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The welfare impact of community based health insurance scheme in Amhara region: Evidence from north wollo zone

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Acronyms

AC:Akaike critteria

ATE:Average treatment effect

ATT:Average treatment on the treated

ATU:Average treatment on the untreated

BIC: Bayesian crittria

CBHI:Comunity based health insurance

CBHIS:Community based health insurance scheme

COVID-19:Corona virus disease-19

EHIA:Ethiopian Health Insurance Agency

ESR:Endogeneous switching regression

ETB:Ethiopian Birr

FA:Fixed asset

FIML:Full Information Maximum Likelihood

GGE:general government expenditure

HI:Health insurance

IID:institute for international development

KII:Key informant interview

LR:likelihood ratio

NWZPDCO:North Wollo Zone Plan and Development Commission Office

OECD:Organization for economic cooperation and development

OOP:out of pokeet

OPP:out of pocket payments

ROC:receiver operating characteristic

SD:Standard deviation

SNNP:southern nations nationalities and peoples

TH:transitional hetrogeniety

TT:treatment on the treated

TU:treatment on the untreated

UHC:Universal health coverage

UNHCR: United nation high commissioner for refugees

USD:United states dolar

VIF:variance inflation factor

WHO:world health organization

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Abstract

This study, the welfare impact of community based health insurance scheme in Amhara region: evidence from north wollo zone, delves into the determinants and impacts of household membership in Community-Based Health Insurance Schemes (CBHIS) through comprehensive data analysis. The research involved 385 household heads, with a majority being members of the CBHIS. Key findings indicate significant associations between membership and socio-economic variables such as gender, marital status, education, and illness history. Logistic regression models reveal critical determinants affecting enrollment, including family size, trust, distance from health centers, and illness history. Furthermore, the study employs an Endogenous Switching Regression model to assess the impact of CBHIS on household income and assets. The results demonstrate that CBHIS membership have a mixed impact on household indicators. On one hand, it have a positive influences on household real asset levels and on the other hand it doesn't improve the household income of beneficiaries. Therefore targeting approach will be important to identify the most vulnerable portion of the society and mitigation strategies of service delivery system to reduce waiting time will be fruitful.

Key words: health insurance, endogenous switching regression, welfare, endogeneity household income

1. Introduction

1.1. Background of the study

On a global scale, a significant number of individuals, exceeding 150 million, experience substantial financial burdens due to healthcare expenses annually. These costs often push people into poverty, primarily due to out-of-pocket payments for medical treatments. This situation leads to approximately 25 million households living in extreme poverty each year. Notably, the majority of these healthcare-related financial challenges and their consequences occur in Sub-Saharan African countries, where resources are limited. As a result, Community-based Health Insurance (CBHI) has gained popularity as an interim solution for financing healthcare expenses in impoverished communities (Atnafu et al., 2018).

A number of countries have contained Community-Based health insurance as part of general health financing strategy for Underprivileged people who are excluded from formal insurance system and premised on the ideals of mutual aid and community self-determination. It is a voluntary and non-profit insurance scheme where community members pool and allocate resources, share risks, negotiate with providers and manage the operation of the scheme. Membership of CBHIS is an indicator of its success because participation is voluntary and measured as the proportion of the target population that is insured and up-to-date with payments. Its main aim is to protect low income households from health related risks through mutual risk sharing at the community level and enables health facilities to mobilize resources and enhance financial burdens (Dror DM., 2016, Mulugeta &Teka, 2020, Fite et al, 2021).

In June 2011, the Ethiopian government implemented a pilot project for Community-based Health Insurance (CBHI) in 13 districts across four major regional states: Tigray, Oromia, Amhara, and SNNP. The project's coverage expanded to an additional 161 districts in 2013. Initially, the project achieved significant success, but in subsequent years, there was an 18% decline in enrollment. It is important to note that the decision to join the scheme is made by the community, as CBHI is community-based in nature. The primary goals of introducing the scheme were to mitigate the financial burden caused by unexpected and irregular out-of-pocket payments and to enhance the pooling of resources for healthcare, thereby improving access to and utilization of health services (Getu and Asmamaw, 2021; Fite et al., 2021).

In north wollo zone of Amhara region, there are 291,425 households (69.1%) who are members of community based health insurance scheme and analyzing the welfare impact of this scheme in the study area is crucial to examine the impact of the program and will contribute for health insurance literature.

1.2. Statement of the problem

Health Insurance arises largely as a result of the unpredictability of ill-health, rather than the unpredictability of the effectiveness of health care, or because of the irregularity of consumption. Therefore utilization of health insurance scheme can help to take care of individual's everyday wellbeing, aids a speedy diagnosis and recovery through reduced waiting times, and helps to pay for some or all of the treatment that they need (Gebremeskel Tesfay, 2014).

In Ethiopia, the burden of household Out-of-Pocket healthcare expenditures is a significant public health problem and accounts about 34% (one-third) of total healthcare expenditure, and is one of the highest in the world and is associated with a lack of health insurance coverage and inadequate coverage. Moreover, household OOP healthcare expenditure is an obstacle for households in accessing healthcare services, however, it is one of the indices to evaluate and address the level of financial risk protection in healthcare systems, and of concern to policymakers and is a key priority in the global health policy agenda (Borde et al 2022).

Studies conducted on the analysis of community based health insurance scheme concluded that, it can increase health access, household welfare as well as health service utilization and the main aim of the Ethiopian community based health insurance is to reduce household's` cost that they expend for health care and to improve health care service utilizations (Yilma et al., 2014, Lesanework, 2018).

A recent systematic review of the literature on CBHI coverage in low-and middle-income countries shows that supply and demand side factors impact enrollment. There is a positive association between enrollment and the socio-economic status and size of households, as well as the educational level and age of household heads in sub-Saharan Africa. On the other hand, trust in the management of a scheme, quality health services and proximity to a health care center are supply side factors and was positively associated with enrollment and rate of renewal (Dror et al., 2016).

Atinafu et al., (2018), shows that there are a significance difference between CBHI member and non-member household heads and the difference is observed on the educational status, family

size, occupation, marital status, and travel time to the nearest health institution, perceived quality of care, first choice of place for treatment during illness and expected healthcare cost of a recent treatment.

Based on the study conducted by Asaye and Engidaw (2021), the logistic regression model shows that community awareness of the scheme utilization, family health condition, community commonality, quality of health service delivered by the health organizations and household wealth, were the major factors that determine community participation in the health insurance system.

As far as my knowledge is concerned, there is no any research conducted on the welfare impact of community based health insurance scheme in north wollo zone on one hand, most of the studies conducted on this area used either difference indifference (Zemzem et al 2020) or propensity score matching method (Yilma et al 2015,) of data analysis and this would increase the probability of endogeneity due to self-selection problems since the two models of impact evaluation techniques are based on observable factors on the other hand. Therefore this research can serve as a preliminary study for other works by using an endogenous switching regression method of data analysis for impact evaluation.

1.3. Objective of the study

1.3.1. General objective

The general objective of this study was analyzing the welfare impact of community based health insurance system in north wollo zone of Amhara region.

1.3.2. Specific objectives

The specific objectives of this study was

- To examine the determinant factors of CBHIS in the study area.
- To evaluate the impact of CBHIS on the economic welfare indicators of the household in the study area.

