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Socioeconomic impacts of community-based health insurance: evidence from Gondar Zuria District, Amhara Regional State, Ethiopia

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Abstract

Background Healthcare insurance is one of the strategies to achieving universal health coverage and reduce health care inequality among rich and poor households. In line with this goal, the Ethiopian government launched a community-based health insurance program in 2011 to protect rural households and informal workers from catastrophic out-of-pocket medical expenditure that would increase health service quality. However, there is a dearth of evidence on the effect of this program on socio-economic spheres of the community in the study area. This study aims to assess the socio-economic impacts of community-based health insurance through a case study in Gondar Zuria district of Central Gondar Zone, north-west Ethiopia.

Methods A concurrent mixed-methods approach was applied, combining a comparative cross-sectional study design for the quantitative section and descriptive analysis for the qualitative part. The quantitative analysis included responses from 407 households, while the qualitative analysis was based on ten in-depth interviews and three key informant interviews (KIIs). Systematic and maximum variation sampling techniques are used to determine the sample sizes of the datasets, respectively. The quantitative data is generated from the responses of households to structured closed-ended questionnaire by trained data collectors. In-depth interviews and key informant interviews are conducted by the authors with tape-recorder to gather the qualitative data. The quantitative data is analysed by propensity score matching method using STATA-14 software. Findings from the qualitative data are generated through descriptive analysis.

Results A quantifiable positive association was found between community-based health insurance (CBHI) and welfare on the basis of quantitative data analysis. The results show that insured households have 17% and 20% lower probabilities of experiencing catastrophic health expenditure and labour absenteeism in the workplace, respectively, compared with non-insured households. Insured households are also more likely to have better vertical social capital compared with non-insured households.

Conclusions Thus, the study concludes that community-based health insurance improves both economic and social status of insured households in the study area, and hence, the program should be scaled-up to include more non-beneficiaries to improve welfare in Ethiopia.

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Keywords Community based health insurance, Catastrophic health expenditure, Labour productivity, Social capital, Propensity score matching

Introduction

Incapability of covering health care costs leads to long-term illness [1], poses severe economic threats to households through affecting productivity and health capital of community members in the long term [2]. Hence, there should be means to alleviate financial burden associated with health expenses. It may be eased either by funding the health services [3] or by risk pooling through health insurance schemes [4]. Healthcare insurance is one of the strategies to reduce health care inequality among households [5]. Since the 1980s, insurance-based health care financing has had wider acceptance globally [6]. Community-based health insurance (CBHI) scheme is a voluntary, community-involved health financing strategy [7, 8]. It is designed to achieve the Sustainable Development Goals for health (SDG3) [9] developed to provide financial protection against unexpected health care costs and to enhance access to modern health care in most low and middle-income countries (LMICs) [10, 11]. It targets rural households and informal workers, who are excluded from formal economic activities [12]. It has gained popularity in many eastern Africa countries, including Rwanda, Kenya, Tanzania and Ethiopia since 1994, 1999, 2001 and 2011, respectively [13].

The Ethiopian government launched the community-based health insurance in 2011 as social protection for the rural poor community and urban community in the informal sector [14]. The pilot program was launched in 13 districts across four main regions of the country and now it is scaled up to all regions and districts in the country [15]. It was designed as the quest for social health insurance [16]. Currently, nearly 9 million households (8 719 388 households and taking average family sizes of about 4.6 into account, 40.2 million people) are insured. Of these, 2 664 031 households are from Amhara National Regional State. The region has 67% coverage, the third largest coverage next to Addis Ababa and Dire Dawa. Gondar province has 601 215 insured households [17]. In Gondar Zuria district, community-based health insurance was introduced in 2018/2019. In the district, there are about 43 965 eligible households. Among those eligible households, 38 261 of them are payable, while 25 231 subscribed to the program. In addition, those indigent households whose health insurance payment is covered by local, regional and federal government reached 5466 in 2022 [18]. In sum, 30 697 households are insured, resulting in a 69.8% CBHI coverage. However, Ethiopia has the lowest share of health expenditure (1%) resulting from health insurance schemes [19].

With the current encouraging CBHI enrolment rate, evidence about the socio-economic impacts of the program on insured households is lacking. Previous studies [20–23] in Africa focused on identifying factors that hinder or facilitate enrolment. There are also studies that applied an impact evaluation model to estimate the impact of CBHI on an insurer's health service utilization, welfare and health expenses [24, 25]. The African counterpart has occurred in Ethiopia's CBHI literature. Several studies [26–31] focused on identifying factors that impede households' enrolment in CBHI programs. Few others studied the impact of Ethiopia's CBHI on household economy [4, 32–34] and on household livelihood [4, 35]. Several studies [36–40] in Amhara region and many studies [41, 42] in Central Gondar Zone focused on household enrolment in CBHI program.

Previous studies [4, 32–35] about CBHI in Ethiopia barely addressed the socio-economic impacts of CBHI generally and its economic impacts, such as labour productivity. Furthermore, unlike previous studies, this study had employed mixed method study design, which is helpful for complete understanding of the socio-economic impacts of CBHI among households. Therefore, this study aimed to evaluate the socio-economic impacts of CBHI on households using concurrent mixed method study design.

Materials and methods

Study design and description of the study area

The study employed concurrent mixed research design (comparative cross-sectional study design for quantitative part and descriptive analysis for the qualitative part) approaches. This gives a more in-depth picture of results than either method [43]. Study conclusion is merely based on researchers' interpretation though the quantitative approach involves the use of larger dataset. Contrarily, qualitative approach helps to incorporate study units view into the study though the sample size is very small. Hence, a mixed research design is commendable in balancing flexibility of qualitative analysis with fixed, theoretical and hypothesis testing inherent in many quantitative approaches [44]. The quantitative results are supported by qualitative findings, as some of the behaviours in relation to the study variable are not quantifiable.

This study was conducted in Gondar Zuria District. It is one of the 12 districts of central Gondar Zone, Amhara National Regional State of Ethiopia. Maksegnit is a central town of the district administration, which is 42 km south of Gondar city, the capital of the administrative zone. The district has 44 kebeles (smallest administrative unit in Ethiopia below the district or woreda in the hierarchy). The district shares a boundary with Lake Tana in the West, East Dembia in the North, Libo Kemkem in the South and West Belesa in the east. The district is located 37° 45′ 43″ E and 12° 7′ 23″ N and its total area is 1286.76 km^2. The projected population size of the district based on the 2007 national housing census is 246 402 people [45]. The district started collecting payment for CBHI in 2014/15 and started service provision in 2018/19. There are eight public health centres serving the entire population of the district in 44 kebeles. However, there are variations in the level of participation of households in the program (CBHI) among kebeles. Some kebeles have a good proportion of households participating in CBHI while in other kebeles enrolment in CBHI is at its lowest. The sample respondents in this study are eligible household heads of selected kebeles in the district. Household heads that have identification cards and belong to the selected kebele were included in the study whereas rural and urban merchant households with no identification card and age younger than 18 years at the time of data collection were excluded from the study.

