

# Does Community-based Health Insurance Have Potential Impacts on Direct and Indirect Outcomes? Evidence from Rural Villages, Savannakhet Province, Lao People's Democratic Republic

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## Abstract

**Background:** As labor-intensive agriculture is a common way of life for rural people, especially in developing countries, good health is often a key input of agriculture production. In addition, selling livestock is a form of coping responses of rural people when facing financial burden. If the community-based health insurance (CBHI) scheme achieves its key function in financial protection and better health promotion, it is assumed to lead to improved outcomes of agriculture production.

**Objective:** To evaluate potential impacts of the CBHI scheme on rice production and livestock holdings among rural households in Savannakhet Province, Lao DPR.

**Method:** We employed the technique of inverse probability of treatment weight (IPTW) to correct for imbalances in pre-intervention covariates between treated and untreated samples.

**Findings:** Findings from this study suggest that the CBHI scheme significantly increases rice production per capita and the number of cow holdings among enrolled households, which both are likely to lead to poverty reduction in the long run.

**Key words:** Community-based health insurance, inverse probability of treatment weight, rural Lao PDR.

## 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 community-based health insurance (CBHI) scheme has been implemented as an attempt to provide financial protection and health equity for those people in developing countries (Mathauer et al., 2017). 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 burdens are 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.

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. (2012) 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 direct outcomes of financial protection and health service utilization (Jutting, 2004; Nguyen et al., 2011; Alkenbrack & Lindelow, 2015; Raza et al., 2016). However,

existing evidence of such direct benefits from developing countries are rather divergent and inconsistent.

Beyond the direct effects, the potential benefits of health insurance might be found on indirect outcomes resulting from less out-of-pocket expenditures (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 (Asenso-Okyere et al., 2011), whereas poor health reduces the capacity to work of the sick individual and the level of output, accordingly (Antle & Pingali, 1994). 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 (Sauerborn et al., 1996; Yilma et al., 2014).

There are few studies that 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. (2012) 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. In this study, direct outcome is defined as the outcomes which are directly targeted by the scheme, including OOPs, service utilizations, and health status, whereas indirect outcome is defined as the outcome indicators which are influenced by the direct outcomes, such as household's income, various expenditure categories (except health expenditure), agricultural production, livestock holdings.

The impacts of the CBHI scheme on the indirect outcomes of informal-sector households in rural villages of Lao People's Democratic Republic (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 Lao PDR has focused on the implementation of the CBHI scheme since 2002. As the majority of the targeted population resides in remote villages and mainly depends upon labor-intensive rice production for income earning and subsistence, good health is often a key input of agriculture production. Unfortunately, we do not have the respondent's data on health status to test this hypothesis. Therefore, we assume that the CBHI scheme has improved the health condition of enrolled households, the improved health status might affect the productivity and reliance on coping responses, especially selling livestock. 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, 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 village fund?

The rest of this paper is structured as follows. The next section is the overview of the CBHI scheme in Lao PDR. Section three describes the methodology including sample selection and the econometric model. Section four discusses the results and main findings. The conclusion is located in Section five.

## 2. CBHI scheme in Lao PDR

In Lao PDR, health risk is expected to be an increasing threat to the poor in particularly remote areas (World Health Organization, 2012), 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 enterprise employees, Health Equity Funds (HEFs) for the extreme poor, and Community-Based Health Insurance (CBHI) for non-poor workers in the informal sector (Ahmed et al., 2013) presented in the 2010 World Health Report. There are more and more voices for the benefit of creating a single national risk pool. Now, a body of literature is emerging on institutional design and organizational practice for universal coverage, related to management of the three health-financing functions: collection, pooling and purchasing. While all countries can move towards universal coverage, lower-income countries face particular challenges, including scarce resources and limited capacity. Recently, the Lao PDR has been preparing options for moving to a single national health insurance scheme. The aim is to combine four different social health protection schemes into a national health insurance authority (NHIA). Among the four schemes, only the CBHI scheme is based on voluntary membership and decentralized implementation.

