ADDIS ABABA UNIVERSITY

GRADUATE STUDIES PROGRAMME

COLLEGE OF COMPUTATIONAL & NATURAL SCIENCES

DEPARTMENT OF STATISTICS

DETERMINANTS OF MARITAL DISSOLUTION IN ETHIOPIA

Bereket Tessema

A Thesis submitted to

The Department of Statistics

Presented in Partial Fulfillment of the Requirements for the Degree of Master of Science Statistics (Applied Statistics)

Addis Ababa University

Addis Ababa, Ethiopia

June, 2012

ADDIS ABABA UNIVERSITY
OFFICE OF GRADUATE STUDIES
COLLEGE OF COMPUTATIONAL & NATURAL SCIENCES
DEPARTMENT OF STATISTICS

DETERMINANTS OF MARITAL DISSOLUTION IN ETHIOPIA

Bereket Tessema

A Thesis submitted to
The Department of Statistics

Presented in Partial Fulfillment of the Requirements for the Degree of Master of Science in Statistics (Applied Statistics)

Advisor: Professor Eshetu Wencheko

Addis Ababa University

Addis Ababa, Ethiopia

June, 2012

Addis Ababa University
School of Graduate Studies

This is to certify that the thesis prepared by Bereket Tessema, entitled: *Determinants of marital dissolution in Ethiopia* and submitted in partial fulfillment of the requirements for the Degree of Master of Science complies (Applied Statistics) with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

Examiner_____ Signature _____Date _____

Examiner_____ Signature _____Date _____

Advisor_____ Signature _____Date _____

Chair of Department or Graduate Program Coordinator

TABLE OF CONTENTS

ABSTRACT

Determinants of marital dissolution in Ethiopia

Bereket Tessema

Addis Ababa University, 2012

Marital dissolution has become an important subject of demographic, sociological, psychological and economic research in Ethiopia. There is very little research on divorce related problems of women in Ethiopia. The objective of this study is to examine the major factors contributing to marital dissolution of women in Ethiopia. The study is based on data from the 2005 EDHS with 7,558 ever married women. Binary logistic regression and descriptive statistical measures are used for the analysis. The result of binary logistic regression analysis revealed that age of woman, place of residence, religion of a woman, education level of a woman and number of living children in the household were the important variables that explain the marital dissolution due to divorce in the Ethiopian context. Women with lower level of education, women in the age group below eighteen years and women with no child experienced the highest rate of divorce.

ACKNOWLEDGEMENT

First and foremost, I would like to express my profound gratitude to my respectable advisor, Professor Eshetu Wencheko, for his exemplary guidance, monitor and constant encouragement throughout the course of this thesis work. His stimulating supports helped me in preparing my thesis. I would like to thank the Central Statistical Agency (CSA) for providing me the 2005 EDHS data. Special thanks to my dear mother, Tadelech Alemu and my sister Abezash Tessema for their kind assistance of materials. I record with appreciation the help rendered by my dear classmates encouraging me to work hard. My best wishes to all who helped directly or indirectly in ensuring a better thesis write-up. Finally, I acknowledge the help of Wolaita Sodo University for funding my MSc study.

1. Introduction

1.1 Background and statement of problem

Marital dissolution has become an important subject of demographic, sociological, psychological and economic research. Traditional demographic data sources - transversal vital statistics and population censuses provided the numbers and structures of divorced people. However, such official statistics usually recorded just the more visible side of the problem-legal divorces. Intrinsically, marital dissolution results when husband and wife have been unable to find a solution for their marital problems and decided to terminate their poor marital adjustments through divorce (Eshelmam and Wilson, 1991). A number of factors that lead to family dissolution have been pointed out by different family and social science researchers (Zastrow, 1996). Dunwiddie (1967) explained that early age at first marriage and lack of preparation are main causes for marital dissolutions. Lesthaege (1995) also suggested that the level of education, religious affiliation, individual age and duration of marriage are among determinants of marital stability that can be easily extracted from traditional demographic data sources. But marital dissolution is a complex phenomenon that also incorporates the influence of previous respondent‟s life stages, the development of an individual in childhood, the conditions of growing up and first steps of independent living after reaching maturity. In Ethiopia, women and to some extent men, are traditionally brought up to believe that their major and most important goal in their life is to marry (Daniel, 1994). Unfortunately, the intense urge from family and friends to form marriage is not backed up by the orientation in parental goals and responsibilities of marriage life.

Thus, many young people who are engaged in marriage at early age discover in the late years that marriage is a serious business and is not always as romantic and exciting as they used to dream it. Due to this, they usually prefer to escape from the unfulfilled marriage commitment by separation or divorce.

The effect of marital dissolution goes beyond the individuals who dissolve the marital union. Children and other relatives of the couples are the immediate victims who share the potential consequences (Kumulachew, 2001). Particularly children will be exposed to various socio-economic developments (ibid).

The extent, magnitude and effects of marital dissolution problems are also recognized not to be the same for men and women (Daniel, 1994). Many women especially women in developing countries, like Ethiopia, have fewer choices in life outside marriage and children (Daniel, 1994). According to Daniel (1994), the great majority of Ethiopian women are predominantly engaged in domestic chores such as food preparation, child bearing and child rearing. Very few women are educated, have marketable skills and have been prepared for career development and are mostly made to be dependent on their husbands.

In view of all the multifaceted factors associated in the women marital dissolution and in spite of its profound effect on their lives, studies on marital dissolution situation with particular emphasis on its causative factors are rare and scarce in Ethiopia. Very little is known about divorce related problems of women in general and the potential causes that lead them to marital discord in particular, the need to expand our knowledge of the determinants of marital dissolution. This study is motivated by scarcity of research

reports in the area described on the one hand, on the severity and the ever increasing prevalence of the problem on the other. Hence, this study intends to contribute to fill the gap in our knowledge about the marital dissolution of women in Ethiopia.

1.2 Objectives

The main goal of this study is to examine the major factors contributing to marital dissolution of women in Ethiopia.

The specific objectives of the study are

- To find out the important socio-economic and demographic determinants leading to marital dissolution of women.

- To provide some recommendations about marital relationships based on the findings of this study.

1.3 Significance of the Study

- The overall analysis of marital dissolution problems and factors associated with it has an important role in solving certain socio-economic and demographic problems such as prostitution, streetism among children and juvenile delinquency, crime and other social evils which are partly the outcome of family dissolution due to divorce or separation (Dunwiddie, 1967).

- It also provides a very good insight in reducing physical and psychological problems as well as other rural-urban migration related problems (beggary and homelessness) due to marital life crises (Daniel, 1994). Thus, examining the determinants of marital dissolution problems helps to plan community and welfare services, social support and development plans and community health and family planning programs including HIV/AIDS.

- The result can provide information to the concerned bodies so as to make efficient strategies regarding marital stability.

Concepts and Definitions of key terms

Marriage is the legal union of person of opposite sex, the legality being established by civil, religious or other means according to the custom and laws of each country.

Marital Instability refers to the characteristics of marital relationship such as the level of disagreement as well as dissatisfaction (unsteadiness) with the relationship that may or

may not result an ultimate ending of the marriage itself (Johnson, Amolaza and Booth, 1992).

