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Factors Associated with Women Unemployment in Ethiopia

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Abstract: Unemployment is one of the main challenges of the modern era in both the developed and developing countries. Employment of women in economic activities has several beneficial effects for women and their families. Unemployment gives rise to private and social problems in the society such as increased crimes, suicides, poverty, alcoholism and prostitution. High level of unemployment rates can also contribute to the spread of HIV/AIDS in developing countries. In general, unemployment affects household income, health, government revenue and hence GDP and development at large. Studying unemployment therefore helps tackle these problems through some kind of policy actions. The average unemployment rate for women age from 15-49 was 48.8%. The unemployment rate is still significantly higher among females. Heavy domestic duties, pregnancy and discrimination are some of the reasons for female unemployment. Ethiopian women also earn less than men. Unemployment is more of a problem of women than that of their counterparts. This issue dictates the researcher to consider the determinants and consequences of unemployment of women in Ethiopia. In line with this, the objective of this study is to study the determinants of unemployment of women in the study area. This study used data from Ethiopia Demographic and Health Survey (EDHS), 2016. A Binary Logistic Regression Analysis is used to identify the most important determinant factors which are associated with the occupational status of women in Ethiopia. The result of binary logistic regression model also revealed that place of residence, educational level of woman, currently pregnant, currently breastfeeding, wealth index, age of the respondent at the first birth and marital status had significant effect on women unemployment at 5% level of significance.

Keywords: Unemployment, Women, Binary Logistic Regression, Ethiopia

1. Background of the Study

Unemployment is one of the main challenges of the modern era in both the developed and developing countries. Employment of women in economic activities has several beneficial effects for women and their families. Unemployment gives rise to private and social problems in the society such as increased crimes, suicides, poverty, alcoholism and prostitution [1, 2]. High level of unemployment rates can also contribute to the spread of HIV/AIDS in developing countries [3]. In general, unemployment affects household income, health, government revenue and hence GDP and development at large. Studying unemployment therefore helps tackle these problems through some kind of policy actions.

At a global level, female unemployment is higher compared to that of male unemployment. They also suffer from a difference in the quality of employment in comparison to men. Vulnerable employment which comprises contributing family workers and own account workers (as opposed to wage and salaried workers) is more widespread for women than men [4].

Ethiopia is a poor agricultural country with per capita income of USD350 [5]. The general unemployment rate was 20.5% in 2009. It was higher for females at 29.9% compared to males which stood at 12.1% [5]. A high level of unemployment indicates the failure of a country’s economy to use its labour resources effectively. There can be various factors explaining unemployment, such as a low level of general economic activity, recession, inflation, rapid changes in technology, disability, willingness to work and discrimination. In the case of Ethiopia, several factors contribute to the causes of youth unemployment.

Among married women, the percentage currently employed was 32% in the 2005 EDHS. This increased moderately to 57% in the 2011 EDHS, and then declined slightly to 48% in the 2016 EDHS. The percentage of employed married women who receive cash earnings increased from 27% 2005 to 36% in 2011, and then remained essentially stable at 35% in 2016. The percentage of married women not paid for their work declined from 60% to 30% between 2005 and 2011 and then increased to 49% in 2016.

According to EDHS 2016 survey, unemployed in the 12 months preceding survey for women age 15-19, 20-24, 25-29, 30-34, 35-39, 40-44 and 45-49 were 59%, 52.7%, 46.5%, 43.9%, 46.1%, 45.1% and 48.1%, respectively. The average unemployment rate for women age from 15-49 was 48.8%. The unemployment rate is still significantly higher among females. Heavy domestic duties, pregnancy and discrimination are some of the reasons for female unemployment. Ethiopian women also earn less than men. Unemployment is more of a problem of women than that of their counterparts. This issue dictates the researcher to consider the determinants and consequences of unemployment of women in Ethiopia. In line with this, the objective of this study is to study the determinants of unemployment of women in the study area.