As of 2014, only 27.2% of the population was covered by any scheme of the health financing system. Moreover, the decomposed coverage by a scheme is rather heterogeneous. While the coverage of the SASS and HEFs schemes, which target nearly 26.5% of the Lao population, achieved approximately 85% of the target, that of the SSO and CBHI schemes made little progress, with only 6.4% of the targeted group enrolled. In particular, the CBHI scheme, which targets approximately two-thirds of the Lao population, achieved only 3.7% of the target by 2014 (National Health Bureau, 2014). In other words, the CBHI scheme has the largest target but lowest achievement. Therefore, this study intentionally evaluates the CBHI scheme 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.

In 2002, the Ministry of Health (MOH) introduced the CBHI scheme as a pilot project in two districts with technical assistance from the World Health Organization and financial support from the United Nations Human Security Fund. 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 is reported at 33,795 households (179,534 people). Currently, the benefit package of the CBHI scheme covers outpatient and inpatient services, including primary health care, specialist services, diagnostic tests, and prescribed pharmaceuticals that are available in hospitals. The household is the unit of enrollment, and the premiums vary depending on urban or rural residence and the number of household members. The premium rates have not been updated since 2005 (World Bank, 2010). The window period of service access is three months upon enrollment. With the gatekeeping system, CBHI members have to first seek services at contracting facilities, such as dispensaries and district hospitals, and only referral patients are sent to provincial or regional hospitals (Annear et al., 2011) in Cambodia at Kampot operational health district and in the Lao People's Democratic Republic at Nambak district. Results: Six key variables were identified as determining the financial flows between the subsidy and the insurance schemes and with health providers: population coverage, premium rate, facility contact rate, capitation rate, cost of treatment and changes in administration costs. Negative cross-subsidization was revealed where capitation was used as the payment mechanism and where utilisation rates of the poor were significantly below the non-poor. The same level of access for the poor could have been achieved with a lower Health Equity Fund subsidy if used as a direct reimbursement of user charges by the Health Equity Fund to the provider rather than through the Community Based Health Insurance scheme. Conclusions: Purchasing premiums for the poor under these conditions is more costly than direct reimbursement to the provider for the same level of service delivery. Negative cross-subsidization is a serious risk that must be managed appropriately and the benefits of a larger risk pool (cross-subsidization of the poor. Since 2012, 50% of the scheme's revenue has come from premium collection, and the other 50% has come from government subsidization (Lao Government, 2012).

### 3. Methodology

#### 3.1. Sample selection and data collection

This study collects data of rural households in Savannakhet Province, which is located in the center of Lao PDR. The province has the largest land area and population size. According to the Center National Health Insurance (NHI) Bureau report in 2015, Savannakhet Province had the largest and most fluctuating number of CBHI members of all the provinces. The household survey is carried out in two districts 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:

- There are 15 districts in Savannakhet Province. Since 2014, eight of the districts reported increasing numbers of CBHI-enrolled households, while the remaining districts have faced a decreasing number of CBHI members over time. Note that the province capital district needs to be removed from our selection because its infrastructure differs from that of the other districts. To ensure that the results account for the views of heterogeneous respondents, we intentionally select two representative districts with increasing and decreasing numbers of CBHI members. Accordingly, we choose Champhone and Xaibouly Districts, which have the largest coverage of CBHI among increasing and decreasing districts<sup>1</sup>, for this study.

- As our focus is households in remote areas, to ensure that the experiment can plausibly be conducted in these areas, we purposely designate only type II villages with a homogeneous infrastructure surveillance of “1 1 0 1 1 1 0”<sup>2</sup>. 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<sup>3</sup>, 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 are 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. Finally, there are 580 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.

The sample households are asked about demographic characteristics, asset endowment, income and expenditure sources, financial activities, CBHI scheme and health related information, social networks, and household shocks during the last 12 months preceding the survey visit. Investigators are employed and trained based on the content of the questionnaire. The questionnaire is pretested prior to the main survey.

As is customary, we visit the chief of each village a few days beforehand to inform the objectives and tentative procedure of the experiment. 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 convenience, every 6 respondents are appointed one-hour intervals from 8 a.m. to 5 p.m.