1.4. Significance of the study

Since the demand for health care service is not similar with the demand for other goods and service, being ill is unexpected in life. To reduce such unexpected risks in the life of the individuals, every country proposes and implements health policies for its citizens. In our country, the community based health insurance is the manifestation of this argument and studying the actual impact of such programs on the household's welfare indicator is a crucial

task. Therefore this study have been contribute to the literature by studying the determining factors of the CBHIS and its impact on household economic welfare in north wollo zone of Amhara region.

2. Literature Review

2.1.Theoretical literature review

2.1.1. Definition and Concepts of Health insurance

Health insurance can be defined as a way to distribute the financial risk associated with the variation of individuals' health care expenditures by pooling costs over time through pre-payment and over people by risk pooling (OECD, 2004). This can be either social or community based health insurance scheme.

Community based health insurance is a non-profit scheme organized to improve financial access to health care services and to protect its members against the financial risks associated with illness. It operates based on solidarity and mutual aid values with its institutional arrangements designed to maximize its key functions of revenue collection, risk pooling and purchasing of health care services. If universal healthcare coverage (UHC) is to be financed through insurance, the risk pool needs the following characteristics;

i. compulsory contributions to the risk pool (otherwise the rich and healthy will opt out)
ii. the risk pool has to have large numbers of people, as pools with a small number cannot spread risk sufficiently and are too small to handle large health costs; and
iii. There is large number of poor, pooled funds will generally be subsidized from government revenue (WHO, 2010, WHO, 2004).

A health shock adds the burden of health expenditure towards the poor households. One of the ways that poor communities manage health risks, in combination with publicly financed health care services, are community-based health insurance schemes (CBHISs). These are small scale, voluntary health insurance programs, organized and managed in a participatory manner. They are designed to be simple and affordable, and to draw on resources of social solidarity and cohesion to overcome problems of small risk pools, moral hazard, fraud, exclusion and cost-escalation (Steven R.Tabor, 2005).

2.1.2. Overview of the health sector in Ethiopia

Even if the Ethiopian health sector has made impressive gains in the last decade, it has been plagued by formidable challenges, particularly in the past two fiscal years. Since March 2019, the health sector has been suffering from the effects of the COVID-19 pandemic that shocked the health system, disrupted essential health services provisions, and has brought additional multifaceted challenges to the health system. It is not only the COVID-19 pandemic, but also armed Conflicts that resulted in internally displaced people in the country have also posed added dimensions to the hurdles the health system. Emergencies that followed conflicts have strained the health system with additional human and material resource needs. Responding to the arising health service needs of the public in the face of an unpredictable and ever changing world has been the key focus of the health system in the last two years to sustain the momentum and build on the gains (Fekadu, 2021)

A well-functioning health system is pivotal for delivering quality health services to every segment of the population in all settings. The world health organization (WHO) has set three goals, that require a health system to deliver high-quality and equitable health services such as improving the health of the population, fairness in financial contribution, and improving the responsiveness of the health system (Fekadu, 2021,WHO, 2010).

2.1.3. Health care expenditure in Ethiopia

Health care in Ethiopia is characterized by low health service utilization 0.34 (which is far behind WHO recommendation of 2 to 3), under financing (which is evidenced by per capita health spending expenditure of $21 (WHO recommendation is USD $60)), high OOP (34%), highly based on external fund (50%) and low health service quality, inequity and troubled sustainability of health care delivery. To solve those challenges and build an effective health care delivery system in order to achieve Universal Health Care, Strong financial base is a prerequisite (Dereje 2018).

Health insurance, together with a very good health system, should provide protection from large health expenditures and reduce the impact of ill health on the work force. However, the main indicator used is much too narrow and is measured in a short-run period. This measure, out of pocket expenditures or payments (OOP), is a standard measure of the financial burden of seeking health care and is measured over a period of a year or less. Household financial burden is distinguished from the cost of health care. High cost health service may not result in any

financial burden for a high income household while even relatively small amounts of expenditure for common illness can be financially disastrous for the poor. The household financial burden is measured in terms a household's capacity to pay rather than an absolute amount of out of pocket payments. A prepayment scheme can reduce a household's financial burden as risks are shared and contributions are pooled across population groups rather than borne exclusively with in an individual household (Gebremeskel., 2012, UNHCR., 2012).

If insurance is effective, we expect insured families to be less likely to take on new loans due to health care costs and less likely to sell land and other assets. If uninsured households sell productive asset or with draw children from school to help pay for care, the result is that a short term health shock can lower long term productivity and worsen long term poverty. Conversely, if health insurance can prevent large out of pocket expenditures, it may promote the accumulation of productive physical and human capital. Health insurance increases access and utilization because it lowers the price of health care. Individuals will have better health if they are utilizing preventive and curative health care when needed and in a timely manner. There is a positive impact of health insurance in low and middle income countries on access and utilization (AIID, 2013).

2.1.4. Health care financing and household financial protection

Ethiopia endorsed a healthcare financing strategy since 1998 that envisioned a wide range of reform initiatives to form the recent health system structure. Since the Ethiopian healthcare system is under tremendous reform, the health insurance (HI) strategy designed to promote equitable access to sustainable quality healthcare, increase financial protection and enhance social inclusion for the majority of Ethiopian families in the health sector (Zemene et al, 2020).

Even though Ethiopia has planned to achieve universal health coverage by 2035, the health service utilization in the country remained low (34.3%) compared to most of the African countries. Studies showed that poor health care financing is a major contributor for the low health service utilization in the country. Consequently, Ethiopia has designed two policy options; community-based health insurance and social health insurance schemes to improve the health care financing system. Community-based health insurance is a voluntary health insurance program designed to improve financial access to health care services for the informal sectors of rural communities (Biset et al., 2022).

2.1.5. Development of Community Based Health Insurance Scheme in Ethiopia

The Ethiopian Health Insurance Agency (EHIA) was established by the Council of Ministers to implement and lead Ethiopian health insurance. Its governance structure includes headquarter and 24 Branch offices located in different parts of the country. The headquarters and branch offices are staffed with the prerequisite human resources, budget and tools necessary to provide the services. The agency introduces social health insurance for formal workers and community based health insurance for informal workers. The second type of insurance, which is the community based health insurance, is an emerging and promising concept which addresses health care challenges faced in particular by the rural poor and workers of informal sector (Dereje., 2018, Gebremeskel., 2012).

In June 2011, the Ethiopian government introduced CBHI as a pilot project in 13 districts of the four major regional states of the country (Tigray, Oromia, Amhara and SNNP), which was then expanded to additional 161 districts in 2013. This project scored substantial success in the initial stage but dropped in the following years, that is, the enrolment decreased by 18%. While the scheme has been introduced by the government, the community determines whether or not to join the scheme since it is "community-based" (Getu and Asmamaw, 2021).

The country had planned to establishing community based health insurance (CBHI) schemes in 80% of woreda's and enroll at least 80% of households in order to reduce out-of-pocket health expenditure to less than 15%, increase general government expenditure on health (GGHE) as a share of total general government expenditure (GGE) from 6% to 10% in 2020 (Dereje 2018).

2.2.Empirical literature review

Community based health insurance scheme in Ethiopia reduces the probability of borrowing and household reliance on potentially harmful coping responses. But there is no evidence weather enrollment in the scheme affects consumption or livestock holdings (Yilma et al 2015).

