS + travel & food cost
Ministerial authority	Ministry of Labor and Social Welfare		Ministry of Health (MOH)	MOH & Development Partners

Table 1: Social Health Protection Schemes in Lao PDR
Source: Modified from S. Ahmed et al. (2013)

In 2002, CBHI was introduced by Ministry of Health (MOH) as a pilot project in two districts with technical assistance from WHO and financial support from the United Nations Human Security Fund. Currently, Agence Française de Développement (AFD) supports the MOH with scheme expansion in 2 provinces. With the gatekeeping system, CBHI members have to first seek services at the contracting facilities, such as dispensary and district hospital, only referral patients are sent to provincial or regional hospitals [3]. The benefit package covers outpatient and inpatient services including primary health care, specialist services, diagnostic tests, and prescribed drugs that are available at the hospitals. Household is the unit of enrollment and the premiums varies depending on urban or rural residence, and number of household members. The premiums are originally set at between 2.5 to 3% of average household income. However, the contribution rates have not been updated since 2005 [4]. The window period of service access is three months upon enrollment. Since 2012, the scheme is obtained the income source from the member contribution, including monk, at the share of 50% and the government share the other 50% [5]. 85% of premium collection is directly managed by contracting hospital (district hospital in this case) and remaining 15% is deducted for NHI administrative expenditure. Except for the salaries of health care workers, all costs associated with the treatment for CBHI insurers should be covered by the scheme income source.

As SASS and SSO are mandatory schemes, meanwhile HEFs scheme is 100% subsidized by the government, CBHI is just voluntary scheme with largest target of more than half of population but fail reaching the satisfactory level of coverage. The total nationwide insurance coverage as of 2014 is a rate of about 27.1% of population (see Figure 1). Particularly, CBHI scheme coverage as of September 2015 is 50 of 148 districts in 17 of 18 provinces, or equivalent to 2,271 of 8,507 villages. The total number of beneficiaries is reported at 33,795 households (179,534 people). As the number of enrolled households is minimal in each area along with high actual use by beneficiaries, district hospitals have beard budget deficit burden. This is the main reason why many district hospitals have disclaimed to contract with the scheme. Recently, even though another half of scheme income source is subsidized by government, another challenge facing the scheme arises regarding financial sustainability of the government. As long as the number of enrollment is not sufficiently large, the scheme cannot afford the cost of services, ultimately leading to poor quality of service and even high dropouts.

One study about CBHI scheme in Lao PDR disclosed that though the theoretical concept of the scheme is to protect low-income people from high health OOP expenditure, the scheme has actually failed reaching that group of people in practice [6]. Ekman (2014) made a systematic review on the evidence of CBHI implementation; the review indicated that the community expectations, especially the poorest and perhaps those in need, may be neglected to take into account in the process of scheme design bringing about to consumer dissatisfaction and low demand.

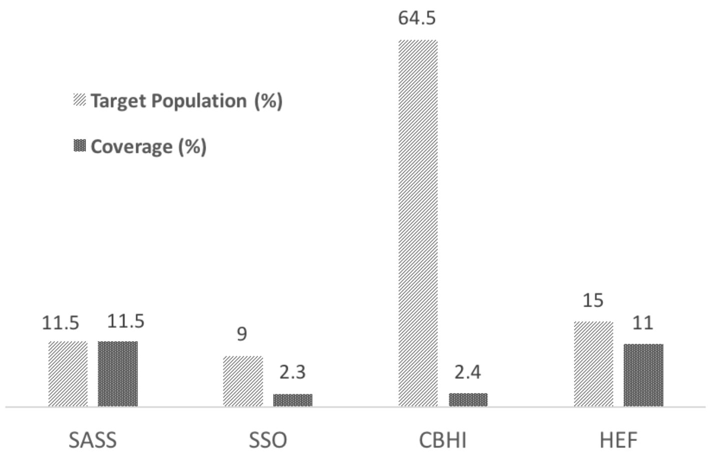

Figure 1: Insurance coverage in Lao PDR, 2014
Source: Central NHI Bureau, Ministry of Health, 2015

The controversy between expected target and achievement of the scheme brought policy makers' attention to the barriers behind. The government is considering every possibility for scaling up to achieving universal coverage by 2030. Nonetheless, the question of how to promote the expansion of the scheme to the satisfactory level of coverage plays a central role in the health insurance literature [3, 7, 8, 9]. In order to develop a health insurance scheme attractive to demands of target population, there is need for policy-makers to have more insight on community's perceptions towards the scheme. Particularly, we cannot deny the fact that benefit package itself does matter in households' decision behavior to enroll or not enroll the scheme [10], but how, exactly?

To answer, some articles carried out experiments to examine households' preferences for health insurance benefit package, a study on CBHI in northwest Cambodia concluded that higher premium leads to disutility, whereas hospital fee coverage induces highest utility of respondents [11]. In addition, some studies evaluated the consumers' maximum Willingess-to-pay (WTP) for community-based health insurance scheme and further examined associated factors in low- and middle-income countries. There are consistent findings that higher income and high educational attainments are significantly associated with WTP for the scheme [7, 12, 13, 14, 15, 16]. In parallel, many studies investigated the causes of the phenomenon of high dropout. In a study in Burkina Faso, for instance, beyond the affordability per se, health demand, service quality and household characteristics do also influence the scheme dropout [17]. Another study conducted in rural region of west Africa also stated that consumers' preference to join the scheme is closely linked to not only benefit package but also health service providers and managerial structure of the scheme[18].