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

- Full sample: we use all CBHI members (as treated subjects), all non-members and all ex-members (as untreated subjects) regardless if subjects simultaneously engaged in the village fund (hereinafter referred to as “VF subjects”)<sup>4</sup>.
- Subsample 1: To observe the results in the absence of the CBHI ex-members, subsample 1 is equivalent to the full sample excluding 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 from the sample.

Table 1 shows the description and measurement of the treatment, 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 2. The mean difference 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 differences in selected outcomes even in the absence of the CBHI scheme enrollment. In particular, the differences are significant for aggregate expenditure, expenditure on education, expenditure on food, other expenditures, rice, number of cows and poultry holdings. However, the imbalances of baseline characteristics are mitigated by the IPTW technique as shown in Table 3.

### 3.2. Estimation model

For the cross-sectional observational study, the marginal causal effect of intervention can be evaluated by three main approaches including instrumental variables (IV), regression discontinuity designs (RDD), and propensity score method (White & Raitzer, 2017). Among the three approaches, propensity score method is gaining widespread use in the non-experiment evaluation literature due to data unavailability (Pirracchio et al., 2012). The propensity score is the probability of treatment assignment conditional on observed baseline covariates (Rosenbaum & Rubin, 1983). 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) (Haukoos & Lewis, 2015). 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 (Morgan & Todd, 2008). 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



Figure 1. Map of Savannakhet Province in Lao PDR.

**Table 1.** Variable description and measurements

Variable	Type	Measurement
<b>Treatment</b>		
CBHI member	Dummy	1 if households are currently the members of CBHI scheme, 0 otherwise
<b>Potential covariates</b>		
Household head		
Gender	Dummy	Gender of the household head. 1 if male, 0 otherwise
Age	Continuous	Age of household head in years
Education	Continuous	Schooling years of household head
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 <sup>a</sup>	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
Behavior		
$\alpha$	Continuous	The degree of respondent's risk aversion towards probability prospect <sup>b</sup>
<b>Outcomes variables<sup>c</sup></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 expenditure to health care facilities)
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 (excluding transportation expenditure to health care facilities)
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

<sup>a</sup> Village party and women union are the local government authorities.

<sup>b</sup> Kahneman and Tversky (1979) suggested that individuals tend to overweigh low-probabilities which may favor of both lottery and insurance. The function would be linear if  $\alpha=1$ , but S-shaped and inverted S-shaped if  $\alpha>1$  and  $0<\alpha<1$ , respectively. Inverted-S shape of 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. We employed the risk elicitation method of Tanaka et al. (2010) to obtain the parameter. The details on methodology and results of the experiment are reported in a separate paper. The parameter represents the behavior variable of the respondents in which 88.45% of our respondents are household heads or spouses.

<sup>c</sup> The various income and expenditure categories, hospitalization, and rice yield are data in the last 12 months preceding the survey.



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 (Linden & Adams, 2012). Unlike the PSM, the IPTW maximizes data available. Austin (2010) showed empirical evidence that the IPTW technique 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 the IPTW in recent years, especially in the field of health economics (Vaughan et al., 2015; Maeda et al., 2016; Nielsen et al., 2017), it is still scarce in the health insurance setting.

As a matter of fact, 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 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 participated 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 each potential covariate on the treatment dummy as the following equation (Linden & Adams, 2012):

$$X = \beta_0 + \beta_1 T \quad (1)$$

where  $X$  is each covariate.  $T$  is treatment.  $\beta_1$  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  $p(x) \equiv Pr(T=1|X)$ , the score can be estimated as follows:

$$\text{logit}\{Pr(T = 1|X)\} = X\beta \quad (2)$$

$X$  is a vector of the observed baseline covariates.

As our interest is the impact of the CBHI scheme among 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):

$$w_i = T_i + (1 - T_i) \frac{\hat{p}(x)_i}{(1 - \hat{p}(x)_i)} \quad (3)$$

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 re-estimate step 1 with weight to construct an artificial population in which individual potential covariates are independent of the treatment assignment.

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

$$ATT_{IPTW} = \frac{1}{N_1} \sum_{i=1}^{N_1} w_i Y_i - \frac{1}{N_0} \sum_{i=1}^{N_0} w_i Y_i \quad (4)$$

where  $Y_i$  is the outcome of household  $i$ .  $N_1$  and  $N_0$  are the number of treated households and untreated households, respectively.

