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Who Wants to Be Healthy? A Contingent Valuation Analysis on Community-Based Health Insurance in Tigray Region

Muuz Hadush[1] , Kidanemariam Gebregziabher[2] *

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Abstract

This research aimed to assess the willingness to pay (WTP) for Community Based Health Insurance (CBHI) and to identify the factors that affect it in Tigray, Ethiopia. A simple random sampling method was employed, involving 332 uninsured household heads. These individuals were interviewed using a semi-structured questionnaire to gather primary data. The study utilized a contingent valuation method (CVM) with both single and double-bound elicitation formats, and the data were analyzed through descriptive and econometric techniques. The findings indicated that approximately 92 percent of respondents expressed a willingness to pay for community-based health insurance. The average willingness to pay ranged from 372.88 Ethiopian Birr (ETB), as determined by the single-bound elicitation method, to 387.23 ETB per year according to the Interval data model. Various factors, including bid amounts, educational attainment, extension contact, household expenditure, perceived risk, monthly discount rate, gender, family size, proximity to health facilities, and loss aversion, significantly impacted households' willingness to pay. It is crucial for government officials and other relevant stakeholders to take these demographic, socioeconomic, and institutional factors into account to improve the willingness to pay for community-based health insurance.

Keywords*:* Willingness to pay (WTP), single-bound, double-bound dichotomous choice (DBDC), and community-based health insurance, Ethiopia.

1 Introduction

Health insurance is becoming increasingly important in low- and middle-income countries as a way to enhance healthcare accessibility and shield families from financial hardships caused by out-of-pocket expenses. The World Health Organization (WHO) views health insurance as a promising tool for achieving universal health coverage. There are various types of health insurance available (WHO, 2013), and their impact on the populations they serve varies. For example, private health insurance (PHI) mainly benefits wealthier individuals, while community-based health insurance (CBHI) is often recommended as a financing mechanism that can particularly assist the poor. Numerous studies suggest that globally, around 150 million people face financial difficulties each year due to the lack of universal healthcare, which assumes equal access to health services (Asfaw & Von Braun, 2005).

In Ethiopia, the strategy of CBHI is based on the traditional practice of Idir, which is a community-based financial institution established to provide support for local finances through long-term savings among neighbors for emergency situations (Atnafu et al., 2018). Similarly, CBHI schemes have become a crucial method of funding healthcare in many developing nations today. In several countries, CBHI schemes are financed through general tax revenues or contributions from social insurance groups (WHO, 2003). The CBHI initiative in Ethiopia was created to facilitate access to healthcare at the community level. Through CBHI programs, individuals within the community pay premiums that encompass all health and treatment services for their households. These contributions are gathered and deposited into a shared fund, which is utilized to address healthcare costs as they arise (Debebe et al., 2014).

After the premiums have been gathered, they are promptly forwarded to the kebele, the primary administrative division. The kebele subsequently channels the payments to the district headquarters, which in turn reimburses medical facilities and clinics. This system facilitates enrolled households in obtaining a CBHI health card, granting them the ability to receive medical care at the nearest clinic without any initial payment (Workneh et al., 2017).

[1] Department of Economics; Mekelle University, Tigrai, Ethiopia. Email: muuz.hadush@mu.edu.et
[2] Department of Economics; MekelleUniversity, P. O. Box 451 Tigrai,Ethiopia
* Corresponding author E-mail: kidane.gebregziabher@mu.edu.et ; ORCID: 0000-0002-6397-4916

The primary goal of CBHI is to narrow the healthcare accessibility gap and offer social protection (Preker et al., 2004).

In Ethiopia, community-based health insurance schemes (CBHI) were implemented in 2003 EC as part of the national health policy. Research has demonstrated that the initiative has led to a significant increase in outpatient healthcare utilization rates. However, a prior study conducted by Mebratie et al. (2015) revealed that only 51.5% of individuals were willing to enroll in CBHI. Factors contributing to low participation in health insurance include religious beliefs, financial constraints, and the perception of being unable to afford the premium due to limited income. Additional CBHI studies, such as those carried out by Mebratie et al. (2015) and Debebe et al. (2014), also suggest that rural households in Ethiopia are less inclined to join the schemes, primarily due to financial limitations and a lack of understanding about the nature of the scheme. Moreover, some participants have opted out of the program due to the adverse selection of poverty, a lack of transparency within the scheme, and moral hazard among members.

Ekman (2004) undertook a study aimed at understanding the reluctance of households in low-income countries to participate in the scheme and the subsequent effects on their well-being. The findings of the study were mixed regarding the correlation between enrollment in CBHI and access to healthcare services. Some individuals contend that CBHI schemes serve as a significant mechanism for safeguarding low-income groups, while others maintain that adverse selection issues result in the exclusion of the impoverished from these schemes. Additionally, Asfaw and Von Braun (2005) found that CBHI schemes possess the capacity to effectively shield the poor from financial shocks related to health.

Risk preference plays a vital role in the decision-making processes of individuals regarding their participation in health insurance. Nevertheless, research on this topic remains limited (Condliff and Fiorentino, 2014; Courbage et al., 2013). Furthermore, individual time preference behaviors have a significant influence on decision-making (Banerjee & Mullainathan, 2010). Decision-makers frequently underestimate the value of future rewards that necessitate patience (Shavit et al., 2014). Additionally, individuals with a high aversion to risk are generally less willing to accept uncertainty concerning future income. However, empirical research on this matter is notably lacking in Africa, especially in Ethiopia. Consequently, this study aims to assess the willingness to pay (WTP) for Community-Based Health Insurance (CBHI) and to identify the associated factors by employing the Contingent Valuation Method (CVM) utilizing both single and double-bound estimation techniques in Northern Ethiopia.

Our research paper provides multiple contributions to the current body of literature. To begin with, we enrich the literature by utilizing unique health insurance survey data to estimate the average willingness to pay (WTP) for Community-Based Health Insurance (CBHI). Additionally, unlike prior research, we collect detailed information on household and community characteristics as well as time preference, and risk preference of each household. The data on risk and time preference uniquely enables us to establish causal relationships using our dataset. Furthermore, unlike previous studies, we utilize both single and double-bound estimation methods to provide information for both low and high-ability payers to CBHI. By considering both ends of the spectrum, the study sheds light on how CBHI can be made more accessible and beneficial for a wider range of individuals. This dual approach enhances the understanding of the effectiveness and implications of CBHI in different economic contexts.

