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BAYESIAN APPROACH TO IDENTIFY PREDICTORS OF WOMEN UNEMPLOYMENT IN URBAN ETHIOPIA

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ABSTRACT

Background: Despite promising growth, unemployment is high and is one of the socioeconomic problems in Ethiopia. Moreover, it is higher for females compared to males. The aim of this study is to identify the determinants of unemployment status of women in urban Ethiopia.

Method: The data for this study was obtained from the 2011 Ethiopia Demographic and Health survey. A sample of 5,274 women in urban Ethiopia was included in the study. Descriptive statistics and Bayesian logistic regression methods were used to analyze the data.

Results and Conclusion: Out of the 5,274 women considered in the analysis, 2,712 (51.42%) women were unemployed and 2,562 (48.58%) women were employed. The results of Bayesian logistic regression indicated that Age, religion, number of household, education level, literacy, mass media, wealth index, pregnancy, number of living children and marital status significantly affect the unemployment status of women in urban Ethiopia.

Key Words: Bayesian Logistic Analysis, MCMC, Unemployment, Ethiopia

1. BACKGROUND

Despite promising growth, unemployment is high and is one of the socioeconomic problems in Ethiopia. Moreover, it is higher for females compared to males. ILO's standard definition of unemployment, as stated in (Macro, 2006), requires three criteria to be satisfied simultaneously. Accordingly, the "unemployed" comprise all persons above the age specified for measuring the economically active population during the reference period. Keynes (1936) defined it as "unemployment is an excess supply of labor resulting from a failure in the market economy". International Labor Organization (ILO) has defined it as "unemployment is a situation of being out of work or need and continuously finding a job in the last four weeks (age 16 or above) but available to join work in the next two weeks. People who voluntarily do not want to work, full time students, retired people and children are not included in unemployed category". The unemployment rate is defined as the number of unemployed persons taken as a percentage of the economically active population, which includes both the unemployed and employed.

A person is considered as unemployed if he or she had actively looked for work and was not employed during the last seven days although he or she was available. Excessive unemployment, as per the economics literature, is an indication of the failure of the economy to utilize the available human resource. Gebeyaw (2011) argued that higher unemployment is one of the most serious macroeconomic problems that affect a society directly and indirectly, and that is why it is a frequent topic of political debate and politicians often claim that their proposed policies would help create jobs.

The 2005 national labor force survey (NLFS, 2005) showed that the unemployment rate for females are higher than that of males and also unemployment rate for urban are higher than that of rural areas. The unemployment rate for the urban areas was estimated at 20.6%, which was about 10 times higher than in the rural areas (2.6%). The incidence of unemployment also varied by sex; where in urban area's unemployment among females were about 27.2% compared to 13.7% among males.

Periodic analysis of unemployment in urban areas of the country shows a declining trend in the four recent survey periods. The overall unemployment rate declined from 20.4 percent in May 2009 to 17.5 percent in March 2012. Regarding sex, a similar downward trend was observed during the four survey periods. However, the differentials of unemployment rates by sex for March 2012 show that female (24.2 percent) unemployment rate is more than two times as compared to male (11.4 percent) indicating the high prevalence of unemployment among females (Ethiopia & Macro, 2012).

Abebe Fikre (2011) also indicated that age, marital status and educational status were important determinants of unemployment in urban Ethiopia. Moreover, Mahlwele (2012) found age, trained obtain, educational level, mass media, marital status, race, and residence province are found to be as significant of women's unemployment. Age is positively related to unemployment because the older women get her chances of being increases.

Despite some improvements in recent years, a high level of unemployment continues to be a serious social problem and major policy challenge facing urban Ethiopia (Kibru, 2012). Urban unemployment in Ethiopia shows the great difference across the regional urban level. The CSA survey in 2012 depicts that high unemployment rate is recorded in Addis Ababa City Administration (23%) followed by Dire Dawa Administration (22.7%); the lowest being 9.3 % and 7.7% registered in Benishangul-Gumuz and Gambella national regional states, respectively. The periodic analysis for this survey years also showed that a declining trend in urban unemployment in Afar, Benishangul-Gumuz, Harari, Addis Ababa City Administration and Dire Dawa Administration while Tigray and Oromiya regional states show an increment in unemployment, which calls for further study (Ethiopia & Macro, 2012).

