International Journal of Science Academic Research
Vol. 02, Issue 07, pp.1751-1759, July, 2021
Available online at http://www.scienceijsar.com
ISSN: 2582-6425

Research Article

MARGINAL EFFECTS ANALYSIS OF CORRELATES OF ENROLLMENT IN A COMMUNITY–BASED HEALTH INSURANCE SCHEME IN ETHIOPIA

[1,] *Emmanuel Gabreyohannes and [2]Tnsue Gebrekidan

[1]Mathematics and Statistics Department, Ethiopian Civil Service University, Addis Ababa, Ethiopia
[2]Center for Training and Consultancy, Ethiopian Civil Service University, Addis Ababa, Ethiopia

Received 18th May 2021; **Accepted** 14th June 2021; **Published online** 13th July 2021

Abstract

Community–based health insurance (CBHI) is advocated as an alternative financing scheme to cater for the unexpected nature of healthcare expenditure for the vulnerable segments of the population in low-income countries. The general objective of this study was to assess households' willingness to enroll in a proposed CBHI scheme in Adama city, Ethiopia. Two-stage cluster sampling was used to collect data from a random sample of members of mutual aid associations (called Iddirs) using structured questionnaires. The impact of covariates on respondents' willingness to enroll in the proposed scheme was explored using average marginal effects and marginal effects at representative values from the fitted binary logistic regression model. The results revealed that the probability of willingness to join the proposed scheme was higher for male respondents, respondents with at least primary education, married respondents, the elderly and respondents who have serious difficulty in finding money in times of ill-health. Marginal effects analysis also revealed that the impact of gender and marital status diminishes as age and level of education increase. Joint marginal effects analysis of covariates indicated that the probability of willingness to enroll in the scheme was significantly lower for unmarried and divorced/widowed female respondents with no education. Thus, there should be selective targeting of the vulnerable groups within the communities in setting up CBHI schemes.

Keywords: Predictive margins, Average marginal effects, Out-of-pocket payment, Healthcare financing, Community-based Health Insurance, Iddir.

INTRODUCTION

Large populations in poor countries remain over-reliant on out-of-pocket payments (OPPs) that include over-the-counter payments for medicines and fees for consultations and procedures. According to the World Health Organization (WHO, 2016), medical fee are a significant obstacle to healthcare coverage and utilization. OPPs create constraints to utilizing essential healthcare services (Ekman, 2004) and push families deeper into poverty (McIntyre *et al.,* 2006). Healthcare financing for the poor population has been one of the most urgent challenges faced by a number of low and middle income countries. Community–based health insurance (CBHI) was advocated as an alternative financing scheme to mobilize resources to fund and deliver healthcare for the poor in rural and urban communities. The main strengths of community-financing schemes are the extent of outreach penetration achieved through community participation, the contribution to financial protection against illness, and the increase in access to health care by low-income rural and informal sector workers (World Bank, 2004). In Ethiopia, healthcare is in the forefront of inadequate social services with significant regional disparities in access to services and health outcomes. Despite encouraging improvements in health service coverage as well as utilization of services at all levels of the Ethiopian healthcare system, the population still faces a high rate of morbidity and mortality (Ethiopian Ministry of Health, 2010). Critical barriers to improved health care financing include inadequate government spending on the health sector; strong reliance on out-of-pocket expenditure; inefficient and inequitable utilization of resources; and poorly harmonized and unpredictable donor funding (Ethiopian Public Health Institute, 2014).

Corresponding Author:** ***Emmanuel Gabreyohannes
Mathematics and Statistics Department, Ethiopian Civil Service University, Addis Ababa, Ethiopia

As a healthy society is one of the major factors for the overall development of a nation, the Ethiopian government has established a Health Insurance Agency to develop risk sharing mechanisms in 2010. Two types of health insurance schemes were introduced. The first scheme, social health insurance, is in the implementation phase and is compulsory for all individuals who are engaged in the formal sectors. The second health insurance scheme is a voluntary CBHI for the rural population and urban informal sector workers. The scheme is government-driven but with community engagement in insurance design, participation, management and supervision. This scheme was established on a pilot basis in rural areas of four regional states of Ethiopia in 2011 (Ethiopian Ministry of Health, 2011), and has had a positive effect on the availability of drugs and other supplies and improved the quality of health services (USAID, 2015).

As discussed above, CBHI is being piloted in a number of rural districts with successful outcomes. However, information about the possibility of extending such schemes to urban areas of the country is scanty. From the methodological aspect, the bulk of studies on CBHI are based on logistic regression model and interpretation of the estimated coefficients in terms of odds ratios. However, odds ratios might be misleading since they do not consider actual differences in the probability of the outcome among various groups. Moreover, most of the studies in the literature focus on separate analysis of covariates without giving due emphasis to the interaction effects among these factors in individuals' decision making process. In this study, we explore the impact of covariates and their interactions on willingness to enroll in a proposed CBHI scheme using marginal effects which are more informative due to the fact that they express effects in the probability scale and enable us to study the joint effect of covariates on the outcome.

This paper is organized as follows: Section one discusses the background and rationale of the study. The second section deals with the description of the research methodology employed including description of the study area, sampling techniques and sample size determination, methods of data analysis and econometric model specification. The results of the study are presented in Section three. Section four is devoted to discussion of results. The last section presents conclusions and recommendations.

METHODS

The study was conducted in Adama city which is located in Oromia National Regional State of Ethiopia. The 2016 projection puts the population size of the city at 338,940. According to the Social Insurance Office in the Bureau of Social Affairs of Adama City Administration, the total number of registered Iddirs in the city is 289. Most of the Iddirs are established with the primary objective of helping members to cope with the costs of funerals and related expenses. In-kind support is also provided for social events such as weddings.