2 Empirical Literature

Community-Based Health Insurance (CBHI) represents a developing initiative designed to offer financial security and enhance access to quality healthcare services for low-income rural families who lack formal insurance coverage. The effectiveness of CBHI is significantly influenced by the level of social capital present within the community (Donfouet et al., 2012). Since the 1990s, health insurance has been advocated as a means to improve healthcare access in developing nations. It enables patients to bypass immediate fee payments and distributes financial risk among all participants in the insurance scheme. Nevertheless, financial constraints present challenges on two fronts: at the point of premium payment and when insured individuals seek to access healthcare services (Morestin et al., 2009).

Community-based health insurance (CBHI) involves pre-payment for healthcare services through community financing mechanisms, relying on voluntary pooling of resources and principles of solidarity. The model aims to distribute financial risks linked to healthcare services. In lower and middle-income countries like Ethiopia, there is often a shortfall in funds or tax revenues to cover healthcare costs for individuals who are near poor, poor, or propoor (Mebratie et al., 2015). Secondly, it is assumed that individuals in impoverished and near-impoverished circumstances, including those employed in the informal sector, incur substantial healthcare expenditures from both public and private providers. As a result, CBHI is increasingly acknowledged as a viable strategy for expanding healthcare insurance coverage to low-income rural populations, enabling households to safeguard themselves against significant healthcare expenses that arise from a heavy dependence on out-of-pocket payments (Carrin et al., 2005).

Community-based healthcare financing mechanisms are important for low-income countries, because of their potential to tackle healthcare obstacles faced by those living in rural areas and working in the informal sector (Jutting, 2004). These mechanisms are typically managed by the community and may go by various names such as mutual health insurance, micro-insurance, or community health funds although these insurance schemes often entail significant administrative and revenue collection costs (UNHCR, 2012).

Ethiopia has limited formal health insurance coverage, with only 50% of government and state-owned enterprise employees receiving coverage before the introduction of community-based health insurance. Currently, the Ethiopian Insurance Corporation (EIC) provides coverage to just 0.02% of the population. This low coverage is due to low government spending and inadequate healthcare infrastructure, making Ethiopia one of the least favorable African countries for health insurance (Wamai, 2009).

According to Huang et al. (2003), CBHI has various benefits. One significant advantage is the separation of healthcare payment from service utilization time, which is particularly advantageous for rural households with seasonal income and expense fluctuations. Due to limited financial resources, individuals with low incomes often struggle to afford healthcare, resulting in decreased medical service utilization. Therefore, implementing a CBHI scheme is considered a viable option, especially for developing countries such as Ethiopia. Dror et al. (2007) conducted a study in India using a CV survey and discovered that the poor were willing to allocate a higher percentage of their income towards health insurance premiums compared to higher-income groups.

Onwujekwe et al. (2010) examined the impact of economic status and residential location on the willingness to pay for health insurance in both urban and rural areas of Nigeria, employing a contingent valuation method. Their findings revealed that fewer than 40% of the 3,070 participants were prepared to pay for CBHI membership. The average monthly premium that respondents were willing to contribute for their own coverage varied, with rural respondents indicating a willingness to pay 250 Naira and urban respondents 343 Naira. Additionally, the research highlighted that males with higher educational attainment demonstrated a greater willingness to pay compared to females with lower educational backgrounds. In a similar vein, Azhar (2018) identified several potential predictors of willingness to accept health insurance, including occupation, education level, gender, marital status, monthly family income, and treatment preferences. Notably, around 46.7% of respondents in Malaysia expressed their readiness to pay a monthly premium for health insurance.

Asfaw and von Braun (2005) determined that the WTP for a community-based health insurance scheme in Ethiopia is US $0.60 per month. They highlighted that despite the seemingly small amount, achieving universal coverage could result in approximately 631 million birr (US $75 million) annually, surpassing the maximum recurrent budget of the country's health sector. Their study suggests that even in one of the world's poorest countries, there is an opportunity to implement CBHI, leading to favorable impacts on healthcare access and utilization (AIID, 2013).

Gustafsson-Wright et al. (2009) conducted a study that delves into the willingness to pay for health insurance and the potential market for a new low-cost health insurance product in Namibia. The study utilized the double-bounded contingent valuation (DBCV) method. The results indicate that 87% of the uninsured respondents are open to participating in the proposed health insurance scheme. On average, respondents are willing to pay NAD 48 per capita per month, and those in the poorest income quintile are willing to allocate up to 11.4% of their income.

In Ethiopia, 78% of private health expenditures are financed through out-of-pocket payments, whereas in Namibia, this figure stands at 18%. Research conducted by Asenso-Okyere et al. (1997) indicated that approximately 64% of participants in Ghana expressed a willingness to pay around Cedi 5000, equivalent to US$3.00 per month, for a National Health Insurance scheme. Additionally, Barnighausen et al. (2007) examined the willingness to pay among informal sector workers in Wuhan, China, and found that these workers demonstrated a greater willingness to pay than the estimated costs of CBHI derived from prior health expenditure data. Furthermore, Dror et al. (2007) employed unidirectional bidding in a contingent valuation survey to assess the willingness to pay for health insurance in India, revealing that individuals from lower-income backgrounds are inclined to dedicate a larger proportion of their income to health insurance premiums compared to those from higher-income brackets. Asgary and colleagues (2004) carried out research regarding the inclination to purchase health insurance in rural Iran. The results indicated that, on average, households are prepared to spend US$2.77 per month on health insurance.

3 Theoretical Model

In this paper, the CV method is utilized to compute the demand for the WTP of CBHI since it is consistent with economic theory (Cameron, 1992; Carson, 1997; Hanemann et al., 1991). Determining the exact amount of money individuals are willing to pay for a product, willing to be compensated or to give it up can be challenging, especially if the product is not currently available in the market. Various methods, such as cost-benefit analysis, cost-effectiveness, travel cost method, and hedonic pricing, have been developed to assess the value of public and non-market goods and services (see for instance, Neumann & Johannesson, 1994; Johannesson et al., 1993; Klose, 1999).