Asif et.al (2015) used multiple logistic regressions to analyze the effect of explanatory variable on dichotomous variable of women employment in Pakistan. According to their results Provinces, Place of residence, Women Education, Women Age, Husband Education, Husband Working Field, Sex of household head, Pregnancy, Marital status and Wealth Status are found to be significant determinant of women employment in Pakistan. Out of 13,558 women 10,833(80%) are unemployed, while just 20% of women are employed at the time of survey. The highest percentage of employment was observed in the age group 30-39 and the lowest employment ratio was observed for age group less than 20 year. Married women positively associated with unemployment and are more likely to be unemployment. Pregnancy has the expected negative impact: women who were pregnant in a given year had a lower probability of getting job than women who had not been pregnant. Thus the main objective of this study is to assess unemployment status and identify factors that influence the unemployment status of women in urban Ethiopia based on Ethiopian demographic and health surveys (Ethiopia & Macro, 2012).

2. METHODS

2.1 Data and Study Area

The study was conducted in Ethiopia, which is situated in the Horn of Africa. The population of Ethiopia was estimated at 73.9 million with growth rate 2.6 percent in 2007. The data for this study were obtained from the 2011 Ethiopian Demographic and Health survey (Ethiopia & Macro, 2012) conducted in Ethiopia as part of the worldwide demographic and health survey project. The 2011 Ethiopia Demographic and Health Survey were conducted by the Central Statistical Agency (CSA) with the support of the Ministry of Health. This is the third Demographic and Health Survey which have been conducted at five-year intervals since 2000. The primary objectives of the 2011 EDHS were to provide up-to-date information for planning, policy formulation, monitoring, and evaluation of population and health programs in the country.

The target population of this study was women aged 15-49 in urban Ethiopia. In the 2011 EDHS a nationally representative sample of women aged 15−49 from approximately 17,817 households in 624 clusters throughout Ethiopia, 187 in urban areas and 437 in the rural areas, were selected. In 17,817 households, 17,385 women were identified as eligible for the individual interview. Interviews were completed by 16,515 women, yielding a response rate of 95 percent. The analysis for this study will be presented based on the 5274 women in urban areas of Ethiopia with complete responses.

2.2 Measurement (Dependent Variables)

The dependent variable for this study was "Unemployment Status of women in urban Ethiopia". It is classified as either employed or unemployed. The response variable is dichotomous and the interest in this study is "unemployed women". Therefore, the outcome for the ith woman is represented by the random variable Yi which take the value 0 if the woman is employed and 1 if the woman is unemployed. That is

$$Y_i = \begin{cases} 0, \text{if the i}^{\text{th}} \text{ woman is employed} \\ 1, \text{if the i}^{\text{th}} \text{ woman is unemployed} \end{cases}$$

2.3 Predictor Variables

The predictor variables that were expected to influence the unemployment status of women in urban Ethiopia were Age, Sex, Region of residence, number of house hold members, sex of household head, educational level of women, literacy level of respondents, exposure to mass media, wealth index of household, Pregnancy of Women, and Number of living children and Marital status of women.

2.4 Bayesian Logistic Regression

Bayesian inference contains complicated mathematical simulations and a variety of statistical techniques, but, the most challenging part is simply the fact that it is grounded in a fundamentally different paradigm than traditional ordinary statistics.

The classical logistic regression treats the unknown parameters as fixed constants, while the Bayesian approach treats them as random variables, which means that the parameters can vary according to a probability distribution. This variation can be regarded as purely stochastic for a data driven model, but it can also be interpreted as beliefs of uncertainty under the Bayesian approach. In a Bayesian formulation the uncertainty about the value of each parameter can be represented by a probability distribution, if prior knowledge can be quantified (Kynn, 2005).

Typically in Bayesian approach, report either mean or median of the posterior samples for each parameter of interest as a point estimate. The 2.5% and 97.5% percentiles of the posterior samples for each parameter give a 95% posterior credible interval (interval within which the parameter lies with probability 0.95).