Sampling design, data type and source

In this study both primary and secondary data have been utilized as sources of information. Secondary data was gathered from journal articles, text books, reports and websites to get background information regarding the newly designed (and on pilot survey stage) CBHI scheme. On the other hand, primary data was collected from members of Iddirs and focused group discussants. The study population consists of all households in the city who are members of any Iddir and whose heads are working in the informal sectors. Both probability (two-stage cluster sampling) and non-probability (purposive) sampling designs have been used. Purposive sampling was utilized to select focused group discussants that have in-depth knowledge about the issues under consideration. The probability sampling design implemented was two-stage cluster sampling. In the first stage, a random sample of Iddirs (clusters or first-stage sampling units) was selected from Adama city. According to the City Administration, the city has a total of 18 Kebeles (14 urban and four rural kebeles). To allow sufficient variations within the city, one Iddir was randomly selected from each of the Kebeles. In the second stage, a random sample of members (second-stage sampling units) was drawn from each of the sampled Iddirs. Primary data was gathered from randomly selected Iddir members at monthly payments collection locations using structured questionnaire. The sample size was determined using the formula for estimating population proportions due to Cochran (Cochran, 1989). According to the municipal administration office of the city, there are roughly 13,200 households who are members of at least one Iddir. Considering a margin of error of 5% and a 95% confidence level, the minimum sample size required was calculated as n = 374. To accommodate for incomplete data and non-response, a 5% allowance was made and a total of n = 393 respondents were approached and the required information was gathered. Some vital information was found missing for nine of the respondents, and hence, information from 384 Iddir members was used in the final analysis.

Variables of the study

In this study, the response variable is whether members are willing to enroll in the proposed CBHI scheme or not. It is a dichotomous (binary) random variable defined as:

$$y_i = \begin{cases} 1 & \text{if } i^{th} \text{ member is willing to enroll in the scheme} \\ 0 & \text{if } i^{th} \text{ member is NOT willing to enroll in the scheme} \end{cases}$$

Based on the literatures reviewed, the explanatory variables selected for this study were the following:

i) **Demographic characteristics of respondents**: gender, age, marital status, family size, level of education and religion. Here age is a continuous variable while the others are all categorical.
ii) **Socio-economic (financial) characteristics of respondents (or their households)**: monthly income (in ETB), monthly amount of payment to Iddir (in ETB) and saving status. The former two covariates are continuous, while the latter one is binary (yes/no-type).
iii) **Health-related characteristics of respondents**: health status of family, presence/absence of chronic illness and/or disability in the family, ease/difficulty of finding money for health care, and presence of any illness or injury in the six months prior to the survey. All of these covariates are categorical.

Methods of data analysis

Both descriptive and inferential statistics have been used to analyze the data. Descriptive analysis was used to describe respondents' demographic, socio-economic and health-related characteristics using percentages and frequency distributions. Furthermore, marginal effects analysis was used to explore the significant correlates of willingness to enroll in CBHI scheme based on binary logistic regression model.

The standard logistic regression model is defined as:

$$\eta = \ln\left(\frac{\pi}{1-\pi}\right) = x'\beta \quad \text{...} (1)$$

where $\pi = E(y \mid x) = \Pr(y = 1 \mid x)$ is the response probability, $x = (x_1, x_2, \ldots, x_p)'$ is the (p×1) covariate vector and $\beta = (\beta_1, \beta_2, \ldots, \beta_p)'$ is the (p×1) vector of unknown regression coefficients. The response probability and the covariate vector are related through $\pi = F(\eta)$, where $F(\cdot)$ is the logit link function defined as:

$$F(\eta) = \frac{\exp(\eta)}{1+\exp(\eta)} = \frac{\exp(x'\beta)}{1+\exp(x'\beta)} \quad \text{.........................} (2)$$

The estimation of parameters in binary choice models is usually based on the method of maximum likelihood. Unlike linear models, the likelihood function is nonlinear and the solution ($\hat{\beta}$) is obtained through an iterative process.

Most studies that utilize the logistic regression model place a strong emphasis on odds ratios and relative risks. However, both could be misleading. As an illustration, consider a situation where the probability of death in a control group is 0.1, while that in the treatment group is 0.05. A difference of five percentage points looks impressive. The interpretation of the odds ratio (OR = 0.47) is that the treatment reduces the odds of death by a factor of 0.47. The relative risk is 0.05/0.1 = 0.5 – meaning that the probability of death is reduced by half in the treatment group. Consider the same situation but now the probabilities of death in the control and treatment groups are 0.001 and 0.0005, respectively. The magnitudes are quite different but the odds ratio is almost the same (OR = 0.5) and the relative risk is still 0.5, while the reduction is just 0.05 percentage point. The implication is that, with odds ratios and relative risks, we do not have a sense of magnitude (that is, no intuitive feel for the size of the difference). Marginal effects are popular means by which the effects of variables in nonlinear models can be made more intuitively meaningful. In logistic regression model, for instance, they are more informative since they express effects in the probability scale (while coefficients are estimated in the log-odds scale), that is, we can better interpret the model in the scale that makes more sense. Marginal effect is a measure of the instantaneous effect that a change in a particular explanatory variable has on the conditional mean of the response (y) (Cameron and Trivedi, 2010).