2. Methods

2.1. Source of Data

This study used data from Ethiopia Demographic and Health Survey (EDHS), 2016. The 2016 Ethiopia Demographic and Health Survey (2016 EDHS) was implemented by the Central Statistical Agency (CSA) from January 18, 2016, to June 27, 2016. The funding for the 2016 EDHS was provided by the government of Ethiopia, the United States Agency for International Development (USAID), the government of the Netherlands, the Global Fund, Irish Aid, the World Bank, the United Nations Population Fund (UNFPA), the United Nations Children's Fund (UNICEF), and UN Women. ICF provided technical assistance through The DHS Program, a USAID-funded project providing support and technical assistance in the implementation of population and health surveys in countries worldwide. During the analysis stage, Statistical Package for Social Science (SPSS) version 23, STATA version 14 and Microsoft-Excel are used as tools of analysis. STATA was used in running the binary logistic regression and other analysis while Microsoft-Excel and SPSS were employed to generate numbers and sorting of data respectively. The dependent variable for this study is occupational status of women (no =1, yes=0) and the independent variables are highest education level, Wealth index, place of residence, currently pregnant, currently breastfeeding, currently marital status, ages of the households and age of women at the first birth. Descriptive statistics and bivariate logistic regression analyses have been used in this study.

2.2. Binary Logistic Regression

Logistic regression is part of a family of models called the Generalized Linear Model used when the response variable is qualitative or categorical in nature and independent variables can be continuous and/ or categorical. Binomial or binary logistic regression is the form of regression which is used when the dependent variable is dichotomous and the independent variables are of any type [6].

Binary logistic regression techniques resolve inconsistencies associated with dichotomous dependent data and the assumptions of linear regression methods. The independent variables that are used for outcome prediction may be dichotomous, categorical or continuous. Binary logistic regression is commonly used in manufacturing and health related studies. It can be used for any application where binary outcomes can be predicted. Logistic regression is based on the logit transformation of the dependent variable. The logit transformation generates a continuous logarithmic curve from non-continuous data so that a regression model can be developed. The outcome probabilities for each dependent variable value are the basis for the model. The logit transformation is necessary since dichotomous dependent data violates ordinary least squares assumptions. Another issue with dichotomous data is that the error terms are not normally distributed, thus ordinary sum of squares regression and all normality tests are invalid [7].

Logistic regression is less restrictive than linear regression. It does not require normally distributed dependent data or homogeneity of variance.

Predictions made by linear regression are based on the observed changes in the independent data itself. Logistic regression is based on the log of the odds of a particular event occurring with a given set of observations. Logistic regression's underlying principles are based on probabilities and the nature of the log curve.

Discriminant analysis and logistic regression will produce similar results with dichotomous dependent data except discriminant analysis is more restrictive and complex. Unlike discriminant analysis, logistic regression does not restrict the nature of the independent variable. In contrast with discriminant analysis, logistic regression doesn't restrict categorical independent variables. Discriminant analysis relies on strict adherence to normality and the equal variance assumptions while logistic regression does not have this requirement [7].

Logistic regression has two main uses:

The first is the prediction of group membership. Since logistic regression calculates the probability of success over the probability of failure, the results of the analysis are in the form of an odds ratio.

Logistic regression also provides knowledge of the relationships and strengths among the variables.

There are two primary reasons for choosing the logistic distribution function. First, from a mathematical point of view, it is an extremely flexible and easily used function, and second, it lends itself to a clinically meaningful interpretation [6].

Logistic regressions work with odds and odds ratio. The odds are simply the ratio of the probabilities for the two possible outcomes. If π is the probability that the event will occur, then $1-\pi$ is the probability that the event will not occur:

$$Odds = \frac{\pi}{1-\pi}$$

In the 2 × 2 contingency table, within row 1 the *odds* of success are $odds_1 = \pi_1/(1-\pi_1)$, and within row 2 the odds of success equal $odds_2 = \pi_2/(1-\pi_2)$. The ratio of the odds from the two rows,

$$\theta = \frac{odds_1}{odds_2} = \frac{\pi_1(1-\pi_2)}{\pi_2(1-\pi_1)}$$

is the odds ratio.