The foundation of Bayesian statistics is the Bayes' theorem which states that if A and B is events and P (B), the probability of event B is greater than zero, then:

$$P(A/B) = \frac{P(A)P(B/A)}{P(B)}$$

The theorem is commonly interpreted such that A represents an event that we think might be true (in frequents terms, a hypothesis) and B represents our observations. In this case:

- The prior estimate of probability $P(A)$ is our initial belief about the probability of A being true.
- The posterior estimate $P(A/B)$ is the probability of A being true given that B has been observed.
- The likelihood factor $P(B/A)$ is the probability of event B occurring if A is true.

2.4.1 The Posterior Distribution

Given the likelihood of logistic regression and the prior distribution given, the posterior distribution of the Bayesian logistic regression contains all the available knowledge about the parameters in the model and the posterior distribution is derived by multiplying the prior distribution over all parameters by the full likelihood function. Then the posterior distribution will be given by:

$$f(\beta|y) = L(y|\beta) * f(\beta) \ = \prod_{i=1}^{n}\left[\left\{\frac{\exp(\beta_0+\beta_1X_{i1}+\beta_2X_{i2}\ldots+\beta_pX_{ip})}{1+\exp(\beta_0+\beta_1X_{i1}+\beta_2X_{i2}\ldots+\beta_pX_{ip})}\right\}^{y_i}\left\{1-\frac{\exp(\beta_0+\beta_1X_{i1}+\beta_2X_{i2}\ldots+\beta_pX_{ip})}{1+\exp(\beta_0+\beta_1X_{i1}+\beta_2X_{i2}\ldots+\beta_pX_{ip})}\right\}^{1-y_i}\right]$$
$$\times\prod_{j=0}^{p}\frac{1}{\sqrt{2\pi\sigma_j{}^2}}exp\left\{\frac{-1}{2}\left(\frac{\beta_{j}-\mu_j}{\sigma_j}\right)^2\right\}$$

Where $f(\beta|y)$ are the posterior distribution which is the product of the logistic regression likelihood and the normal prior distributions for the β parameters.

The posterior distribution is now used to make statements about β, which is still a random quantity. For example, the mean of the posterior distribution can be used as a point estimate of β. Computing the estimate of β of the posterior distribution may be difficult, for this reason, we need to use non-analytic method such as simulation techniques. The most popular method of simulation technique is Markov Chain Monte Carlo (MCMC) methods.

Once convergence is reached, all simulation values are from the target posterior distribution and a sufficient number should then be drawn so that all areas of the posterior are explored.

2.4.2 Assessment of Convergence

To assessment the convergence of model Autocorrelation, Time series plots, Gelman-Rubin statistic, and Density plot were used in WinBUGS Software.

2.4.3 Assessing Model Accuracy

After model convergence has been achieved, we need to run the simulation for a further number of iterations to obtain samples that can be used for posterior inference. The more samples we save, the more accurate will be our posterior estimates. As a rule of thumb, the simulation should be run until the Monte Carlo error for each parameter of interest is less than about 5% of the sample standard deviation. The Monte Carlo error (MC error) and sample standard deviation (SD) are reported in the summary statistics table of WinBUGS statistical package.

3. RESULTS

There were 5,274 women between the ages of 15-49 years in urban Ethiopia were included in the study. The study showed that, out of the 5,274 women considered in the analysis, 2,712(51.42%) women were unemployed while 2562 (48.58%) women were employed at the time of data collection. As shown in Table 1, the rate or proportion of unemployment varied from one age group to another. The highest proportion of unemployment was observed in the age group 15-19 (73.2%) and the women in the age group 20-24 had the second highest proportion of unemployment, that is, 52.3%. In the same way, Table 1 shows that the proportion of unemployment differed from one region to another. In the urban areas of Somali, 68.6% of the women were unemployed and 62.5% of the women in Afar were unemployed. Conversely, the smallest proportion (45.1%) of unemployed women was recorded in Amhara urban areas followed by Addis Ababa with 47.0% of the women unemployed. The proportion of unemployment was 47.6% for women in households with at most 5 family members whereas 58.0% and 56.7% of the women from medium size households (6-10 household members), and large household sizes (above 10 household members), respectively, were unemployed. Unemployment status was also associated with sex of household head. About half (49.6%) of the women in female headed households and 52.2% of the women in male headed households were unemployed. The rest variables are also interpreted in the same manner.