The marginal effect for a continuous variable x_j is obtained by computing the derivative of the conditional mean function with respect to this covariate:

$$\frac{\partial E(y \mid x)}{\partial x_j} = \frac{\partial F(x'\beta)}{\partial (x'\beta)} \cdot \frac{\partial (x'\beta)}{\partial x_j} = f(x'\beta)\beta_j \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots (3)$$

where $f(\cdot)$ is the density function that corresponds to the cumulative distribution function $F(\cdot)$. In a linear regression setting, the marginal effect is simply the relevant slope coefficient. In nonlinear regression models, however, the marginal effect of an explanatory variable (x_j) on the response variable depends not only on the regression coefficient attached to it (β_j) but also on the full parameter vector (β) and covariate vector (x). For the logit model, the marginal effect of x_j is given by:

$$\frac{\partial E(y \mid x)}{\partial x_j} = F(x'\beta)[1 - F(x'\beta)]\beta_j \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$

(4)

We can clearly see from Equation (4) that the marginal effects will vary with the values of x. Thus, one can evaluate the expressions at the sample means of the data or evaluate the marginal effects at every observation and use the sample average of the individual marginal effects to obtain the average marginal effects. The two approaches in general yield different results since the marginal effects are nonlinear functions of the parameters and levels of the explanatory variables ($F(E[Y]) \neq E[F(Y)]$). In small or moderate sized samples, averaging the individual marginal effects is preferred (Greene, 2003). One complication in computing marginal effects in a binary choice model is the presence of dummy variables in the covariate vector (x). Simply taking the derivative with respect to such variables as if they were continuous might not be appropriate. The appropriate marginal effect for a binary independent variable, say x_k, would be:

Marginal effect = $\Pr(y = 1 \mid \overline{x}^*, x_k = 1) - \Pr(y = 1 \mid \overline{x}^*, x_k = 0)$ … (5)

where $\overline{x}^*$ denotes a vector of means of all other variables in the model.

The predicted probabilities and the estimated marginal effects can be computed as $F(x'\hat{\beta})$ and $f(x'\hat{\beta})\hat{\beta}$, respectively. Note again that both are nonlinear functions of the parameter estimates. Under certain regularity conditions, Greene (2003) has shown that the estimators are consistent and asymptotically normally distributed. To compute the standard errors, we can use linear approximation approaches such as the delta method (linear Taylor series expansion). In this study, the impact of covariates was explored using adjusted predictions at representative values (APRs), average marginal effects (AMEs), and marginal effects at representative values (MERs).

RESULTS

The section begins with descriptive statistics of various demographic, socio-economic and health-related characteristics of the sample respondents. This is followed by binary logistic regression and marginal effects analyses whereby the determinants of members' willingness to enroll in the proposed CBHI scheme were identified and explored.

Descriptive statistics

Demographic and socio-economic characteristics of respondents: Table 1 presents descriptive statistics of demographic and socio-economic characteristics of respondents. The number of female respondents was 156 (40.6%), and the majority was married (254 or about 66.1%). When we consider the level of education, 47 (12.2%) of the respondents were illiterate, while 97 (25.3%) of them reported that they can only read and write. The remaining respondents had primary, secondary or higher education (240 or 62.5%). Moreover, the mean age and family size of the respondents were about 48.5 years and 4.4, respectively. The mean monthly household income of respondents was ETB 2824.12 with a standard deviation of ETB 2252.61. The coefficient of variation of about 80% tells us that there is large variation in the household income of respondents.

Table 1. Summary of demographic and socio-economic characteristics of respondents

		Frequency	Percent
Gender	Female	156	40.6
	Male	228	59.4
Marital status	Married	254	66.1
	Unmarried	62	16.1
	Divorced/Widowed	68	17.7
Level of education	Illiterate	47	12.2
	Read and write	97	25.3
	Primary	61	15.9
	Secondary	108	28.1
	Certificate and above	71	18.5
	Mean	Std. Dev.	CV (%)
Age	48.4557	13.79004	28.46
Family size	4.3888	1.92224	43.80
Income (ETB per month)	2824.12	2252.61	79.76

Health-related characteristics of respondents: Descriptive statistics of health-related characteristics of respondents are displayed in Table 2. Sixty nine percent (265) of respondents rated the health status of their family as very good/good, while 50 (13.0%) of them reported that the same is poor or very poor. Moreover, 109 (28.4%) and 184 (47.9%) of respondents or their family members have chronic illness/ disability and encountered illness/injury during the six months prior to the survey, respectively. The majority of respondents (209 or 54.5%) reported that finding money for medication was difficult or so difficult. When inquired about the quality of healthcare service in town, 70 (18.2%) of the respondents were of the opinion that it is poor or very poor.

Table 2. Descriptive statistics of health-related characteristics of respondents

		Frequency	Percent
Health status of family	Very good/good	265	69.0
	Medium	69	18.0
	Poor/very poor	50	13.0
Chronic illness/disability in family	No	275	71.6
	Yes	109	28.4
Illness/injury in family during the six months prior to the survey	No	200	52.1
	Yes	184	47.9
Ease/difficulty of finding money for health care	Easy/so easy	63	16.4
	Moderate	112	29.2
	Difficult	120	31.3
	So difficult	89	23.2
Quality of healthcare service in town	Very good/good	174	45.3
	Medium	140	36.5
	Poor/very poor	70	18.2

Willingness to enroll in CBHI scheme: Among the participants of this survey, 308 (80.2%) of them have expressed their willingness to enroll in the proposed CBHI scheme with an annual installment of ETB 360 through Iddir (paid on monthly basis). Focus group discussants were inquired as to why some Iddir members were unwilling to join the proposed scheme. According to them, one of the reasons is that the community is wary of new initiatives and has serious doubts about the practicality of the scheme. They suggest thorough awareness creation forums whereby the community is addressed about the advantages and details of the operation of the scheme. A number of studies have cited factors such as knowledge and understanding of insurance and CBHI; trust in CBHI scheme; and adequate legal and policy frameworks to support CBHI as potential enablers for enrolment (Dror *et al.,* 2016; Fadlallah *et al.,* 2018; Donfouet *et al.,* 2011; Mirach *et al.,* 2019). Another reason raised by discussants was the community's concern on the quality of health service provision in public healthcare institutions (sole providers of healthcare services under CBHI). They claimed that, due to lack of diagnostic equipment and adequate qualified professionals, one hardly gets treatment altogether in public hospitals without some sort of additional diagnosis in private health institutions. Even if the scheme is materialized, they argued that high co-payments may have a significant deterrent effect on the poor in the use of services.