Little studies, particularly in the area of health insurance scheme, conducted research on the causal effects of attribute levels on the consumers' choice probabilities. In Lao PDR, it is recognized that the currently low enrollment of CBHI scheme may be at least, in part, explained by low satisfaction on scheme design [19]. Understanding the right combinations of attribute values is a useful guidance for decision makers to optimize the scheme. And to date there have been no sufficient evidences to verify for that matter. In consequence, we address efforts to disclose if consumers have to pay their money for the scheme, how they wish to see their expectations met.

In complement to the previous studies on CBHI in Lao PDR, this article intends to explore the stated preferences of households in rural area. More importantly, we relies on the method of randomized conjoint analysis, which attribute values, attribute orders, and pair of alternatives are randomly assigned. The application of this randomization method advances us to address the gap of literature and seek answers for four questions: First, which attributes of benefit package do most affect respondents' preferences for scheme enrollment? Second, if attitudes toward scheme enrollment are shaped by CBHI experience or other consumers' characteristics concerns, should one expect that the effects of attributes will differ across subgroups? Third, do complementaries and substitutabilities of interactions between attributes exist? Forth, what are the source of maximum surplus gain from policy changes? The remaining sections of this paper is structured as follows; the next section mentions in more detail the experiment design, econometric approach used, and how to select the samples. We then describe the results of average marginal component effects (AMCEs), effect heterogeneity, average interaction component effects (AICEs), and surplus gain in section three. The discussion of policy implications and limitations of this study are situated in section four. In the last section, we concisely sum up whole context as well as raise up remaining areas that merit further study in the future.

2. Methodology

We employ experimental method to explore the effects of attribute values on respondents' preferences for scheme enrollment. Hainmueller, Hopkins and Yamamoto (2014) proposed numerous advantages of randomized conjoint analysis, in particular to estimate the effects of multiple treatments jointly. When the attribute values are independently randomized, the estimates of AMCEs and AICEs using the approach of ordinary least squares (OLS) with clustered standard errors provide unbiased and consistent estimates [1].

2.1. Experiment design

At the time this study is conducted, little empirical evidences from low-income countries on what elements would be considered by community as essential attributes in relation to CBHI scheme operation. Table 2 presents the attributes and levels applied in the experiment, seven attributes identified a priori in the scenarios employed in the experiment are compilation of literature reviews [20, 10], reports of CBHI in Lao PDR [4], local CBHI staff interview [2]. Note that the fees shown in Table 2 are the current premium for rural residence.

<table>
<tr><th>Attributes</th><th colspan="2">Descriptions</th><th colspan="4">Levels</th></tr>
<tr><td rowspan="6">Premium (kip/hh/month)</td><td>HH size</td><td>Fee</td><td>1</td><td>2</td><td>3</td><td>4</td></tr>
<tr><td>1</td><td>12,000</td><td rowspan="5">-2,000</td><td rowspan="5">0</td><td rowspan="5">+2,000</td><td rowspan="5">+4,000</td></tr>
<tr><td>2-4</td><td>20,000</td></tr>
<tr><td>5-7</td><td>25,000</td></tr>
<tr><td>>7</td><td>28,000</td></tr>
<tr><td colspan="2">Levels are price difference relatives to current fee</td></tr>
<tr><td>Medical consultation</td><td colspan="2">Coverage of the cost of medical consultation and diagnostic test</td><td>No</td><td>Yes</td><td></td><td></td></tr>
<tr><td>Hospitalization</td><td colspan="2">Coverage for hospitalisation due to medical treatment or surgery</td><td>No</td><td>Yes</td><td></td><td></td></tr>
<tr><td>Traffic accident</td><td colspan="2">Coverage of the medical treatment cost due to traffic accident</td><td>No</td><td>Yes</td><td></td><td></td></tr>
<tr><td>Drugs</td><td colspan="2">Coverage for pharmaceuticals incl-uding those which are not available and provided by other facilities</td><td>Partly</td><td>Fully</td><td></td><td></td></tr>
<tr><td>Transportation</td><td colspan="2">Coverage of patients travel cost to health care facilities out of the town</td><td>No</td><td>1 way</td><td>2 ways</td><td></td></tr>
<tr><td>Pre-payment discount</td><td colspan="2">Discount for 1 year payment of premium advance</td><td>No</td><td>5%</td><td>10%</td><td></td></tr>
</table>

Table 2: Attributes and levels

Note: Levels of scheme status quo are bold italicized.
For simplicity, the first levels are set as the baseline categories.

[1]See Hainmueller, Hopskins and Yamamoto (2014) for precise definitions of AMCEs and AICEs and model development.

[2]The various values of the seven attributes provide a total of 23+32-1(status quo scenario) =575 possible scenarios. These can be combined as a pair in 575 x 574 = 300,050 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, so we need to estimate causal effects using 115 choice sets in total.

Each alternative [3] takes on seven attributes, which the attribute levels are randomly assigned for each alternative. In the case of this study, alternative policy represents a hypothetical CBHI scheme. Each respondent is asked to complete five choice tasks. In each choice task, participants compare two hypothetical alternatives and status quo of the scheme and rank the policies that they think will maximize their benefit most from the scheme implementation [4]. Figure 2 is an example of the choice task presented to respondents. Seven attributes are employed in each hypothetical benefit package. To avoid any possible biases resulting from the attribute order effect, its order is randomized for each respondent [5].