Lisa Oberländer (2013) under takes a research on community based health insurance in Burkina Faso through regression discontinuity design and propensity score matching methodology. Initially, he restricts the sample size by age of the individual and incorporates only those who have the age of more than 16 years. This was due to the fact that medical expenses are expected to be covered by parents. Out of pocket expenditure was estimated as a share of total expenditure and the result ensures that community based health insurance scheme didn't reduce the out of

pocket expenditures. The researcher argues that this can be due to unfavorable incentive structures between community based health insurance scheme and health care providers.

Amenti and Sisay (2022) examine the associated factors of community based health insurance in Akaki distric of oromia region. Their study concludes that age, sex, household family size, household income and trustworthiness were the main and significant factors of community-based health insurance utilization.

The study conducted on Kilte Awelaelo District by Hellina Haileselassie (2014), illustrates that human capital variables such as household head age, education, participation of local meetings and awareness level regarding the CBHIS have a positive impact on the decision of a household to join the program. The access of microcredit service, on the other hand have a negative impact on their decision.

3. Research Methodology

3.1. Description of the study area

North Wollo is one of the eleven zones located in the Amhara region of northern Ethiopia. It is bordered by South Gonder Zone to the West, Wag-Humera Zone to the North West, Tigray Region to the North, Afar Region to the East, and South Wollo to the South. The zone's precise geographical coordinates extend between 110:21' - 120:24' N latitude and 380:27' - 390:57'E longitude. It comprises eleven woredas (districts) and seven town administrations.

According to the North Wollo Zone Plan and Development Commission Office (NWZPDCO) in 2022, the current total population of the zone is 1,813,765, with 907,421 males and 906,344 females. The majority of the population, approximately 81.88%, resides in rural areas. The National Community Health Insurance scheme has been implemented in all woredas and town administrations, with a total of 291,425 member households. However, the NWZPDCO reports that 14.4% of these households were unable to pay the renewal payment during the 2022 fiscal year, indicating financial challenges.

3.2. Type, Source and method of data collection

This study utilized both primary and secondary data. The primary data was collected through structured questionnaires and key informant interviews to gather information on socio-economic variables that could impact household enrollment and utilization of the community-based health insurance scheme. The questionnaires were administered to selected household heads, while the key informant interviews involved zone and woreda health officers and workers who provided valuable insights into the barriers to access and enrollment in the scheme. On the other hand, the secondary data was obtained from the zone health office and focused on households participating in the scheme in both rural and urban areas since its inception.

The methods of data collection that was applied in this research were;

A. Structured questionnaire

Structured questionnaires were used to collect data from a selected sample of both scheme members and non-members who were household heads. These questionnaires consisted of both open-ended and closed-ended questions and were initially developed in English and later translated into Amharic, the local language spoken in the study area. The questionnaires were administered after conducting a pilot survey.

B. Key informant interview (KII)

Key informant interviews were conducted with community-based health insurance specialists at the zone level and randomly selected household heads. The aim of these interviews was to assess the perspectives of households regarding CBHIS utilization, the challenges they encountered during their involvement in the scheme, and the procedures for renewal. An open-ended questionnaire was prepared to guide these interviews.

3.3. Sampling method and sample size determination

In the study area, there are 421,806 household heads. To select the representative sample of the target population (household heads), the Cochran's (1963) formula of sample size determination for infinite population was used and which is presented as follows.

$$n_0 = \frac{z^2 pq}{(e)2}$$

$$= n_0 = \frac{(1.96)^2 * (0.5)^2}{(0.05)2}$$

$$= 385$$

Where, n_0 = sample size, e = the level of precision at 95% of confidence interval

Even though the Cochran formula can be extended for correction formulae, in this case the sample size is less than 5% of the target population. Therefore n_o is taken as the sample size of this study, *n*.

To obtain the above representative sample, the study applied multi-stage probability sampling method. In the first stage, the representative samples was classified in to two strata's based on the area they live as urban and rural settlers. In the second stage, systematic random sampling was applied in each stratum to select two town administrations (woldia and lalibela) and three rural woreda's (habru, gidan and wadila). In the third stage, representative kebelles was selected in each stratum proportionally through systematic random sampling. In the last stage, based on the status of the household they have in CBHIS, households in the selected kebelles have been stratified as users and non-users of the scheme and the sample was selected from each strata proportionally as

$$n_i = {}^{N_i}\!/_{N} \times n,$$

where

$$ni = sample\ size\ of\ the\ strata\ i, Ni = total\ househlds\ of\ strata\ i,$$
$$N = total\ households\ of\ the\ sample\ unit\ and\ n = total\ sample\ size$$

3.4. Method of data analysis

3.4.1. Descriptive analysis

Descriptive method of data analysis was used to explain the socio-economic and demographic characteristics of the respondents and the information obtained from the key informant interview through simple mean, frequency and pie charts.

3.4.2. Econometric analysis

3.4.2.1. The logistic regression model

To examine the factors influencing household access and utilization of the community-based health insurance scheme, a logistic regression model was employed. This choice was made due to the nature of the variables, particularly the dependent variable. The logistic regression model

is suitable for assessing the relationship between a set of independent variables and a binary outcome variable.

Unlike linear regression models, logistic regression can handle non-linear relationships between the dependent and independent variables by applying a non-linear log transformation. Furthermore, the logistic regression model does not assume that the error terms (residuals) follow a multivariate normal distribution. However, having multivariate normality can lead to a more stable solution, and it assumes independence of observations. Additionally, the model requires minimal multicollinearity and does not necessitate a linear relationship between the dependent and independent variables (Peng, C. J. & So, T. H., 2002).

It is worth noting that the logistic regression model requires larger sample sizes compared to ordinary least squares used in linear regression models, as maximum likelihood estimates are less powerful. Given that the dependent variable in this study is dichotomous (access to CBHIS or no access), a logistic model, which is a type of univariate binary model, is preferred. The predictor variables consist of socioeconomic and demographic status indicators, as well as information on household dwelling endowment.

The dichotomous dependent variables were expressed as:

$$y_i = \begin{cases} 1 \;\; if \;\; y_i^* > 0 \\ 0 \;\; Otherwise \end{cases}$$

Where y* is a latent variable expressing the decision of households in CBHIS participation which is a function of the household characteristics (X_i), as expressed in the form of

$$y_i^* = \beta_0 + \sum_{j=1}^{n} \beta_i X_{ij} + \mu_i \ldots\ldots\ldots\ldots\ldots \text{eq}_1$$

A logit model depends on the assumption of the logistic distribution of the error term in equation 1. In the dichotomous analysis of outcome variable, Wooldridge, J. (2004) pointed out that the logistic distribution (logit) has an advantage over the other models because of its extreme flexibility and ease of use from mathematical point of view and results in a meaningful interpretation. The cumulative logistic probability function was specified as:

$$p_i = f(Z_i) = F\left(\beta_0 + \sum_{i=1}^{n} \beta_i X_i\right) = \frac{1}{1 + e^{-Z_i}} \ldots\ldots\ldots\ldots eq_2$$

Where Pi is the probability that a household is using community based health insurance scheme given its X_i, and β_0 and β_i are the parameters to be estimated. To understand the interpretation of

the coefficients, the logit model could be written in terms of the odds and log of odds. The odds ratio implies the ratio of the probability p_i that an individual would choose an alternative to the probability $(1-p_i)$ that the person would not choose it. After a simple mathematical manipulation of the above equation, equation 2, it can be written as

$(1-p_i) = \frac{1}{1+e^{Z_i}}$ $Or\left(\frac{P_i}{1-P_i}\right) = \frac{1+e^{Z_i}}{1+e^{-Z_i}} = e^{Z_i}$; Which implies the odds ratio.