Table 01: Distribution of women unemployment in urban Ethiopia for Demographic Factors and Bivariate Statistical Analysis

Variables	Categories	Unemployed Women				
		No		Yes		Chi-square (Sig.)
		Count	%	Count	%	
Age	15-19	342	26.8	936	73.2	369.567 **(0.000*)**
	20-24	542	47.7	595	52.3	
	25-29	644	58.9	449	41.1	
	30-34	347	54.4	291	45.6	
	35-39	321	59.2	221	40.8	
	40-44	212	63.7	121	36.3	
	45-49	154	60.9	99	39.1	
	Tigray	178	46.4	206	53.6	
	Affar	94	37.5	157	62.5	

Region of residence	Amhara	139	54.9	114	45.1	75.298 **(0.000*)**
	Oromiya	184	51.7	172	48.3	
	Somali	98	31.4	214	68.6	
	Benishangul-	75	45.2	91	54.8	
	SNNP	126	52.9	112	47.1	
	Gambela	105	47.3	117	52.7	
	Harari	325	49.9	326	50.1	
	Addis Ababa	916	53.0	813	47.0	
	Dire Dawa	322	45.2	390	54.8	
Religion of women	Orthodox	1615	53.1	1424	46.9	103.518 **(0.000*)**
	Catholic	21	61.8	13	38.2	
	Protestant	318	52.6	286	47.4	
	Muslim	602	38.1	980	61.9	
	Other	6	40.0	9	60.0	
Sex of household head	Male	1792	47.8	1955	52.2	2.938 **(0.087*)**
	Female	770	50.4	757	49.6	
Marital status	Never married	919	42.9	1222	57.1	158.809 **(.000*)**
	Married	958	46.1	1121	53.9	
	Widowed	131	68.9	59	31.1	
	Divorced	238	71.3	96	28.7	
	Other	316	59.6	214	40.4	

*The Chi-square statistic is significant at the 0.05 level.

Table 02: Distribution of women unemployment in urban Ethiopia for Socio- economic Factors and Bivariate Statistical Analysis

Variables	Categories	Unemployed Women				
		No		Yes		Chi-square
		Count	%	Count	%	(Sig.)
Number of household members	0-5	1733	52.4	1572	47.6	52.843 (0.000*)
	6-10	758	42.0	1047	58.0	
	Above 10	71	43.3	93	56.7	
Educational level	No education	564	49.4	578	50.6	104.759 (0.000*)
	Primary	942	44.4	1179	55.6	
	Secondary	501	43.9	639	56.1	
	Higher	555	63.7	316	36.3	
Literacy level	Cannot read at all	726	50.0	725	50.0	14.091 (0.007*)
	Able to read only parts	248	48.1	268	51.9	
	Able to read whole	1561	48.5	1656	51.5	
	No card with required	27	30.3	62	69.7	
	Blind/visually impaired	0	0.0	1	100.0	

Exposure to any mass media	Not at all	425	46.1	496	53.9	7.33 (.026*)
	Less than once a week	744	51.4	703	48.6	
	At least once a week	1393	47.9	1513	52.1	
Wealth index of household	Poor	47	32.9	96	67.1	14.784 (.001*)
	Medium	18	45.0	22	55.0	
	Rich	2497	49.0	2594	51.0	
Pregnancy	No or unsure	2473	49.2	2556	50.8	15.439 (.000*)
	Yes	89	36.3	156	63.7	
Number of living children	No child	1148	44.6	1428	55.4	46.968 (.000*)
	1-2	876	54.5	730	45.5	
	3-4	359	52.4	326	47.6	
	Above 5	179	44.0	228	56.0	

*The Chi-square statistic is significant at the 0.05 level.

3.1 Factors Influencing Women Unemployment

The chi-square test of association showed that all the 12 independent variables considered were significantly associated with unemployment status of women at 25% significance level. That is, significant association was observed between women unemployment and the independent variables: age of women, region, religion, number of house hold member, sex of household head, education, literacy, mass media, economic status, pregnancy, number of living children, and marital status.

3.2 Bayesian Logistic Analysis

The Bayesian model used is normal-normal, in which the dependent variable, unemployment status of women is assumed to follow a normal distribution with the prior of the coefficients normally distributed non-informative priors, we assume that the regression parameters of interest all follow a normal distribution with mean = 0 and precision =0.001.