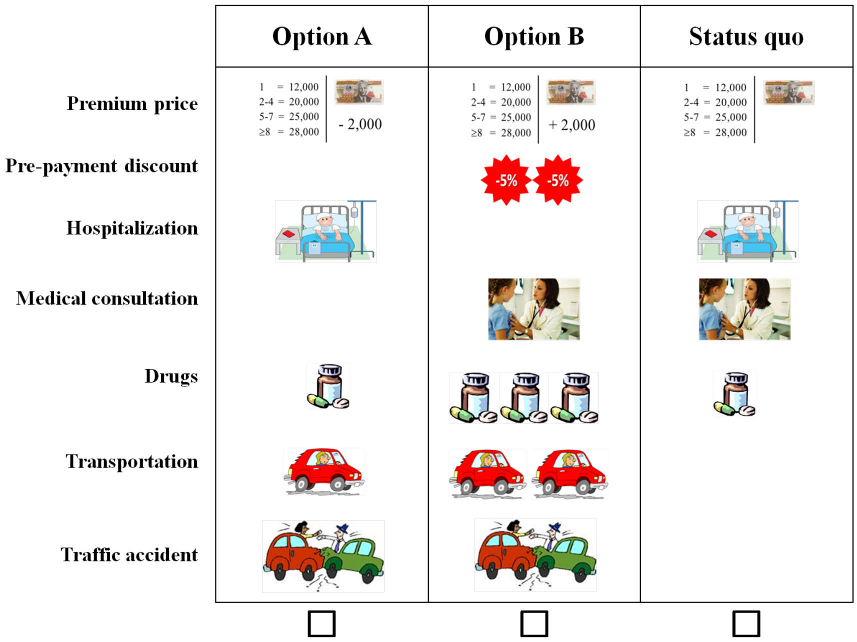

Figure 2: Example of the choice task

One should always notice that the most significant concerns of researchers in choice experiments is to construct a realistic as well as manageable experiment for participants. To ensure that our experiment setup is well understandable, we conduct pretest of 20 random samples with all CBHI status – members, ex-members and non-members [6]. To minimize biases occurred with communication process, the survey is carried out in two sessions: First, five investigators conduct one-on-one session of in-depth interview and as a supplemental method to observe the reported reasons for not enrolling. Second, respondents whom completes the first session is passed on to one of another three conductors for experiment session [7]. Before progressing the second session, three investigators explain face-to-face the rule of experiment and meaning of each picture shown to respondents [8]. The pretest confirms that the design of the experiment is appropriate and understandable, only the numbers of choice tasks cause tiresome but manageable by utilizing pictures instead of words. By so doing, the bias associated with illiteracy effect is also removed.

[3] We sometimes use the terms of policy or component throughout the text.

[4] In this experiment, “1”, “2” and “3” indicates most, average and less preferred policies, respectively.

[5] A respondent receives identical attribute order across the five choice tasks.

[6] Members, ex-members and non-members are defined as households that currently enroll, drop out and never enroll the CBHI scheme. Note that those 20 households are excluded in the main survey.

[7] For the first day, eight locally employed investigators are well trained. In total, there are nine survey conductors including an author.

[8] We allow the respondents to see five choice sets all at once.

2.2. Econometric approach

2.2.1. Estimation of choice probabilities

To estimate causal effects of the scheme component values, this paper follows the approach proposed by Hainmueller, Hopkins and Yamamoto (2014) . However, Hninn et al. (2016) introduced two types of estimates, internal choice probability when an alternative is preferred to the other and external choice probability when an alternative is preferred to the status quo.

To simplify, in the conceptual framework we suppose that an alternative has only three attributes; its costs and other two characteristics, c, a_1 and a_2. $Y_{ij}(c, a_1, a_2)$ is a choice indicator function: if an individual i puts higher rank on alternative j than status quo, $Y_{ij}(c, a_1, a_2) = 1$, while $Y_{ij}(c, a_1, a_2) = 0$ if the subject puts lower rank on the alternative than the status quo [9], and .

Under the full-randomization design of the conjoint experiment, the choice probability $E[Y_{ij}(c, a_1, a_2)]$ can be estimated by

$$E\left[Y_{ij}(c, a_1, a_2) \mid C_{ij} = c, A_{ij1} = a_1, A_{ij2} = a_2\right] \tag{1}$$

where C_{ij} is the costs of alternative j of individual i in a sample, A_{ij1} and A_{ij2} are also the values of attributes 1 and 2 in a sample, respectively. The marginal choice probabilities can be defined as:

$$E\left[E\left[Y_{ij}(c, a_1, a_2)\right]\right] = \sum_{a_2} E\left[Y_{ij}(c, a_1, a_2)\right] \tag{2}$$

The full-randomization design still allows us to simply estimate the marginal choice probabilities by

$$E\left[Y_{ij}(c, a_1, a_2) \mid C_{ij} = c, A_{ij1} = a_1\right] \tag{3}$$

Finally, the estimation model employed in this context is defined as [10]:

$$Y_{ijk} = \beta_0 + \sum_{l=1}^{7} \sum_{d=2}^{D_l} \beta_{ld} X_{ldijk} + \sum_{l=2}^{7} \sum_{l'>l} \sum_{d=2}^{D_l} \sum_{d'=2}^{D_m} \gamma_{ll'dd'} X_{ldijk} X_{l'd'ijk} + \varepsilon_{ijk} \tag{4}$$

where $Y_{ijk} \in \{0, 1\}$ is the choice dummy, if an individual i prefers alternative j over other alternative (or over status quo in external choice probabilities), $Y_{ijk} = 1$. X_{ldijk} denotes as the dummy for d^{th} level of attribute l in alternative j in task k of respondent i. Note that l is c, a_1, a_2 in conceptual function. D_l and D_m are the total number of attribute levels. Note that $D = 1$ is taken as the reference category. β_{ld} represents the estimate of AMCEs. $\gamma_{ll'dd'}$ is the observed coefficient of interaction between d^{th} level of attribute l and d'^{th} level of attribute l' or technically known as estimate of ACIEs. Under the randomization design of the choice experiment, ε_{ijk}, which is error terms, is independent of Y_{ijk}.