Marital Dissolution is a condition in which parameters of marital union cease to live together as husband or wife especially due to divorce or separation.

Divorce refers to dissolution of valid marriage usually freeing the parties to remarry.

Separation is a decision that husband and wife make to live apart while they are still legally married. This term is used throughout this study to represent separation of spouses due to some misunderstanding but have not terminated their marriage by law or custom.

Enumeration Area (EA) is a unit of land delineated for the purpose of enumerating population and housing units without omission and duplication. An EA in rural areas usually consists of 150-200 households, and in urban areas EA constitutes 150-200 housing units (CSA, 2001).

Household consists of a person or groups of persons, irrespective of whether related or not, who normally live together in the same housing units or group of housing units and have common cooking and eating arrangements (CSA, 2001).

1.4 Limitation of the study

A limitation of the study is that variables related to husbands are not included. This is due to the fact that missing values and there were no responses issues related to husbands in the data collection process.

2. Literature Review

There are a number of factors that contribute to high rate of divorce (Zastrow, 1996). Zastrow (1996) identified some obvious causes as alcoholism, adultery, the changing status of women and their economic dependence on their husbands, incompatibility in sexual matters, infidelity, and interference from relatives and friends. The demographic determinants of divorce are also evident as they characterize the individual or the spouse to divorce prone or not.

A paper by Clarke and Brington (2000) examined the demographic and socio-economic factors of divorce in Canada. The analysis was confined to ever married women. Both bivariate and multivariate analyses have been performed to describe the determinants of divorce. The bivariate analysis was applied to examine the association of divorce cases and women‟s demographic and socio-economic characteristics. Besides bivariate analysis, the net effect of each predictor variable on the response variable after controlling for the effect of other predictors has also been measured through multivariate analysis. The regression analysis revealed that age at marriage, duration of marriage, number of alive children in the marriage and status of migration were the most important variables that explained the variability in divorce. The results indicated that women who considered a higher number of children as ideal and those who reside in rural areas were more likely to have high rate of divorce. Having children is one of the main reasons why people form co-residential unions in the first place. Earlier studies have shown that having common children decreases the risk of divorce.

According to Cherlin (1977) the relationship between the presence of children and marital dissolution can be seen from different perspectives. The first is that children are deterrent to divorce only when they are in pre-school ages. On the other hand, in Africa, it is believed that the value attached to children and barreness of a woman is often considered important causes of marital dissolution in many Africa populations (Isiugo-Abanihe, 1998; Reiners, 2003). Reiners (2003) conducted a study in Malawi using proportional hazard model. The results revealed that divorce rates are moderately lower for those who have children than among infertile of childless women. In rural Bangladesh childbearing soon after marriage is desired and that the birth of a child after marriage signifies a degree of spousal satisfaction which is conducive to marriage stability. This condition is often peculiar virtually to all African countries. That is, families attach more value to having children from marriage. Using multi-process methodology on British data Haskey (1997) found that preschool children have a stabilizing effect on parents married relationship. It is also possible that the presence of several children might deter dissolution for a negative reason that a heavy burden of child care would fall on the parent who would have custody of the children after dissolution (Cherlin, 1977).

The findings of Tilson and Larsen (2000) on the impact of early marriage and childless on divorce in Ethiopia using logistic regression analysis showed that for women with no child the risk of divorce is higher than women with children.

Age at marriage is consistently found to have a strong impact on the propensity to divorce, with lower ages at marriage being associated with higher risks of marital dissolution (Teachman, 2002). Kornblum (2001) studied that age at marriage is one of the leading factors in divorce. The logistic regression analysis revealed that women who

marry while still in their teens are twice as likely to divorce as women in their thirties. But those who marry in their thirties are half again as likely to divorce as those who marry in their twenties.

Bumpass and Sweet (1972) also confirmed that women who marry before age twenty have substantially higher rates of marital dissolution than women who marry at older ages. Age at marriage is often found to have a considerable positive effect on marriage stability both in western context and African population (Martin and Bumpass, 1989; Reiners, 2003). But Isiugo-Abanihe (1998) did not find a significant effect on age at marriage and marital stability decreases with an increasing age at marriage. Martin and Bumpass (1991) examined the relationship between age at marriage and selected demographic and socio-economic variables using logistic regression technique. Currently married women aged 15-49 were interviewed in 2000 and 2004 for Malawi Demographic and Health surveys. The most important predictor of divorce were age at marriage, religion and education. As the policy measure, the study recommended that policies that aim at increasing the women‟s age at marriage should be promoted.

Balakishnan (1987) examined the effect of selected socio-economic and demographic factors on marital dissolution using hazard model analysis of the covariates of marital dissolution in Canada. The hazard model analysis revealed that age at marriage, duration of marriage, cohabitation before marriage, a premarital birth of conception, urban-rural place of residence and religion are significantly correlated with marital dissolution, while religion and education do not seem to affect the marital dissolution probabilities when other factors are controlled.

South (1995) attempted to examine the levels of education of women for divorce risk in United States. The logistic regression analysis revealed that the risk of divorce is significantly higher among those with lower levels of education. Balakishnan (1987) found that little difference in the risk of marital dissolution according to educational attainment in Canada. Rohwer (1993) shows that the relationship between education and the propensity to divorce will change over time and countries. Education is positively associated with divorce in countries such as Italy where the overall level of divorce is low, but that education is negatively associated with divorce in countries where divorce is more common. The evidence from some European countries is mixed. A study by Portman (2002) reported a positive effect of the woman‟s higher education on the risk of divorce in the Netherlands.

The studies by Clark and Brington (2000) and Kumulachew (2001) suggested that there is an inverse relationship between education of women and marital dissolution.

Adedokun (1998) studied the relationship of divorce and education level of women in Nigeria using logistic regression analysis. The result showed that the higher the level of education, the higher the incidence of divorce. The reason why there is high incidence of divorce among women is that educated women are more likely to embrace new ideas about marriage.

Adegoke (2010) studied the socio-cultural determinants of divorce rates among women of reproductive age in Ibadan, Nigeria. The study suggests that the educational background of women has a significant effect on marital dissolution.

Tilson and Larsen (2000) saw education often used as proxy for women empowerment. But Isiugo-Abanihe (1998) observed that, in some cases the relationship between women education and divorce is found to be positive. The findings of Tilson and Larsen (2000) on the impact of early marriage and childlessness on divorce in Ethiopia using logistic regression analysis showed that women with no education as well as those who had attended a literacy programme showed lower risk of divorce than women with primary education. Women with secondary and higher education higher divorce risk compared with women with primary education.

Place of residence is one of the determinants responsible for the marital dissolution. A study conducted by Cherlin (1977) showed that dissolution rates are higher in urban areas, reflecting in part the brighter remarriage prospects associated with large concentration of people. South (1995) found that rural based women are at high risk of marital dissolution in Nigeria. A study by Megerssa (1999) reveals that place of residence has a profound effect on marital dissolution in Ethiopia. It was found that marital dissolution is higher in Ethiopia in rural areas than in urban areas.

Using Finnish register data from the early 1990s Clarke and Brington (2000) estimated relative divorce risks for combinations of the spouse‟s employment status. The result shows that higher earnings of women than husband‟s and stressful working situations are found to have positive association with the risk of marital dissolution. Zastrow (1996) and Megerssa (1999) show the existence of a direct relationship between marital dissolution and women‟s employment status. However, as South (1995) points out, it is uncertain whether the negative association between marital dissolution and employment status of women represents a cause to effect relationship.