Asfaw & von Braun (2005) utilized a double-bounded dichotomous contingent valuation method to evaluate the potential of CBHI in rural areas of Ethiopia. The contingent valuation method (CVM) was employed to gather information about willingness to pay through direct questioning (Haab and McConnel, 2002). Our study is based on the compensated or equivalent variation theory of microeconomics as the theoretical foundation for CV research. The WTP for insurance schemes can be determined as the disparity between their indirect utility functions with and without the presence of the schemes. Consider a household that maximizes a utility function subject to a budget constraint, and the household's indirect utility function is as follows:

$$V = V\ (p, q, y) \tag{1}$$

Where p is the vector of the prices of the market commodities; q is the status of health insurance services acquired by the household; and y is the household income. If we denote q^0 as the existing status of health services received by the household and q^1as the health insurance services. The value of the change to the household in monetary terms is represented by the Hicksian measure, the compensating variation c which satisfies:

$$V = V(p, \mathrm{q}^1, y - c\ ) = V(p, \mathrm{q}^0, y) \tag{2}$$

An improvement in the health services is represented by the change in q from q^0 to q^1 and this change increases the household's utility level which is c would be positive. In this case, c measures the household's willingness to pay (WTP)

$$V(p, \mathrm{q}^1, y - \mathrm{WTP}) = V(p, \mathrm{q}^0, y) \tag{3}$$

WTP in this case, is the maximum value of money the household will pay in exchange for improved health services from q^0 to q^1. Rearranging Equation (3) for WTP produces WTP function as under;

$$\mathrm{WTP} = \mathrm{WTP}(p, y, \mathrm{q}^0, \mathrm{q}^1) \tag{4}$$

The WTP function in Equation (4) indicates that WTP is not only influenced by the prices of the market commodities (p) and the household income (y) but also by the existing status of health services acquired by the household (q^0), and the insurance services (q^1). Consulting the work of Gustafsson Wright et al.'s (2009) model of WTP for health microinsurance, we may add other exogenous variables to the WTP function as follows

$$\mathrm{WTP} = \mathrm{WTP}(p, y, \mathrm{q}^0, \mathrm{q}^1, X, \varepsilon) \tag{5}$$

Where $\mathrm{q}^1$and q^0 are the levels of utility associated with and without paying to CBHI, y is household income, X represents a vector of socio-economic characteristics (age, sex, education, risk and time preference, etc.) and ε represents other unobserved factors. The estimation of Equation (5) is contingent upon the choice of elicitation method utilized (Hammerschmidt, 1991) among different methods. In this study, the double-bounded dichotomous choice model proposed by Hanemann (1985) is employed. Subsequently, we adhere to the estimation techniques outlined by Haab and McConnel (2002) and Asim & Lohano (2015).

4 Study Area and Method

4.1 Study Area and Data

The study was conducted in the Western Tigrai region of Ethiopia, where a random selection of 332 sample households was made from a pool of 2,303 uninsured households. Humera city, located in the western section of the Tigrai regional state, is approximately 1,000 kilometers north of Addis Ababa, situated along the primary route linking Sudan/Eritrea to Gondar and Sudan to Mekelle. The district CBHI coordinating office supplied the list of targeted uninsured households.

A sample comprising 332 households was selected from a total of 2,303 uninsured households, ensuring a 5% margin of error and a 95% confidence level, in accordance with the methodologies outlined by Israel (2012) and Van Dessel (2019). Information regarding household characteristics was obtained using a semi-structured questionnaire. Data collection was conducted through face-to-face interviews with 332 households from September 1 to September 30, 2020. Additionally, the questionnaire was tested between August 20 and August 30, 2020.

4.2 Elicitation Mechanisms

In the double-bounded dichotomous choice method, respondents are given a subsequent question based on their answers to the first question. Hanemann & Loomis (1991) found that adding a follow-up question significantly improves the statistical accuracy of estimating Willingness-To-Pay (WTP). This approach enables respondents to modify or update their WTP value when presented with the follow-up question (Asim & Lohano, 2015). After making an initial bid, each respondent is asked a second follow-up question, with the bid amount increasing if the response to the first bid is "Yes" and decreasing if it is "No". The respondent is then required to respond with a yes or no to the second question.

Following this explanation, the study participants were instructed to indicate their willingness to pay (WTP) for the proposed Community-Based Health Insurance (CBHI) using the dichotomous choice Contingent Valuation Method (CVM) based on the methodologies employed in previous research (Garedew et al., 2020; Kaso et al., 2022; Negera & Abdisa, 2022; Asgary et al., 2004). Upon agreeing to take part, each respondent received a description of a typical CBHI scenario and was then asked if they would be willing to contribute financially to it. Subsequently, four initial bids were set according to the payment information provided by the local government. An individual willing to pay 340 per year would qualify for enrollment in the CBHI program in Ethiopia. The researcher introduced three additional initial bids, slightly above or below the standard payment in the area, to establish a range of willingness to pay that represents the financial capacities of both the less affluent and the more affluent individuals. Participants were then randomly assigned to one of the initial bid amounts.

Four distinct levels were set for the initial bid, which were Birr 400, Birr 340, Birr 300, and Birr 200. The subsequent bid amount is determined based on the response to the initial bid. If the respondent agrees to the initial bid, the follow-up bid is calculated as the initial bid plus half of the initial bid. Conversely, if the initial bid is declined, the follow-up bid is calculated as the initial bid minus half of the initial bid. This results in lower follow-up bids of Birr 200, Birr 170, Birr 150, and Birr 100, and higher follow-up bids of Birr 600, Birr 510, Birr 450, and Birr 400, respectively. Additionally, we gathered data on individual and community characteristic variables. From the initial and follow-up bid questions posed, we received four combined responses from the sample households: yes-yes, yes-no, no-yes, and no-no.

4.3 Econometric Model Specification

In order to estimate the WTP function using household-level data, a specification of the econometric model is needed. Assume that all households face the same prices of the market commodities (p) and the same health services(q^1). Depending on the household income (y) and the existing status of health services(q^0), WTP varies across households. Furthermore, other household characteristics may affect the households' WTP. Thus, the econometric model for WTP is specified as

$$\text{WTP}= e^{x\beta+\varepsilon} \tag{6}$$

Where x is the vector of explanatory variables, β is the vector of unknown parameters, and ε is the error term representing the unobserved other factors. The exponential WTP function in Equation (6) ensures that the predicted WTP is positive and thus does not provide any negative predicted values of WTP. Maintaining this property is important, as WTP is the maximum amount of money the household will pay for the insurance in exchange for its quality service. For estimating WTP function, Equation (6) can be re-write as:

$$\ln(WTP) = x\beta + \varepsilon \tag{7}$$

In this study, the explanatory variables for the above econometric model include household and community characteristics. Haab and McConnell (2002) raise the concern that the researcher has to decide whether to use probit, interval regression, and bivariate moles based on initial or follow-up responses.

4.4 Estimation Strategy

With dichotomous choice closed-ended questions, most of the previous studies have used one of the following models: probit model, interval data model, and bivariate probit models. In this study, three econometric approaches, namely, the probit model, interval data model, and bivariate probit model were used (Asim and Lohano, 2015 & Lopez, 2012) to estimate the WTP for the CBHI in the urban Tigrai Setit Humera town.