Analysis of correlates of willingness to enroll in CBHI scheme

Logistic regression analysis: We employed a multiple binary logistic regression analysis (model) to identify significant correlates of households' willingness to enroll in the proposed CBHI scheme by incorporating all candidate independent variables (individual and household attributes). Our response variable is a dichotomous (binary) variable that takes the value of 1 if a respondent is willing to involve in the scheme and 0 otherwise. The model fits the data well as judged by the *Omnibus tests of m*odel *coefficients and* the Hosmer-Lemeshow test. Among the candidate explanatory variables, gender, age, marital status, level of education, family health status, presence of chronic illness and/or disability in the family, and ease (difficulty) of finding money for health care were statistically significant. On the other hand, religion, family size, household monthly income, saving status, presence of any illness or injury in the six months prior to the survey and monthly amount of payment to Iddir were found out to have no significant influence on households' willingness to voluntarily enroll in the proposed scheme.

Marginal effects analysis: As discussed earlier, interpreting the coefficients of the fitted logistic regression model in terms of odds ratios (or in the log-odds scale) might be misleading since odds ratios do not consider actual differences in the probability of the outcome among various groups (categories). The marginal effects, on the other hand, are more informative since they express effects in the probability scale. In this section we explore the impact of covariates on the outcome using marginal effects.

Adjusted predictions at representative values: Figure 1 displays the adjusted predictions (or predictive margins) of the joint effect of gender and marital status on the probability of enrollment of an 'average' (or 'typical') individual to enroll in the proposed scheme at different levels of age. The results show that the probability of enrollment for an average 30 year old married male was 86.8 percentage points. This figure declined to 51.8 percent for an unmarried woman and to 45.3 percent for a divorced/widowed female of the same age. At the age of 70, the respective figures increased to 94.9, 66.8 and 72.4 percentage points. Thus, the combined effect of gender and marital status differs greatly by age.

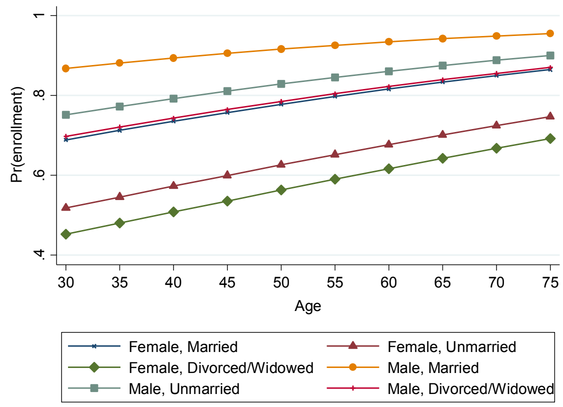


Fig. 1. Adjusted predictions for gender and marital status by age

The adjusted predictions of the joint effect of gender and level of education on the probability of enrollment at different levels of age are presented in Figure 2. We can see that male respondents with primary, secondary and tertiary level of education had the highest probability of joining the CBHI scheme, while female respondents who are illiterate and can only read and write were on the other extreme. However, the effects exhibited a considerable variation with an increase in age for the latter group. At the age of 35, for instance, female respondents who are illiterate and can only read and write had a 40.3% and 46.7% chance of joining the scheme, respectively. The respective figures have increased to 63.5% and 69.1% at the age of 75. Note that the effects show little variation across age for male respondents with at least primary education (the three curves on the top). The implication is that the effect of age is highly pronounced for female respondents who are illiterate and can only read and write.

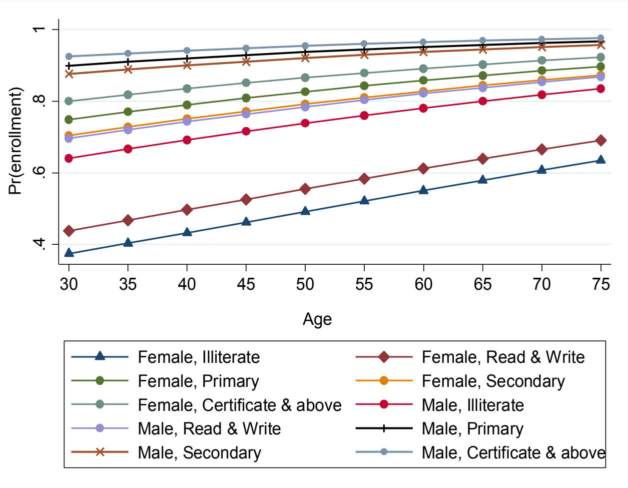


Fig. 2. Adjusted predictions for gender and education by age

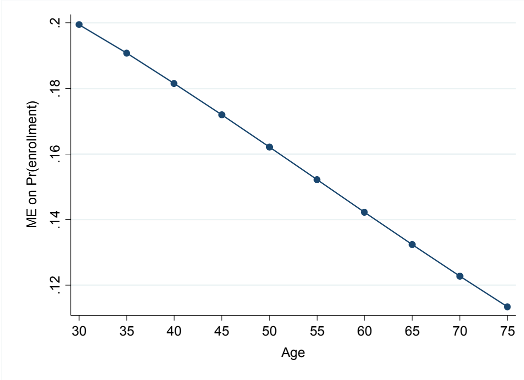
Average marginal effects: The average marginal effect (AME) gives us the effect of a covariate on the probability of the outcome. For a continuous covariate, it is the average change in probability when that covariate increases by one unit. For categorical variables, the AME shows the difference in the predicted probabilities for cases in one category relative to the reference category (discrete change effects). Unlike linear models, the effect differs from one individual to another (since a logit is a non-linear model). What the AME does is compute the predicted probability for each individual with their observed levels of covariates. These values are then averaged across all individuals.