Two basic reasons motivated the authors to conduct the study in Gondar Zuria District. Most households in the district are insured in the CBHI program. One, there is no study so far that evaluated the socio-economic impact of the program in the study area. Hence, the findings of this study may help policy-makers to get inputs on the overall impact of the program across insured and non-insured individuals and determine the need for escalation of the program. Two, there is a lack of comprehensive empirical evidence on the joint effects (social and economic aspects) of CBHI in the Ethiopian context. This study may contribute to filling the literature gap on CBHI within a developing country context.

Sampling technique and sample size

Multistage stratified sampling was used to select study participants. In the first stage, five kebeles (Chinchaye, Degoma Town, HamsaFeji, Infraz Town and Merdo) were randomly selected. Then, households were stratified into “CBHI insured” and “non-insured” households. The calculated sample size was proportionally allocated to each kebele on the basis of the size of CBHI insured and non-insured households. Finally, systematic sampling technique (with a sampling interval of 15 obtained from 6257-target households and 422 sample households) was employed to recruit study households in the sample *kebeles* (Table 1). The names of 6257 households from the five kebeles were listed alphabetically. The technique used in the sampling process involves picking at an interval that provides a total of 422 households. The size of the interval is determined by dividing the target population size by the expected sample size (6257/422 = 14.83 ≈ 15).

Heterogeneity in experience of CBHI membership (maximum variation sampling) was applied to recruit participants during the in-depth interviews. Individual variation was accounted by five respondents from each group (insured households who renewed their membership regularly, and non-insured households for different reasons: one dropout household, two waiting to satisfy criteria for the program, one community leader and one community-based health insurance officer). The marginal effect of including more respondents on the information set was minimal. The same number of insured and non-insured guaranteed data balance as it is the case with quantitative dataset. Moreover, three key informant interviews were conducted with participants purposively selected from three partner organizations (social affairs office, finance and economic development office and health sector), which closely work with CBHI program and are jointly accountable for the performance of the program. The criteria used to determine the sample

Table 1 Sample Distribution among selected kebeles in Gondar Zuria district, 2022

Sampled kebele	Number of households	Population share	Proportional sample	Number of insured	Number of non-insured
Meredo	1492	24%	101.00	37.00	64.00
Degoma	1016	16%	68.00	36.00	32.00
Chinchaye	759	12%	51.00	31.00	20.00
Hamsa Feji	790	13%	53.28	34.46	18.82
Infraz	2200	35%	148.38	70.82	77.56
Total	6257	100%	422	209	213

size of KII is based on the number of organizations that provide pertinent and relevant information.

Data quality management technique

A pilot survey was conducted among 5% of study sample of the selected five kebeles. Lessons (such as the need to provide conclusive choices/alternatives, and clarity for differences in sense during translation into local language for some questions) were found and incorporated to improve the survey instrument before the final data collection was conducted. For instance, splitting non-food expenditure as health (detail list of health service spending) and non-health expenditure was done after testing because we find this is important to recall the exact amount of expenditure a household has spent. Moreover, the validity, reliability and generalizability of the qualitative data was examined after data collection via constant data consideration to maintain the quality of the collected data.

Overall, different methods of triangulation are involved to perform data quality management: data triangulation, where both qualitative and quantitative data are collected from different sources or at different times and results are compared; investigator triangulation, where different researchers independently collect data on the same issues and results are compared; and triangulation of theories, where different theoretical perspectives are used and compared to explain the same issue. Moreover, along with the data collectors, the researchers attempted to become familiar with respondents before any data collection took place. The purpose of data quality assurance, in this study, was to guarantee the trustworthiness and honesty of the data via reviewing relevant sources that back up and cross-check the reliability of the collected data. Thus, the entire interview guides were checked before and on field; the collected data were thoroughly related; recorded data were cleaned, and the data were systematically analysed.

Data collection techniques

Quantitative and qualitative data collection techniques were employed to generate primary data. Interviewer administered structured questionnaires were used to collect quantitative data, whereas in-depth interview and key informant interview guides were employed to generate qualitative data. Both quantitative and qualitative data were collected in the period between 8 May 2022 and 24 June 2022. Both instruments were pretested before the actual data collection.

Prior to quantitative data collection, seven data collectors (four for the two large kebeles and three for the remaining three Kebeles) and five supervisors were trained to have a good understanding regarding the questionnaire. The data collectors used oral interview to fill-in the questionnaires with the responses from the respondents. It took 30–60 min for each data collector to finish filling-in a single questionnaire. In total, five-to-eight questionnaires were filled-in each day by each data collector, and on average, the data collection took about 12 days to collect 422 questionnaires.

Semi-structured interview guides prepared in the Amharic language (the local language spoken by the interviewee) consisting of questions that shade light on specific issues were used to collect qualitative data. Ten in-depth and three key informant interviews each took an average of 30 min. The interviews were tape-recorded. The collected data were translated and transcribed back to English by a language professional.

Data analysis

Propensity score matching (PSM) method of analysis design that reduces bias in baseline covariates is used for quantitative analysis. In addition, qualitative data obtained from in-depth interviews and key informant interviews were analysed using narrative analysis to support findings from the quantitative analysis of the socio-economic impacts of the program. The main method of analysis applied for this study is econometric method of analysis, PSM for all objectives discussed hitherto. The first thing for PSM is estimating the propensity score. This study used a logit model to estimate the propensity score.

After identifying the propensity score for the entire sample, we calculate the propensity score for each household group (insured and non-insured). Using two groups' PSs, we determine the common support region, which is computed by taking the minimum propensity score value of treated group as lower bound and the maximum value of control group as upper bound [46], obtained from the calculated PSs.

Selecting the best matching algorithm is the next step once the common support region is set. Nearest neighbour matching, radius matching-caliper and Kernel matching are in the alternative list for matching algorithm selection. To determine the best algorithm from the list of algorithms discussed earlier, we look for the pseudo R^2 and sample size. The pseudo R^2 and sample size are the basic criteria used to determine the best algorithm. An algorithm that has the smallest pseudo R^2 and larger sample size would be selected.

To remove the outliers from the analysis, a PSM balancing test was applied. After the balancing test, households in the common support region were identified. Therefore, two groups (treated and control) will be, on average, the same in the absence of treatment (no outlier in the sample) based on the observable socio-economic characteristics. Therefore, it is possible to run regression analysis and observe the impact of the program on the outcome variable (catastrophic health expenditure).