4.4.1 Estimation Method with Single Bound Dichotomous Choice

Equation (7) presents the WTP function for an individual i and can be rewritten as:

$$\ln(\boldsymbol{WTP_i}) = \boldsymbol{x_i}\beta + \varepsilon_i \tag{8}$$

In this case, respondents are asked whether he or she would be willing to pay a certain yearly payment for the insurance using a single-bound dichotomous choice question format. Once each individual is offered a single bid value, he or she is expected to answer yes or no. The individual will answer yes if his/her WTP is greater than the offered bid amount and will answer no if his/her WTP is less than the offered bid amount.

$$\boldsymbol{WTP_i} \geq \boldsymbol{bid_i} \; if \; the \; answer \; is \; yes$$

$$\boldsymbol{WTP_i} < \; \boldsymbol{bid_i} \; if \; the \; answer \; is \; no$$

Denoting y_i=1 if the individual answers yes and y_i=0 if the answer is no, the probability of

$y_i = 1$ is a function of the explanatory variables and can be written as

$$Pr(y_i = 1|x_i) = Pr(\boldsymbol{WTP_i} > \boldsymbol{bid_i}\;) \tag{9}$$

$$Pr(y_i = 1|x_i) = Pr(\ln(\boldsymbol{WTP_i}) > \ln(\boldsymbol{bid_i})) \tag{10}$$

If we plug Equation (8) into Equation (10), the Equation will yield this expression;

$$Pr(y_i = 1|x_i) = Pr(\boldsymbol{x_i}\beta + \varepsilon_i > \ln(\boldsymbol{bid_i})) \tag{11}$$

$$Pr(y_i = 1|x_i) = Pr(\varepsilon_i > \ln(\boldsymbol{bid_i}) - \boldsymbol{x_i}\beta) \tag{12}$$

It is assumed that the error term ε_i has a normal distribution $N\;(0, \sigma^2\;)$ in the case of the probit model. Following this Equation (11) will be:

$$Pr(y_i = 1|x_i) = \Phi\left(\frac{x_i\beta}{\sigma} - \frac{\ln(\boldsymbol{bid_i})}{\sigma}\right) \tag{13}$$

$\phi(\cdot)$ is the standard cumulative normal distribution function. Two approaches are available to estimate this model where the first one is to use an Equation (13) and apply maximum likelihood estimation methods to estimate β and σ. The other approach directly estimates the probit model with x_i and $\ln(\boldsymbol{bid_i})$ as explanatory variables, which can enable us to obtain the estimates of β/σ and –1/σ after estimating the probit model (see Equation(13)). Denoting $\grave{\beta}/\grave{\sigma}$ as the vector of coefficient estimates associated with each one of the explanatory variables and -$1/\grave{\sigma}$ as the coefficient estimate on $\ln(\boldsymbol{bid_i})$, the expected value of WTP can be computed for the individuals with given values of explanatory variables $\tilde{x}$ as:

$$E(WTP|\tilde{x}\;) = e^{\tilde{x}\grave{\beta}+0.5\grave{\sigma}^{\;2}} = e^{-\frac{\tilde{x}\grave{\beta}/\grave{\sigma}}{-1/\grave{\sigma}}+0.5\grave{\sigma}^{\;2}} \tag{14}$$

4.4.2 Estimation Method with Double-Bound Dichotomous Choice

In the single-bound dichotomous choice question format, each individual is offered a single bid value and expects to answer yes or no only once. In the double-bound dichotomous choice, the individual is followed up by a second question about willingness to pay contingent upon the response to the first question. Denote $\boldsymbol{bid_1}$ as the bid amount in the first question. The second question would be asked with a higher bid amount ($\boldsymbol{bid_2}$ (max)) if the answer to the first question is yes, or with a lower bid amount ($\boldsymbol{bid_2}$ (min)) if the answer to the first question is no. Each respondent is expected to answer yes or no to the second question. With double-bound dichotomous choice questions, either an interval data model or bivariate probit model can be used to estimate WTP for CBHI.

4.4.2.1 Interval Data Model: Ordered Probit Model

The interval data model (also referred to as the ordered probit model) can be used to estimate WTP with double-bound dichotomous choice questions format. Given the responses to two questions, the bounds on the WTP depend on the answers to the two questions:

1) WTP $\geq \boldsymbol{bid_{2(max)}}$ if the answers are yes and yes
2) $\boldsymbol{bid_1} <$ WTP $\leq \boldsymbol{bid_{2(max)}}$ if the answers are yes and no
3) $\boldsymbol{bid_{2(min)}} <$ WTP $< \boldsymbol{bid_1}$ if the answers are no and yes
4) WTP $< \boldsymbol{bid_{2(min)}}$ if the answers are no and no

Given these expressions, the probability of every expression is given as follows;

1) yes and yes

$$\mathrm{Pr}(\mathrm{y_{1i}} = 1 \,\&\, \mathrm{y_{2i}} = 1|\mathrm{x_i}) = \mathrm{Pr}\left(\mathrm{WTP_i} > \mathrm{bid_{2(max)}}\right) \quad (15)$$

and can be converted to:

$$\mathrm{Pr}(\mathrm{y_{1i}} = 1 \,\&\, \mathrm{y_{2i}} = 1|\mathrm{x_i}) = \Phi\left(\frac{\mathrm{x_i}\beta}{\sigma} - \frac{\ln\left(\mathrm{bid_{2(max)}}\right)}{\sigma}\right) \quad (16)$$

2) yes and no

$$\mathrm{Pr}(\mathrm{y_{1i}} = 1 \,\&\, \mathrm{y_{2i}} = 0|\mathrm{x_i}) = \mathrm{Pr}\left(\mathrm{bid_1} < \mathrm{WTP} \leq \mathrm{bid_{2(max)}}\right) \quad (17)$$

$$\mathrm{Pr}(\mathrm{y_{1i}} = 1 \,\&\, \mathrm{y_{2i}} = 0|\mathrm{x_i}) = \Phi\left(\frac{\mathrm{x_i}\beta}{\sigma} - \frac{\ln\left(\mathrm{bid_1}\right)}{\sigma}\right) - \Phi\left(\frac{\mathrm{x_i}\beta}{\sigma} - \frac{\ln\left(\mathrm{bid_{2(max)}}\right)}{\sigma}\right) \quad (18)$$