There is a widely accepted belief that religion is an important deterrent to divorce. A household where the spouses differ in their religious preferences is characterized by less efficiency and more conflicts (Lehrer and Chiswick, 1990). Also, religious views on marriage age and divorce may deter individuals from dissolving their unions directly, but there may also be more indirect pathways of influence involving social factors. Indeed, the risk of divorce is lower for persons who are strongly religious (Lehrer and Chiswick, 1990). Religious homogeneity seems to reduce divorce risk somewhat. The effect of religion on marital dissolution was found out to be the lowest among Jewish couples and the highest among Protestants (Bumpass and Sweet, 1972).

Haskey (1997) shows higher levels of marital dissolution among marriages that were made legally as opposed to religious ceremonies. Religious practice has also been found to be strongly associated with a reduced level of marital dissolution in Australia (Bracher, 1995) and the United States (Teachman, 2002). It seems likely that those who are religiously active will hold more traditional attitudes towards divorce.

Different scholars perceived relationship between religious practice and marital dissolution in different perspectives. For instance, Isiugo-Abanihe (1998) and Tilson and Larsen (2000) revealed in their studies that Muslim unions are found to be more stable than their Christian counterparts; but according to Bradson (1990), this pattern is opposite in Nigeria. The declining divorce rates among the Muslim unions are likely as a result of rigorous religion practices (Jones, 2000).

In Bangladesh, there are Muslim divorce customs and laws for Muslim marriage. For instance, a divorce of Muslim marriage is an option which is available to spouses. Thus,

Muslim divorce customs and laws serve as a check to the incessant divorce rates, which were accompanied by trends in rigorous practices among Muslims (Jones, 2000). This position also supports Tilson and Larsen (2000) and Isiugo-Abanihe (1998) that Muslim unions are more stable.

Reiners (2003) argues that it is difficult to make generalization of the impact of various religions in different contexts.

Adegoke (2010) conducted a study on the socio-cultural determinants of divorce rates among women of reproductive age in Ibadan. The chi-square analysis result indicates that there is significant relationship between religious affiliation of women and divorce rates.

The 1995 fertility survey of Addis Ababa, Ethiopia, revealed that marital dissolution due to divorce was highest among Orthodox Christian women followed by Muslims and the lowest was observed among catholic religion followers (CSA, 1997).

3. Data and Methodology

3.1 Data source

The source of data for this study is the 2005 Ethiopian Demographic and Health Survey (EDHS) done by the Central Statistical Agency (CSA). EDHS which is the second comprehensive survey designed to provide estimates for the health and demographic variables of interest for the following domains: Ethiopia as a whole, urban and rural areas of Ethiopia (each as a separate domain), and all geographic areas (nine regions and two city administrations), namely: Tigray, Affar, Amhara, Oromiya, Somali, Benishangul-Gumuz, Southern Nations, Nationalities and Peoples (SNNP), Gambela and Harari regional states and two city administrations, that is, Addis Ababa and Dire Dawa. In the 2005 EDHS a representative sample of approximately 14,500 households from 540 clusters was selected. The sample was selected in two stages. In the first stage, with 540 clusters (145 urban and 395 rural) were selected from the list of Enumeration Areas (EA) from the 1994 Population and Housing Census sample frame. In the second stage, a complete listing of households was carried out in each selected cluster. Between 27 and 32 households from each cluster were then systematically selected for participation in the survey. All women aged 15-49 who were either permanent residents of the households in the 2005 EDHS sample or visitors present in the household on the night before the survey were eligible to be interviewed. In addition, in a sub-sample of half of all the households selected for the survey, all men aged 15-59 were eligible to be interviewed if they were either permanent residents or visitors present in the household on the night before the survey. From among the 14,500 households, 14,717 women were identified as eligible for the individual interview. Interviews were completed with 14,070 women, yielding a

response rate of 96 percent. Of the 6,778 eligible men identified in the selected sub-sample of households, 89 percent were successfully interviewed. Response rates were higher in rural than in urban areas, with the rural-urban difference in response rates most marked among eligible men. Thus, the analysis presented in this study on marital dissolution of women based on the 7,558 ever married women.

3.2 Variables used in this study

3.2.1 The Response Variable

The response variable of this study is "marital status of women". For study purpose the response variable "marital status of women" is coded 0 if a woman is either separated, widowed, etc. the coding for a divorced woman is 1. The response variable for the i^{th} couple is represented by a random variable Y_i with two possible values coded 0 and 1. In view of this, the response variable of the i^{th} couple Y_i was measured as a dichotomous variable.

3.2.2 The Explanatory Variables

The predictor variables considered in this analysis include age at first marriage, number of living children, level of education of women, religion of a woman, place of residence and employment status of a woman.

Table 3.1: Description of variables and coding

The description of socioeconomic and demographic variables about marital status of women is presented below.

The Response Variable

Variable	**Representation of variable**	**Factor categories**
Marital status of a woman	Y	1 = Divorced 0 = includes those separated, widowed, …

Explanatory Variables

No.	**Factors/variables**	**Categories**
1	Age at first marriage(AGEW)	(0) <18 years (1) ≥ 18 years
2	Place of residence(PLACE OF RES)	(0) Urban (1) Rural

3	Number of living children in the household (NUMchild)	(0) No child (1) 1 or 2 children (2) Three or more children
4	Religion of a woman(RELIGION)	(0) Coptic Orthodox (1) Protestant (2) Muslim (3) Others
5	Woman‟s educational level(EDUW)	(0) No education (1) Primary education(1-8) (2) Secondary and above(9+)
6	Employment status of a woman(EMPLSW)	(0) Not employed (1) Employed

3.3 Logistic Regression Analysis

Binary logistic regression analysis is employed in analyzing the data. The binary or binomial logistic regression is the type of regression which is used when the response variable is dichotomous and the predictor variables are of any type. In binary logistic

regression, a single outcome variable Y_i (i=1, 2,…,n) follows a Bernoulli probability distribution that takes on the value 1 with probability p_i and 0 with probability 1- p_i. Then p_i varies over the observations as an inverse logistic function of a vector X_i of predictors for the i^{th} individual which includes a constant and k explanatory variables, that is,

$$p_i = \frac{e^{\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\cdots+\beta_k x_{ki}}}{1+e^{\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\cdots+\beta_k x_{ki}}}$$

$$= \frac{e^{X_i{}'\beta}}{1+e^{X_i{}'\beta}}, \text{ i=1,2,…,n} \quad \text{……………………………………………………. (1)}$$

where: $\beta = (\beta_0, \beta_1, \ldots, \beta_k)'$ and $X_i = (x_{0i}, x_{1i}, \ldots, x_{ki})'$ with $x_{0i} = 1$

In logistic regression, the response variable is a logit, which is the natural log of the odds, that is,

$$\text{Log (odds)} = \text{logit } (p_i) = \ln\left[\frac{pi}{1-pi}\right]$$

$$= \beta_0 + \beta_1 x_{1i} + \cdots + \beta_k x_{ki}$$

$$= X_i{}'\beta \text{……………………………………………………………………. (2)}$$

where:

$p_i = P(Y_i = 1 | Xi = x_i)$ is the probability of success or chance of being in the divorced category. A model parameter β_i is interpreted as a change in the log odds for a one unit increase in X_i, holding all the other predictors constant, or after adjusting for the other predictors. In logistic regression, the odds of an event happening (e.g. the event that $Y =$

1) is defined as the ratio of the probability that the event will occur by the probability that the event will not occur. That is, the odds of event E is given by $odds(E) = \frac{P(E)}{1-P(E)}$

3.4 Estimation of parameters

In fitting a logistic regression model, the maximum likelihood and non-iterative weighted least squares are the two commonly used estimation methods (Green, 1993 and Hosmer and Lemeshow, 1989). In this study the maximum likelihood estimation technique is employed to estimate the parameters of the model.