Three chains of parameters were simulated for 50,000 iterations each. A total posterior sample of 90,000 is saved for summarization and convergence checks after discarding the first 20,000 iterations as burn-in by checking the history plots (time series) of all the parameters. The Bayesian logistic regression analysis results showed that Age, religion, number of household, education level, literacy, mass media, wealth index, pregnancy, number of living children and marital status significantly contribute for the prediction of the dependent variable (unemployment status of women).

3.3 Assessment of Model Convergence

There are a lot of commonly used methods to assess the convergence of MCMC output, but in this study only some of them are used.

Time series plot: Time series plots (iteration number on x-axis and parameter value on y-axis) are commonly used to assess convergence. If the plot looks like a horizontal band, with no long upward or downward trends, then we have evidence that the chain has converged. The three independently generated chains demonstrated good “chain mixture”, an indication of convergence. The Time series plots show that the chains with three different colors overlap one over the other.

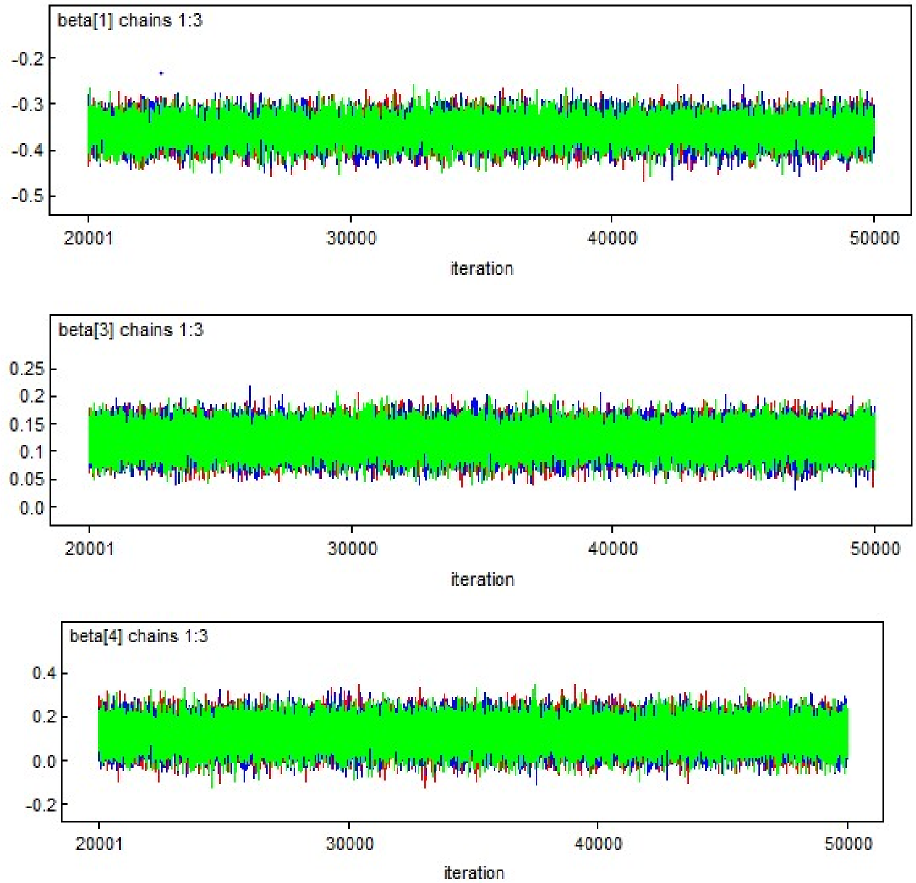

Figure 01: Convergences of Time Series Plots for the Coefficients of Age of respondents, Religion and number of house hold member

Kernel Density: The plots of all statistically significant covariates indicated that none of the coefficients have bimodal density and hence the simulated parameter values have converged. Some of these are displayed in Figure 2.