Table 3 presents the AMEs for the significant covariates considered in this study. The results indicate that, on average, a one year increase in the age of respondents is associated with a 0.34% increase in the probability of participation. Moreover, male respondents have a 16.4% higher probability of enrolling in the CBHI scheme as compared to their female counterparts. Married women have an 11.6% and 16.8% higher probability of participation compared to the unmarried and the divorced/widowed, respectively. Regarding education, respondents with primary, secondary and tertiary level of education have a 25.4%, 22.9% and 28.1% higher probability of participating in the CBHI scheme as compared to those who are illiterate, on average. Family health status was among the covariates that has a significant average marginal effect. Respondents who rated their family health status as medium have an 11.2% higher probability of participating in the CBHI scheme as compared to those who rated the same as good/very good. However, there is no significant difference in the probability of the outcome among those who rated the same as good/very good and poor/very poor. The results also revealed that, on average, respondents who find it so difficult to get money for healthcare have an 11.3% and 18.3% higher probability of enrolling in the CBHI scheme as compared to those who rated the level of difficulty as difficult and moderate, respectively. However, there is no significant difference in the probability of participation among those who rated the same as easy/so easy and so difficult. Surprisingly, respondents with no chronic illness and/or disability in the household have a 20.1% higher probability of enrolling in the proposed scheme as compared to those who reported that members of their family have chronic illness and/or disability.

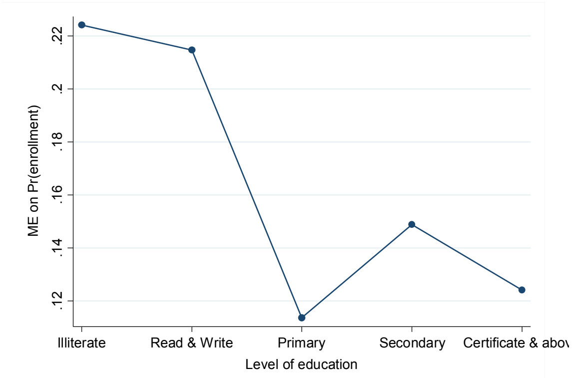
Marginal effects at representative values: One of the problems with the average marginal effects is that they only produce a single estimate of the marginal effect. Moreover, the averages can obscure differences in effects across cases. In reality, the effect of a given covariate on the probability of an outcome may vary with the characteristics of an individual. Marginal effects at representative values (MERs) are often a superior alternative. They can be both intuitively meaningful, while showing how the effects of variables vary by other characteristics of the individual. With MERs, we can choose ranges of values for one or more variables, and then see how the marginal effects differ across that range.

Table 3. The AMEs from the fitted binary logistic regression model (for significant covariates)

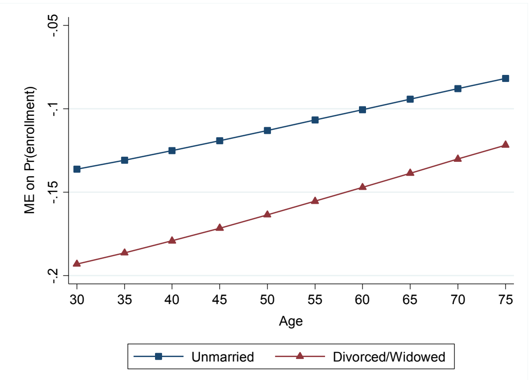
		Delta-method				
	dy/dx	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
Age	0.003	0.002	2.150	0.032	0.000	0.006
Gender: Male	0.164	0.040	4.160	0.000	0.087	0.242
Marital status: Married (Ref.)						
Unmarried	-0.116	0.058	-1.990	0.047	-0.231	-0.002
Divorced/Widowed	-0.168	0.055	-3.050	0.002	-0.276	-0.060
Education: Illiterate (Ref.)						
Read & write	0.052	0.074	0.710	0.480	-0.093	0.197
Primary	0.254	0.077	3.280	0.001	0.102	0.405
Secondary	0.229	0.079	2.880	0.004	0.073	0.385
Certificate & above	0.281	0.077	3.660	0.000	0.130	0.431
Chronic illness: Yes	-0.206	0.048	-4.250	0.000	-0.301	-0.111
Family health: Very good/Good (Ref.)						
Medium	0.112	0.040	2.780	0.006	0.033	0.191
Poor/Very poor	-0.023	0.060	-0.390	0.696	-0.140	0.093
Level of difficulty: So difficult (Ref.)						
Difficult	-0.113	0.043	-2.610	0.009	-0.199	-0.028
Moderate	-0.183	0.046	-3.990	0.000	-0.273	-0.093
Easy/So easy	-0.001	0.050	-0.010	0.988	-0.099	0.097