The analysis also involves dataset examinations which are conducted pre-and post-estimation. The dataset was subjected to different preliminary tests, such as homoscedasticity, normality, multicollinearity and balancing conditions, which may affect the validity results. In the presence of the above problems, the OLS model provides biased estimates. As a robustness check for the findings presented in this study, the dataset is also evaluated for tests of balancing condition, model specification and sensitivity analysis after estimation.

In the method of analysis section, we have made strong identifying assumptions about conditional independence or unconfoundedness assumption, as if we can observe all variables simultaneously influencing the participation decision and outcome variables [46]. It is a question of whether unobserved factors can alter inference about treatment effects [47]. Checking sensitivity of estimated results with respect to deviations from identifying assumptions becomes an increasingly important topic in the applied literature evaluation [46]. Sensitivity analysis depends on research design. Alpha sensitivity is used for weighting designs [48], and gamma sensitivity is for matching designs [49]. This study employs matching design and hence gamma sensitivity is applied.

The variables employed in the quantitative analysis were identified on the basis of empirical literature discussed in section one. Moreover, theoretical literature are used to hypothesize the relationships among themselves. In this study, the data were thematically analysed and interpreted using several techniques. The goal of thematic data analysis is to offer a framework for qualitative data analysis and methods for managing topics and data. In-depth interviews were used to gather the data, and key informant interviews were then thematically evaluated. The process in thematic analysis involves familiarization, transcribing, organization, coding and themes. Furthermore, to distinguish between several themes and the connections among them, the researchers were coded. Qualitative data obtained from in-depth and key informant (KII) interviews were coded by one of the authors (sociologist) according to the specific themes-social and economic impacts. Interview quotes are presented alongside the quantitative analyses to further elaborate the issues under discussion.

Operational definition

- Health expenditure is said to be "catastrophic" when the proportion of health care expenditure exceeds 10% of the household's total expenditure [3, 50].
- Labour productivity refers to the average product of labour. It is total output per unit of labour embodied in the specific production function. However, households in this study have different sectoral backgrounds, with varying labour intensity. On account of this, following similar approaches in previous studies [51], workplace labour absenteeism is used as a proxy measure for labour productivity.
- Social capital is a stock property of a group or community, or even a nation and constitutes features of social organization, norms and social ties that facilitate coordination and cooperation for mutual benefits of community members [52].
- Social network is voluntary interaction of groups or individuals with the merit of maximizing mutual benefit [53]

Model specification

This study made use of PSM to quantify the socio-economic impact of CBHI, considering those who join CBHI scheme (the insured) as "treated" group and those who do not join (the non-insured) as "controls". The treated group had similar socio-economic observable characteristics before the program as a "control" group. The PSM model is advantageous in assessing the impact of independent variables on outcome variables. Let i denote an individual household from a population (N) under consideration for $i=1,\ldots,N$; and D_i be a treatment indicator whether the household i takes treatment ($D_i=1$) or not ($\mathrm{D_i}=0$). Y_{1i} and Y_{0i} are the values of the variable Y under the two states (insured or non-insured, respectively). The effect of the treatment on the ith household is the difference between the values under the two states ($Y_{1i} - Y_{0i}$). Hence, the mean of outcomes across all the insured and non-insured households is given by the average treatment effect (ATE) [54] for the population:

$$\mathrm{ATE} = E(Y_{1i} - Y_{0i}) \tag{1}$$

where E stands for operator of expected value or mean. The sample equivalent equation is given:

$$ATE = \sum_{i=1}^{n} (Y_{1i} - Y_{0i}) \tag{2}$$

where n is the sample size. However, the intention is to estimate the impact of treatment on treated, which is the average impact of membership in CBHI only for those households that are insured. Accordingly, the impact is measured as the gap between what is happening to households participating in CBHI and what would have happened for the same households that had not participated in it. Mathematically:

$$\text{ATT} = E((Y_{1i} - Y_{0i})|D_i = 1) = E(Y_{1i}|D_i = 1) - E(Y_{i0}|D_i = 1) \quad (3)$$

where ATT represents average treatment effect on the treated and the treatment indicator (D_i) is the membership dummy taking the value of *1* if the household is insured in CBHI, and 0 otherwise. The sample equivalent is given:

$$\text{ATT} = \sum_{i=1}^{n}(Y_{1i} - Y_{0i})|D_i = 1 \quad (4)$$

The factual outcome with CBHI ($Y_{1i}|D_i=1$) is observable for household participating in CBHI but the counterfactual outcome, CBHI ($Y_{0i}|D_i=1$) is not observable for the same household as it is impossible to get the same individual with and without CBHI, this is a problem of missing data [54]. Had the impact of the program on non-participants is nullified, that is if E ($Y_{0i}|D=1$) and E ($Y_{0i}|D=0$) were equal, there would not be any variation between what we want to measure and what we observe, making our impact evaluation straight forward. However, the impact evaluation measures the causal effects of the program; it is not a simple comparison of outcomes between treated and control groups. To deal with this problem, we measure the outcomes of non-treated households to capture what treated households would have received had they not participated in the program [54]. Thus, the average treatment effect on the treated is stated as follows:

$$\begin{aligned}\text{ATT} &= E(Y_{1i}|D_i = 1) - E(Y_{0i}|D_i = 0)\\ &= E((Y_{1i} - Y_{0i})|D_i = 1) + [E(Y_{0i}|D_i = 1) - E(Y_{i0}|D_i = 0)]\end{aligned} \quad (5)$$

The difference between the last two terms in Eq. (5) shows the effect of treatment on the control group $[E(Y_{0i}|D_i = 1) - E(Y_{i0}|D_i = 0)]$, and is referred as average treatment effect on the untreated (ATU). Our interest is on ATT, and hence, results are not interpreted for ATU. Equation (5), however, would lead to the problem of selection bias, which shows variables that affect a household's participation in CBHI could affect a household's socio-economic condition. The difference in the outcome of interest is not only from participation in CBHI but could also be from other factors [55]. Two strong assumptions overcome self-selection bias. These assumptions are conditional independence assumption (CIA), which assumes outcome and participation are independent given the propensity score $P(x_i)$, where x_i represents a set of observable covariates that are not affected by treatment [49]; and balancing condition assumption which considers conditional independence of participation in terms of control variables given the propensity score [47]. Once the propensity score is calculated and the balancing condition met, ATT can be estimated using [47] modified as in Eq. (6).

$$\begin{aligned}\text{ATT} &= E((Y_{1i} - Y_{0i})|D_i = 1) = E[E(Y_{1i} - Y_{0i})|D_i = 1, P(x_i)]\\ &= E[E(Y_{1i}|D_i = 1, P(x_i)) - E(Y_{0i}|D_i = 0, P(x_i))|D_i = 1]\end{aligned} \quad (6)$$