When the response variable is binary, there is considerable empirical evidence that the shape of the response function should be nonlinear. A monotonically increasing or decreasing S-shaped or reverse S-shaped function. For a binary response variable Y and an explanatory variable X, let π =P(Y=1/X=x) =1-P(Y=0/X=x). One possible logistic regression model is given by

$$\pi = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}$$, where β_0=intercept and β_1=slope

Thus, if the event of interest occurs, in our case tuberculosis, with probability

$$\pi = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}$$, then the odds in favor of success is

$$\frac{\pi}{1-\pi} = \frac{e^{\beta_0+\beta_1 x}/1+e^{\beta_0+\beta_1 x}}{1/1+e^{\beta_0+\beta_1 x}} = e^{\beta_0+\beta_1 x}$$

Taking the natural logarithm of each side of equation

$$\log it(\pi) = \ln\left(\frac{\pi}{1-\pi}\right) = \ln\left[e^{\beta_0+\beta_1 x}\right] = \beta_0 + \beta_1 x$$

Thus, modeling the probability π with logistic function is equivalent to fitting a linear regression model in which the continuous response y has been replaced by the logarithm of the odds of success for a dichotomous random variable. Instead of assuming linear relationship between π and x, we assume the linear relationship between $\ln\left(\frac{\pi}{1-\pi}\right)$ and x. The technique of fitting a model of this form is known as logistic regression.

Maximum likelihood (ML) estimation is the most common method used to calculate the logit coefficients.

The *log likelihood* is defined as

$$L(\beta) = \ln\left[l(\beta)\right] = \sum_{i=1}^{n}\left\{y_i \ln(\pi_i) + (1-y_i)\ln(1-\pi_i)\right\}$$

The maximum likelihood estimates are the values of β that maximize the above log-likelihood function. Through maximization of the log-likelihood function we can theoretically estimate the vector of parameter β. But the equation is nonlinear in β, and as a result the estimates do not have a closed form expression. Therefore, β will be obtained by maximizing log-likelihood using iterative algorithm method [8].

Goodness of fit of the model

The goodness of fit or calibration of a model measures how well the model describes the response variable. Assessing goodness of fit involves investigating how the predicted values are closer to the observed values.

The Hosmer–Lemeshow (H-L) test

A better way of assessing the fit of a logistic regression model is comparing the observed and expected numbers of positives for different subgroups of the data. The Hosmer-Lameshow goodness of fit test is useful for assessing overall model fit, particularly when we have many predictor variables, or some of predictor variables are continuous.

The test is similar to a χ^2 goodness of fit test and has the advantage of partitioning the observations into groups of approximately equal size, and therefore there are less likely to be groups with very low observed and expected frequencies. The observations are grouped into g (mostly, g=10) based on the predicted probabilities. For either grouping strategy, the Hosmer-Lemeshow goodness-of-fit statistic, $\hat{C}$, is obtained by calculating the Pearson chi-square statistic from the $g\times 2$ table of observed and estimated expected frequencies. A formula defining the calculation of $\hat{C}$ is as follows:

$$\hat{C} = \sum_{k=1}^{g}\frac{(o_k - n_k'\bar{\pi}_k)^2}{n_k'\bar{\pi}_k(1-\bar{\pi}_k)} \sim \chi^2_{(g-2)}$$

where, g denotes the number of groups, n'_k is the total number of observations in the k^{th} group, c_k denotes the number of covariate patterns in the k^{th} decile, o_k is the number of responses among the c_k covariate patterns, and $\bar{\pi}$ is the average estimated probability. The distribution of the statistic $\hat{C}$ is well approximated by the chi-square distribution with *g - 2* degrees of freedom, $\chi^2_{(g-2)}$ [6].

If p-value for the Hosmer-Lemeshow goodness-of-fit test is greater than 0.05, we will not reject the null hypothesis that there is no difference between observed and model predicted values, implying that the model estimates are adequate to fit the data at an acceptable level or if the observed and expected numbers are sufficiently close, then we can assume that we have an adequate model.

3. Results and Discussion

3.1. Results

Information on the occupational status of women obtained from a total of 23,666 women in Ethiopia was studied. Based on table 1, 5,015 (21.2%) women was unemployed. Conversely, 78.8% of the women was employed in Ethiopia.