Let p_i be the probability of success, which is equivalent to the probability that the response variable Y_i assumes the value one. Then:

$p_i = P(Y_i = 1 | Xi = x_i) = \frac{1}{1+e^{-x_i'\beta}}$, i=1, 2,……, n…….. (3)

where: $X_i = (x_{1i}, x_{2i}, \ldots, x_{ki})$ is the vector of predictors for the i^{th} individual.

Each observation (response) can be considered as an outcome of a Bernoulli trial. Thus, for the i^{th} observation Y_i, the Bernoulli distribution is:

$P((Y_i = y_i | X_i)) = p^{y_i}(1-p)^{1-y_i}$, i=1, 2,….,n ……(4)

Then the likelihood function is the joint probability distribution of all n observations and is given by:

$L = \prod_{i=1}^{n} p_i^{y_i}(1-p_i)^{1-y_i}$ …….…….. (5)

Taking the natural logarithm of both sides gives:

$$\ln L = \sum_{i=1}^{n} y_i ln\left(\frac{1}{1+e^{-x_i'\beta}}\right) + \sum_{i=1}^{n}(1-y_i) ln\left(\frac{e^{-x_i'\beta}}{1+e^{-x_i'\beta}}\right) \quad \text{..... (6)}$$

Thus, by maximizing the log-likelihood function in equation (6) we can estimate the parameter vector β. Since the equation of the maximize log-likelihood function is nonlinear in β, the estimates do not have a closed form expression, we can obtain $\hat{\beta}$, the estimator of β, using a numerical iterative method (Agresti, 1996).

3.5 Variable selection and Model assessment

3.5.1 Variable selection

The goal of logistic regression is to correctly predict the category of outcome for individual cases using the most appropriate model. To accomplish this goal, a model that includes all predictor variables that are useful in predicting the response variable is considered. Several different options are available during model creation. Variables can be entered into the model in order specified by the researcher or logistic regression can test the fit of the model after each coefficient is added or deleted, called stepwise regression. The basic procedures involve (1) identifying an initial model, (2) iteratively "stepping" that is, repeatedly altering the model at the previous step by adding or removing a predictor variable in accordance with the "stepping criteria", and (3) terminating the search when stepping is no longer possible given the stepping criteria, or when a specified maximum number of steps has been reached. The two major categories of stepwise regression techniques are: (1) the forward stepwise and forward entry and (2) the backward stepwise and backward removal.

3.5.2 Assessing goodness of fit

After developing the model for our data, it is necessary to investigate how effective the model is in describing the outcome variable. The Pearson‟s chi-square, the likelihood ratio test (deviance), the Hosmer-Lemeshow test and the Wald test are the most commonly used measures of goodness of fit for categorical data. Among them, some are briefly discussed in the following section. See detailed discussion in Agresti (1996).

3.5.2.1 The Hosmer-Lemeshow Test

The Hosmer-Lemeshow test is one of the methods used in testing the hypothesis that the model fits the data. In this approach, data are divided into 10 groups. From each group, the observed and expected number of events will be computed and the test statistics is given by

$$\hat{C} = \sum_{k=1}^{g} \frac{(O_k - E_k)^2}{V_k}$$

where $E_k = nP_k$, $V_k = nP_k(1-P_k)$, g is the number of group, O_k is observed number of events in the k^{th} group, E_k is expected number of events in the k^{th} group, and V_k is a variance correction factor for the k^{th} group. If the difference between the observed number of events and what is expected by the model is large, then the statistic $\hat{C}$ becomes large and there will be evidence against the null hypothesis that the model is adequate to fit the data. This statistics has an approximate chi-square distribution with g-2 degrees of freedom (Hosmer and Lemeshow, 1989).

3.5.2.2 The Likelihood Ratio Test

The likelihood ratio statistic, G^2, is the other commonly used approach which is based on the comparison of the fitted and the observed counts.

The likelihood ratio statistic, G^2, is given by

$$G^2 = -2(LLR - LLF) = -2ln\left(\frac{likelihood_R}{likelihood_F}\right)$$

where -2(log likelihood R) for a restricted (smaller) model and (-2log likelihood F) for a full (larger) model. G^2 is distributed as χ^2. The full or larger model has all the parameters of interest in it whereas the restricted is nested in the larger model. The restricted model has one or more of parameters in the full model restricted to some value (usually zero). The parameters in the nested model should be a proper subset of the parameters in the full model. Here the chi-square test is employed to see whether including a variable improves goodness-of-fit measure. If chi-square is significant, the variable is considered to be a significant predictor in the equation. A large value of G^2 indicates lack of fit of the model. If the fit of the model is not good, residuals and other diagnostic measures describe the influence of individual observations on the model fit (Chatterjee and Hadi, 2006).

3.5.2.3 The Wald Test

Another measure of goodness of fit is what we call the Wald statistic which is commonly used to test the significance of individual logistic regression coefficients for each predictor variable. The Wald statistic also provides information whether the β coefficient of an explanatory is significantly different from zero. It is analogous to the „t" test in

multiple linear regression. The Wald statistic is obtained by dividing the value of the β coefficient of the factor of interest by its standard error. For the large sample the likelihood ratio and Wald squared give approximately the same value. In the case of small and moderate sized samples the two statistics may give different results. In that a case the likelihood ratio statistic is better than Wald statistic. For a dichotomous independent variable, the Wald statistic is given by

$$W = \frac{\widehat{\beta}^2}{(s.e.(\widehat{\beta}))^2}$$

When the sample size is large, the statistic has an approximate chi-square distribution with one degree of freedom (Stevenson, 2008).

3.6 Model Diagnostics

The fitted model may be inadequate because of particular observations, outliers or influential values. These observations may affect the conclusion to be drawn from the analysis, thus, detection and treatment of such observations should be part of the model adequacy check. Detection and treatment of outliers and influence diagnostics are some of the statistical techniques that are used to examine the adequacy of a fitted model.