After dealing with the selection bias, logit model with binomial logistic regression distribution function [56] for CBHI membership decision on different socio-economic factors that determine participation in the study area is specified as:

$$\begin{aligned}\text{prob}\left(Y = \frac{1}{X} = F(X_i\beta) = \pi_i = F\left[\beta_0 + \sum_{i=1}^{m}\beta_i X_i\right]\right.\\ = \left[\frac{1}{1 + e^{-[\beta_0 + \sum_{i=1}^{m}\beta_i X_i]}}\right]\end{aligned} \quad (7)$$

where e represents the base of natural logarithms, Xi is the ith independent variable, the βs are estimable parameters, m represents the number of slope coefficients, and π_i is the probability of a "yes" response of the ith household participation in CBHI. The odds ratio is defined as the ratio of the probability that a household participates (π_i) to the probability that the household does not ($1-\pi_i$). Then the interpolation of estimated regression coefficients would have been carried out on the basis of a one-unit change in the independent variable in question holding all other independent variables constant.

This paper used multiple outcome variables: catastrophic expenditure and labour productivity proxy for economic change. In addition, horizontal social capital, vertical social capital and social network as indicators for social impact of the program were used. Catastrophic health expenditure is a binary outcome variable indicating whether out-of-pocket health payment (OOP) exceeds 10% of non-health expenditures [57]. Other outcome variables, such as labour absenteeism from the workplace, social capital (horizontal and vertical) and social network, are clearly measured as indicated in the operational definition section.

The primary independent variable is enrolment in CBHI programs. For this independent variable, we created a dummy variable $CBHI_{hi}$ to represent the ith household (hi) who is insured in the scheme would be coded as 1, and 0 otherwise. The study used other explanatory variables, such as sex of the household head, which is a dummy variable (0 = female, 1 = male), household heads' education level (1 = no formal education, 2 = basic education, 3 = primary education, 4 = secondary education and 5 = diploma and above) and household head current marital status (married = 1, single = 2, divorced = 3 and widowed = 4). In addition, place where the household is located (rural = 1, urban = 0), religious affiliation (Christian = 1, Muslim = 0), occupation (farmer = 1, merchant = 2, daily labour = 3 and other = 4) are dummy variables included as model explanatory variables. Furthermore, total asset is a continuous variable, measured in Birr; distance to the nearest health centre is a continuous variable, measured in terms of how long it takes in minutes to walk on foot; number of children in the household is a continuous variable; number of adults in the household is a continuous variable; and age is a continuous variable, measured in years. Moreover, household food expenditure and non-food expenditures are continuous variables measured in Birr; school expenditure is another explanatory variable measured by money spent for schooling; health visit is a continuous variable measured by frequency of visits. All these are explanatory variables included in the model specified above.

Results and discussion

Results

Demography

The primary data gathered from different sources are presented, analysed and interpreted using PSM econometric and descriptive analyses in this section. It presents a descriptive account of the socio-economic and demographic attributes of respondents used as quantitative and qualitative data analysis discussed in the next section. In total, 407 respondents and ten interviewees were engaged to collect quantitative and qualitative data, respectively. The difference between the original size (422) and 407 here is accounted for non-response error (3.5%) during quantitative data collection. Of 407 households, 201 are insured and 206 are non-insured (Table 2).

The majority of the respondents (75% insured and 79% non-insured) were male-headed households in the quantitative data. Most of the households (73.6% of insured and 72.8% of non-insured) were headed by married individuals residing in rural kebeles. Furthermore, more than half of the respondents (60.2% insured and 57.8% non-insured) had not completed primary education. Again, the majority (60.54%) of the respondents have poor or chronic health status which may be associated with poor access to health facilities or CBHI service as the majority were non-insured households. However, in terms of chronic diseases, the insured families account for a higher share.

Out of the ten respondents, the majority (80%) were male participants in the qualitative data. They were selected from three kebeles, namely Degoma, Hamsa Feji and Maksegnit, which are dominated by respondents engaged in three main activities: small business, farming and daily casual work. Half of the respondents are insured. Most of respondents (60%) are farmers, which is proportional to total population.

Table 2 Socio-demographic characteristics of study participants on socio-economic impact of community-based health insurance in Gondar Zuria district, Ethiopia in 2022

Explanatory variables (household characteristics)	CBHI membership		Sample (quantity/share)
	Non-insured (quantity/share)	Insured (quantity/share)	
Sex			
Female	41 (19.90%)	50 (24.87%)	91 (22.35%)
Male	165 (79.10%)	151 (75.12%)	316 (77.64%)
Age, years			
21–40	104 (50.50%)	51 (25.40%)	155 (38.00%)
41–60	83 (40.30%)	131 (65.20%)	214 (52.60%)
> 60	19 (9.20%)	19 (9.40%)	38 (9.40%)
Current marital status			
Married	150 (72.80%)	148 (73.60%)	298 (73.20%)
Single	18 (8.70%)	30 (14.90%)	48 (11.80%)
Divorced	26 (12.60%)	13 (6.50%)	39 (9.60%)
Widowed	12 (5.80%)	10 (5.00%)	22 (5.40%)
Educational level			
No formal education	98 (47.60%)	82 (40.80%)	180 (44.20%)
Basic education	21 (10.20%)	39 (19.40%)	60 (14.70%)
Primary education	54 (26.20%)	67 (33.30%)	121 (29.70%)
Secondary education	16 (7.70%)	10 (5.00%)	26 (6.40%)
Diploma and above	17 (8.30%)	3 (1.50%)	20 (5.00%)
Residence			
Rural	130 (63.00%)	121 (60.20%)	251 (61.20%)
Urban	76 (37.00%)	80 (39.80%)	156 (38.80%)
Religion			
Christian	191 (92.70%)	185 (92.00%)	376 (92.40%)
Muslim	15 (7.30%)	16 (8.00%)	31 (7.60%)
Occupation			
Farmer	134 (65.00%)	126 (62.60%)	260 (64.00%)
Merchant	21 (10.20%)	34 (17.00%)	55 (13.50%)
Daily labour	9 (4.40%)	12 (6.00%)	21 (5.10%)
Other	42 (20.40%)	29 (14.40%)	71 (17.40%)
Family size			
< 4	54 (26.20%)	27 (13.40%)	81 (20.00%)
4–6	74 (36.00%)	63 (31.40%)	137 (33.60%)
> 6	78 (37.80%)	111 (55.20%)	189 (46.40%)
Health condition			
Good health	87 (42.20%)	74 (36.80%)	161 (39.50%)
Poor health	111 (53.80%)	94 (46.80%)	205 (50.40%)
Chronic health	8 (4.00%)	33 (16.40%)	41 (10.10%)

Test results

On the basis of the minimum propensity score of the treated group and maximum propensity score of the control group, the common support region (0.0965, 0.9069) is calculated. Since the pseudo R^2 and sample size for all algorithms are equal, the nearest matching is randomly applied to determine the sample size to be available within common support region. Thus, with the range mentioned above, we used 394 sampled households from the total 407 households. This implies that 13 households are out of the common support region (Table 3).