3) no and yes

$$\mathrm{Pr}(\mathrm{y_{1i}} = 0 \,\&\, \mathrm{y_{2i}} = 1|\mathrm{x_i}) = \mathrm{Pr}\left(\mathrm{bid_{2(min)}} < \mathrm{WTP} < \mathrm{bid_1}\right) \quad (19)$$

$$\mathrm{Pr}(\mathrm{y_{1i}} = 0 \,\&\, \mathrm{y_{2i}} = 1|\mathrm{x_i}) = \Phi\left(\frac{\mathrm{x_i}\beta}{\sigma} - \frac{\ln\left(\mathrm{bid_{2(min)}}\right)}{\sigma}\right) - \Phi\left(\frac{\mathrm{x_i}\beta}{\sigma} - \frac{\ln\left(\mathrm{bid_1}\right)}{\sigma}\right) \quad (20)$$

4) no and no

$$\mathrm{Pr}(\mathrm{y_{1i}} = 0 \,\&\, \mathrm{y_{2i}} = 0|\mathrm{x_i}) = \mathrm{Pr}\left(\mathrm{WTP} < \mathrm{bid_{2(min)}}\right) \quad (21)$$

$$\mathrm{Pr}(\mathrm{y_{1i}} = 0 \,\&\, \mathrm{y_{2i}} = 0|\mathrm{x_i}) = \Phi\left(\frac{\mathrm{x_i}\beta}{\sigma} - \frac{\ln\left(\mathrm{bid_{2(min)}}\right)}{\sigma}\right) \quad (22)$$

The parameters of the model β and σ will be estimated by the maximum likelihood estimation method using the above probability functions presented in the Equations(16), (18), (20), and (22). The expected value of WTP can be computed for individuals with given values of explanatory variables $\tilde{x}$ given the maximum likelihood estimates $\tilde{\beta}$and $\tilde{\sigma}$as:

$$E(WTP|\tilde{x}\,) = e^{\tilde{x}\widehat{\beta}+0.5\widehat{\sigma}^2} \quad (23)$$

4.4.2.2 Bivariate Probit Model

The bivariate probit model is used for two-response surveys with double-bound dichotomous choice questions, allowing for different distributions of willingness to pay (WTP) between initial and follow-up questions (Cameron and Quiggin, 1994). This model relaxes the restrictive assumptions of the interval data model and solves the problem of potential bias caused by these assumptions.

We use probit because it allows for non-zero correlation, while the logistic distribution does not. In the bivariate probit model, the WTP functions for an individual i can be written as:

$$\ln(WTP_{1i}) = x_i\beta_1 + \varepsilon_{1i} \quad (24)$$

$$\ln(WTP_{2i}) = \boldsymbol{x_i}\beta_2 + \varepsilon_{2i} \quad (25)$$

We assume that the error terms, ε_1 and ε_2, are normally distributed with mean zero and respective variances σ_1 and σ_2, and have a bivariate normal distribution with correlation coefficient ρ. The researcher must choose a distribution for estimating WTP, even after estimating both distributions in the bivariate probit model. Initial WTP distribution in Equation (24) is used. The expected value of WTP can be computed for individuals with given values of explanatory variables $\tilde{x}$ once the bivariate probit model is estimated and specified as:

$$E(WTP|\tilde{x}\,) = e^{\tilde{x}\widehat{\beta}+0.5\widehat{\sigma}^2} = e^{-\frac{\tilde{x}\widehat{\beta}/\widehat{\sigma}}{-1/\widehat{\sigma}}+0.5\widehat{\sigma}^2} \quad (26)$$

5 Results and Discussions

5.1 Descriptive Statistics

Analyzing survey data from 332 uninsured households in Setit Humera town, this research explores willingness to pay with descriptive and econometric analyses. The descriptive analysis discusses the socioeconomic characteristics of the households. The econometric analysis examines the factors influencing households' willingness to pay, employing a probit model for estimation. The average willingness to pay among households is calculated and reported based on the results obtained from the single bound, double bound, and ordered probit models (interval).

Table 1 Descriptive Statistics of Continuous Variables

Variable	Nonwilling		Willing		Both		P-Value
	Mean	Std	Mean	Std	Mean	Std	
Bid1(amount in Birr)	341.5	60.98	292.17	73.20	310	72.91	0.000
Age in years	33.88	8.07	35.65	9.29	35.01	8.89	0.081
Distance to Health center	14.75	9.07	12.63	6.81	13.40	7.76	0.000
Family size in number	3.39	1.57	4.21	1.88	3.92	1.81	0.000
Owned land	0.74	2.51	2.59	5.31	1.92	4.59	0.014
Extension contacts	8.29	6.87	8.69	7.04	8.55	6.97	0.000
Education in year	4.83	4.55	4.83	4.38	4.83	4.38	0.976
Yearly Expenditure (Birr)[1]	26075	10754	34553	13439	31463	13161	0.000

Source: Own survey, 2020*** p<0.01, ** p<0.05, * p<0.1 and (Birr)[1]=Ethiopian Currency, where 1$≈40ETB in 2020/21

Table 1 presents the data indicating that the average bid value for non-willing households was 341.5 Birr ($8.5), while for willing households it was 292.17 Birr ($7.3). This suggests a notable disparity in bid values between the two groups. Additionally, the average age of non-willing household heads was 33.88 years, compared to 35.65 years for willing household heads. Furthermore, the average distance was 14.75 km for non-willing households and 12.63 km for willing households, indicating a significant difference in the proximity of households to the health center. The average family size of non-willing household heads was 3.39, whereas for willing household heads, it was 4.21. Moreover, the average owned land of non-willing households was 0.74, while for willing households it was 2.59. The expenditure for non-willing households was Birr 26075.16, whereas for willing households was Birr 34553.17, indicating a significant disparity in yearly expenditure.

Table 2 Descriptive Statistics of Categorical Variables

Variables		Non-willing		Willing		Both		P-Value
		F	%	F	%	F	%	
Sex	Female	57	17.17	97	29.22	154	46.39	0.759
	Male	63	18.98	115	34.64	178	53.61	
Training	No	14	4.22	16	4.82	30	9.04	0.208
	Yes	106	31.93	196	59.04	302	90.96	
Patient	Impatient	82	24.70	79	23.80	161	48.49	0.000
	Patients	38	11.45	113	40.06	171	51.51	

Source: Own survey, 2020*** p<0.01, ** p<0.05, * p<0.1

Table 2 indicates that, among 212 willing respondents, 196 (63.86%) received training on health insurance, while 16 (4.82%) did not receive any training. On the other hand, out of the 120 (36.15%) non-willing respondents, 106 (31.93%) received training on insurance, while 14 (4.22%) did not receive any training. Moreover, table 2 shows that among the 120 (36.15%) non-willing respondents, 82 (24.70%) were inpatients and 38 (11.45%) were patients. On the other hand, out of the 212 (63.86%) willing respondents, 113 (40.06%) were patients and 79 (23.80%) were inpatients.