3.6.1 Residual Analysis

The i[th] ordinary residual will assume one of the two values as:

$$\hat{\varepsilon}_i = \begin{cases} 1 - \hat{\pi}_i, Y_i = 1 \\ -\hat{\pi}_i, Y_i = 0 \end{cases}$$

The ordinary residuals will not be normally distributed and, indeed their distribution under the assumption that the fitted model is correct is unknown. Plots of ordinary residuals against fitted values will generally be uninformative. In linear regression a key assumption is that the error variance does not depend on the conditional mean E (Y|X=x). However, in logistic regression, the errors follow a binomial distribution and, as a result, the error variance is a function of the conditional mean as $V(Y/X=x)=\pi(1-\pi)$. Hence, the ordinary residual can be made more comparable by dividing them by the estimated standard error of Yi which is known as Pearson residual denoted by pr_i and defined as:

$$pr_i = \frac{\hat{\varepsilon}}{\sqrt{\hat{\pi}_i\left(1-\hat{\pi}_i\right)}} = \frac{Y_i - \hat{\pi}_i}{\sqrt{\hat{\pi}_i\left(1-\hat{\pi}_i\right)}}$$

The Pearson residuals are directly related to the Pearson chi-square goodness-of-fit statistic. The square of Pearson residual measures the contribution of each binary response to the Pearson chi-square test statistic but the test statistic does not follow an approximate chi-square distribution for binary data without replicates. The Pearson residuals do not have unit variance since no allowance has been made for the inherent variation in the fitted value. A better procedure is to further standardize the ordinary residuals by their estimated standard deviation that is called studentized Pearson residuals. Then studentized Pearson residuals spr_i are defined as:

$$spr_i = \frac{Y_i - \hat{\pi}_i}{\sqrt{\hat{\pi}_i(1-\hat{\pi}_i)(1-h_{ii})}} = \frac{pr_i}{\sqrt{1-h_{ii}}}$$

where h_{ii} is the i^{th} diagonal element of the n×n estimated hat matrix $\hat{H}$.

Studentized Pearson residuals are primarily helpful in identifying influential observations whereas Pearson residuals do not. More influential cases with high leverages result in high studentized Pearson residuals. Studentized Pearson residuals approximately follow the standard normal distribution for large (n≥30) sample and it can be used as an approximate chi-square distribution (Rawlings, 1998).

Deviance residual is another type of residual. It measures the disagreement between any component of the log likelihood of the fitted model and the corresponding component of the log likelihood that would result if each point were fitted exactly. Deviance residuals can be useful for identifying potential outliers or misspecified cases in the model. The deviance residuals can also be used to detect extreme or outlying observations. The deviance residual for the i^{th} case is defined as the signed square root of the contribution of that case to the sum for the model deviance as:

$$dr_i = sign\left(Y_i - \hat{\pi}_i\right)\left\{-2\left[Y_i \ln\left(\hat{\pi}_i\right) + \left(1 - Y_i\right)\ln\left(1 - \hat{\pi}\right)\right]\right\}^{1/2}$$

The standardized and deviance residuals are the most commonly used statistic in identifying points for which the model fits poorly. The presence of outliers is signaled if the standardized residuals lie outside the range of the interval (-3, 3). If the presence of outliers affects the inference, the decision whether or not to include them or revise the model must also require a close subjective examination of the data in addition to statistical grounds (Chatterjee and Hadi, 2006).

Detecting outliers is common practice and it is important to distinguish between two types of outliers. Outliers in the response variable represent model failure. Such

observations are called outliers. Outliers with respect to the predictors are called leverage points. They can affect the regression model, too. However, they may almost uniquely determine regression coefficients. They may also cause the standard errors of regression coefficients to be much smaller than they would be if the observation were excluded.

Leverage is a term used in connection with regression analysis and, in particular, in analyses aimed at identifying those observations which have a large effect on the outcome of fitting regression models. Leverage points are those observations, if any, made at extreme or outlying values of the explanatory variables such that the lack of neighboring observations means that the fitted regression model will pass close to that particular observation. Leverages values are given by diagonal element of the $n \times n$ estimated hat matrix $\hat{H}$.

$$\hat{H} = \hat{W}^{1/2} X \left(X' \hat{W} X \right)^{-1} X' \hat{W}^{1/2}$$

Leverage is a measure of the importance of an observation to the fit of the model. In the expression above $\hat{W}$ is the $n \times n$ diagonal matrix with elements $\hat{\pi}_i \left(1 - \hat{\pi}_i \right)$ i.e., $\hat{W} = Diag\{\hat{\pi}_1 (1 - \hat{\pi}_1), \ldots, \hat{\pi}_n (1 - \hat{\pi}_n) \}$ and X is the $n \times (k+1)$ design matrix (Cook, 1998).

3.6.2 Influential Statistics

Cook's Distance Cook"s distance is designed to measure the shift in $\hat{\beta}$ when a particular observation is omitted. It is a combined measure of the impact of that observation on all regression coefficients (Cook, 1998).

Cook‟s D_i statistic is defined as:

$$D_i = \frac{\left(\hat{\beta}_i - \hat{\beta}_{(i)}\right)' \left(X'\hat{W}X\right) \left(\hat{\beta}_i - \hat{\beta}_{(i)}\right)}{ps^2}$$

Computationally, D_i is more easily obtained as

$$D_i = \frac{r_i^2}{p}\left(\frac{h_{ii}}{1-h_{ii}}\right), \text{ i} = 1, 2, \ldots, \text{n}$$

where r_i is the studentized residual, and h_{ii} is the i^{th} diagonal element of $\hat{H}$ computed from the full regression and p is the number of unknown parameters. D_i measures the difference between the regression coefficients obtained from the full data and the regression coefficients obtained by deleting the i^{th} observation. Or equivalently, the difference between the fitted values obtained from the full data and the fitted values obtained by deleting the i^{th} observation. The Cook‟s distance statistic assesses the influence of individual cases and is a measure of the change in the regression coefficient if an observation is deleted from the model (Chatterjee and Hadi, 2006).

Cook's distance considers the influence of the i^{th} value on all n fitted values and not on the fitted value of the i^{th} observation. It yields the shift in the estimated parameter from fitting a regression model when a particular observation is omitted. All distances should be roughly equal; if not, then there is reason to believe that the respective case(s) biased the estimation of the regression coefficients. Relatively large Cook statistics (or Cook's distance) indicate influential observations. This may be due to a high leverage, a large

residual or their combination. It has been suggested that points with D_i values greater than 1 as being influential (Chatterjee and Hadi, 2006).

DFBETAS: Cook"s distance reveals the impact of the i^{th} observation on the entire vector of the estimated regression coefficients. The influential observations for the individual regression coefficients are identified by DFBETASj(i), j = 0, 1, 2. . . p, where each DFBETASj(i) is the standardized change in $\hat{\beta}_j$ when the i^{th} observation is deleted from the analysis. Thus,

$$DFBETAS_{j(i)} = \frac{\hat{\beta}_j - \hat{\beta}_{j(i)}}{s_i \sqrt{c_{jj}}}$$

where c_{jj} is the j^{th} diagonal element from $\left(X'\hat{W}X\right)^{-1}$. DFBETASj(i) measures the change in $\hat{\beta}_j$ in multiples of its standard error. Although this looks like a t-statistic, it should not be interpreted as a test of significance. Values of DFBETASj(i) greater than 2 would certainly indicate a major, but very unlikely, impact from a single point. The cutoff point of $\frac{2}{\sqrt{n}}$ is the point that will tend to highlight the same proportion of influential points across data sets (Chatterjee and Hadi, 2006).