The control groups observable characteristics are on average similar with the treated group except for those that are found in the off-support region. In Fig. 1, two green bars located in the right upper corner are outliers (13 households) and are excluded from the analysis. The vertical and horizontal axis measures the weighted mean of controlled and treated groups, respectively. Households in the common support region are safe for analysis based on balancing condition test (Fig. 2).

Test results for homoscedasticity and normality show that both problems are imminent and hence the choice of the probit or logit model to the PSM method of estimation is fairly justified. A variance inflation factor (VIF) of 8.92 (which is less than 10) is a good indicator of the absence of the problem of multicollinearity among the explanatory variables. The balancing test result before estimation shows the blocks are similar or balanced in terms of covariate characteristics. Therefore, the difference in insured and non-insured outcome variables is merely owing to the CBHI program. Comparisons of treated and controlled after matching shows that the balancing condition is still satisfied in the post estimation stage.

The test result for model specification does not provide evidence of an omitted variable problem. The result of the sensitivity analysis shows that unobservable characteristics did not affect both membership and outcome variables. For instance, if we take the maximum value 6 for gamma, it gives an upper bound value of 0.000019 for catastrophic health expenditure and 0.000024 for vertical social capital with action; other outcome variables have even smaller upper bounds for these two. Hence, all variables are below the standard threshold upper bound (0.05), revealing no hidden

Table 3 Matching algorithm for catastrophic health expenditure

Matching methods	Pseudo R^2	On support	Off support	Sample SIZE
Nearest neighbour matching	0.15	394.00	13.00	407.00
Radius matching—caliper				
Caliper (0.01)	0.15	386.00	21.00	407.00
Caliper (0.05)	0.15	394.00	13.00	407.00
Kernel matching	0.15	394.00	13.00	407.00

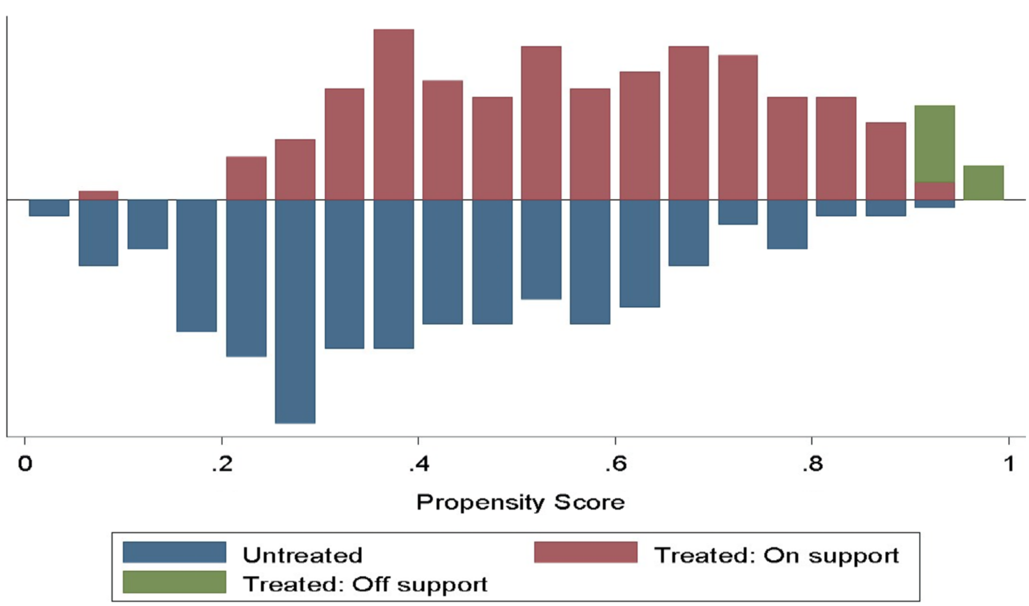

Fig. 1 Unmatched propensity score graph of insured and non-insured households in Gondar Zuria district, Ethiopia, 2022

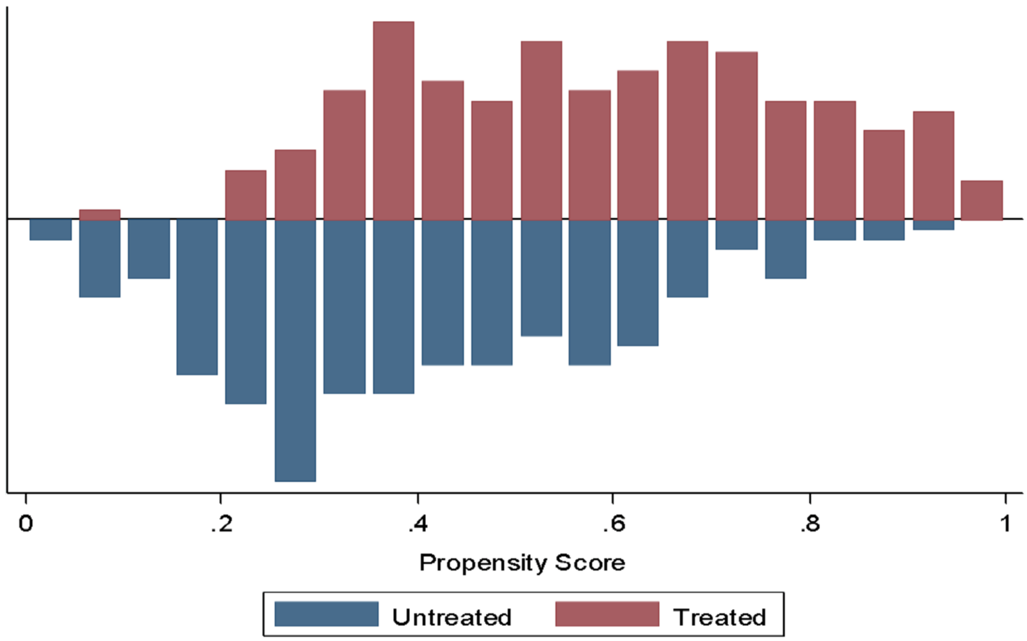

Fig. 2 Matched propensity score graph of insured and non-insured households in Gondar Zuria district, Ethiopia, 2022

Table 4 Rosenbaum sensitivity test result of a study on socio-economic impact of community-based health insurance in Gondar Zuria district, Ethiopia in 2022