By taking the natural logarithms of the odds ratio with the consideration of the expected errors made during the research process, the Logit model becomes

$$Z_i = ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \sum_{j=1}^{n} \beta_i X_i + \mu_i$$

Therefore, the coefficient of the logit model β_i, presents the change in the log of the odds associated with a change in the explanatory variables, X_i.

3.4.2.2. The endogenous switching regression model

The decision of households to participate in a community-based health insurance scheme is not random, as they self-select based on their perceptions of the benefits. Households choose to use the insurance scheme only if they believe it will provide increased healthcare services and reduce their health expenditures. Therefore, comparing the income and accumulated assets of member and non-member households is not feasible due to selection bias, which introduces potential endogeneity issues. To address this problem of selection bias and control for structural differences between member and non-member households, the endogenous switching regression model is commonly employed.

The endogenous switching regression model tackles the issue by dividing individual household heads into different groups or positions and examines the impact of these positions on outcome variables, such as welfare indicators. The model consists of two components: the selection equation and the outcome equation. The selection equation focuses on the decision-making process or participation equation, while the outcome equation analyzes the relationship between the positions and the outcome variables.

The selection or participation equation is formulated as

$$I^* = \alpha Z_i + u_i \quad with \; I_i = \begin{cases} 1, if \; I^* > 0 \\ 0, otherwise \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

Where I^* is the latent variable, which is not observed and be expressed as a function of some observed household and institutional characteristics.

As already seen in the above equation, I_i is a binary variable which takes a value of '1' for those who participate in insurance scheme and '0' for those who didn't participate. Z_i, represents factors that affect the scheme utilization decision and incorporates at least one explanatory variable which is not available in the regime equation. α, denotes the vector of parameters indicating the magnitude and direction of each explanatory variable's effect on the decision to participate in insurance scheme. The residual u_i captures the unobserved factors and measurement errors.

The outcome or regime equation on the other hand can be shown as;

$$R_1: lnY_{1i} = \begin{Bmatrix} ln\, y_{1i} \\ ln\, FA_{1i} \end{Bmatrix} = \beta_1 x_{1i} + \varepsilon_{1i} \;\; if\; I_i = 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

$$R_2: lnY_{2i} = \begin{Bmatrix} ln\, y_{2i} \\ ln\, FA_{2i} \end{Bmatrix} = \beta_2 x_{2i} + \varepsilon_{2i} \;\; if\; I_i = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

Where, lnY_{1i} and lnY_{2i} are the natural logs of welfare indicators (outcome variables) for regime 1 and regime 2 respectively which are determined by the exogenous variables X_{ji}, β_1 and β_2, are parameters that show the direction and strength of the relation between the outcome variable and the independent variables. In this research welfare will be captured by household income (Y) and fixed assets (FA) where, lnY_{1i} and $lnFA_{1i}$ represents the natural logs of income and fixed assets for members of the insurance scheme and lnY_{2i} and $lnFA_{2i}$ are natural logs of income and fixed assets for non-members of the program.

The error terms of the above three consecutive equations (equations 1, 2 and 3) are assumed to have a trivariate normal distribution with zero mean and covariance matrix Σ, where

$$\Sigma = \begin{bmatrix} \sigma_u^2 & \cdot & \cdot \\ \sigma_{1u} & \sigma_1^2 & * \\ \sigma_{2u} & * & \sigma_2^2 \end{bmatrix}$$

Where,

- σ_u^2, is the variance of the error terms in selection equation which is assumed to be one and coefficients are estimated up to a scale factor,
- σ_1^2 and σ_2^2 are the variance of the error terms in the outcome equation and
- σ_{1u} and σ_{2u} are the covariance of the participation equation and each outcome equation error terms.

On the other hand the * sign reflects the covariance of the error terms between each individual outcome equations since Y_{1i} *and* Y_{2i} are not observed simultaneously.

The most important implication of the error terms structure is that, the correlation of error terms in the selection and outcome equations and their conditional expectation is non-zero

$$E[\varepsilon_{1i} / I = 1] = Cov(\varepsilon_{1i}, u_{1i}).\frac{\phi(\alpha Z_i)}{\Phi(\alpha Z_i)} = \sigma_{1u}.\lambda_{1i} \text{.....[4]}$$

$$E[\varepsilon_{2i} / I = 0] = Cov(\varepsilon_{2i}, u_{2i}).\frac{\phi(\alpha Z_i)}{1-\Phi(\alpha Z_i)} = -\sigma_{2u}.\lambda_{2i} \text{.....[5]}$$

The efficient way of estimating endogenous switching regression model is by using the Full Information Maximum Likelihood (FIML) technique (Lokshin & Sajaia, 2004). Given the assumptions of error term distribution, the logarithmic likelihood function becomes

$$\ln L_i = \sum_{i=1}^{n} I_i[\ln \phi(\frac{\varepsilon_{1i}}{\sigma_1}) - \ln \sigma_1 + \ln \Phi(\tau_{1i})] + (1 - I_i)[\ln \phi(\frac{\varepsilon_{2i}}{\sigma_2}) - \ln \sigma_2 + \ln(1 - \Phi(\tau_{2i}))] \text{.....[6]}$$

Where; $\tau_{ji} = \dfrac{(Z_i \alpha + \rho_j \varepsilon_{ji} / \sigma_j)}{\sqrt{1-\rho_j^2}}$, $j = 1,2.....k$

ρ_j, denotes the correlation coefficient between the error terms of the selection equation (u_i) and the outcome equations [(ε_{1i}) and (ε_{2i})].

The conditional expectation of the treatment and the counterfactual group of CBHI utilization is shown as follows.

$$E(Y_{1i} / I_i = 1) = X_{1i}\beta_1 + \sigma_{1u}\lambda_{1i}$$

$$E(Y_{1i} / I_i = 0) = X_{2i}\beta_1 + \sigma_{1u}\lambda_{2i}$$

$$E(Y_{2i} / I_i = 1) = X_{1i}\beta_2 + \sigma_{2u}\lambda_{1i}$$

$$E(Y_{2i} / I_i = 0) = X_{2i}\beta_2 + \sigma_{2u}\lambda_{2i}$$

According to Heckman *et al.* (2001), we can calculate the treatment effect on the treated, which is the main concern of policy makers, and it is the difference between the treated group and the counterfactual as well as the ATU as follows.

$$ATT = E(Y_{1i} / I_i = 1) - E(Y_{2i} / I_i = 1) \Rightarrow X_{1i}(\beta_1 - \beta_2) + (\sigma_{1u} - \sigma_{2u})\lambda_{1i} \text{.....[7]}$$

$$ATU = E(Y_{2i} / I_i = 0) - E(Y_{1i} / I_i = 0) \Rightarrow X_{2i}(\beta_2 - \beta_1) + (\sigma_{2u} - \sigma_{1u})\lambda_{2i} \text{.....[8]}$$

Individual households who are community based health insurance scheme members may have more income and accumulate more asset than the non-members regardless of the fact that they decided to use insurance scheme but due to the unobservable characteristics and this is called the effect of base heterogeneity. Base heterogeneity (BH_1) for those households who decide to participate in insurance scheme becomes

$$BH_1 = E(Y_{1i} / I_i = 1) - E(Y_{1i} / I_i = 0) \Rightarrow (X_{1i} - X_{2i})\beta_{1i} + \sigma_{1u}(\lambda_{1i} - \lambda_{2i}) \text{.....[9]}$$