## 4. Empirical analysis

### 4.1. Estimation results

To estimate ATT that is not confounded, we need to mitigate the covariate imbalances as summarized in Table 2 by propensity score weighting. Table 3 shows the results 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. As shown, the unweighted estimates report the statistically significant imbalances of many baseline covariates. The CBHI households tend to have a more educated household head, larger household members, more toilets at home, engage in the village party and women union, and live in the villages that are relatively closer to the district hospital.

**Table 3.** Covariate weighting

Covariates	Unweighted				Weighted			
	Full sample (579)	Subsample 1 (507)	Subsample 2 (408)	Subsample 3 (365)	Full sample (579)	Subsample 1 (507)	Subsample 2 (408)	Subsample 3 (365)
Gender	-0.098 (0.238)	-0.105 (0.249)	-0.405 (0.283)	-0.419 (0.295)	-0.011 (0.261)	-0.023 (0.282)	0.050 (0.320)	0.133 (0.348)
Age	1.982 * (1.158)	2.492 ** (1.197)	0.418 (1.431)	0.686 (1.466)	-0.192 (1.216)	-0.382 (1.322)	-0.463 (1.500)	-0.746 (1.586)
Education	0.927 *** (0.333)	1.145 *** (0.342)	1.388 *** (0.398)	1.638 *** (0.405)	-0.126 (0.406)	-0.19 (0.488)	-0.313 (0.508)	-0.453 (0.642)
Size	0.704 *** (0.184)	0.754 *** (0.195)	0.512 ** (0.221)	0.523 ** (0.231)	0.025 (0.215)	0.033 (0.236)	-0.021 (0.261)	-0.035 (0.293)
Land	96.108 (1,904.94)	-635.833 (2,067.75)	628.894 (2,479.48)	-96.206 (2,637.02)	840.8 (1,945)	1,234 (2,067)	487 (3,238)	1,263 (3,094)
Toilet	0.958 *** (0.230)	1.133 *** (0.235)	1.543 *** (0.342)	1.675 *** (0.345)	0.018 (0.241)	0.038 (0.253)	-0.003 (0.355)	-0.002 (0.367)
Village party	0.060 *** (0.021)	0.063 *** (0.022)	0.055 ** (0.025)	0.055 ** (0.027)	0.010 (0.033)	0.027 (0.032)	0.015 (0.038)	0.033 (0.035)
Women union	0.087 ** (0.037)	0.101 *** (0.038)	0.118 *** (0.044)	0.137 *** (0.045)	-0.009 (0.045)	-0.010 (0.050)	-0.019 (0.057)	-0.024 (0.064)
$\alpha$	0.053 * (0.029)	0.054 * (0.030)	0.026 (0.033)	0.012 (0.035)	-0.009 (0.034)	-0.013 (0.039)	-0.021 (0.040)	-0.029 (0.046)
Distance	-1.571 *** (0.463)	-1.966 *** (0.479)	-2.172 *** (0.547)	-2.56 *** (0.564)	0.059 (0.400)	0.171 (0.419)	0.035 (0.426)	0.102 (0.437)

Robust standard errors in parentheses

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

However, once the weight is used, the imbalances are all removed. We now ensure that the ATT estimates is less confounding by the selected covariates.

The estimates of ATT for the full sample and subsamples are reported in Table 4<sup>5</sup>. Subsample 3 is particularly 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 comparable.

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 excluded, it might be caused by fewer baseline covariates controlled. To be more precise, the rice per capita increases 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 rather similar irrespective of whether CBHI ex-members are present or not. The CBHI households own almost two heads of cow more than non-CBHI households. More interestingly, the effect is stronger in the absence 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.

#### 4.2. 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 (Iacus et al., 2012). Estimates of sample average treatment effect on the treated (SATT) based on the CEM method is presented in Appendix C. The findings show consistent signs and significance levels, only the degree of effects slightly varies. Overall, the estimates by the CEM method provides supporting evidence for the robustness perspective.





livestock holdings, which both are likely to lead to poverty reduction in the long run.