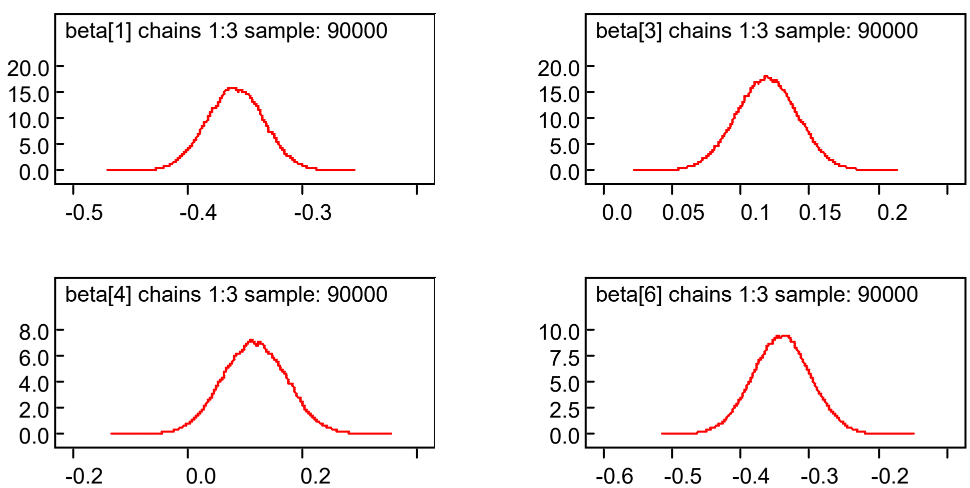

Figure 2: Convergence using kernel density plot for coefficient of age, religion, number of household and education level.

3.4 Gelman-Rubin Statistic

Gelman-Rubin statistics is used for assessing convergence. For a given parameter this statistic assesses the variability within parallel chains as compared to variability between parallel chains. The model is judged to have converged if the ratio of between variability to within variability is close to 1. The green line represents the between variability, the blue line represent the within variance and the red line represents the ratio. Evidence for convergence comes from the red line being close to 1on the y-axis. Since in our plot the red line seems exactly on 1, providing evidence for convergence.

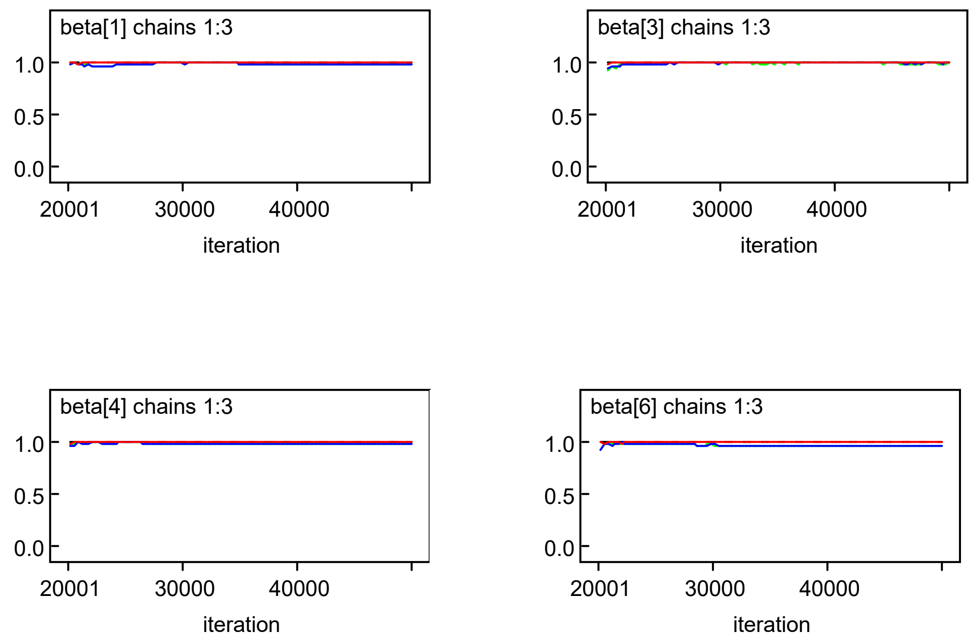

Figure 3: Convergence using Gelman-Rubin Statistics for age, religion, number of household and education level

Autocorrelation: This option produces lag-autocorrelations the monitored parameters within each chain. High autocorrelation indicates slow mixing within a chain and usually slow convergence to the posterior distribution. The plots show that the three independent chains were mixed or overlapped to each other indicating convergence. The plots displayed in Figure 4 indicate low autocorrelation and efficient sampling.