Outcome	Catastrophic health expenditure		Labour productivity		Vertical social capital without action		Vertical social capital with action		Social network	
Gamma	Sig+	Sig−	Sig+	Sig−	Sig+	Sig−	Sig+	Sig−	Sig+	Sig−
1	0	0	0	0		0	0	0		0
1.5	1.10×10^{-16}	0	0	0		0	2.20×10^{-16}	0		0
2	4.60×10^{-16}	0	0	0	4.70E−14	0	9.90×10^{-13}	0		0
2.5	8.40×10^{-11}	0	0	0	1.30×10^{-11}	0	1.60×10^{-10}	0		0
3	2.80×10^{-9}	0	8.90×10^{-16}	0	5.90×10^{-10}	0	4.60×10^{-9}	0	1.40×10^{-15}	0
3.5	3.40×10^{-8}	0	8.70×10^{-14}	0	8.90×10^{-9}	0	5.20×10^{-8}	0	1.30×10^{-13}	0
4	2.20×10^{-7}	0	2.80×10^{-12}	0	6.90×10^{-8}	0	3.30×10^{-7}	0	4.00×10^{-12}	0
4.5	9.60×10^{-7}	0	4.10×10^{-11}	0	3.40×10^{-7}	0	1.40×10^{-6}	0	5.70×10^{-11}	0
5	3.10×10^{-6}	0	3.50×10^{-10}	0	1.20×10^{-6}	0	4.30×10^{-6}	0	4.80×10^{-10}	0
5.5	8.30×10^{-6}	0	2.10×10^{-9}	0	3.50×10^{-6}	0	0.000011	0	2.80×10^{-9}	0
6	0.000019	0	9.20×10^{-9}	0	8.50×10^{-6}	0	0.000024	0	1.20×10^{-8}	0

characteristics or confounding problems on outcomes (Table 4).

Discussion

Economic impact of community-based health insurance

This section discusses the (economic) impact of CBHI on catastrophic health expenditures and labour absenteeism of households who are on average similar based on observable characteristics except membership in the program. According to data obtained from Gondar Zuria District CBHI Scheme office, the program has reached all 44 kebeles, health service utilization has significantly improved since the commencement of CBHI, and the scheme is serving an increasing number of clients. The number of payable subscribers reached 25 231 in 2022, whereas those poor households whose payment was covered by the regional government reached 5466 in 2022. Comparing the revenue collected and health expenditure made, there was a deficit of more than 3.6 million Ethiopian Birr in the district. Thus, given this deficit, one may wonder about the socio-economic impacts of the CBHI program on the households.

Table 5 Nearest matching result of insured and non-insured households with catastrophic health expenditure as outcome variable in Gondar Zuria district, Ethiopia in 2022

Variable	Mean treated	Mean control	%Bias	*t*-value	*P*>|*t*|	V(T)/V(C)
Total asset	70 994.00	66 672.00	5.10	0.61	0.54	1.23
Distance	47.17	43.60	8.60	0.90	0.37	0.81
Children	2.05	1.90	11.30	1.09	0.28	1.13
Adult	3.73	3.64	5.30	0.51	0.61	1.30
Age	48.25	49.06	−7.10	−0.72	0.47	0.87
Sex	0.75	0.70	12.20	1.11	0.27	–
Education	2.09	2.07	1.00	0.10	0.92	0.67*
Food expenditure	63 246.00	61 700.00	3.50	0.33	0.74	2.85*
Non-food expenditure	12 472.00	11 606.00	5.60	0.53	0.60	2.65*
School expenditure	1757.40	1553.40	6.40	0.62	0.53	0.70*
Health visit	3.62	3.61	0.20	0.02	0.98	0.56*

On the basis of the selected matching algorithm, there is no significant difference between treated and control groups on unobserved characteristics. As a result, any difference between the two groups would be because of the treatment assignment, that is, membership in CBHI. Therefore, variation in catastrophic health expenditure is explained by variation in treatment (Table 5). An asterix indicates a significant variable at different levels of significance (the higher the number of asterix the stronger the level of significance).

The finding revealed that the probability of incurring catastrophic health expenditure is 17% lower for insured households than non-insured households (Table 6). The result revealed that uninsured households are 17 times more likely to face catastrophic health expenditure compared with insured households. This is because both inpatient and outpatient insured households' health expenditure is covered by the CBHI program.

The quantitative result also supported by qualitative findings obtained from insured households. For instance, a 33-year-old married woman (hereinafter referred as "D-F-01") explained the importance the CBHI as follows.

...Health insurance is where we pay once a year and get treated throughout the year. In the absence of the program, if a child felt ill, we would borrow money from someone which might take some time. But then we use the membership card and go to the health center soon to get treatment. It helps us to get our children back to health immediately. Certainly, without the health insurance program, our survival would have been questionable... (Interview conducted in Degoma Kebele on 12 May 2022 in the morning, 9:00 AM).

Similarly, a businessperson with a better living standard (hereinafter referred as "D-M-02") had boldly acknowledged the importance of the program as:

…Health insurance is a means of covering substantial health expenses by pooling money from members. As long as one bears the membership card, he/she would have access to medical care from any government health facility anywhere in the region... (Interview conducted in Degoma Kebele on 12 May 2022 in the morning, 10:30 AM).

Table 6 Economic impact of community-based health insurance among households in Gondar Zuria district, Ethiopia in 2022

Variables	Treated	Controls	Difference	S. E	*t*-stat
Catastrophic health expenditure	0.25	0.25	0.00	0.23	0.14
Average treatment effect on treated (ATT)	0.25	0.42	−0.17	0.07	−2.33
Average treatment effect on untreated (ATU)	0.24	0.19	0.05	–	–
Average treatment effect (ATE)	–	–	−0.12	–	–
Labour productivity	0.47	0.47	0.00	0.05	0.03
Average treatment effect on treated (ATT)	0.47	0.67	−0.20	0.04	−2.47
Average treatment effect on untreated (ATU)	0.47	0.40	0.07	–	–
Average treatment effect (ATE)	–	–	−0.13	–	–

Another participant who is a 62-year-old insured household head (hereinafter referred as "H-M-03") shared his opinion.

> *Before the introduction of the insurance program, we incurred high health related expenditure particularly associated with the common outbreak of malaria in our district. Many lives are lost. Because of widely held public misconceptions about the program, many refrained from being enrolled into the program. I regretted that failure because I had to pay more to cover my household's health expenditure. Now people have become aware of the importance of the program as they learnt medical expenses are extremely costly these days. As a result, most members couldn't wait to renew their membership in time. (Interview conducted in Hamsa Feji Kebele on 15 May 2022 in the morning, 11:35 AM)*

An interview with a 63-year-old farmer (hereinafter referred as "H-M-04"), who was insured since the inception of the program gave us in-depth information about the economic importance of the program.