2.2.2. Causal effects on the WTP distribution

The analysis of WTP using choice experiment data intensively follows the study of Hninn et al. (2016) , and Kaneko et al. (2016) . The authors showed how the distribution of WTP can be recovered from estimated choice probabilities.

First, we define the (individual) WTP of an alternative. Let $u_i(c, a_1, a_2)$ denotes the utility function of an individual i if the subject chooses an alternative with $\{c, a_1, a_2\}$, and υ_i denotes the utility in the status quo. We make three assumptions on u_i;

(i) u_i is a decreasing function of c, which implies that $u_i(c, a_1, a_2) \leqslant u_i(c', a_1, a_2)$ if and only if $c \geqslant c'$ (monotonicity).

(ii) u_i is a continuous function of c (continuity).

[9] For internal choice probability, $Y_{ij}(c, a_1, a_2) = 1$ if an individual i puts higher rank on alternative j than alternative $j\prime$

[10] This equation is modified from Horiuchi et al. (2015).

(iii) $Y_{ij}(c, a_1, a_2) = 1$ if and only if $u_i(c, a_1, a_2) \geqslant \upsilon_i$ (rationality) [11].

Individual i's WTP of an alternative with a_1 and a_2 can be defined as:

$$u_i(WTP_i(a_1, a_2), a_1, a_2) \tag{5}$$

Note that we can never estimate the individual WTP, while the distribution of WTP can be estimated if sample size is infinitely large.

First, the cumulative distribution function of WTP is denoted by

$$Pr[WTP_i(a_1, a_2) \leqslant X] \tag{6}$$

Assumption (i) means that $u_i(X, a_i, a_2) \leqslant u_i(WTP_i(a_1, a_2), a_1, a_2)$ if $WTP_i(a_1, a_2) \leqslant X$. Therefore, from assumption (iii) and equation (5),

$$\upsilon_i = u_i(WTP_i(a_1, a_2), a_1, a_2) \geqslant u_i(X, a_1, a_2) \tag{7}$$

Above equation implies that $\upsilon_i \geqslant u_i(X, a_1, a_2)$ if and only if $WTP_i(a_1, a_2) \leqslant X$, and the cumulative distribution function (15) can be rewritten as:

$$Pr[WTP_i(a_1, a_2) \leqslant X] = Pr[\upsilon_i \geqslant u_i(X, a_1, a_2)] \tag{8}$$

Additionally, from assumption (iii), $Y_{ij}(X, a_1, a_2) = 0$ if $\upsilon_i \geqslant u_i(X, a_1, a_2)$, and the above equation can be then modified as:

$$Pr[WTP_i(a_1, a_2) \leqslant X] = Pr[Y_{ij}(X, a_1, a_2) = 0] = 1 - E[Y_{ij}(X, a_1, a_2)] \tag{9}$$

Equation (9) shows the first identification results; the cumulative distribution function must be equal to the share of individuals who put higher rank on status quo over an alternative with $\{X, a_1, a_2\}$.

Now, let's consider how the WTP distribution looks like by changing an attribute. We still focus on the change of first attribute from 0 to 1. The conditional causal effect of a_1 is defined as:

$$[WTP_i(1, a_2) \leqslant X] - [WTP_i(0, a_2) \leqslant X]$$

From equation (9), for any given a_2, the distribution of WTP in each $a_2 = 0$ and $a_2 = 1$ are obtained as:

$$[WTP_i(0, a_2) \leqslant X] = 1 - E[Y_{ij}(X, 0, a_2)]$$

$$[WTP_i(1, a_2) \leqslant X] = 1 - E[Y_{ij}(X, 1, a_2)]$$

and the conditional causal effect on WTP distribution is also identified as:

$$[WTP_i(1, a_2) \leq X] - [WTP_i(0, a_2) \leq X] = E[Y_{ij}(X, 0, a_2)] - E[Y_{ij}(X, 0, a_2)] \tag{10}$$

The marginal effect on WTP distribution is then defined as:

$$E[[WTP_i(1, a_2) \leqslant X] - [WTP_i(0, a_2) \leqslant X]] = \sum_{a_2} [[WTP_i(1, a_2) \leqslant X] - [WTP_i(0, a_2) \leqslant X]] \tag{11}$$

From equation (10), the marginal causal effect can be identified as:

$$\begin{aligned} E[[WTP_i(1, a_2) \leqslant X] - [WTP_i(0, a_2) \leqslant X]] &= \sum_{a_2} [E[Y_{ij}(X, 0, a_2)] - E[Y_{ij}(X, 1, a_2)]] \\ &= E[Y_{ij} \mid C_{ij} = X, A_{ij} = 0] - E[Y_{ij} \mid C_{ij} = X, A_{ij} = 1] \end{aligned} \tag{12}$$