Further, the lack of significant evidence on direct benefits of the scheme might be a reason explained why the current CBHI scheme has 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. In addition, 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. To observe the direct impacts, we fail to capture the direct OOPs, the frequency of health care seeking, and the frequency of hospitalization. Also, we use quantity instead of a monetary value of livestock holdings in analysis.

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## Endnotes

- <sup>1</sup> However, CBHI coverage in Champhone and Xaibouly Districts accounted for only 0.21% and 0.1% of the province population in 2015, respectively.
- <sup>2</sup> 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).
- <sup>3</sup> Household is defined as a group of people in a housing unit living together as a family and sharing the same kitchen.
- <sup>4</sup> The village fund program is available in all eight selected villages of our study, the program targets the similar group of population with the CBHI scheme. The unit of enrollment is household. However, the program is implemented by different organizations.
- <sup>5</sup> See Appendix A for covariate balancing and Appendix B for propensity score distributions of the selected models.

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### Appendix A. Covariate balancing for ATT estimation

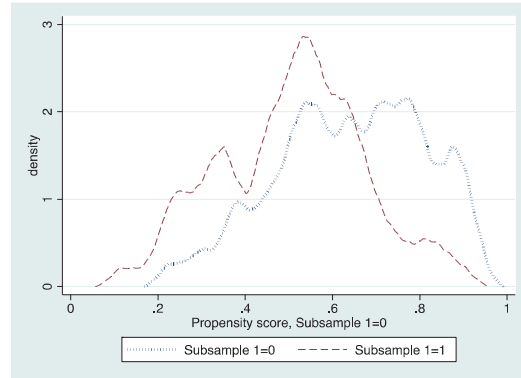
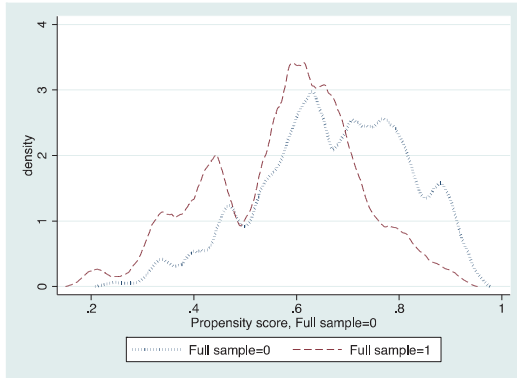
Covariates	(1)				(2)				(3)				(4)			
	Standardized differences		Variance ratio		Standardized differences		Variance ratio		Standardized differences		Variance ratio		Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
<b>Full sample</b>																
Gender	-0.035	-0.006	1.072	1.011					-0.035	0.003	1.072	0.994	-0.035	0.000	1.072	1.000
Age	0.150	-0.015	0.799	0.823					0.150	0.009	0.799	0.861	0.150	-0.011	0.799	0.837
Education	0.244	-0.027	0.833	0.670	0.244	-0.005	0.833	0.689								
Size	0.322	0.009	1.274	1.139	0.322	0.008	1.274	1.133	0.322	-0.010	1.274	1.112	0.322	0.011	1.274	1.154
Land	0.004	0.044	0.818	0.901												
Toilet	0.388	0.009	0.573	0.981	0.388	0.012	0.573	0.976	0.388	0.007	0.573	0.986	0.388	0.010	0.573	0.979
Distance	-0.309	0.018	0.477	0.683	-0.309	0.017	0.477	0.667					-0.309	0.022	0.477	0.689
Village party	0.233	0.032	2.313	1.093	0.233	0.053	2.313	1.161	0.233	-0.008	2.313	0.978	0.233	0.018	2.313	1.049
Women union	0.200	-0.023	1.263	0.980	0.200	-0.029	1.263	0.975	0.200	0.011	1.263	1.010	0.200	-0.012	1.263	0.989
$\alpha$	0.162	-0.023	1.099	0.970					0.162	-0.009	1.099	0.980	0.162	-0.010	1.099	0.988
<b>Subsample 1</b>																