4. Statistical Data Analysis

4.1 Introduction

The aim of this chapter is to identify socio-economic and demographic determinants of divorce of women in Ethiopia based on the 2005 Ethiopian Demographic Health Survey (EDHS) data. The response variable of this study is "marital status of women" which is binary assuming two outcomes "divorced" or the complementary category to divorce consisting of status like "separated, widowed, …". Descriptive and binary logistic regression methods are employed to measure the effect of the determinants of divorce. The descriptive part provides percentages of divorce status of women. The binary logistic analysis is employed to assess the determinants of marital dissolution due to divorce and to predict the odds of divorce in Ethiopia.

4.2 Summary of descriptive statistics

The Table 4.1 below indicates that divorce case differs by women"s age at first marriage. The highest number of divorce practicing women was observed among women age group of less than 18 years (74%) and the remaining 26% was observed among women age group of greater or equal to 18 years. The educational level of a woman is also an important variable. Those who had no, primary level and secondary and above level of education were (71%), (17%) and (12%), respectively. The percentages of number of living children in the household were 29%, 46% and 25% for divorced women who had no child, one or two children and three or more children, respectively. About 67% of women who divorced reside in rural areas and 33% of those women who divorced reside in urban areas. With regard to religion, the majority of divorced women are followers of

Coptic Orthodox (70%) followed by Muslims (22%), Protestant (6%) and followers of religions other than the above (2%).

Table 4.1 Descriptive statistics of divorce status of women.

Background statistics	Divorced	
	count	percent
Age at first marriage		
< 18 years	391	74
≥ 18 years	138	26
Total	529	100
Number of living children in household		
No child	151	29
1 or 2 children	244	46
Three or more children	134	25
Total	529	100
Place of Residence		
Urban	174	33
Rural	355	67
Total	529	100
Educational level of a woman		
No education	377	71
Primary education	92	17
Secondary and above	60	12
Total	529	100
Religion of a woman		
Coptic Orthodox	372	70
Protestant	33	6

Muslim	117	22
Others	7	2
Total	529	100
Employment status of a woman		
Not employed	174	33
Employed	355	67
Total	529	100

4.3Analysis of binary logistic regression

Table 4.2 Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	7558	100.0
	Missing Cases	0	.0
	Total	7558	100.0
Unselected Cases		0	.0
Total		7558	100.0

a. If weight is in effect, see classification table for the total number of cases.

Table 4.3 Dependent Variable Encoding

Original Value	Internal Value
Either separated or widowed	0
Divorced	1

Block 0: Beginning Block

Table 4.4 classification table

Classification Table[a,b]

Observed			Predicted		
			Current marital status		
			Either separated or widowed	Divorced	Percentage Correct
Step 0	Current marital status	Either separated or widowed	7029	0	100.0
		Divorced	529	0	.0
	Overall Percentage				92.0

a. Constant is included in the model.

b. The cut value is .5

The beginning Block evaluates our model with only the constant in the equation (sometimes called the null model). The constant is analogous to the y-intercept in OLS regression. Table 4.4 is an SPSS classification table for the response variable based on how well the model does with only a constant term included. The overall classification for the model is equal to 92%. What this means is that the model doesn't do a good job at classifying subjects, which actually is expected at this stage of the analysis since we only have the constant term included in the model. That is, we have yet to use more predictors to aid in classification and to sharpen our predictive power.

Table 4.5 Variables in the Equation

		B	S.E.	Wald	Df	Sig.	Exp(B)
Step 0	Constant	-2.587	.045	3292.0	1	.000	.075

In the model equation we see that the intercept-only model or null model is ln(odds) = -2.587. If we exponentiate both sides of this equation we find that our predicted odds, [Exp ($\hat{B}$)] = 0.075. That is, the predicted odd of divorce is 0.075.

Block 1: Method = Enter

Table 4.6 Omnibus Tests of Model Coefficients

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	433.908	11	.000
	Block	433.908	11	.000
	Model	433.908	11	.000

Consider the model which includes all predictors. Omnibus Tests of Model Coefficients (Table 4.6) gives a Chi-Square of 433.908 which is significant at 0.01. This is a test of the null hypothesis that adding the predictors to the model has not significantly increased our ability to predict divorce. Since the omnibus test is significant we can conclude that adding predictors to the model has significantly increased our ability to predict divorce.

Table 4.7 Model Summary

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	3399.788[a]	.056	.140

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001

The most common assessment of overall model fit in logistic regression is the likelihood ratio test, which is simply the chi-square difference between the null model (i.e., with

constant only) and the model containing the predictors which is given by $-2(LLR - 2LLF)$. Under model summary (Table 4.7) we see that –2Log Likelihood statistic is 3399.788. This statistic measures how poorly the model predicts divorce, the smaller the statistic the better the model. SPSS does not give this statistic for the model that had only the intercept; we know it to be 3833.696 (3399.788 + 433.908). Adding the predictors reduced the -2Log Likelihood statistic by 3833.696 - 3399.788 = 433.908, which is the χ^2 statistic for omnibus test.

Table 4.8 Hosmer and Lemeshow Test

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8.852	8	.355

Contingency Table for Hosmer and Lemeshow Test

		Current marital status =either separated or widowed		Current marital status = Divorced		
		Observed	Expected	Observed	Expected	Total
Step 1	1	687	682.878	5	9.122	692
	2	620	618.743	9	10.257	629
	3	779	774.914	11	15.086	790
	4	728	734.052	30	23.948	758
	5	615	621.780	35	28.220	650
	6	721	724.667	40	36.333	761
	7	725	717.348	33	40.652	758
	8	691	690.281	60	60.719	751
	9	697	702.584	102	96.416	799
	10	766	761.753	204	208.247	970

Another method of assessment for overall goodness of fit is by using the Hosmer-Lemeshow test. The Hosmer-Lemeshow test is performed by dividing the predicted

probabilities into deciles (10 groups based on percentile ranks) and computing a Pearson chi-square that compares the predicted to the observed frequencies (in 10×2 table). An insignificant chi-square indicates a good fit to the data and, therefore, good overall model fit. Since the p-value is 0.355 which is insignificant therefore our fitted logistic regression model is good fit (Table 4.8).

Table 4.9 Classification table for block one

Classification Table[a]

Observed			Predicted		
			Current marital status		
			Either separated or widowed	Divorced	Percentage Correct
Step 1	Current marital status	Either separated or widowed	6998	31	99.6
		Divorced	524	5	.9
	Overall Percentage				92.7

a. The cut value is .500

A classification table is another way of summarizing the results of a fitted logistic regression model. A classification table gives the result of the outcome variable Y which is cross classified with a dichotomous variable (Hosmer and Lemeshow, 1989). Here also, we can assess the goodness of fit of a model. As we can see, this percentage has increased from 92.0% (see Table 4.4) for the null model to 92.7% for the full model (Table 4.9) which is considered sufficient.