> *…Although I have been a member since the beginning of the program, I had not applied for insurance for two years since no one was sick in my household. When the program officer asked me to pay and renew my membership for the third year, I refused. I felt that it was like tampering with God paying for health insurance while you are healthy. Then the officers explained to me the procedures underlying the program. I got it and renewed my membership for the third year. Later, I and all members of the household became sick due to the malaria epidemic. Were it not for my membership in the program, I would not afford the medical expenses. I would not be able to cover the cost even if I sold cattle. You see how the program has helped me to protect my assets? (Interview conducted in Hamsa Feji Kebele on 15 May 2022 in the afternoon, 15:00 PM)*

Therefore, both the quantitative result and qualitative findings shows that insured households health spending is less than none-insured households. This study result is consistent with the program objective of pooling health risks of insured households [14] by waving some portion of health expenditures.

This study finding is consistent with previous studies [4, 58–61]. For instance, studies in Ethiopia [4] and in Rwanda [62] show 23.2% and 15.1% lower catastrophic health expenditures, respectively, for insured households compared with their counterpart (non-insured) households. Similarly, studies in Nigeria [58], Ghana [59], Mongolia [60], Cambodia [63], Vietnam [64], Morocco [61] and Tanzania [65] revealed that insured households are less likely to experience catastrophic health expenditure than uninsured households.

Conversely, studies conducted in China, India and Vietnam found that CBHI membership has no effect on catastrophic health expenditure [66–68]. These differences may originate from differences in program setup and benefit packages. For instance, China's insurance benefit package prioritize inpatient [66], whereas, Ethiopia' CBHI benefit package gave equal opportunity both inpatient and outpatient services [14].

An insured father of eight (hereinafter referred as "H-M-02") has much to say about the benefits of the health insurance program.

> *…the importance of health insurance ranges from the clinic to the hospital and beyond. I was able to take care of a baby with the membership fee of four hundred and eighty birr, which would cost me about ten thousand Birr if I were not insured. He had taken X-rays three times. He had also taken four doses of injection in 24hrs while he was being treated at Gondar University Hospital. You see! One of my blood relatives who did not complete his registration spent seven thousand Birr when his family member was in medical treatment. After getting the insurance card some months later, he was able to safeguard the health of his ten family members with the premium of six hundred birr only. (Interview conducted in Hamsa Feji Kebele on 15 May 2022 in the morning, 10:15 AM)*

An uninsured 36-year-old man who has three children (hereinafter referred as "H-M-05") told us that he considered membership as a savings bank account. If someone is insured, he can get the treatment using the cards any time they feel sick.

> *I wanted to be a member of the health insurance program, but due to certain inconveniencies, I couldn't join. I incurred massive costs because I already missed that chance. This year, I spent twice as much on health as I would have spent on membership. Health insurance is just like going to the bank with your bank account when you need to withdraw money; if you are a member of the health insurance program, you can get medical care free of charge as long as you bear the insurance card. (Interview conducted in Hamsa Feji Kebele on 15 May 2022 in the evening 22:00 PM)*

To better capture the economic impact of membership in CBHI, the impact of the program on labour productivity is studied. The PSM result revealed that the likelihood of labour absenteeism in the workplace is 20% lower for insured households than the non-insured counterparts (Table 6). The result revealed that uninsured households are 20 times more likely to absent from workplace because of illness compared with insured counterparts. The higher the likelihood of workplace absenteeism, the less will be productivity and labour income. It is more likely for uninsured households to be absent from the workplace, because they might wait more time for treatment until they get the required money. Therefore, CBHI has reduced labour absenteeism, which improves both labour productivity and income of insured households. This study result also supported by qualitative findings. Interview participants have confirmed that the CBHI program is important in reducing labour absenteeism. For instance, H-M-03 shared his experience oh how CBHI program saves working time mainly in seasons when malaria infection is widespread.

> *...Once upon a time, four of my children were infected by malaria. Immediately I took all of them to the nearest health and returned home after treatment on the same day. This would not have happened if I had not been a member of the health insurance program. In the absence of the program, many people would be distracted from their work. Not only sick, but also the caregiver would be out of work for several days.*

Thus, both qualitative findings and quantitative results revealed that membership in CBHI reduces the likelihood of absenteeism from workplace. This may happen because insured households' have better health service utilization than uninsured counterparts, CBHI members' per capita outpatient visit is twice and more higher than the nationwide average [14]; per capita OPD visits of CBHI members is 9.1% higher compared with non-CBHI members [69].

Similarly, a study [70] in Ghana found that health insurance has reduced illness-related workplace labour absenteeism [51]. This study result shows worker with health coverage misses on average 76.54% fewer workdays than uninsured workers. Another study [71] result shows employees who benefit from employer-provided insurance have a record of fewer working days lost compared with their counterpart workers who self-finance their health spending.

Conversely, a study [72] that investigated how health insurance affects illness-related absenteeism among older workers, found no differences in the number of days missed between insured and uninsured workers. This may be because the unit of analysis for this study was older workers, illness-related absenteeism among older workers less likely to vary among insured and non-insured individuals since both groups are equally vulnerable for age related illness, can't be easily recovered.

The current study has also conducted key informant interviews, the interviews findings from the social, economic, and health sector informants confirmed that welfare conditions are relatively improved after the introduction of the CBHI program in their locality, and the improvement is higher among the insured households.

In general, findings of the current study are consistent with previous studies in that CBHI has positive impacts on the local economy through reducing catastrophic health expenditure and enhancing labour productivity for insured households compared with non-insured households. Therefore, insured households are more protected against catastrophic health expenditures and have lesser labour absenteeism than uninsured households.

Social impact of community-based health insurance

The result shows no difference in terms of horizontal social capital and social networking but vertical social capital among insured and non-insured households. The program does not affect trust among families, community project participation, and helping others (horizontal social capital) when a need arises. Unlike the quantitative result, interview finding shows that CBHI has contributed positively for horizontal social capital. For instance, D-M-02 explained the impact of the program on horizontal social capital as:

> *... I am a member of the program. I did not become a member just to utilize the benefit packages; rather I thought with the little money I contribute, there is someone who can get rid of the pain. The amount you pay per year is four to six hundred. If you don't get sick, other members will use the money you contributed. Otherwise, you will get medical care that costs thousands in times you get sick (Interview conducted in Degoma Kebele on 12 May 2022 in the morning morning, 10:30 AM).*

This might not be because of the strength of the program but rather because of the enduring community ties that exist among members, which is unlikely to be disturbed by government policy variables, such as health insurance. Similarly, the CBHI does not create differences between insured and non-insured groups with regard to relationship with neighbours, participation in social affairs, membership in local associations and cooperation with community members (social networking).