For the group of households that decided not to participate, "the effect of base heterogeneity" will be

$$BH_2 = E(Y_{2i} / I_i = 1) - E(Y_{2i} / I_i = 0) \Rightarrow (X_{1i} - X_{2i})\beta_{2i} + \sigma_{2u}(\lambda_{1i} - \lambda_{2i}) \text{.....[10]}$$

Finally, the effect called "transitional heterogeneity" (TH) estimates whether the effect of using CBHIS is larger or smaller for households that are members of CBHIS or for the households that are not members in the counterfactual case that they be a member. It is the difference between (Equation 7) and (Equation 8), *i.e.* (ATT) minus (ATU):

$$TH = ATT - ATU \text{.....[11]}$$

3.5. Description and expected sign of working variables

The descriptions and expected sign of the working variables were described in the following table.

variable	Description of variables	Expected sign
Community based health insurance scheme (CBHIS)	1= if they are members, 0 = otherwise	
Household income	the total income accrued per year	
Fixed asset	total fixed asset of the household converted in to ETB	
Gender	1=male, 0 = female	+
age	Years of the age of the household head	-

Marital status	0=single, 1=married, 2=divorced, 3=widowed	+
Education	0 = illiterate, 1 = read and write, 2 =primary education, 3=secondary education, 4 = tertiary education and above	+
Family size	0=household members <3, 1=household members 4-5 2= household members >6	+
Location	0= rural, 1= urban	+
Farm size	Total land size owned in hectare	+
occupation	0= agricultural worker, 1=off-farm worker, 2=service worker, 3= small business4=housewife, 5= unemployed, 6= others	+
Awareness	0=low 2= medium 3= high	+
Trust	1= have high trust on CBHIS, 0=otherwise	+
Affordability of registration fee	1=easy, 2 = difficult	+
Distance from health center	the household distance from the health center in km	-
Access to credit	1= credit user, 0= non-user	+
Income share of OOP	the share of out of pocket expenditure from the household total income	+
Illness history	0=illness<2 times,1=illness history 2-4, 2=illness 4-6 times	+

Table 1: Description of working variables

4. Data analysis and Discussion of results

4.1. Descriptive analysis

4.1.1. Background of the respondents

As mentioned earlier, this study was conducted by using the primary data collected from 385 household heads of which 65.97% were members of the community based health insurance scheme, depicted in the following pie chart.

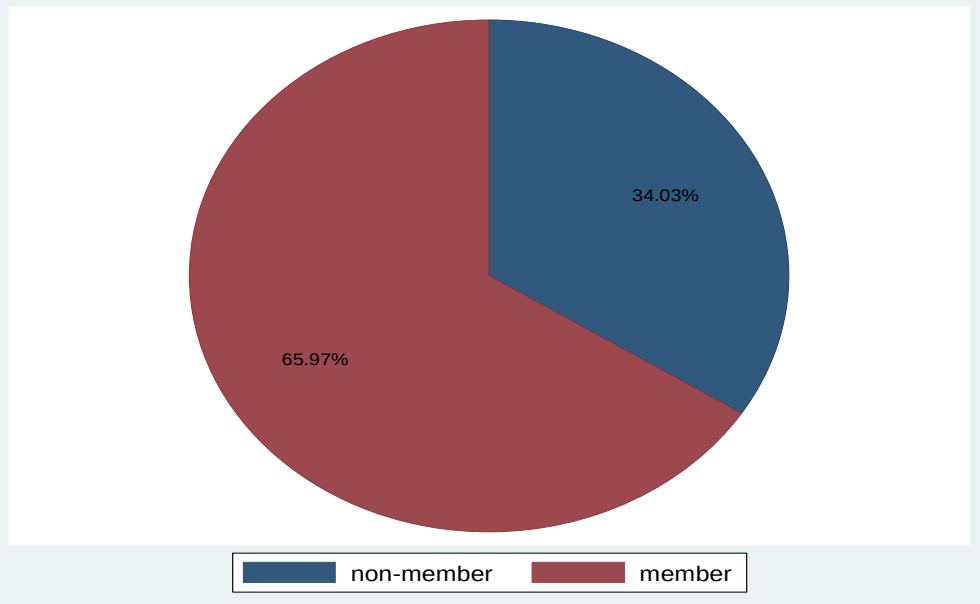

Figure 1: Background information of the respondents

The household level characteristic variables are explained by the following table preceded by the explanation derived from it.

Summary of dichotomous variables									
Variables		Household membership status of CBHS				Total		Pearson chi^2	P-value
		Members		Non-members					
		Frequency	Percentile	Frequency	Percentile	Frequency	Percentile		
Gender	Male	172	44.68	96	24.49	268	69.61		
	Female	82	21.39	35	9.09	117	30.39	1.265	0.261
Marital status	Single	40	10.39	19	4.49	59	15.32		
	Married	135	35.06	73	18.96	208	54.03		
	Divorced	40	10.39	40	10.39	58	15.06		
	Widowed	39	10.13	39	10.13	60	15.58	0.45	0.930
Educational status	Illiterate	56	14.55	70	7.79	86	22.34		
	Read &write	71	18.44	35	9.09	106	27.53		
	Primary educ.	73	18.96	32	8.31	105	27.27		
	Secondary educ.	34	8.83	25	6.49	59	15.32		
	Tertiary educ. & above	20	5.19	9	2.34	29	7.53	2.612	0.625

Summary of continuous variables						
Variables	Household membership of CBHS	Mean	St.Err	St.Dev	t-value	p-value
Age of the household head	Member	45.562	0.588	9.386	-0.872	0.383
	Non-member	44.664	0.845	9.676		
Family size	Member	1.031	0.049	0.784	3.844	0.000
	Non-member	1.358	0.069	0.794		

Table 2: Description of respondent's background

As already seen in the above table, table 2, the majority of the respondents was male headed and married households which constitutes 69.61% and 54.03% respectively. The educational status of the household head shows that most of the respondents can read and write. Based on the membership category, the majority of the household heads are educated (65.97%) than the non-members. The chi^2 distribution of those dichotomous household characteristics variables show there is the distributional difference between the two groups. The mean age of the household heads for the members were slightly higher than the non-members. There is no distributional difference between the family size of member and non-member household heads in the study area as the p value of the two-way t-test is statistically significant.