This study utilized four preliminary bids to assess the WTP of respondents (Table 3). The initial bids consisted of amounts of 200 ($5), 300($7.5), 340 ($8.5), and 400 ($10) birrs. The formulation of these bids was grounded in the

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present value of the insurance. The sample respondents were evenly allocated across the four bids, as demonstrated in the table below.

Table 3 Respondent's Distribution on Bid Design

Bids [lower, Initial, higher] per year	Sample Respondents'
[100, 200, 400]	83
[150, 300, 450]	83
[170, 340, 510]	83
[200, 400, 600]	83

Source: Own survey, 2020/21; 1$≈40ETB in 2020/21

We used the current insurance value of 340 as a baseline for the first bid. Subsequent bids were then determined by doubling or halving the initial bid, based on the response to the initial bid values. Table 4 presents the summary statistics of households' reactions to the initial bids. The results show that 63.86% of the participants accepted the initial bids, while the remaining declined. The average initial bid accepted by the participants was calculated to be 310 ETB.

Table 4 Households' Response to the Initial Bids

Initial bid values in Birr ($)	No	Yes	Total
200(5)	12	71	83
300(7.5)	24	59	83
340(8.5)	37	46	83
400(10)	47	36	83
Total	120	212	332

Source: Own survey, 2020/21: 1$≈40ETB in 2020/21

In this research, the starting bids utilized were 200, 300, 340, and 400. According to Table 4, among the 83 participants, 12 were unwilling to pay for the initial bid of 200. However, the remaining 71 participants were willing to pay. Regarding the second initial bid of 300, out of the total participants (83), 24 were unwilling to pay, while the remaining 59 participants were willing to pay the specified bid. Moving on to the third initial bid of 340, out of the total participants (83), 37 were unwilling to pay, and the remaining 46 participants were willing to pay the specified bid. Lastly, for the final initial bid of 400 birr, 47 participants were unwilling to pay, whereas the remaining 36 participants were willing to pay. Following the responses to the initial bid, the participants were then asked for follow-up bids.

Upon acceptance or rejection of the initial bids by the respondents, a higher second bid was offered to 63.86% of the respondents who accepted the initial bid. This was conducted in order to ascertain their true willingness to pay for insurance, which could potentially exceed the initial bids. Conversely, a lower second bid was proposed to the remaining 35.14% of respondents who rejected the initial bids. The descriptive statistics reveal the outcomes of the responses to the second bids.

Table 5 Households' Response for the Double Bound Dichotomous Choice

Initial & Follow -up bid values in Birr	No-No	No-Yes	Yes-No	Yes-Yes	Total
[100, 200, 400]	7	5	39	32	83
[150, 300, 450]	2	22	34	25	83
[170, 340, 510]	4	33	30	16	83
[200, 400, 600]	16	31	25	11	83
Total	29	91	128	84	332

Source: own survey, 2020/21: 1$≈40ETB in 2020/21

Table 5 illustrates that out of all the participants, 303 (91.27%) expressed their willingness to pay either the initial bid, the follow-up bid, or both, depending on their financial capacity. On the other hand, 29 (8.73%) respondents stated that they were not willing to pay at all. More specifically, the research revealed that 25.30% of the participants agreed to both the first and second higher bids presented. Moreover, 95 (28.62%) respondents were prepared to pay an amount falling within the range of the second lower bids, indicating their inability to pay more than the second lower bids. Additionally, around 130 (39.16%) respondents were willing to pay either the initial bid or a higher amount.

The starting bid of 200 was rejected by 12 sample respondents, but 7 were willing to pay for the lower follow-up bid of 100. Conversely, 71 respondents were willing to pay the initial bid of 200, but only 39 were not willing to pay the doubled value of 400. Moreover, 32 households were willing to pay for both the initial and follow-up bids of 200, whereas only 7 respondents were not willing to pay for either.

For a bid amount of 300, 25 participants expressed a willingness to pay for both the initial bid and the subsequent doubled amount, whereas 2 participants indicated they were unwilling to pay for either the initial bid or the reduced follow-up bid of 150. Furthermore, 34 respondents were prepared to pay only for the initial bid and not for the doubled amount, while 22 households initially declined to pay for the initial bid but later agreed to pay for the lower follow-up bid value.

Four respondents indicated they would not pay for the original offer or the lesser follow-up bid value of 170, at a bid value of 340. In contrast, sixteen respondents were willing to pay for both the initial bid and the doubled value upfront. Furthermore, 33 households changed their original unwillingness to pay for the higher follow-up bid value to one of 30 respondents who were only willing to pay for the initial bid value rather than the doubled value.

The final starting bid of 400 attracted 11 respondents who were willing to pay for both the initial and higher follow-up bids. On the other hand, 16 respondents refused to pay for either the initial bid or the lower follow-up bid values. In contrast, 31 respondents rejected the initial bid but agreed to the lower bid value. Moreover, 25 household respondents were ready to pay for the initial bid but not for the higher follow-up bid value.

5.2 Econometric Results

5.2.1 The Probit Model Estimation Result

A probit model was utilized to estimate the willingness to pay (WTP) value and the determinants affecting WTP for community-based health insurance through a single-bound dichotomous choice. Initially, Table 6 displays the estimated coefficient, sign, and marginal effects of the single-bound model excluding explanatory variables. The findings indicate that the overall model is statistically significant at a 1% level of significance.

Table 6 Estimation of Single bound without Control Variable

Variables	**Marginal Effect (Pr(WTP))**
Initial bid	-0.00234***
	(0.000391)
Observations	**332**

NB: Standard errors in parentheses where *** p<0.01, ** p<0.05, * p<0.1

The data presented in Table 6 demonstrates that the coefficient associated with initial bid amounts is negative and shows statistical significance at the 1% level. This suggests that as the initial bid price rises, the likelihood of individuals being willing to pay for CBHI decreases by 0.23%. Subsequently, we compute the willingness to pay without controlling any explanatory variables**.**

Table 7 WTP using Single Bound without Control Variable

answer1	Coefficient.	Std. Err.	z	P>|z|	[95%Conf. Interval]	
WTP	372.70	14.51	25.68	0.000	344.26	401.14

Source: Own Estimate, 2020

Table 7 presents the average willingness to pay (WTP) for Community-Based Health Insurance (CBHI) as determined by the single bounded elicitation method. The computed value stands at 372.70 Birr annually for each household. Based on a 95% confidence interval, Table 8 below provides the expected results for the factors impacting households' willingness to pay (WTP) for CBHI, which were obtained using a single-bound elicitation procedure. All explanatory factors except for the monthly subjective discount rate showed expected signals. At the 1% level, the coefficient connected to the starting bid price is statistically significant and negative. This negative

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coefficient indicates that a household's WTP for CBHI in birr is 0.3% less likely to grow by one unit in the starting bid price, which may be a reflection of cash poverty or income scarcity. Additionally, the results show that when the price increases, so does the demand for CBHI. This finding supports the conclusions made by Getachew (2018), Gebremariam and Edriss (2012), Limaei (2014), Seifu et al. (2017), and Tilahun et al. (2012).