With regard to vertical social capital, however, the PSM result revealed that insured households have 17% higher probabilities of getting health support, sufficient medical assistance, prescribed drugs, health consulting, organized health service and better treatment than

Table 7 Social impact of community-based health insurance among households in Gondar Zuria district, Ethiopia in 2022

Variables	Treated	Controls	Difference	S. E	*t*-stat
Horizontal social capital	0.47	0.48	−0.01	0.05	0.04
Average treatment effect on treated (ATT)	0.47	0.38	0.09	0.10	1.05
Average treatment effect on untreated (ATU)	0.47	0.50	− 0.03	–	–
Average treatment effect (ATE)	–	–	0.06	–	–
Vertical social capital without action	0.34	0.20	0.14	0.04	3.19
Average treatment effect on treated (ATT)	0.34	0.17	0.17	0.08	2.56
Average treatment effect on untreated (ATU)	0.20	0.25	−0.05	–	–
Average treatment effect (ATE)	–	–	0.12	–	–
Vertical social capital with action	0.38	0.11	0.27	0.04	6.84
Average treatment effect on treated (ATT)	0.38	0.10	0.28	0.05	5.18
Social network	0.52	0.40	0.12	0.05	2.53
Average treatment effect on treated (ATT)	0.52	0.37	0.15	0.07	1.93
Average treatment effect on untreated (ATU)	0.40	0.49	−0.09	–	–
Average treatment effect (ATE)	–	–	0.06	–	–

non-insured households. Similarly, insured households have 28% higher chance of having vertical social capital with action (provision of relevant information, build strong trust in the program and sufficiently understood and utilized CBHI benefit packages) compared with non-insured households (Table 7).

The results are also supported by findings from qualitative data. For example, a 40-year-old man (hereafter referred as H-M-01) commented on the mistreatment of CBHI members in health service delivery (a measure of vertical social capital in this paper).

> *I am very much concerned about the mistreatment by health professionals. I think this will frustrate members and will be forced to withdraw from the program. I want the program to be well coordinated so that clients get appropriate health services. (Interview conducted in Hamsa Feji Kebele on 15 May 2022 in the morning, 9:30 AM)*

Similarly, D-M-03 has also questioned the vertical social capital in CBHI service delivery.

> *I heard that CBHI members' health expenditure is covered by health insurance. However, being a member of the program by itself is not enough in waiving health expenses; membership with family health professionals makes the optimal membership packages utilization. In addition, people who have received referral services have not been able to get their money back and were not happy in the program. That is why my family is not yet a member. (Interview conducted in Degoma Kebele on 12 May 2022 in the afternoon, 16:00 PM)*

In general, both quantitative results and qualitative findings show that the social capital impact of CBHI is limited to vertical social capital. Therefore, the CBHI members' relationship with health service professionals for accessing healthcare services, as well as with CBHI officers for registration, renewal and referral refunds, has been more significantly impacted by the program than horizontal social capital (trust among families, community project participation and helping others).

Strengths and limitations of the study

This study may be favoured over other similar studies from Ethiopia or other developing countries that evaluate impacts of CBHI at least for the following two reasons. One, it supplements the traditional quantitative analysis with qualitative data to incorporate two different sources of data. The facts derived from the analysis of both types of data come to the same conclusion. Two, it examines the social and economic effects of the program. The social aspect of the problem is rarely examined in many previous studies.

The authors, however, were not able to obtain data on the characteristics of the insured individuals prior to the implementation of the program. Hence, it was not possible to implement a more rigorous method, such as difference-in-difference, which evaluates the situation of beneficiaries before and after the program. This method resolves the problem of missing data and selection bias that prevails in PSM. Nevertheless, adjustments are made to reduce the impact of these problems as shown in the main text.

Last but not least, this study may promote participatory or bottom-to-top policy design process that takes input from the beneficiaries and evidence based research, such as the current one. In addition, this study may be used to learn the behaviour of households who are not yet members, and develop strategy to create awareness among this group to join the program and improve the overall welfare of the society.

Conclusions and recommendation

The propensity scores matching results show that CBHI has a better (positive) impact in reducing the level of catastrophic health expenditure and labour workplace absenteeism on insured compared with non-insured households. The result also revealed that vertical social capital is stronger for insured than non-insured households. Findings from the qualitative analysis also strengthened the quantitative analysis results. Participants of the in-depth interview explained the socio-economic importance of the program from their lived experience. Furthermore, there is some established evidence that supports the socio-economic relevance of the CBHI program in the study area. Local government officials, researchers and policy-makers may exploit the findings of this study for further intervention. Local governments should create awareness about the relevance of the program among local communities to promote inclusivity. Researchers should evaluate program implementation through the application of other impact evaluation approaches that could overcome limitations of the PSM method applied in this study. Policy-makers should promote a comprehensive and inclusive CBHI program that benefits more sections of the society; for example, they may promote a pooling mechanism among heterogeneous groups across regions of the country instead of implementing area- or region-specific programs to balance the costs and benefits of the program. Moreover, cost–benefit analysis that accounts for the social benefit (externality) of the program in addition to the economic benefit (profit) should be conducted before policy-makers decide to expand the program into new areas.

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M.W.T. contributed to conceptualization, formal analysis, methodology, project administration, resources and validation, writing of the original draft and reviewing the final manuscript; A.H.G. contributed to conceptualization, formal analysis, supervision, validation and reviewed the final manuscript; F.B.S. contributed to formal analysis, investigation, methodology, validation and reviewed the final manuscript. All authors gave final approval of the version to be published, have agreed on the journal to which the article has been submitted and agreed to be accountable for all aspects of the work.

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Availability of data and materials
The datasets generated and/or analysed during the current study are not publicly available to protect from unnecessary abuse of full data of the participants, but are available from the corresponding author and will be shared upon reasonable request.

Declarations
We declare that this article is our original work and all sources of materials used for the paper are duly acknowledged. Its abstract has been presented in 26th RSEP International Conference on Economics, Finance & Business: https://rsepconferences.com/wp-content/uploads/2022/08/26th-RSEP-Book-of-Abstracts.pdf

Ethics approval and consent to participate
The study was approved by the ethical review committee of the University of Gondar with a reference number of SoCI300/2014. Participants were informed with written consent forms after the objectives of the study were briefed. Participants involved in the study were in a condition to provide informed consent willingly and with full understanding of the study purposes. All methods were carried out in accordance with relevant guidelines and regulations.

Consent for publication
Not applicable because confidentiality was kept and participants were sufficiently anonymous. All authors have read the manuscript and agreed on its publication.

Competing interests
The authors declare no competing interests.

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