4.1.2. Description of socio-economic variables

Summary of dichotomous variables								
Variables	Household membership status of CBHS				Total		Pearson chi^2	P-value
	Members		Non-members					
	Freque	Percen	Freque	Percen	Freque	Percen		

		ncy	tile	ncy	tile	ncy	tile		
Location	Rural	198	51.43	95	24.68	293	76.1	1.403	0.236
	Urban	56	14.55	36	9.35	92	23.9		
Occupation	Agricultural worker	132	34.29	68	17.66	200	51.95		
	Off-farm worker	24	6.23	7	1.82	31	8.05		
	Civil servant	12	3.12	10	2.60	22	5.71		
	Small business	46	11.95	25	6.49	71	18.44		
	House wife	2	0.52	3	0.78	5	1.30		
	Unemployed	31	8.05	14	3.64	45	11.69		
	Others	7	1.82	4	1.04	11	2.86	4.833	0.565
Awareness	Low	100	25.97	87	22.60	187	48.57		0.000
	Medium	79	20.52	26	6.75	105	27.27	25.943	
	High	75	19.48	18	4.68	93	24.16		
Trust	Low	94	24.42	104	27.01	198	51.43	62.145	0.000
	High	160	41.56	27	7.01	187	48.57		
Fee affordability	Difficult	148	38.44	44	11.43	192	49.87	21.056	0.000
	Easy	106	27.53	87	22.60	193	50.13		
Access to credit	User	109	28.31	86	22.34	195	50.65	17.872	0.000
	Non-user	145	37.66	45	11.69	190	49.35		
Illness history	< 2 times	59	15.32	46	11.95	105	27.27	7.693	0.053
	2-4 times	38	9.87	22	5.71	60	15.58		
	5-6 times	87	22.60	37	9.61	124	32.21		
	>6 times	70	18.18	26	6.75	96	24.94		

Summary of continuous variables

Variables	Household membership of CBHIS	Mean	St.Err	St.Dev	t-value	p-value
Farm size	Member	0.586	0.029	0.466		
	Non-member	2.067	1.515	17.344	0.977	0.33
Distance from health center	Member	9.261	0.25	3.997	-5.595	0.000
	Non-member	6.851	0.35	4.01		
Income share of OPP	Member	0.319	0.004	0.071	-7.542	0.000
	Non-member	0.254	0.007	0.084		

Table 3: description of socio-economic variables

The above table, Table 3, provides a clear depiction of the socio-economic variables. An important determinant of household membership in the community-based health insurance scheme is the awareness of household heads regarding its benefits. The table shows that 24.16% of respondents have a high level of awareness about the utilities of CBHIS, while the majority (48.57%) have a low level of awareness. Since CBHIS membership is based on the free enrollment of household heads, individuals' trust in the system plays a crucial role in determining the enrollment rate. In this study, 41.56% of member household heads exhibit a high level of trust in CBHIS procedures, whereas 27.01% of non-members have low trust in the scheme. Another significant variable that affects CBHIS membership is the affordability of insurance premiums and renewal fees. The majority of members state that the registration and renewal fees, or insurance premiums in general, are difficult to afford.

Furthermore, members of the community-based health insurance scheme have a higher frequency of illness history, which occurred 5-6 times in the previous fiscal year of 2021. Additionally, continuous socio-economic variables such as farm size, distance from the health center, and income share of out-of-pocket expenditures reveal that members of the scheme, on average, have larger farm sizes, are located farther from the health center, and utilize a higher income share compared to non-members.

4.2. Econometric analysis

4.2.1. Determinants of household membership to community based health insurance scheme

The logistic regression model used in this study was evaluated for multicollinearity using the variance inflation factor (VIF) and for model sensitivity and specificity through receiver operating characteristic (ROC) curve analysis. The VIF results indicated that there was no issue of high multicollinearity, as the mean VIF was 3.74. Additionally, the area under the ROC curve was 0.84, suggesting that the model did not exhibit problems with model selection.

The maximum likelihood estimates of the logistic regression model revealed several important factors that influenced household membership in the community-based health insurance scheme. These factors included family size, individuals' trust in the scheme, and distance from the health center, access to microcredit services, household members' illness history, household head age, and household location. Since the coefficients of the logistic regression model are interpreted in terms of odds ratios, the following table presents the marginal effects of the logit model.

y = Pr (Household membership of CBHIS) (predict)
= .72616734

variable	dy/dx	Std.Err.	Z	P>z	[95% C.I.]		X
gender*	-0.092	0.061	-1.500	0.133	-0.211	0.028	0.696
age	0.005	0.003	1.720	0.086	-0.001	0.011	45.257
Marital status	-0.055	0.031	-1.760	0.079	-0.117	0.006	1.309
education	-0.030	0.021	-1.410	0.158	-0.071	0.011	1.582
Family size	-0.101	0.036	-2.780	0.005	-0.172	-0.030	1.143
location*	0.125	0.073	1.710	0.087	-0.018	0.268	0.239
Farm size	-0.003	0.002	-1.610	0.107	-0.006	0.001	1.090
occupation	-0.003	0.017	-0.170	0.868	-0.037	0.031	1.556
trust*	0.393	0.048	8.110	0.000	0.298	0.488	0.486
Distance from health center	0.037	0.008	4.890	0.000	0.022	0.052	8.441
Access to credit*	-0.213	0.053	-4.030	0.000	-0.317	-0.110	0.506
Illness history	0.074	0.025	2.980	0.003	0.026	0.123	1.548

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Table 4: Marginal effects after logit

According to the findings, several factors were found to be significant in determining the likelihood of joining a community-based health insurance scheme (CBHIS). Firstly, the age of the household head was found to be significant at a 90% confidence interval. The results indicate that for every one-year increase in the age of the household head, the probability of joining the CBHIS increased by 0.005 times. This suggests that as individuals grow older, they tend to seek more security and social capital, leading to a higher likelihood of joining the program. This finding is consistent with previous studies conducted by Chanie and Ewunetie (2020), Amenti and Sisay (2022), and Hellina (2014).

Secondly, marital status was found to be another important determinant. Specifically, being widowed was found to significantly reduce the probability of joining the scheme at a 10% level of significance. The reason behind this result is attributed to the financial difficulties faced by widowed household heads in meeting the renewal fees of the insurance scheme compared to single heads. This finding aligns with the research conducted by Bantie et al. (2020).

Moreover, the number of members in the household was found to have a negative relationship with joining the CBHIS. For every additional individual in the household, the probability of joining the scheme decreased by 0.1 at a 95% level of significance. This suggests that the addition of a new member to the household reduces the available resources, income, and wealth base, thereby decreasing the likelihood of joining the insurance scheme. This finding is consistent with the study by Amenti and Sisay (2022).

Additionally, the area of residence was found to influence the likelihood of joining the CBHIS. Specifically, residing in urban areas was associated with a 0.125 increase in the probability of membership, all else being equal. It is not in line with the previous studies like Wondesen T (2022). This can be attributed to the proximity of urban dwellers to information and awareness about the CBHIS, which affects their decision to join the program.

Furthermore, trust and confidence in the supply of quality and affordable healthcare services were found to play a significant role in determining membership in the CBHIS. Individuals with higher trust in the scheme's delivery system were 0.393 times more likely to join compared to those with low trust. This finding aligns with the study conducted by Chanie and Ewunetie (2020).

Moreover, proximity to healthcare centers was found to influence the likelihood of joining the CBHIS. For every one kilo meter increase in distance from the health center, the probability of

joining the scheme increased by 0.04 times. This can be attributed to the lack of alternative healthcare centers for household heads living far from the health centers, leading them to opt for the insurance scheme. Interestingly, this finding contradicts the results of Asfaw et al. (2022), but the details of their study are not provided.

The use of micro-credit loans was found to have an inverse relationship with CBHIS membership. If a household received a micro-credit loan, the probability of joining the scheme decreased by 0.213. This finding is consistent with the results of Hellina (2014) and Asfaw et al. (2022).

Finally, the household's illness history in the previous year was found to be a key indicator of CBHIS membership. There was a positive relationship between the number of illnesses experienced by the household and the decision to join the scheme. If the household had a history of more than six illnesses in the previous year, the probability of membership increased by 0.07 times compared to households with a lower patient history. This result is supported by the study conducted by Asaye and Engidaw (2021).