[11] See Kaneko et al. (2016) for the details on assumptions

To estimate the marginal causal effect, we need to estimate the right-hand side of equation (12). The population model is defined as [12]:

$$E\left[Y_{ij} \mid C_{ij}, A_{ij1}\right] = \beta_0 + \beta_1 C_{ij} + \beta_2 A_{ij1} + \beta_3 \left(C_{ij} \times A_{ij1}\right) \tag{13}$$

By using estimated coefficients, the right-hand side of equation (12) can be rewritten as:

$$\begin{aligned} E\left[\left[WTP_i\left(1, a_2\right) \leqslant X\right] - \left[WTP_i\left(0, a_2\right) \leqslant X\right]\right] &= -\left[\beta_{1X} + \beta_2 + \beta_{3X}\right] + \left[\beta_{1X}\right] \\ &= -\beta_2 - \beta_{3X} \end{aligned} \tag{14}$$

where β_{3X} are the coefficients of interaction term with $C_{ij} = X$.

In this context, by using estimated coefficients from equation (4), the marginal WTP, denoted as ΔWTP, on the change of attribute levels compared against its baseline reference can be recovered as:

$$\Delta WTP_{l^*d^*} = -\beta_{l^*d^*} - \gamma_{l^*d^*d^p} \tag{15}$$

where $\beta_{l^*d^*}$ denotes for the AMCEs coefficients of interesting attribute levels except premium levels. Similarly, $\gamma_{l^*d^*d^p}$ is the interaction estimate between observed attribute levels and premium level, denoted by d^p.

2.3. Samples

This study aims to survey households' preferences in Savannakhet Province [13] as the CBHI condition presented in the area is relevant to the study. According to the report of Center National Health Insurance (NHI) Bureau in 2015, Savannakhet province has the highest share over other provinces and most variation over the time of CBHI members. We focus on Champhone and Xaibouly Districts for the following reasons:

- 7 of total 15 districts have increasing number of enrolled households especially from 2014, of which the province capital district is excluded to mitigate selection bias. As the target groups of study are members, ex-members and non-members, we intentionally choose Champhone District which has the largest coverage of CBHI among others as the representative of increasing districts. However, the coverage accounts for only 0.21% of province population in 2015,

- In turn, with the same criteria Xaibouly District which has the highest number of CBHI members among decreasing districts, with the share at 0.1% of province population, is selected.

- As our focus is rural households and plausible condition to conduct experiment, we designate only **type II** villages with homogeneous infrastructure surveillance of **"1 1 0 1 1 1 0"** [14]. Finally, we identify three villages from Champhone District and six villages from Xaibouly District. Due to geographic constraint, one village is abandoned from Xaibouly District.

- All existing households excluding those from formal sectors, who are not the target population of the scheme, and monks, who are not plausible to interview, are eligible population in this study. Then, 580 households are random [15] yielding 46% of eligible population. Of these, 36%, 51%, and 13% are active members, non-members and ex-members, respectively (see Figure 3).

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[12] Actually it is the same model with equation (4).

[13] It is the south center province of Lao PDR, sharing east and west borders with Vietnam and Thailand, respectively. The province owns the largest land area and also population.

[14] Village **type I** indicates urban village with road access, electricity, water supply, regular market, administrative office, Village **type II** is rural village with road access, Village **type III** is 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 medicine bag (yes), primary school (yes), regular market (no).

[15] We exclusively identify household head or spouse as a representative of household to the experiment. In the local context, household head or spouse is the key decision maker over the allocation of economic resources within the household. Exploring their preferences may result in acceptable and successful health insurance intervention in the future. However, just 88.45% of respondents are household heads or spouse in practice.

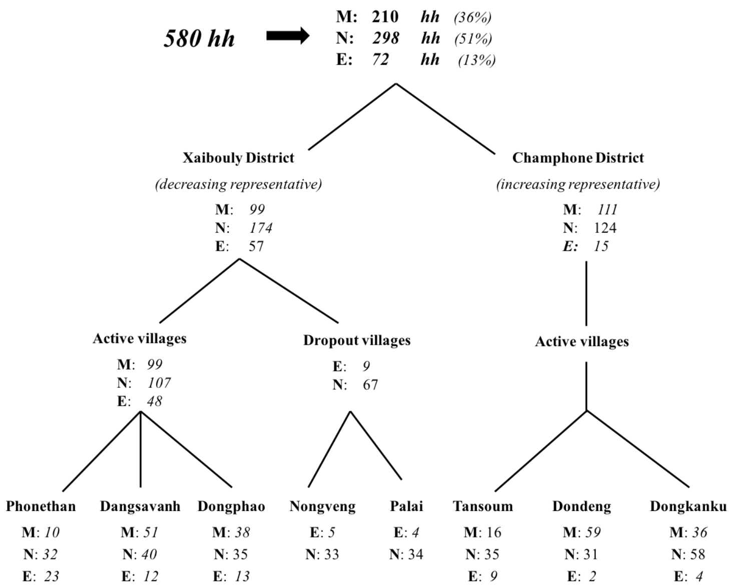

Figure 3: Stratified sampling design
Note: M, N, E abbreviate for scheme active member, non-member, and ex-member.

Selecting respondents with different CBHI status in two distinct districts ensures the purpose that diverse views of participants are taken into consideration. we then stratify the respondents in three groups: CBHI active member, non-member, and ex-member. Member respondents are randomly drawn from a list of currently active CBHI members of each village, whereas the representatives of ex-members are randomly selected from a list of those who dropped out. The list of households in each village excluding households that work in formal sectors, member households, and dropout households are finally random as the respondents of non-members [16].