Table 8: Estimation of Single Bound with Control Variable

Variables	Marginal Effect (Pr(WTP))
Initial bid in Birr	-0.00323***(0.0005)
Age of household head in years	0.00406(0.0046)
Schooling in year	0.0205**(0.0085)
Distance to health in walking minutes	-0.00716*(0.0039)
Gender(Male=1& Female=0)	0.123*(0.0635)
Family size (number)	0.0369*(0.0202)
Total land in hectares	0.0141(0.0091)
Extension contact (count)	0.0156***(0.0047)
LOSS Aversion(number)	-0.0241(0.0150)
RISK Aversion(Number)	-0.0509***(0.0115)
Monthly Subjective Discount Rate	0.0104**(0.00518)
Ln (Expenditure in Birr)	0.336***(0.0881)
Observed probability	0.6385
Predicted probability	0.7312
Observations	332

NB: Standard errors in parentheses where *** p<0.01, ** p<0.05, * p<0.1

Additionally, the outcomes of the probit model revealed a significant and favorable relationship between the educational level of the participants and their WTP for CBHI. Furthermore, the results showed that keeping all other variables constant, a one-year increase in the educational level of the household head led to a 2.05% rise in the probability of accepting the initial offer. These results align with the research conducted by Seifu et al. (2017) and Getachew (2018) but contradict the findings of Lorenzo et al. (2000).

Regarding gender differences, male participants exhibited a 12.3% greater propensity to pay for the CBHI in comparison to female participants. In numerical terms, males were prepared to contribute roughly 12 Birr more than their female counterparts. Furthermore, a higher frequency of interaction with extension services was associated with an increase of approximately 1.7% in the likelihood of accepting the initial bid. This phenomenon can be explained by the fact that access to extension services equips respondents with essential information offered by the CBHI.

The walking distance to the healthcare facility was incorporated as a variable in the probit model. This model assessed the impact of this variable on the willingness-to-pay (WTP). The direction of the variable aligned with our initial expectations, revealing a negative and significant correlation with the WTP. This noteworthy finding suggests that households situated farther from the healthcare facility, even by a single minute of walking, exhibited a lower likelihood of agreeing to the initial bid. In particular, the analysis indicated that an increase in distance resulted in a reduction of approximately 0.72% in the probability of accepting the proposed prices.

The size of the family has a significant positive effect on the household head's willingness to pay for health insurance at a 10% level of significance. The data reveals that with each additional unit increase in family size, there is a 3.6% rise in the likelihood of the household's willingness to pay while keeping all other factors constant. This implies that households with more members are more likely to pay a higher premium for health insurance. This outcome aligns with the findings of Zhang et al. (2006). The rationale behind this is that larger families base their payment choices on household size, as bigger households tend to have higher healthcare costs. Consequently, larger families bear a heavier financial burden in terms of healthcare expenses.

Risk preference is acknowledged as a crucial element in the decision-making processes of individuals. The research indicated that risk has a detrimental impact on households' willingness to pay for CBHI at a significance level of 1%.

The findings reveal that households exhibiting greater risk aversion experience a 5.1% reduction in their willingness to pay for CBHI. This suggests that more risk-averse households are less inclined to take advantage of the CBHI program. These findings align with the conclusions drawn by Condliffe & Fiorentino (2014). Additionally, the Monthly Subjective Discount Rate (MSDR) serves as an explanatory variable that significantly and positively influences households' WTP at a 5% significance level. The marginal effect indicates that household heads who reported a higher discount rate demonstrated an increased WTP for the CBHI scheme by 1.0%. These outcomes stand in contrast to earlier research conducted by Shavit et al. (2014). The justification is that since this program is mainly designed for the poor section of society and the poor is mostly impatient, this makes sense.

The expenditure measured in Birr serves as a significant explanatory variable that positively influences households' willingness to pay, achieving a 1% level of significance. The marginal effect indicates that an increase of one Birr in log expenditure raises the likelihood of accepting the initial bid by roughly 34%, assuming other variables remain unchanged. This finding suggests that households with higher expenditure possess a greater capacity to pay than those with lower expenditure.

Table 9. Mean WTP using Single Bound with Control Variables

answer1	Coefficient	Std. Err.	z	P>|z|	[95%Conf. Interval]	
WTP	372.88	11.64	32.04	0.000	350.07	395.68

Source: Own Estimate, 2020

The mean payment willingness of an individual respondent with a control variable is 372.88 birr (Table 9). The disparity in payment willingness with and without a control variable is negligible, just 0.18 birr.

5.2.2 Double Bound

The mean WTP and the determinant factors were estimated using the double-bounded dichotomous choice format, based on responses from both the initial and subsequent bids. The results of the estimation, along with the values of WTP, including and excluding control variables, can be found in Tables 10, 11, and 12 below.

Table 10 Mean WTP using Double Bound without Control Variables

	Coefficient.	Std. Err.	z	P>|z|	95%Conf	Interval
Beta						
WTP	373.31	9.625	38.79	0.000	354.45	392.18
Sigma	161.02	8.645031	18.63	0.000	144.08	177.97

Source: Own Estimate, 2020

Using the double-bounded elicitation method without a control variable, the study found that the average willingness to pay (WTP) for CBHI was 373.31 Ethiopian Birr (ETB) per year per household. The 95% confidence interval indicates that the WTP ranges from 354.45 to 392.18 ETB.

The level of education completed by the household head was discovered to have a significant impact on the CBHI scheme. Essentially, a rise in the educational attainment of the household head is associated with a 6.73% rise in the readiness to contribute towards health insurance, assuming all other variables remain unchanged. Furthermore, it contributes to a more thorough comprehension of healthcare, health insurance, and the original assumptions of the study.