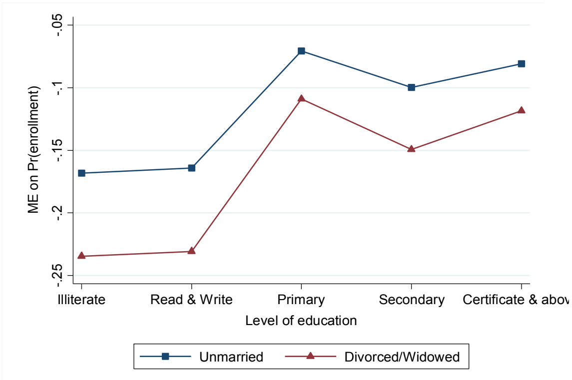
(a) AME of gender by age



(b) AME of gender by education



(c) AME of marital status by age



(d) AME of marital status by education

Fig. 3. Average marginal effects at representative values

a) **Average marginal effects of gender by age**: Earlier, the AME for gender was 16.4 percent. But, when we estimate the same for different ages, we see that the effect of gender differs greatly by age: it is about 19.9 percentage points at age 30 and about 11.3 percentage points at age 75, on average (Figure 3 (a)). Thus, the effect of gender was more pronounced at younger ages than older ages.

b) **Average marginal effects of gender by level of education**: From Figure 3 (b) we can see that, on average, the probabilities of joining the CBHI scheme for female respondents who are illiterate and who can only read and write are 22.4 and 21.5 percentage points lower than their male counterparts with the same level of education, respectively. This figure dropped down to 12.4 percentage points for those with post-secondary education (certificate and above). Thus, the effect of gender diminishes as the level of education increases, in general.

c) **Average marginal effects of marital status by age**: Figure 3 (c) displays the average marginal effects of marital status by age. The marginal effect of marital status on the probability of enrolling in the CBHI scheme significantly varies across age, on average. At the age of 30, for instance, the probabilities of joining the scheme for unmarried and divorced/widowed respondents were 13.6 and 19.3 percentage points lower than married respondents. The differences steadily decreased to 8.8 and 13.0 percentage points at the age of 70, respectively. The implication is that age reduces the effect of marital status on the probability of joining CBHI.

d) **Average marginal effects of marital status by education**: The probabilities of joining the CBHI scheme for unmarried respondents who are illiterate and who can only read and write are 16.8 and 16.4 percentage points lower than married respondents of the same level of education, respectively, on average. This figure drops down to 8.1 percentage points for those with post-secondary education (Figure 3 (d)). Similarly, the probability of the outcome for divorced/widowed illiterate respondents is 23.5% lower than married respondents with the same level of education. The respective figure is 11.8 percentage points for those with post-secondary education. Again, the effect of marital status diminishes as the level of education increases.

DISCUSSION

The results of our study revealed that as the age of a responding member increases, the probability of willingness to get involved in the scheme also increases (significant at the 5% level). Predictive margins at representative values indicated that the same is true regardless of gender and marital status. The positive association between age and willingness to enroll in health insurance schemes may emanate from the fact that older people do need hospital care more often than the young. Several studies reported similar findings regarding the positive effect of age on enrollment (Dror *et al.,* 2016; Bukola, 2013). In contrast, a study in Namibia revealed that young respondents showed more interest in joining a health insurance scheme (Gustafsson-Wright *et al.,* 2009). The probability of enrollment in the proposed CBHI scheme was 16.4 percentage points (95% CI: 8.70% – 24.2%) higher for male respondents as compared to their female counterparts, keeping all other covariates constant. When we see the picture across different ages, this figure increased to 19.9 percentage points at the age of 30 and declined to 11.3 percentage points at the age of 75. Moreover, the average marginal effects were as large as 22.4 and 21.5 percentage points for female respondents who are illiterate and who can only read and write, respectively, and dropped down to 12.4 percentage points for those with post-secondary education. Thus, the effect of gender diminishes as age and level of education increase. Our result is consistent with studies in India (Dror *et al.,* 2007), China (Ying *et al.,* 2007), Tanzania (Macha *et al.,* 2014) and Burkina Faso (Dong *et al.,* 2003b) which found that males are more willing to purchase health insurance than female headed households. Contrary to our result, a meta-analysis of similar studies found that enrolments in CBHI were positively associated with female-headed households (Dror *et al.,* 2016). Regarding marital status, the probabilities of participating in the scheme were 11.6% (95% CI: 0.2% – 23.1%) and 16.8% (95% CI: 6.0% – 27.6%) higher for married women as compared to the unmarried and the divorced/widowed, respectively. These figures, however, vary with age and level of education. At the age of 30, for instance, the respective figures were 13.6 and 19.3 percentage points and then dropped down to 8.8 and 13.0 percentage points at the age of 70. Moreover, the difference in the probability of the outcome for divorced/widowed illiterate respondents was as large as 23.5 percentage points in favour of married respondents with the same level of education. This figure dropped down to 11.8 percentage points for those with post-secondary education. The implication again is that age and level of education reduce the effect of marital status on the probability of joining the proposed CBHI scheme. Some studies have shown that marital status influences the behavior of individuals towards health services. According to a study in Southwest Ethiopia, marital status of the head is a statistically significant factor with married heads more likely to enroll in CBHI schemes (Haile *et al.,* 2014). Similar findings are also reported by a number of studies (e.g., Dror *et al.,* 2016; Bukola, 2013).