It is recognized that educational attainments and income levels often affect the enrollment probability [2], so we report the descriptive statistics over the three subgroups. Table 3 shows the respondents have intuitively analogous means of education levels throughout subgroups. Member of Non-member respondents have closely similar share of educational attainment, over half of respondents has equally illiterate or primary level of education, followed by secondary level. Ex-member respondents are likely to have better education and lower mean income relative to the other two subsamples.

Respondents' education						
	Member		Ex-member		Non-member	
	Qty	%	Qty	%	Qty	%
Illiterate + Primary	85	51	20	38	102	54
Secondary	47	28	22	41	43	23
High school	31	19	8	15	35	19
Higher education	4	2	3	6	7	4
Mean annual household income (mil. Kip)						
	Obs	Mean	SD	Min	Max	
Member	210	16.57	16.45	1.07	97.32	
Ex-member	72	12.91	11.44	0.6	51	
Non-member	298	14.9	27	0.5	300	

Table 3: Descriptive statistics

[16] The main survey was conducted between 13-27 September 2016, two days per village on average. Participants are recruited and gathered with assistance of chiefs of visited villages.

3. Results

3.1. Causal effects of scheme components

By estimating equation (1), preferences regarding the specific components of the scheme are presented in two versions: internal and external choice probabilities. Figure 4 displays the results of full regression models. Point estimates of AMCEs for each attribute value on the respondents' choice probability to join the scheme compared against its baseline level are indicated by dots, where lines illustrate 95% confidence intervals. The solid dots along the vertical axis are the reference categories of each attribute. For the estimated coefficients, the signs, magnitudes and levels of significance are meaningful and mostly identical between the two results, suggesting robustness of the respondents' preferences. The premium stands out clearly as a greater barrier affecting the choice probabilities, in particular the effect is roughly monotonic. It is likely to most influence the preference when premium increases another additional 4,000 kip, against its baseline category, leading to lower probability of joining the scheme by about 25 percentage points when this attribute value is presented. This may be unsurprising, given that price attribute is usually the major concern for people with low income. The empirical results confirm the findings from prior studies [2] and be consistent with the survey-based interview about the reason why they do not enroll or even abandoned the scheme. 82% of the respondents reported inability to pay contribution as the most constraint.

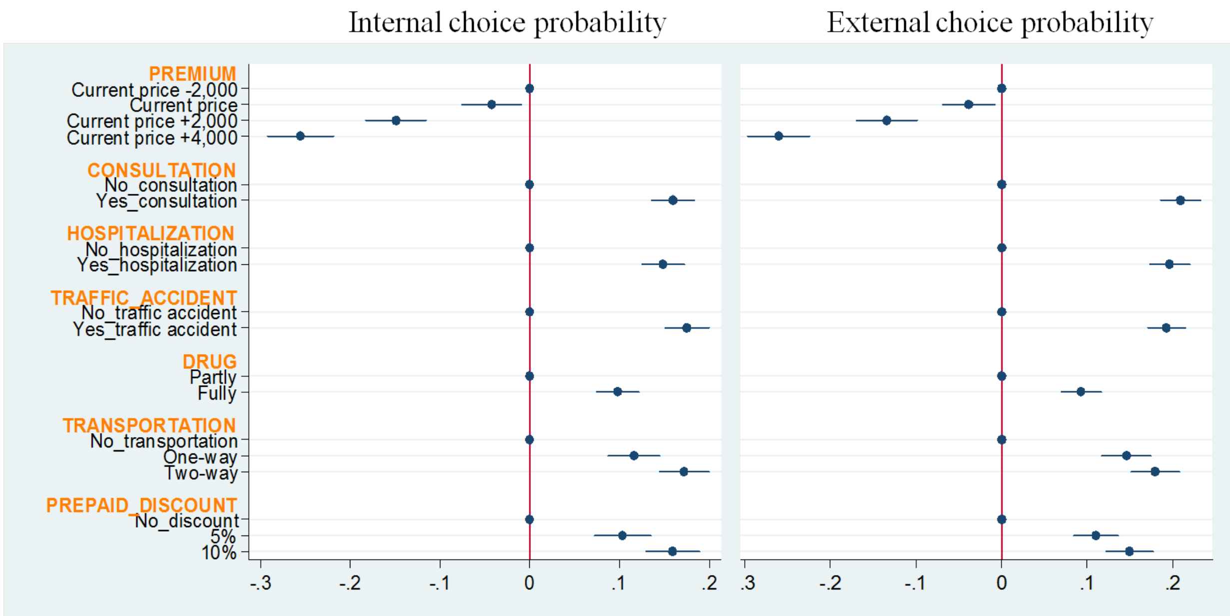

Figure 4: Average effects of hypothetical attributes on respondents' preference

The AMCEs analysis of pooled samples alone may conceal significant messages on their preferences' variation, we further examine the degree of heterogeneity with respect to subsamples of specific respondents. To this end, we reestimate equation (1) for the group-specific average effect of each attribute value across respondents grouped by their CBHI experiences [17]. Figure 5 illustrates estimates of CBHI members, ex-members, and non-members, respectively.

Although the overall specific-group AMCEs are distributed tightly around the pooled AMCEs shown in Figure 4 with little variability across groups, the results disclose a striking answer of respondents who dropped out the scheme. Specifically, the effect of current premium is indistinguishable from zero at 5% significance level and the effect of the highest premium level compared against its baseline level is relatively smaller than that of members and non-members with largest standard errors. In contrast, the effects of other attributes are likely homogeneous irrespective of the CBHI status of respondents.