Based on the insights shared by key informants, it is apparent that one of the primary objectives of the scheme is to deliver high-quality health services. However, this goal has not been fully accomplished thus far due to the presence of numerous health service delivery institutions that lack effective management processes. Additionally, patients often face long waiting times, and there seems to be a tendency to prioritize cases where out-of-pocket payments are made. Consequently, the researcher concludes that while a majority of respondents from both kebelles hold positive attitudes towards the quality of services offered by the scheme, there are underlying issues that they are unaware of. Moreover, the key informants stress the significance of affordability in establishing the scheme, as it relies on the income potential of the community. Some individuals even feel compelled to register twice and make a single payment, assuming that if they did not visit the clinic in the previous year, their payment would suffice for the following year.

In summary, the scheme's objective of providing high-quality health services has not been fully achieved due to deficiencies in management processes and challenges related to waiting times and prioritization. The affordability aspect, dependent on community income, is crucial. The practice of double registration in a single payment further highlights the need for improvements and clarity in the scheme's implementation.

4.2.2. The impact of community based health insurance scheme on household income and asset

4.2.2.1. The impact of community based health insurance scheme on household income

The ESR model was estimated using the efficient method of full information maximum likelihood estimation, as suggested by Lokshin and Sajaia (2004). The estimated coefficients for both the decision to join the community-based health insurance (CBHIS) and household income and asset formation were found to be statistically different from zero in both regime one and regime two. The covariance between the participation equation (CBHIS membership) and the outcome equations (household income and asset) was found to be non-zero, indicating the presence of endogenous switching in the model, as proposed by Madala (1986). This makes the rationality of using the ESR model.

The correlation coefficients between CBHIS participation equation and the income of member and non-member households (ρ_1 and ρ_2), respectively are both negative and statistically significant which indicates the presence of self-selection in the participation equation due to sample selection bias. This negative correlation coefficients suggest that there are unobserved factors influencing both the decision to enroll in CBHIS and the level of household income which implies that households with lower unobserved income potential are more likely to enroll in CBHIS, while households with higher unobserved income potential are less likely to enroll.

The likelihood ratio test was significant at 95% level of significance, implying that the three equations (the participation equation and the two outcome equations) are jointly dependent, which give an evidence for the existence of endogeneity that needs to be controlled. The ESR estimates of CBHIS on household income is shown below.

Endogenous switching regression model Number of observation = 385

Wald chi^2 (12) = 13.63

Log likelihood = -332.17472 Prob > chi^2 = 0.3246

Variables	Household income for members			Household income for non-members			Household income for both households		
	Coef.	Std.Err.	P>z	Coef.	Std.Err.	P>z	Coef.	Std.Err.	P>z
Gender	0.045	0.069	0.516	0.089	0.079	0.263	-0.021	0.211	0.920
Age	0.001	0.003	0.732	0.000	0.003	0.935	0.014	0.009	0.123
Marital status	-0.006	0.034	0.853	-0.012	0.038	0.751	-0.111	0.102	0.274
Education	-0.017	0.026	0.516	0.031	0.028	0.256	-0.085	0.080	0.287

Family size	0.032	0.038	0.394	-0.049	0.040	0.221	-0.302	0.114	0.008
location	-0.093	0.104	0.371	-0.163	0.098	0.096	0.642	0.292	0.028
Farm size	-0.013	0.095	0.890	0.003	0.002	0.069	-0.015	0.042	0.727
Occupation	0.012	0.021	0.585	0.032	0.020	0.114	-0.054	0.056	0.329
Trust	-0.104	0.064	0.107	-0.018	0.093	0.848	1.297	0.182	0.000
Distance from health center	-0.020	0.008	0.009	0.007	0.010	0.467	0.120	0.025	0.000
Access to credit	0.054	0.059	0.358	0.029	0.069	0.669	-0.571	0.170	0.001
Illness history	0.016	0.028	0.565	0.028	0.028	0.323	-0.021	0.086	0.807
Fee affordability							-0.259	0.168	0.124
Income share of OOP							8.160	1.201	0.000
_cons	12.074	0.222	0.000	11.662	0.216	0.000	-3.023	.716	0.000
sigma_1	0.432	0.021	0.000						
sigma_2	0.334	0.022	0.000						
rho_1	-0.398	0.135	0.000						
rho_2	-0.173	0.272	0.000						
LR test of independent equations:		**chi2 (1) = 5.39**			**Prob > chi^2 = 0.0203**				

Table 5 : The ESR estimates of CBHIS on household income in the study area

The crucial question is whether households that are members of CBHIS experience improvements in their income. The following table, table 6, compares the conditional expectation of household income between CBHIS members and non-members. According to the table, the observed difference in income between members and non-members (ATE) is 0.02 (2%). However, this simple comparison can be misleading since it does not account for unobserved factors that may affect the outcome variables.

To obtain a more accurate impact estimate, Carter and Milon (2005) suggest incorporating the underlying heterogeneity due to potential unobservable effects on household income. Under the counterfactual conditions, where CBHIS members are placed in non-member households (BH1), it is expected that their average income would be 27% lower than that of non-members. Similarly, if non-member households were placed in member households (BH2), their income would be increased by 10%.

Therefore, based on the counterfactual conditions of household income, non-members under the status of being CBHIS members perform worse off than CBHIS members. This indicates that the CBHIS effects are lower for the counterfactual non-member households, resulting in a positive heterogeneity effect on household income. The heterogeneity effect (TH) was -0.27, indicating that there is a negative impact on household income for CBHIS member households compared to

CBHIS non-member households after accounting for the unobserved heterogeneity. The decision of households to be enrolled or not is presented by the following table.

	Decision stage				
	Enroll		Not-enroll		
	Mean	Standard deviation	Mean	Standard deviation	**Treatment effects**
Members of CBHIS	11.87	0.005	11.95	0.021	TT=-0.08
Non-members of CBHIS	12.14	0.011	11.85	0.009	TU=0.29
Heterogeneity effect	-0.27	0.012	0.1	0.026	TH=-0.37

Table 6: Estimation of the average treatment effects of CBHIS on household income

4.2.2.2. The impact of community based health insurance scheme on household asset

The second welfare indicator of this research was household real asset. Similarly, the FIML estimates of the endogenous switching regression model of household asset are reported in the following table, Table 7. The correlation coefficients of the CBHIS and household asset are positive and significantly different from zero which indicates that there is a positive correlation between the unobserved factors affecting the decision to enroll or not to enroll in CBHIS and the level of household assets for CBHIS member and non-member households. Since the coefficients are positive, which implies that being a member of CBHIS, had a significant impact on household real asset protection and that farmers which have below average asset margin are more likely to join the scheme.