Table 4.10 Variables in the Equation
Results of binary logistic regression model

Covariates		$\hat{B}$	S.E($\hat{B}$)	Wald	Df	Sig.	$\widehat{OR}$=Exp($\hat{B}$)	95.0% C.I.for $\widehat{OR}$	
								Lower	Upper
Step 1[a]	Place of residence			38.534	1	.000			
	Rural	.781	.126	38.444	1	0.000	2.183	1.706	2.793
	Urban(Ref)						1.000		
	Age at first marriage			3.5891	1	0.05			
	<18 years	.216	.111	3.813	1	.051	1.241	.999	1.542
	≥18 years(Ref)						1.000		
	Living children			190.351	2	.000			
	No child	1.739	.128	184.336	1	.000	5.693	4.429	7.318
	1 or 2 children	1.075	.113	90.456	1	.000	2.930	2.348	3.657
	Three or more children(Ref)							1.000	
	Employment status								
	Not employed	-.141	.104	1.830	1	.176	.868	.708	1.065
	Employed(Ref)							1.000	
	Education			9.067	3	.028			
	No education	.293	.372	.619	1	.431	1.340	.647	2.776
	Primary educ.	.192	.375	.260	1	.610	1.211	.580	2.527
	Sec . and above(Ref)						1.000		
	Religion			100.920	3	.000			
	Coptic orthodox	1.183	.393	9.078	1	.003	3.264	1.512	7.047
	Protestant	-.050	.427	.014	1	.907	.951	.412	2.197
	Muslim	.239	.399	.357	1	.550	1.270	.580	2.778
	Others(Ref)								
	Constant	-4.545	.540	70.774	1	.000	.011		

a. Variable(s) entered on step 1: residence, Amarriage, Living, Work, Education, Religion.

.

Variable(s) entered on step 1: residence, Amarriage, Living, Work, Education, Religion.
Ref indicates reference category.

The result of the binary logistic regression model is presented in Table 4.10.

- The estimated odds ratio 2.183 (95% CI: 1.706-2.793) indicates that women in rural area are 2.183 times more likely to get divorced compared to those women reside in urban area controlling for other variables in the model.
- The estimated odds ratio 1.340 (95% CI: 0.647-2.776) indicates that illiterate women are 34% more likely to get divorced compared to those who have secondary and above level of education (the reference category) controlling for other variables in the model.
- The estimated odds ratio 1.211 (95% CI: 0.580-2.527) indicates women with primary education are 21.1% more likely to divorce compared to those with secondary and above education (the reference category) controlling for other variables in the model.
- The estimated odds ratio 3.264 (95% CI: 1.512-7.047) indicates that women who are followers of the Coptic orthodox religion are 3.264 times more likely to divorce compared to those women who are followers of religions other than Protestantism, Islam and Coptic orthodox (the reference category) controlling for other variables in the model.
- The estimated odds ratio 5.693 (95% CI: 4.429-7.318) indicates that no child women are 5.693 times more likely to get divorced compared to those who have three or more children women in the marriage controlling for other variables in the model.

- The estimated odds ratio 2.93 (95% CI: 2.348-3.657) indicates that one or two children women are 2.93 times more likely to get divorced compared to those who have three or more children women controlling for other variables in the model.
- The estimated odds ratio 1.241 (95% CI: 0.999-1.542) indicates that age of women below eighteen years of age are 24.1% more likely to divorce compared to those women eighteen and above years age group controlling for other variables in the model.

5. Discussion, Conclusions and Recommendations

5.1 Discussion and Conclusions

The effect of marital dissolution goes beyond the individuals who dissolve the marital union. Children and other relatives of the couples are immediate victims who share the potential consequences particularly children will be exposed to various socio-economic developments. The extent, magnitude and effects of marital dissolution problems are also recognized not to be the same for men and women. Many women in developing countries, like Ethiopia, have fewer choices in life outside marriage and children (Kumulachew, 2001).

The findings in chapter four show that the education level of women is a key determinant of divorce. The result obtained in this study showed that the rate of divorce among better educated women is lower than among less educated women. As a result better educated women lead their families in a better way than less educated women because of higher literacy and greater likelihood of rejecting a fatalistic attitude towards life. Education exposes women to information, empowers women and makes them more aware of their own health and the health of their children. This, therefore, supports the research findings of South (1995) who found that the risk of divorce is significantly higher among those with lower levels of education. This finding supports the research findings of Adegoke (2010) who found that the educational background of women have a powerful effect on marital dissolution. This is consistent with the results of Clark and Brington (2004) and Kumulachew (2001). Also, the results are consistent with a previous study by Rohwer (1993), who found that the relationship between education and the propensity to divorce

will change over time and between countries. The result confirms that women‟s education level increases the awareness of practicing divorce indeed decreased.

The result of our study shows that there is difference in women‟s divorce status among rural and urban residence. Rural-based women are more likely to divorce than urban-based women. The reason could be that women who live in rural areas tend to marry at younger age than those in urban areas. Rural women may be more likely dependent on husbands because of less access of education as well as other social amenities in rural areas. This supports the result by South (1995) who shows that rural based women are at high risk of marital dissolution consistent with Megerssa (1999). These studies indicate that place of residence has a profound effect on marital dissolution in that marital dissolution is higher among women who reside in rural areas than for urban women.

The result of this study has indicated that age at marriage is an important variable which is found to be a determinant of marital dissolution. The reason could be young women tend to be less mature and make less forward looking decision and poor role model performance which results from lack of adequate role models during adolescence. This result supports the finding of Teachman (2002) who found that lower ages at marriage is associated with higher risk of marital dissolution. The finding of Bumpass and Sweet (1972) indicates that women who marry before the age of twenty have substantially higher rates of marital dissolution than women who marry at older ages consistent with Balakishnan (1987) and Martin and Bumpass (1991).

Religion appears to be an important determinant of divorce. High prevalence of divorce cases has been observed among coptic orthodox women followed by muslims and then

by protestant women showing that religious affiliation of women has a significant effect on divorce. This result therefore, to some extent negates the findings of Isuigo-Abanihe (1998) and Tilson and Larsen (2000) that, the Muslim unions are more stable when compared with their Christian counterparts. In the same vein, Jones (2000) observed that Muslim divorce customs and laws serves as deterrent to the incessant divorce rates as a result of rigorous religion practices among Muslims. On the other hand, the result in this study agrees with the findings of Adegoke (2010) that there is significant relationship between religious affiliation of women and divorce rates. This finding of the study is consistent with the results of the study conducted by (CSA, 1997) which shows that marital dissolution due to divorce was highest among Coptic orthodox Christians followed by Muslims; the lowest case was observed among Catholics.

The result of this study revealed that number of living children in the household is an important variable which significantly affects marital dissolution due to divorce. Women with no child experienced the highest rate of divorce compared to women who have one or two children and three or more children showing that the larger the number of children in the household the lower the rate of divorce. The reason could be children can be considered as examples of union-specific capital and earlier contributions have usually found that having common children decreases the risk of divorce (Reiners, 2003). According to Cherlin (1977) children are deterrent to divorce only when they are in the pre-school ages because of high costs of child care for pre-school in terms of time, money and effort seems to act as a deterrent to divorce. On the other hand, the result in this study agrees with the findings of Reiners (2003) in the sense that there is widely accepted belief that divorce is moderately lower for those who have children than infertile or childless

women. This finding is consistent with the result of the study by Tilson and Larsen (2000) who found that women with no child showed high risk of divorce than women with children.

5.2 Recommendations

This study recommends that raising the level of education of women to at least primary and secondary education could contribute to decrease in the rate of divorce among Ethiopian women.

To the extent possible, awareness creation of the effect of early marriage should be promoted by family counselors, social workers and other helping professionals.