[17] Only the results of external choice probabilities are reported.

Figure 5: Effect heterogeneities of benefit attributes on respondents' preference

Apart from premium, respondents who either members, ex-members or non-members equally value medical consultation as the first most effects, whereas the second most effects vary over subsamples, member, ex-member, and non-member values traffic accident, 10% discount, and hospitalization, respectively. In addition, we consider differences in responses based on respondents' occupations. Just like overall AMCEs, the patterns of subgroup AMCEs are positive except that of premium. The effect of premium is mixed, for the respondents involved in agriculture sector premium is likely to be associate with lower preference. Though the estimates in remaining groups may show akin trend, but not enough to reach an acceptable significance level with 95% confidence intervals. Additionally, we also test the difference of respondents' preferences if the educational attainments vary. The estimates are uniformly indifferent across subgroups.

Moving beyond attribute effects in isolation, we further examine interaction effects [18] between attribute levels. Only 7 of total 50 comparisons are found statistically significant. Figure 6 illustrates the average interaction effects varying over combinations of attribute levels with their 95% confidence interval. The upper figure illustrates that the average interaction effect "Current premium x Two-way transportation" is positive and statistically significant, whereas other attribute level combinations fail to be significant. Nevertheless, no significant interaction effects are found as long as premium does not take on its lowest level and transportation highest level. In other words, the cheapest premium and maximum transportation coverage is perceived as complements. This outcome illustrates a high degree of consistency with respondents' suggestion that they cannot bear the burden of transportation cost to the contracted health care facilities, which is probably higher than treatment cost per se, leading to lack of interest to join the scheme to this end.

On the contrary, the bottom Figure illustrates six statistically significant estimates of interactions. The pairs of "Full drugs x Hospitalization", "Full drugs x One-way transportation", "Full drugs x Two-way transportation", "Traffic accident x Medical consultation", "5% discount x Medical consultation", and "10% discount x Medical consultation" are strikingly found to be negative. These findings identify the substitutive rather than complementary relationship of the levels of these elements.

3.2. Surplus gain of policy implementation

We further investigate how the distribution of surplus gain adjusts when the value of attribute shifts from one to another by computing equation (2). Note that we recover from the estimates of external choice probabilities. Figure

[18]The terms of "Interaction" is also mathematically known as the "cross partial derivative of the choice probabilities or difference in difference" [16]. And only estimates of external choice probabilities are reported here.

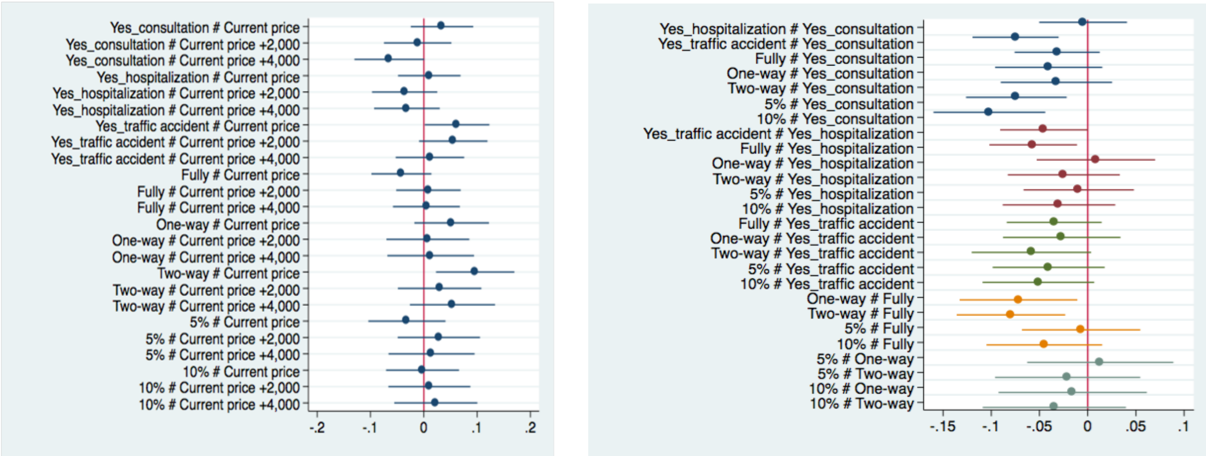

Figure 6: Average interaction effects

7 presents the percentage of respondents whom are willing to pay when an attribute level shifts to the new value. Outstandingly, it is found that the presenting of two-way transportation in the current premium is associated with 23% of potential surplus gains, followed by that of traffic accident about 22%. In contrast, the surplus gain from full drug remains the lowest regardless of premium variation. The results of subgroups are mostly in line with that of pooled samples.