Table 1. *Percentage of occupational status.*

		Number	percent
Occupational	unemployed	5,015	21.2%
status	employed	18,651	78.8%

From table 2 show that 8.9% and 12.3% of urban and rural women were unemployed in the 12 months before the survey, respectively. The percent of unemployment women of currently pregnant and not pregnant were 72.9% and 19.3%, respectively. Similarly, the percent of unemployment women for age of households from less than 20, 20-40 and above 40 were 0.1%, 8.6% and 12.4%, respectively. In addition, 4.2% and 17% of unmarried and married women were unemployment, respectively. Moreover, the percent of unemployment women for currently breastfeeding, not currently breastfeeding, no educated, primary, secondary, higher, poor, middle and rich were 6.8%, 14.4%, 15.1%, 2.2%, 3.5%, 0.4%, 8.4%, 4.4% and 8.4%, respectively.

15.7%, 5.5% and 0.004% of age of women at first birth from less than 20, 20-40 and more than 40 were unemployed, respectively.

Table 2. *Frequency of the variables.*

Variable	category	Occupational status	
		no	yes
Types of place of residence	urban	2098 (8.9)	5388 (22.8%)
	rural	2917 (12.3%)	13263 (56%)
Currently pregnant	no	4575 (19.3%)	440 (1.9%)
	yes	17247 (72.9%)	1404 (5.9%)
Age of households	Less than 20	33 (0.1%)	120 (0.5%)
	20-40	2042 (8.6%)	7253 (30.6%)
	More than 40	2940 (12.4%)	11278 (47.7%)
Currently marital status	unmarried	989 (4.2%)	2485 (10.5%)
	married	4026 (17%)	16166 (68.3%)
Currently breastfeeding	no	3408 (14.4%)	13284 (56.1%)
	yes	1607 (6.8%)	5367 (22.7%)
Age of respondent at the first birth	Less than 20	3705 (15.7%)	14235 (60.1%)
	20-40	1309 (5.5%)	4415 (18.7%)
	More than 40	1 (0.004%)	1 (0.004%)
Highest education level	No education	3573 (15.1%)	14629 (61.8%)
	primary	526 (2.2%)	2084 (8.8%)
	secondary	819 (3.5%)	1663 (7%)
	higher	97 (0.4%)	275 (1.2%)
Wealth index	poor	1978 (8.4%)	9210 (38.9%)
	middle	1049 (4.4%)	4190 (17.7%)
	rich	1988 (8.4%)	5251 (22.2%)

Table 3 shows that the p-value =0.051 > 0.05 at 5% level of significance, we don't reject the null hypothesis of no difference between observed and model predicted values and conclude that the model is adequate

Table 3. *Hosmer and Lemeshow Test.*

Step	Chi-square	df	Sig.
1	15.43	8	0.051

Table 4. *Binary logistic regression analysis for factors found to be associated with unemployment women in Ethiopia.*

Occupational status	Odds Ratio	Std. Err.	z	P>z	[95% Conf.	Interval]
Place of residence						
Rural	0.70554	0.029337	-8.39	0.000	0.650322	0.765447
Highest education level						
Primary	0.925744	0.049246	-1.45	0.147	0.834084	1.027476
Secondary	1.509644	0.075722	8.21	0.000	1.368293	1.665597
Higher	0.983328	0.121377	-0.14	0.892	0.772024	1.252466
Currently pregnant						
Yes	1.431974	0.085529	6.01	0.000	1.273779	1.609815
Currently breastfeeding						
Yes	1.334616	0.048473	7.95	0.000	1.242913	1.433084
Age of households						
20-40	1.06595	0.214393	0.32	0.751	0.71868	1.581021
above 40	1.005348	0.201816	0.03	0.979	0.678335	1.490009
Wealth index						
middle	1.098474	0.047789	2.16	0.031	1.008691	1.196249
rich	1.343304	0.061486	6.45	0.000	1.228042	1.469386
Age of respondent at the first birth						
20-40	1.177109	0.043767	4.39	0.000	1.094378	1.266094
above 40	3.287822	4.728374	0.83	0.408	0.196225	55.08864
Currently marital status						
married	0.684879	0.029697	-8.73	0.000	0.629077	0.745629
_cons	0.326726	0.0677	-5.4	0	0.217676	0.490409