Gender	-0.038	-0.008	1.077	1.015					-0.038	-0.010	1.077	1.019	-0.038	-0.011	1.077	1.020
Age	0.189	-0.028	0.808	0.848					0.189	0.002	0.808	0.871	0.189	-0.026	0.808	0.857
Education	0.303	-0.036	0.859	0.631	0.303	0.006	0.859	0.663								
Size	0.341	0.012	1.228	1.091	0.341	0.003	1.228	1.065	0.341	-0.004	1.228	1.062	0.341	0.021	1.228	1.130
Land	-0.029	0.061	0.712	0.899												
Toilet	0.472	0.019	0.536	0.961	0.472	0.025	0.536	0.950	0.472	0.013	0.536	0.974	0.472	0.020	0.536	0.959
Distance	-0.383	0.039	0.465	0.711	-0.383	0.025	0.465	0.680					-0.383	0.039	0.465	0.713
Village party	0.251	0.089	2.527	1.299	0.251	0.095	2.527	1.327	0.251	0.025	2.527	1.071	0.251	0.051	2.527	1.156
Women union	0.233	-0.024	1.326	0.980	0.233	-0.022	1.326	0.981	0.233	0.003	1.326	1.002	0.233	-0.025	1.326	0.979
$\alpha$	0.166	-0.032	1.093	0.902					0.166	0.006	1.093	0.967	0.166	-0.001	1.093	0.950
<b>Subsample 2</b>																
Gender	-0.146	0.020	1.325	0.969					-0.146	0.002	1.325	0.997	-0.146	0.001	1.325	0.998
Age	0.031	-0.048	0.815	0.871					0.031	-0.004	0.815	0.911	0.031	-0.035	0.815	0.878
Education	0.368	-0.067	0.857	0.634	0.368	-0.035	0.857	0.645								
Size	0.235	-0.008	1.084	0.986	0.235	-0.002	1.084	1.016	0.235	-0.016	1.084	0.937	0.235	-0.001	1.084	0.999
Land	0.026	0.027	1.031	0.762												
Toilet	0.555	0.004	0.354	0.987	0.555	0.011	0.354	0.966	0.555	0.002	0.354	0.995	0.555	0.014	0.354	0.958
Distance	-0.440	0.008	0.425	0.801	-0.440	0.012	0.425	0.809					-0.440	-0.002	0.425	0.802
Village party	0.211	0.050	2.091	1.154	0.211	0.045	2.091	1.135	0.211	0.002	2.091	1.006	0.211	0.015	2.091	1.043
Women union	0.268	-0.040	1.351	0.971	0.268	-0.035	1.351	0.974	0.268	0.014	1.351	1.011	0.268	0.002	1.351	1.001
$\alpha$	0.089	-0.058	0.922	0.799					0.089	-0.004	0.922	0.863	0.089	-0.013	0.922	0.836
<b>Subsample 3</b>																
Gender	-0.151	0.054	1.338	0.919					-0.151	0.016	1.338	0.975	-0.151	0.018	1.338	0.971
Age	0.051	-0.063	0.826	0.918					0.051	-0.013	0.826	0.925	0.051	-0.051	0.826	0.905
Education	0.438	-0.087	0.886	0.570	0.438	-0.037	0.886	0.599								
Size	0.237	-0.011	1.044	0.937	0.237	0.006	1.044	0.964	0.237	-0.017	1.044	0.886	0.237	0.000	1.044	0.963
Land	-0.004	0.053	0.938	0.828												
Toilet	0.618	0.007	0.336	0.977	0.618	0.020	0.336	0.939	0.618	-0.000	0.336	1.000	0.618	0.022	0.336	0.935
Distance	-0.513	0.020	0.411	0.822	-0.513	0.011	0.411	0.809					-0.513	0.004	0.411	0.808
Village party	0.212	0.111	2.102	1.400	0.212	0.093	2.102	1.320	0.212	0.017	2.102	1.046	0.212	0.040	2.102	1.118
Women union	0.317	-0.047	1.457	0.966	0.317	-0.032	1.457	0.977	0.317	0.007	1.457	1.006	0.317	-0.007	1.457	0.995
$\alpha$	0.046	-0.079	0.847	0.702					0.046	0.004	0.847	0.805	0.046	-0.009	0.847	0.759