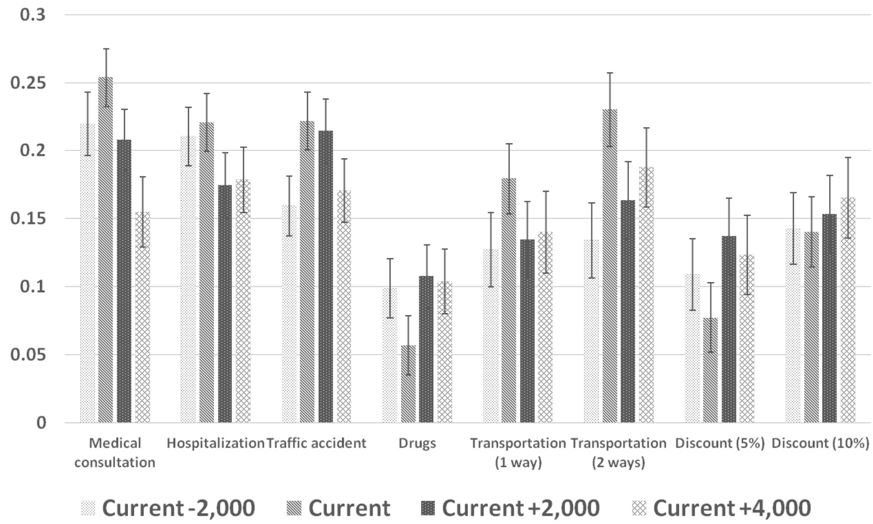

Figure 7: Distribution of Surplus gain

Note: Estimates are all statistically significant at 1% level. Vertical axis is the share of surplus gain, while the line represents standard error with 95% confidence interval.

4. Discussion

Some is probably curious about the broader import of the findings of this research in other areas of Lao PDR. The lack of notable difference of the AMCEs in both models may point out that respondents change their preferences for several attributes and attribute values of hypothetical policy over status quo of the scheme. Furthermore, the finding of no striking difference between subsamples of members, ex-members, and non-members also suggests that understanding households' preferences alone provides only a partial answer to explaining enrolment phenomenon of the scheme. And though this study may fall sort of providing sufficient guidance to the success of the scheme development, but it provides importantly unexplored evidence that scheme enrollment is likely to increase when the sources of respondents' preferences, in particular the combination of current premium and two-way transportation, are addressed.

Unsurprisingly, inability to pay for contribution when premium takes higher values is highlighted as the foremost reason for not joining the scheme, especially respondents who are involved in agriculture sector. There is always a trade-off between paying for premium and daily subsistence, in most cases household heads allocate the limited resource to basic daily needs and educational expenditures. On the other hand, current premium or higher premium is not likely to be the main determinant of the scheme dropout. One of the most attribute effects for ex-member is 10% discount corresponding to the pooled sample finding of preference for discount over full drugs. One could judge that the reason of dropout or not joining the scheme is not only affordability, policy makers should reflect other barriers alongside. One should always notice that confidence in the plan solely may not translate into higher coverage. To this end, it is suggested that the promotion of other development programs in parallel, microfinance [26], for instance, alongside with information promotion to enhance households' understanding on risk-pooling system are solicited [27].

An ideal experiment should allow only household heads exclusively as the respondents, but there are many acceptable reasons why this is not always plausible in this study [19]. Another important limitation of this study is associated with the fact that we fail to conduct group discussions of sample respondents to obtain the most relevant attributes of scheme enrollment [20]. It is a challenge for future scholars to devote more attention to experiment design. This study could shed light on the studies of other remaining areas of health care reform in Lao PDR, factors such as quality of health care facilities, services and even trust on the scheme, have been verified by several studies as the foremost determinants affecting the enrollment irrespective of whether the benefit package per se corresponds consumers' preferences or not. By employing alike methodological approach, policy makers could understand a priori what hypothetical policy bundles or candidate attributes may best suit a given population within a given context and interventions. For better insights, with the same group of respondents a series of studies on the relationship of households' risk preference, time preference, social networks, and microfinance accessibility on the CBHI enrollment are further analyzed in separate articles.

5. Conclusion

To achieve the goal of universal health coverage, CBHI was introduced alongside with other three protection schemes. Given that the concept of the scheme is to protect people against direct OOP payments and enhance access to health care services via promotion more enrollment in the scheme. However, how to expand the scheme coverage has been sophisticated question to answer, policy makers need comprehensive understanding of existing impediments. Scholars need to rely on various methods of analysis to statistically derive answers from several perspectives of development possibilities. By identifying specific attributes and appropriate levels shaping the rural households' preferences on the scheme enrollment, we then conduct conjoint experiment. The method of randomization advances our comprehension in critical ways.

This study illustrates that the compositions of the scheme benefit package has, in part, an impact on respondents' choice of enrollment. One of the striking findings is respondents value hypothetical alternative policy over status quo. The finding also verifies that respondents express a pronounced preference for the scheme with current or lower premium, while significant increase in preference is noted for presenting of traffic accident and transportation. It is also highlighted that the current premium does statistically not matter the choice preferences of those who dropped out the scheme. More interestingly, the enrollment tends to increase if two-way transportation cost is covered by benefit package of current premium. In addition, the findings also show that when two-way transportation is presented in

[19] In some cases, household head is too old to understand our experiment, we then shift to the key man of the household instead. Another reason is parents both work in other areas and will visit home a few times in a year leaving their children home alone. So, the decision maker in the household is usually the eldest child.

[20] In fact, the attributes employed in the experiment are highly relevant relying on recommendations of the local CBHI staff whom have long working experience for the scheme, reports of the scheme operation, and literature reviews of the studies in low-income countries.

the current premium, the potential surplus gain increases about 23%, followed by that of traffic accident about 22%. In contrast, the surplus gain from full drug remains the lowest regardless of premium variation. The findings of this study become a useful input in the policy improvement of CBHI scheme in Lao PDR and possibly other low-income countries. For a full picture of development process of the scheme, an all-round analysis of deficiencies, particularly quality of health care services and trust on the system merits further investigation.

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