Table 4 shows the effect of explanatory variables on dependent variable. When we look at place of residence, the odds of unemployment of women for living in rural was 0.7 times lower than urban area. Similarly, Women whose pregnant status for currently pregnant were 1.4 times more likely to be unemployed than those women had not currently pregnant while women who were currently breastfeeding a child were 1.3 times more likely to be unemployed than those women who were not currently breastfeeding.

Women whose educational level was secondary were 1.5 times more likely to be unemployed than those women had no education. In addition, Married women were 0.7 times less likely to be unemployed than unmarried women.

The odds of unemployment of women for age of respondent at the first birth from 20-40 were 1.2 times higher than the odds of unemployment of women whose age less than 20, controlling other variables in the model. Moreover, the odds of unemployment women for rich and medium households were 1.1 and 1.3 times more likely to poor households, respectively.

3.2. Discussion

A Binary Logistic Regression Analysis is used to identify the most important determinant factors which are associated with the occupational status of women in Ethiopia. Women whose educational level was secondary were more likely to be unemployed than those women had no education. This finding is contrary by the previous researchers [9, 10]. This study also showed that pregnant women were more likely to be unemployed than not pregnant women. Women who were pregnant in a given year had a lower probability of participating in the labor market than women who had not been pregnant [1]. For the education level, the result reveals that the education level of secondary school were more likely to be unemployed than those women had no education, consistent with [12]. The present study also showed that Unmarried women were less likely to work than are married women, consistent with [13, 14].

According to this findings, as compared with women residing in higher economic status households were more likely to be unemployed than for poor households. This finding is inconsistent with other studies [9] showing that women of very poor or poor (low economic status) households have the highest rates of unemployment. In addition, women who were currently breastfeeding a child were more likely to be unemployed than those women who were not currently breastfeeding. This result is confirmed by the previous researches [15]. Moreover, the odds of unemployment of women for age of respondent at the first birth from 20-40 were higher than the odds of unemployment of women whose age less than 20, controlling other variables in the model. This is consistent with [16].

4. Conclusion and Recommendation

4.1. Conclusion

In this study the determinants of unemployment in Ethiopia and its impact on household welfare is investigated using data from the EDHS 2016. The main objective of this study was to identify determinants of women unemployment in Ethiopia. The study revealed the effect of demographic and socio-economic determinants on women unemployment. The result of binary logistic regression model also revealed that place of residence, educational level of woman, currently pregnant, currently breastfeeding, wealth index, age of the respondent at the first birth and marital status had significant effect on women unemployment at 5% level of significance.

4.2. Recommendation

Based on the findings of this study the following recommendations are made:

The age of women at the first birth significantly determines the women unemployment. Age of women at first birth (less than 20 years) are less affected by unemployment as compared to youths (20-40). Hence, the government should give special attention to youngsters by providing them different job opportunities. Women with highest economic status of households are more likely unemployed than women with poor households. Highest economic status through family planning can increase burden of women to their family and in turn decreases women's labor market participation. Hence, the concerned bodies should provide women family planning program. Currently pregnant and currently breastfeeding women are more likely unemployed than unmarried women. They are busy in home activities like taking care of their children, preparing food, washing clothes etc. Hence, their husbands should share burden of them and motivate them to participate in labor market and generate income. Since women with higher level of education (secondary) and unmarried women are more likely unemployed than women with lower level of education and married women, respectively. Policies and strategies that create more job opportunities should be implemented.

Abbreviations

EDHS: Ethiopia Demographic and Health Survey
CSA: Central Statistical Agency
USAID: United States Agency for International Development
UNFPA: United Nations Population Fund
UNICEF: United Nations Children's Fund
UN: United Nation
ICF: International child fund
HIV: Human Immunodeficiency Virus
AIDS: Acquired Immunodeficiency Syndrome
SNNPR: Southern Nations, Nationalities, and People's Region

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