The other significant factor was the level of education of respondents. Holding all other covariates constant, the probability of voluntary participation in the proposed scheme was 25.4, 22.9 and 28.1 percentage points higher for respondents with primary, secondary and tertiary level of education as compared to those who are illiterate, respectively. The marginal analysis also indicated that the effect of gender and marital status diminishes as the level of education increases. In health financing, as in other public health areas, better education may create greater openness towards the innovation that the health insurance scheme represents and a better understanding of the mutualist system and its advantages. Various studies on community health insurance schemes show consistent correlations between the propensity to enroll in such schemes and increasing education (Dror *et al.,* 2016; De Allegri *et al.,* 2006; Mebratie *et al.,* 2019). Our analysis revealed that ease (difficulty) of finding money for health care in times of ill health was a significant predictor of whether an Iddir member is willing to participate in the proposed CBHI scheme or not. Respondents who find it so difficult to get money for healthcare had an 11.3% and 18.3% higher probability of participating in the scheme as compared to those who rated the same as difficult and moderate, respectively. This finding clearly highlights the need for introducing the CBHI scheme in the study area. The results also showed that there is no significant difference in the probability of participation among those who rated the level of difficulty as easy/so easy and so difficult. This might be explained by the fact that those who can afford out-of-pocket treatment fees are likely to have fewer apprehensions regarding their future capacity to pay for health care expenses without being enrolled in a CBHI scheme. The study revealed that there was no significant difference in the probability of the outcome among those who rated their family health status as good/very good and poor/very poor. This finding is inconsistent with much of the literature which suggests that adverse selection is one of the problems faced by CBHI schemes, that is, those with poor health status are more likely to be attracted to CBHI schemes compared to those with good health status due to the voluntary nature of membership (Mirach *et al.,* 2019; Wang *et al.,* 2005; Dror *et al.,* 2005;Gnawali *et al.,* 2009). However, some studies reported that enrolment in CBHI is not associated with (self-assessed) household health status (De Allegri *et al.,* 2006; Panda *et al.,* 2014; Mebratie *et al.,* 2015). One of the strange findings of our study was that respondents who (or members of their family) have no chronic illness and/or disability have a 20.6 percentage points (95% CI: 11.1% – 30.1%) higher probability of participation as compared to those having such problems. Much of the literature (e.g., Dror *et al.,* 2016; Mirach *et al.,* 2019) suggests that the presence of chronic illness in the household was rather an enabler to enroll in such schemes. Focus group discussants attributed this finding to reporting bias, that is, they suspect that respondents have chosen not to reveal the presence of such incidences for fear of possible social exclusion. Another possible explanation is the non-availability of benefits associated with chronic non-infectious diseases (such as diabetes mellitus, heart failure, cancer, etc.) in the benefit package.

Conclusion and recommendations

The main objective of this study was to analyze the impact of demographic, socio-economic and health related characteristics on willingness to participate in a proposed CBHI scheme for informal sector workers in Adama city using the Iddir as an intermediary organ. The results revealed that the probability of getting involved in the scheme was higher for male respondents, responding members with at least primary level of education, married respondents and respondents who claimed that finding money in times of ill-health was so difficult. Moreover, there was a positive association between age and willingness to enroll in the proposed health insurance scheme. Contrary to much of the literature, there was no significant difference in the probability of willingness to join the proposed scheme among those who rated their family health status as good/very good and poor/very poor (absence of adverse selection). Average marginal effects analysis at representative values indicated a significant variation in the impact of gender and marital status on the probability of joining the scheme depending on age and level of education.

Based on the findings, the following key recommendations are forwarded:

- **Curbing gender disparity through education**: Our result indicated that the probability of willingness to enroll in the proposed CBHI scheme was significantly higher for males. However, gender differentials were found to diminish as the level of education increases. This finding highlights the role of education in curtailing the gender gap in scheme participation.

- **Awareness creation about insurance principle and state of CBHI schemes**: Focus group discussion revealed that the community is not familiar with the concept of insurance, is wary of new initiatives and has serious doubts about the practicality of the proposed scheme. Thus, there is a dire need for extensive mobilization of the community about insurance principles as well as the state of the scheme through media and health centers. Awareness creation and understanding of the scheme will hopefully encourage more interest in the scheme, and hence, can lead to higher enrollment.

- **Targeting of the vulnerable groups**: Marginal effects analysis revealed that the probability of willingness to participate in the proposed scheme was significantly lower for unmarried and divorced/widowed female respondents with no education. In establishing community-based healthcare financing scheme, therefore, there should be selective targeting of the vulnerable groups within the communities (e.g., women and the uneducated).

- **The need for introducing CBHI schemes**: The results of our analysis indicated that the likelihood of willingness to join the proposed CBHI scheme was higher for members who had serious difficulty in finding money in times of ill-health. This was also true for the elderly regardless of gender and marital status. Thus, launching the proposed scheme is essential in order to address the needs of such community members.

- **Improving the quality of public healthcare facilities**: The principal providers of medical service in CBHI schemes are public health facilities. Focus group discussants stated that, due to lack of medical equipment in public health facilities, some of the treatments are often referred to private health facilities. Thus, health seekers (even if the scheme is materialized) will still be exposed to out-of-pocket payments. To alleviate this concern, stakeholders and concerned bodies should strive to improve the capacity of health personnel in public health institutions and provide them with necessary medical equipment.

Acknowledgements

The authors would like to express their sincere gratitude to the Head and employees of the Social Insurance Office of Adama City Administration. Our appreciation also goes to the Chiefs (Chairs) of Iddirs for facilitating the data collection process and bringing together the focus group discussants. Financial assistance from the Ethiopian Civil Service University is gratefully acknowledged.

Competing interests: The authors declare that they have no competing interests.

List of Abbreviations: CBHI – community-based health insurance; OPP – out-of-pocket payment, ETB – Ethiopian Birr; WHO – World Health Organization; APR – adjusted predictions at representative values; AME – average marginal effects; MER – marginal effects at representative values

REFERENCES

Bukola U. Willingness to Pay for Community Based Health Care Financing Scheme: A Comparative Study among Rural and Urban Households in Osun State, Nigeria. *Journal of Dental and Medical Sciences*. 2013; 5(6):27–40.