Appendix B. Distributions of propensity score

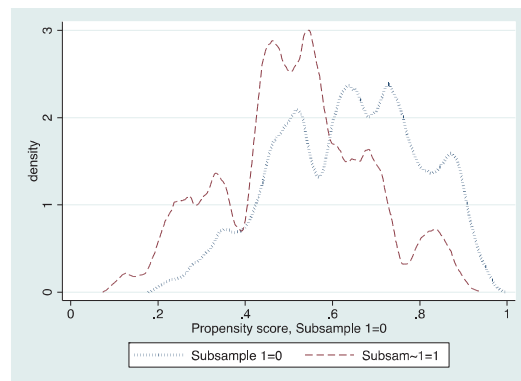
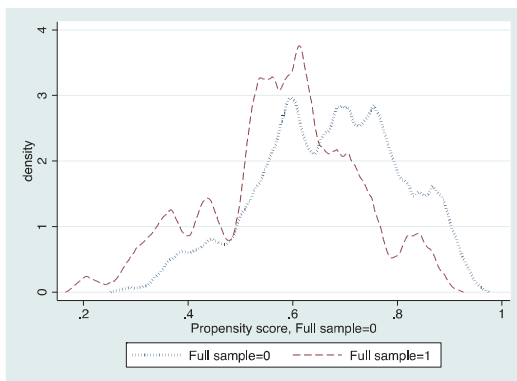
Full sample

Subsample 1

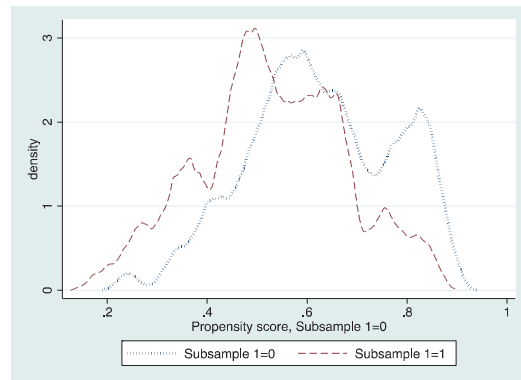
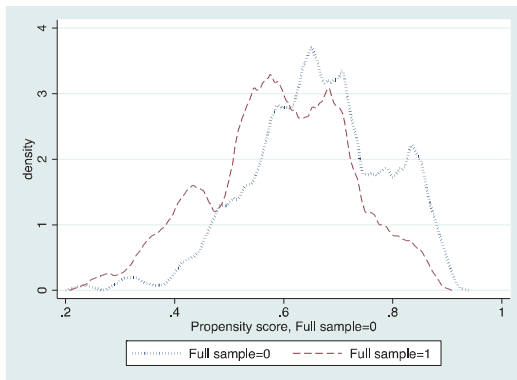
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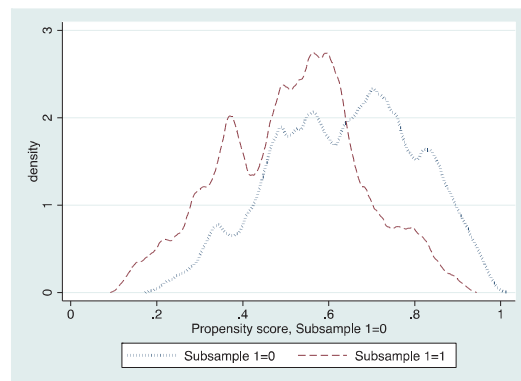
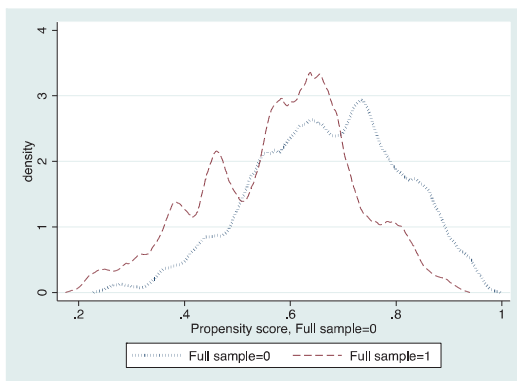
(2)