Table 11: Estimation of Double bound with Control Variable

Variables	Marginal Effect (Pr(WTP))
Age of household head in years	1.006(1.152)
Schooling in year	6.730***(2.188)
Distance to health in walking minutes	-0.603(0.972)
Gender (Male=1& Female=0)	35.86**(16.45)
Family size (number)	12.80**(5.158)
Total land in hectares	2.593(1.946)
Extension contacts (count)	3.226***(1.177)
LOSS Aversion(number)	-6.809**(3.432)

RISK Aversion (Number)	-10.83***(3.003)
Monthly Subjective Discount Rate	4.273***(1.170)
Ln (Expenditure in Birr)	113.4***(20.29)
Constant	-899.1***(207.7)
Sigma	122.9***(6.715)
Observations	332

NB: Standard errors in parentheses where *** p<0.01, ** p<0.05, * p<0.1

The findings suggest that men expressed a greater readiness to pay compared to women. This aligns with the study by Onwujekwe (2010), which indicates that men typically have higher incomes than women, leading to an income effect. One potential reason for this is that women may be more susceptible to risks and perceive them more strongly, prompting them to prioritize paying more to safeguard themselves in the context of a voluntary health insurance program (Asfaw et al., 2008).

The household size has a significant impact on participation in CBHI. It positively influences the willingness to pay, with a 5% probability level. Specifically, for each additional family member, there is a 12.83% increase in willingness to pay for CBHI. Similar results have been found in studies conducted in Nigeria and India.

Access to extension services had a notable effect on the readiness of household leaders to invest in insurance, as demonstrated by the 1% significance level. These services offer households vital information regarding the significance of CBHI, which positively impacts their choice to take part. As expected, the greater the access households had to these services, the higher their probability of participating in CBHI insurance. This discovery is consistent with the research carried out by Falola et al. (2013), which identified a positive connection between extension services and the willingness to buy insurance among Nigerian farmers.

Courbage and Rey (2008) assert that individuals exhibiting loss aversion tend to hesitate in embracing new innovations on a trial basis. Conversely, those who are more inclined to take risks are generally more open to adopting new interventions on a broader scale. Abebe and Bogale (2014) define risk as the lack of complete knowledge regarding the likelihood of loss or the possible outcomes associated with a particular action. The realm of insurance is marked by uncertainty and risk.

Research has indicated that personal financial decisions are impacted by individual time preferences. Risk-averse people tend to have less tolerance for uncertainty regarding their future earnings. Consequently, those who are unsure about their future income typically exhibit a greater discount rate for future earnings, as emphasized by Shavit et al. (2014). Nevertheless, their study reveals a positive correlation, suggesting that individuals with a higher discount rate are more inclined to invest in CBHI. This outcome challenges the current body of literature.

Households' annual expenditure is frequently utilized in place of income, as individuals often struggle to accurately assess their actual financial status. The findings reveal a strong and positive correlation between the natural logarithm of household expenditure and their WTP for CBHI. Specifically, for each birr increase in household expenditure, the likelihood of WTP for CBHI rises by roughly 113.4%. This pattern mirrors the connection between food expenditures and income, as highlighted by Perthel (1975).

Table 12 WTP using double Bound with Control Variable

answer1	Coefficient	St. Err	z	P>|z|	[95% Conf.	Interval]
WTP	374.67	7.76	48.26	0.000	359.45	389.88

Source: Own Estimate, 2020

The willingness to pay, as assessed through the double-bound method incorporating a control variable, amounts to 374.67 birr. A minor discrepancy of 1.36 birr exists between the willingness to pay values derived with the control variable and those obtained without it...

5.2.3 The Interval Data Model

The estimation technique outlined in this section involves the interval data model, commonly referred to as the ordered probit model. This method employs a double-bound dichotomous choice question format**.**

Table 13 WTP using Interval Regression without Control Variable

	Coefficient	St. Err.	z	P>|z|	[95%Conf.	Interval]
WTP	387.23	9.45	41.00	0.000	368.72	405.74
Ln sigma	5.06	0.05	96.13	0.000	4.96	5.16
Sigma	157.27	8.28			141.86	174.35

Source: Own Estimate, 2020

The findings presented in Table 13 reveal that the average yearly willingness to pay for Community-Based Health Insurance (CBHI) among heads of households amounted to 387.23 ETB.

6 Conclusion and Policy Implications

The Ethiopian government is striving to enhance health insurance coverage for all its citizens within the framework of the GTP2 strategic plan. A key approach to realizing this objective involves conducting studies to evaluate the community's readiness to invest in insurance. This study aims to assess the willingness to pay (WTP) for Community-Based Health Insurance (CBHI) and to identify the associated factors by employing the Contingent Valuation Method (CVM) utilizing both single and double-bound estimation techniques in Northern Ethiopia.

The descriptive findings of the study indicated that around 303 participants (91.27%) expressed a willingness to pay either the initial or subsequent bids, or both, contingent upon their financial means. Conversely, 29 participants (8.73%) indicated a complete unwillingness to pay anything. Furthermore, the study estimated the average amount that households are prepared to pay (WTP) for community-based health insurance (CBHI) utilizing the double-bounded dichotomous choice method, both with and without the inclusion of control variables.

The results demonstrated that the mean WTP was 374.67 birr annually when control variables were included, and 373.31 birr annually when they were not included. Additionally, the single-bound model produced an average WTP of 372.88 birr with control variables and 372.70 birr without control variables. The interval data also suggested an average WTP of 387.23 birr. It is essential to recognize that these WTP estimates may vary slightly from current expenditure levels in both models. Nonetheless, from a normative perspective, the introduction of insurance in urban communities is expected to improve the overall social welfare of the majority.

The findings derived from the probit model reveal that a significant insight from the study is the robust correlation between the WTP and the bid value. It was noted that an increase in bid value corresponds with a decrease in the WTP for insurance, confirming the economic demand theory. Moreover, the correlation between educational attainment and the propensity to engage in a CBHI can be explained by the observation that higher education levels enhance individuals' health-seeking behaviors. The research also identified a strong relationship between extension contacts, annual household expenditure, and the WTP for the CBHI) scheme. Additionally, a notable negative correlation was found between risk-averse household heads and their WTP for the CBHI scheme.

The results of the study suggest that socio-economic attributes of the household are crucial in influencing a household's readiness to contribute towards a CBHI scheme. As a result, strategies designed to assist marginalized groups in the research location should carefully account for these key factors to ensure their success. To make an informed decision, people must have access to adequate information and education regarding the insurance plan. Individuals are more motivated to protect their family's health by participating in risk-sharing arrangements, such as contributing to health insurance. The government should implement a dedicated awareness-raising initiative and provide supplementary subsidies aimed at supporting impoverished and vulnerable populations.

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