Cameron, A.C. and Trivedi P.K. 2010. Microeconometrics Using Stata. Rev. ed. College Station, TX: Stata Press; 2010

Cochran W. Sampling Techniques. 3rd US Edition. John Wiley and Sons, Inc.; 1989.

De Allegri M., Kouyanté B., Becker H., Gbangou A., Pokhrel S., Sanon M., et al. Understanding enrolment in community health insurance in sub-Saharan Africa: a population-based case-control study in rural Burkina Faso. *Bulletin World Health Organization*. 2006; 84(11):852–858.

Donfouet H., Makaudze E., Mahieu P. and Malin E. The determinants of the willingness-to-pay for community-based prepayment scheme in rural Cameroon. *International Journal of Health Care Finance and Economics*. 2011; 11(3):209–220.

Dong H., Kouyate B., Cairns J., Mugisha F. and Saureborn R. Gender Effect on Willingness-to-pay for Community-based Insurance in Burkina Faso. *Health Policy*. 2003b; 69:45 – 53.

Dror D., Hossain S., Majumdar A., Pérez K., John D. and Panda P. What Factors Affect Voluntary Uptake of Community-Based Health Insurance Schemes in Low- and Middle-Income Countries? A Systematic Review and Meta-Analysis. *PLoS ONE*. 2016; 11(8).

Dror D., Radermacher R. and Koren R. Willingness to Pay for Health Insurance among Rural and Poor Persons: Field Evidence from Seven Micro-health Insurance Units in India. *Health Policy*. 2007; 82(1):12-27.

Dror D., Soriano E., Lorenzo M., Sarol J., Azcuna R. and Koren R. Field Based Evidence of Enhanced Healthcare Utilization among Persons Insured by Micro Health Insurance Units in Philippines. *Health Policy*. 2005; 73(3):263–71.

Ekman B. Community-based health insurance in low-income countries: A systematicreview of the evidence. *Health Policy Plan*. 2004; 19(5):249–70.

Ethiopian Ministry of Health. A directive to provide legal backing for piloting and promotion of CBHI. Addis Ababa; 2011.

Ethiopian Ministry of Health. Health Sector Development Programme IV (2010/11 – 2014/15). Final draft. Addis Ababa; 2010.

Ethiopian Public Health Institute. Improving Healthcare Financing in Ethiopia: An Evidence Brief for Policy. Technology Transfer and Research Translation Directorate. Addis Ababa; 2014.

Fadlallah R., El-Jardali F., Hemadi N., Morsi R., AbouSamra C., Ahmad A., et al. Barriers and facilitators to implementation, uptake and sustainability of community-based health insurance schemes in low- and middle-income countries: a systematic review. *International Journal for Equity in Health*. 2018; 17 (13).

Gnawali D., Pokhrel A., Sanon M., De Allegri A., Souares H. and Sauerborn R. The Effect of Community-based Health Insurance on the Utilization of Modern Healthcare Services: Evidence from Burkina Faso. *Health Policy*. 2009; 90(2-3):214–22.

Greene W. Econometric Analysis. Fifth Edition, Prentice Hall, New Jersey; 2003.

Gustafsson-Wright E., Asfaw A. and van der Gaag J. Willingness to pay for health insurance: an analysis of the potential market for new low-cost health insurance products in Namibia. *Social Science and Medicine*. 2009; 69(9):1351–9.

Haile M., Ololo S. and Megersa B. Willingness to join community-based health insurance among rural households of Debub Bench District, Bench Maji Zone, Southwest Ethiopia. *BMC Public Health*. 2014; 14(1):591.

Macha J., Kuwawenaruwa A., Makawia S., Mtei G. and Borghi J. Determinants of community health fund membership in Tanzania: a mixed methods analysis. *BMC Health Services Research*. 2014; 14:538.

McIntyre D., Thiede M., Dahlgren G. and Whitehead M. What are the economic consequencesfor households of illness and of paying for health care in low-and middle-income countrycontexts? *Social Science and Medicine*. 2006; 62(4):858.

Mebratie A., Sparrow R., Yilma Z., Abebaw D., Alemu G. and Bedi A. The impact of Ethiopia's pilot community based health insurance scheme on healthcare utilization and cost of care. *Social Science and Medicine*. 2019; 220(C):112–119.

Mebratie A., Sparrow R., Yilma Z., Alemu G. and Bedi A. Enrollment in Ethiopia’s Community-Based Health Insurance Scheme. *World Development*. 2015; 74(C):58–76.

Mirach T.H., Demissie G.D. and Biks G.A. Determinants of community-based health insurance implementation in west Gojjam zone, Northwest Ethiopia: a community based cross sectional study design. *BMC Health Services Research*. 2019; 19:544.

Panda P., Chakraborty A., Dror D. and Bedi A. Enrolment in community-based health insurance schemes in rural Bihar and Uttar Pradesh, India. *Health Policy Plan*. 2014; 29(8):960–74.

USAID. Ethiopia’s Community-based Health Insurance: A Step on the Road to Universal Health Coverage; 2015.

Wang H., Yip W., Zhang L., Wang L. and Hsiao W. Community-Based Health Insurance in Poor Rural China: The Distribution of Net Benefits. *Health Policy and Planning*. 2005; 20(6):366–374.

World Bank. Health financing for poor people: resource mobilization and risk sharing. 2004. http://documents.worldbank.org/curated/en/519081468780547446/pdf/289860PAPER0Health0financing010the0poor.pdf

World Health Organization. Universal Health Coverage (UHC) - Fact sheet. 2016. http://www.who.int/mediacentre/factsheets/fs395/en/.

Ying X., Hu T., Ren J., Chen W., Xu K. and Huang J. Demand for Private Health Insurance in Chinese Urban Areas. *Health Economics*. 2007; 16(10):1041–1050.

****