(3)



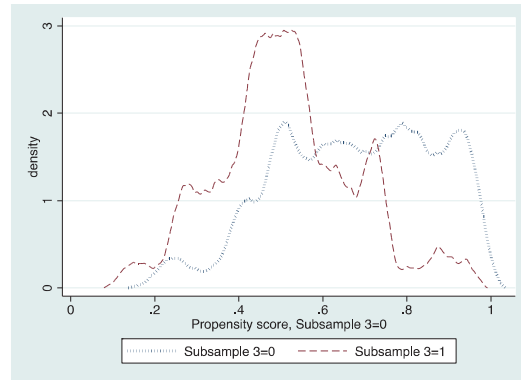
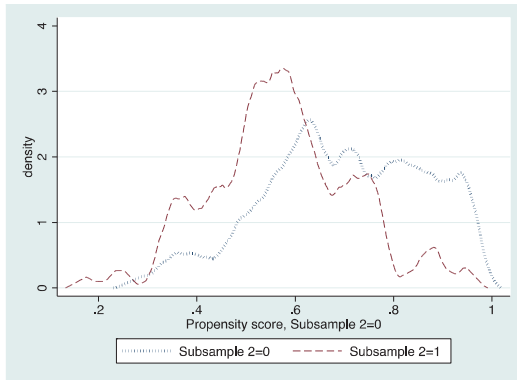
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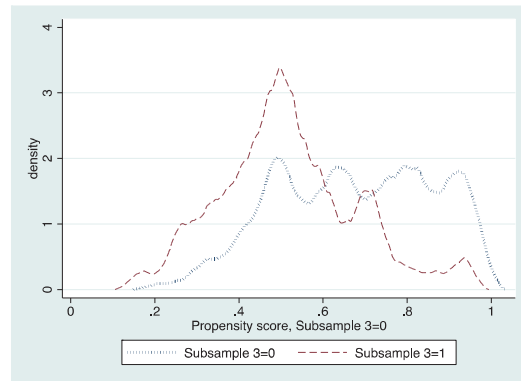
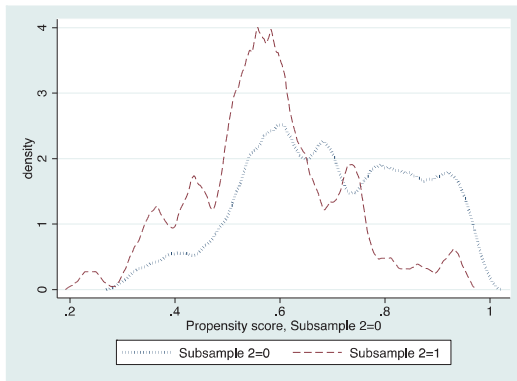
Subsample 2

Subsample 3

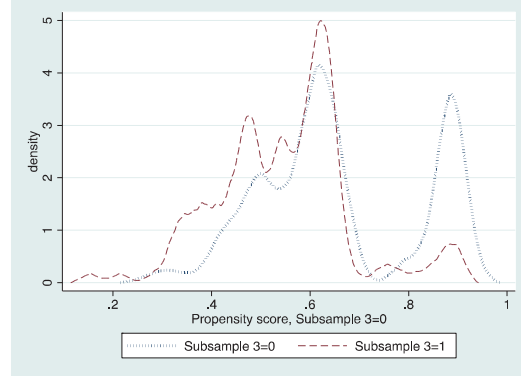
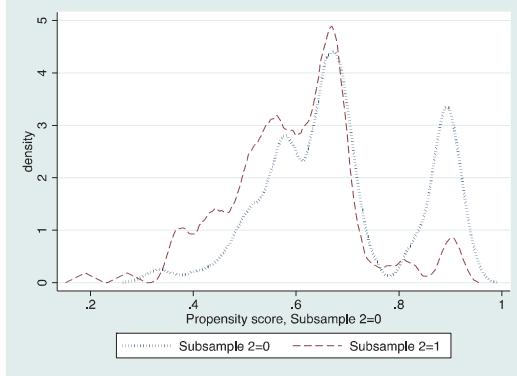
(1)



(2)



(3)



(4)