Endogenous switching regression model Number of observation = 385
Wald chi^2 (12) = 82.58
Log likelihood = -198.58362 Prob > chi2 = 0.0000

Variables	**Household asset for members**			**Household asset for non-members**			**Household asset for both households**		
	Coef.	Std.Err.	P>z	Coef.	Std.Err.	P>z	Coef.	Std.Err.	P>z
Gender	0.015	0.045	0.739	0.049	0.063	0.433	-0.271	0.198	0.171
Age	0.000	0.002	0.921	-0.001	0.003	0.754	0.013	0.009	0.118
Marital status	-0.006	0.022	0.793	-0.003	0.031	0.927	-0.149	0.095	0.117
Education	-0.087	0.016	0.000	-0.049	0.022	0.026	-0.085	0.071	0.234
Family size	-0.002	0.024	0.931	0.043	0.035	0.229	-0.242	0.105	0.021
Location	-0.144	0.065	0.027	-0.117	0.078	0.132	0.295	0.258	0.254
Farm size	-0.040	0.059	0.496	-0.003	0.001	0.012	-0.006	0.025	0.810
Occupation	0.004	0.013	0.782	-0.003	0.015	0.826	-0.039	0.053	0.462
Trust	0.100	0.050	0.044	0.093	0.105	0.377	1.106	0.164	0.000
Distance from health center	0.013	0.006	0.017	0.008	0.009	0.377	0.100	0.022	0.000
Access to credit	-0.065	0.041	0.112	-0.048	0.061	0.438	-0.567	0.166	0.001
Illness history	0.059	0.018	0.001	0 .024	0.025	0.333	0.204	0.076	0.007
Fee-affordability							-0.166	0.159	0.297
Awareness							0.361	0.097	0.000

_cons	11.855	0.152	.000	12.003	0.173	0.000	-0.850	0.583	0.145
sigma_1	0.280	0.020	0.000						
sigma_2	0.258	0.016	0.000						
rho_1	0.600	0.210	0.000						
rho_2	0.068	0.408	0.000						
LR test of independent equations:		**chi2 (1) = 3.57**				**Prob > chi2 = 0.0587**			

Table 7: Endogenous switching regression estimation of CBHIS on household asset

Similarly to the analysis of the impact of CBHIS on household income, the question arises as to whether households that are members of CBHIS experience improvements in their real assets. Table 8 below presents the observed difference in household real assets between members and non-members (ATE), which is 0.0. However, this simple comparison may be biased due to unobserved factors.

In line with the findings of Carter and Milon (2005), accounting for the underlying heterogeneity caused by potential unobservable effects provides valid estimates. The estimated treatment effect (TT) of enrolling in CBHIS on household assets is 0.225. This suggests that, on average, CBHIS member households have a higher level of household assets compared to CBHIS non-member households. Conversely, the estimated treatment effect on the untreated (TU) is -0.175. This indicates that, on average, if CBHIS non-member households were to enroll in the program, their household asset level would decrease.

Based on the counterfactual conditions of household real assets, non-members who remain non-members fare better than members who become non-members. This implies that the effects of CBHIS are less pronounced for the counterfactual member households, resulting in a positive transitional heterogeneity effect on household assets, which is improved by 4% compared to non-members.

	Decision stage				
	Enroll		Not-enroll		
	Mean	Standard deviation	Mean	Standard deviation	**Treatment effects**
Members of CBHIS	11.99	0.01	11.77	0.06	TT=0.225
Non-members of CBHIS	11.82	0.01	11.99	0.01	TU=-0.175
Heterogeneity effect	0.178	0.01	-0.222	0.05	TH=0.4

Table 8 : Estimation of the average treatment effects of CBHIS on household asset

5. Conclusion and Recommendations

This study, the impact of community based health insurance scheme on household welfare in Amhara region, specifically north wollo zone was conducted by using the data collected from 385 selected households of which 65.97% was members of the health insurance program. The study sheds light on the nuanced factors influencing household membership in CBHIS and the subsequent impacts on economic indicators. The socio-economic analysis reveals disparities in gender, education, and area of residence between members and non-members. Logistic regression identifies significant determinants, emphasizing the role of trust, family size, and geographical proximity. The Endogenous Switching Regression model underscores the positive influence of CBHIS on household assets but not on household income, affirming its potential to uplift economic conditions by protecting household asset. Despite the observed benefits, challenges in service quality and affordability persist and the researcher suggests the following policy recommendations.

- Address Affordability Concerns: it is important to develop policies in order to alleviate the financial burden on households, ensuring that renewal fees are manageable. Consider income-based subsidies to promote inclusivity since 14.4 % of the member households are unable to pay the renewal fee in 2014 Ethiopian fiscal year, it is crucial to identify the specific characteristics or subgroups of households that benefit the most from the scheme and focus on providing adequate support and resources to these groups. This could help maximize the positive impact of CBHIS on household income while minimizing any potential negative effects.
- It will be very important to recognize and address the unique challenges faced by vulnerable household heads, possibly offering targeted financial support or framing flexible payment options.
- In order to mitigate any negative impact on household income, policymakers should consider implementing support mechanisms alongside CBHIS. This could include income-generation programs, skills training, or job placement initiatives to help enrolled households enhance their income-generating capacity.
- The last but not the least mechanism is a regular evaluation of quality of healthcare services provided under CBHIS, addressing issues related to waiting times and prioritization. Implement mechanisms for continuous improvement based on feedback from beneficiaries.

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Appendices

A. Estimates of the logit model

Household membership status of CBHIS	Coef.	St.Err.	t-value	p-value	[95% Conf Interval]	Sig
Gender	-.483	.339	-1.43	.154	-1.146 .181	
Age	.025	.015	1.71	.087	-.004 .054	*
Marital status	-.277	.158	-1.75	.08	-.587 .033	*
Education	-.149	.106	-1.41	.159	-.356 .058	
Family size	-.509	.185	-2.75	.006	-.871 -.146	***
Location	.688	.442	1.56	.12	-.179 1.555	
Farm size	-.014	.008	-1.63	.103	-.03 .003	
Occupation	-.015	.087	-0.17	.868	-.186 .157	
Trust	2.072	.287	7.23	0	1.511 2.634	***
Distance from health center	0.188	0.038	4.94	0	0.114 .263	***
Access to credit	-1.086	.277	-3.93	0	-1.628 -.544	***
Illness history	.374	.124	3.01	.003	.131 .618	***
Constant	-1.404	1.008	-1.39	.164	-3.379 .572	
Mean dependent variable	0.660	SD dependent variable	0.474			
Pseudo r-squared	0.277	Number of observation	385.000			
Chi-square	97.332	Prob > chi2	0.000			
Akaike crit. (AIC)	382.739	Bayesian crit. (BIC)	434.131			
*** p<.01, ** p<.05, * p<.1						

B. Link test results

Iteration 0: log likelihood = -246.86493
Iteration 1: log likelihood = -181.39981
Iteration 2: log likelihood = -177.75328
Iteration 3: log likelihood = -177.43107
Iteration 4: log likelihood = -177.43008
Iteration 5: log likelihood = -177.43008

Logistic regression Number of obs = 385
LR chi2(2) = 138.87
Prob > chi2 = 0.0000
Log likelihood = -177.43008 Pseudo R2 = 0.2813

Household status of CBHIS	Coef.	Std.Err.	P>z
_hat	0.925	0.115	0.000
_hatsq	0.088	0.063	0.160
_cons	-0.110	0.160	0.494

C. The Variance inflation factor

Variable	VIF	1/VIF
age	11.95	0.083664
distancefr~r	5.40	0.185016
gender	4.01	0.249202
maritalsta~s	3.52	0.284202
familysize	3.35	0.298165
education	3.25	0.307434
illnesshis~y	3.11	0.321531
occupation	2.70	0.370359
location	2.54	0.393625
accesstocr~t	2.06	0.485057
trust	2.00	0.500311
farmsize	1.03	0.968362
Mean VIF	3.74	

D. Diagnosis test for sensitivity and specificity by receiver operating characteristics (ROC) analysis