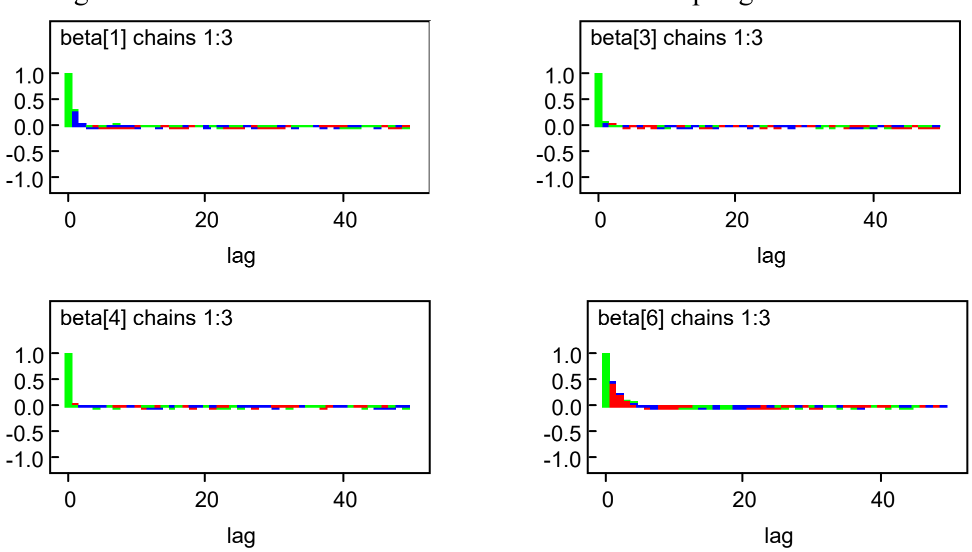

Figure 4: Convergence of autocorrelation plots for coefficients of age, religion, number of household and education level.

3.5 Assessing Accuracy of Bayesian Model

To have accurate posterior estimates, the simulation should be run until the Monte Carlo error for each parameter of interest is less than about 5% of the sample standard deviation. In Table 4, MC errors for all parameter are less than 5% of its posterior standard error. This implies that the convergence and accuracy of the posterior estimates are attained and the model is appropriate to estimate posterior statistic.

Table 4: Comparison of MC error with 5% of sd

Parameters	**node**	**5 % of sd.**	**MC error**
Age of respondent	beta[1]	0.0012495	2.283E-4
Region of residence	beta[2]	0.0004552	9.403E-5
Religion of women	beta[3]	0.00111115	1.343E-4
Number of hh members	beta[4]	0.002809	3.134E-4
Sex of hh head	beta[5]	0.0032095	9.422E-4
Educational level of women	beta[6]	0.002129	4.42E-4
Literacy level of respondents	beta[7]	0.0023115	5.129E-4
Expose to any mass media	beta[8]	0.0021685	3.992E-4
Wealth index of household	beta[9]	0.005015	0.002456
Pregnancy of women	beta[10]	0.00713	5.168E-4
Number of living children	beta[11]	0.0024155	4.43E-4
Marital status of women	beta[12]	0.0013035	1.507E-4

Once model convergence and model accuracy is achieved, we can talk about the variables which have significant contribution for the prediction of the response variable. Using Bayesian logistic regression, Age of respondent, religion of women, number of household members, Educational level of women, Literacy level of respondents, exposure to mass media, Pregnancy of Women, Number of living children, and Marital status of women were found significant at 5% level of significance. Table 5 displays summary statistics for the posterior samples of all parameters for Bayesian logistic regression analysis. The 95% posterior credible intervals fall above 0(covers positive values) for beta[1], beta[6], and beta[12] indicating that unemployment status of women is positively and significantly influenced by age, education and marital status. Similarly, The 95% posterior credible intervals fall below 0(covers negative values) for beta[3], beta[4], beta[7], beta[8], beta[10],and beta[12] indicating that unemployment status of women is positively and significantly influenced by religion, number of household members, literacy, mass media, pregnancy, and number of living children.

Table 5: Posterior summaries of parameters in Bayesian Logistic Regression Model

Parameters	Node	Posterior Mean	Standard deviation	MC error	95% Credible set	
Alpha	alpha	1.002	0.2215	0.006051	0.5643	1.432*
Age of respondent	beta[1]	-0.3581	0.02499	2.283E-4	-0.4073	-0.3092*
Region of residence	beta[2]	-0.01002	0.009103	9.403E-5	-0.0277	0.0078
Religion of women	beta[3]	0.1199	0.02223	1.343E-4	0.07637	0.1635*
Number of hh members	beta[4]	0.1172	0.05618	3.134E-4	0.00757	0.2275*
Sex of HH head	beta[5]	-0.1134	0.06419	9.422E-4	-0.2408	0.0132

Educational level of women	beta[6]	-0.3405	0.04258	4.42E-4	-0.4238	-0.2567*
Literacylevel of respondents	beta[7]	0.2878	0.04623	5.129E-4	0.1968	0.3783*
Mass media	beta[8]	0.1198	0.04337	3.992E-4	0.03496	0.2044*
Wealth index of Household	beta[9]	-0.1746	0.09537	0.002456	-0.3588	0.00509
Pregnancy of Women	beta[10]	0.4864	0.1426	5.168E-4	0.2084	0.7683*
Number of living children	beta[11]	0.366	0.04831	4.43E-4	0.2719	0.4617*
Marital status of women	beta[12]	-0.1615	0.02607	1.507E-4	-0.2124	-0.1103*

*=Significant variables.

4. DISCUSSIONS

This study attempted to identify some socio-economic and demographic determinants of unemployment status of women in urban Ethiopia based on Ethiopia Demographic Health survey (EDHS, 2011) data. Accordingly descriptive method and Bayesian logistic regression analysis were used for analysis. We fitted Bayesian logistic regression model to know the effect of the factors associated with the probability of unemployment of women in urban Ethiopia. The results which are obtained are discussed as follows.

The descriptive analysis of the study revealed that, about 51.42% of the women in urban Ethiopia were unemployed and about 48.58% were employed. This showed that more than half of the women that included in the survey were unemployed. This is in line with the result of Mesfin (2012) and Asif (2015).

In this study the researchers showed that age, religion, number of household members, educational level of women, literacy level of women, number of living children, and exposure to mass media, pregnancy, and marital status were important predictors for women's unemployment.

As the above analysis showed, age has its own impact on the unemployment status of women by controlling other factors. This is consistent with the findings by Abebe (2011) and Mahlwele (2012). The study showed that, education level was an important predictor for unemployment status of women and had a negative effect. This result is similar with the results by other researchers (Foley, 1997; Morries, 2006, but it is not similar with the result of Yang (1992) and Serneels (2004) that education has a positive effect on unemployment status of women. Marital status of women has a negative significant contribution on unemployment of women in urban areas.

Number of living children is another predictor and positively related with unemployment status of women. Women with large number of children were more likely to be unemployed compared women with no children controlling for other variables in the model. This result is similar with the finding of Asif et al. (2015) and Mesfin (2012). Exposure to mass media is also one of the predictors of the unemployment of women and this is similar with the finding by Mahwele (2012).

5. Conclusions and Recommendation

This study revealed that women unemployment is quite prevalent in urban Ethiopia. Among women who did participate in this study, 51.42% were unemployed. Therefore, in our country women unemployment rate in urban areas of Ethiopia was 51.42% at the time of survey. The Bayesian logistic regression revealed that most of the predictors considered in the study are associated with unemployment status of women in urban Ethiopia. Age of respondents and unemployment rate are related inversely. Pregnancy and number of living children are positively associated with unemployment status of women. Exposure to mass media is positively associated with unemployment status of women. Thus the government should expand vocational education and different training to reduce women's unemployment in urban Ethiopia. Finally, we recommend further study with additional predictor variables should be conducted to identify determinants of unemployment status of women in urban Ethiopia.

Authors' Contributions

Abay Kassa carried out study design, data collection, and data analysis. Aweke Abebaw and Ashenafi Abate were involved in the manuscript preparation and revisions. Finally all authors read and approved the final manuscript.

Competing Interest

The authors declare that they have no competing interests.

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