Further study with additional predictor variables have to be made so as to address the issues raised in this study.

REFERENCES

Adedokun OA. 1998. Widowhood, divorce and Waiting time: A neglected aspect of nuptiality studies in Nigeria. Journal of Social Work Education 2(2): 38-54.

Adegoke, T.G, 2010. Socio-cultural Factors as Determinants of Divorce Rates among Women of Reproductive Age in Ibadan Metropolis, Nigeria. Stud Tribes Tribal‟s 8(2): 107-114.

Agresti, A. 1996. An introduction to categorical data analysis second edition. John Wiley and Son Inc, New York.

Balakrishnan, J. 1987. A hazard model analysis of the covariates of marriage dissolution in Canada. Demographic Research 24: 395-406.

Bracher, M. 1995. Marriage dissolution in Austria Models and explanations. Population studies 47:403-425.

Brandson, A. 1990. Marriage Dissolution, Remarriage and Childbearing in West African: A Comparison Study of Cote d‟ Ivore, Ghana and Nigeria. Ph.D. Thesis, Philadelphia: University of Pennsylvania.

Bumpass, L. and **Martin, T. 1991.** The impact of family background and early marital factors on marital disruption. Journal of Family Issues 12: 22-42.

Bumpass, L. and **Sweet, J. 1972.** Differentials in Marital Instability. Journal of Marriage and Family 47(1): 67-75.

Central Statistical Authority (CSA), 2001. Ethiopia and ORC MACRO, Ethiopia demographic and health survey, 2001. Addis Ababa, Ethiopia.

Chatterjee, S. and **Hadi, A.S 2006.** Regression analysis by example. Fourth edition, John Wiley and Sons, Inc., Hoboken, New Jersey.

Cherlin, A. 1977. The effect of Children on Marital Dissolution. Demography research 14(3): 256-272.

Clarke, L. and **Brington, A. 2000.** Socio-demographic predictors of Divorce. Family policy studies center and London school of Hygiene and Tropical Medicine, London.

Cook, R.D., 1998. Regression graphics: ideas for studying regression through graphics. Wiley and Sons, New York.

Daniel Teffera 1994. The Social and Economic Problem of Divorced women: An assessment of the case of Divorced women in Addis Ababa. IDR, Addis Ababa University, Ethiopia.

DHS (2005) ***Demographic and Health Survey.*** Central Statistical Authority, Addis Ababa, Ethiopia.

Dunwiddie W.E. 1967. Problems of Democracy in Political, Social and Economic Aspects. Ginn and company New Edition.

Eshelmam R.J and **Wilson S.J, 1995.** The Family. Canadian Edition, Allyn and Bacon publishers.

Ethiopia Statistical Association report on Fertility, **1997**.

Haskey, J. 1997. Children who experience divorce on their family. Population trends 87: 5-10.

Hosmer, D.W and **Lemeshow, S., 1989.** Applied logistic regression. 2nd Edition John Wiley and Sons, Inc; New York.

Isiugo-Abanihe, Uche. 1998. Stability of Marital Unions and Fertility in Nigeria. Journal of Biosocial Sciences 30: 33-41.

Johnson D.R., **Amolaza T.O.**, and **Booth, A. 1992.** Stabilizing and Development Change in Marital Quality: A Three-Wave Panel Analysis. Journal of Marriage and Family 54(3): 582-594.

Jones, G. 2000. Modernization and divorce: Contrasting trends in Islamic Southwest Asia and the West. Population and Demography Review 23 (1): 94-114.

Kornblum, W. 2001. Marriage and Divorce. Sociology in a changing World. Orlando Harcourt Brace and Company.

Kumlachew Yemanebirhan 2001. Socio-Demographic Determinants of Marital Dissolution in Ethiopia: The case of Amhara Region. Unpublished MSc Thesis, DTRC, IDR, Addis Ababa.

Lehrer L. and **Cheswick U. 1990.** On marriage specific capital: It‟s Role as a Determinant of Remarriages. Journal of Population Economics 6(3): 193-213.

Lesthaege, R. 1991. The second demographic transition in Western countries: an interpretation. IPD Working paper 1991-1992. Inter-University Programme in Demography. Vrije University, Brussels.

Megerssa Gobena 1999. Rural-Urban Differentials in Family Formation and Dissolution in and around Debrezeit, unpublished MSc Thesis, DTRC, IDR, Addis Ababa University.

Portman, A. R, 2002. Women‟s labour market position and divorce in the Netherlands: Evaluating economic interpretations of the work effect. European Journal of Population 18(2): 175-202.

Rawlings, J.O, 1998. Applied Regression Analysis. Second edition. Springer-Verlag.Inc, New York.

Reiners G. 2003. Divorce and Remarriages in Rural Malawi. Demographic Research 1(6): 191-193.

Rohwer, G. 1993. Education, Modernization, and the risk of marital dissolution: Differences in the effect of women‟s educational attainment in Sweden, West Germany and Italy. Stockholm Research Reports in Demography 76: 435-450.

South, S. 1995. Do you need to shop around? Age at marriage, Spouses alternatives and Marital Dissolution. Journal of Family Issues 16: 432-449.

Stevenson, M 2008. An introduction to logistic regression. Epicenter, Massey University, Newzeland. Page 1-28.

Teachman, J. 2002. Early marriage, premarital fertility, and marital dissolution: Results for Blacks and Whites. Journal of Family Issues 4: 105-126.

Tilson, D. and **Larsen, U. 2000.** Divorce in Ethiopia: The impact of early marriage and childlessness. Journal of Biosocial Science32 (1):355-372.

Zastrow, C. 1996. Social Problems, Issues and Solutions. 4th edition Nelson Hall Publishers Inc; Chicago.

Appendix

Logistic Regression output:

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	residence(1)	104.605	1	.000
		Education	14.226	3	.003
		Education(1)	11.005	1	.001
		Education(2)	2.482	1	.115
		Education(3)	6.307	1	.012
		Work(1)	13.175	1	.000
		Religion	166.631	3	.000
		Religion(1)	164.343	1	.000
		Religion(2)	36.413	1	.000
		Religion(3)	59.049	1	.000
		Amarriage(1)	2.892	1	.089
		Living	265.961	2	.000
		Living(1)	164.103	1	.000
		Living(2)	42.390	1	.000
	Overall Statistics		462.014	11	.000

		Frequency	Parameter coding		
			(1)	(2)	(3)
Religion	Coptic Orthodox	3300	1.000	.000	.000
	Protestant	1161	.000	1.000	.000
	Muslim	2852	.000	.000	1.000
	Others	245	.000	.000	.000
Highest educational level	No education	5828	1.000	.000	.000
	Primary	1136	.000	1.000	.000
	Secondary	514	.000	.000	1.000
	Higher	80	.000	.000	.000
Number of living children	No child	865	1.000	.000	
	One or two children	2514	.000	1.000	
	Three or more children	4179	.000	.000	
Age at first marriage	Below eighteen years	5341	1.000		
	Eighteen years and above	2217	.000		
Respondent currently working	No	5591	1.000		
	Yes	1967	.000		
Type of place of residence	Urban	1273	1.000		
	Rural	6285	.000		

Categorical variable coding

Block 0: Beginning Block

Iteration History[a,b,c]

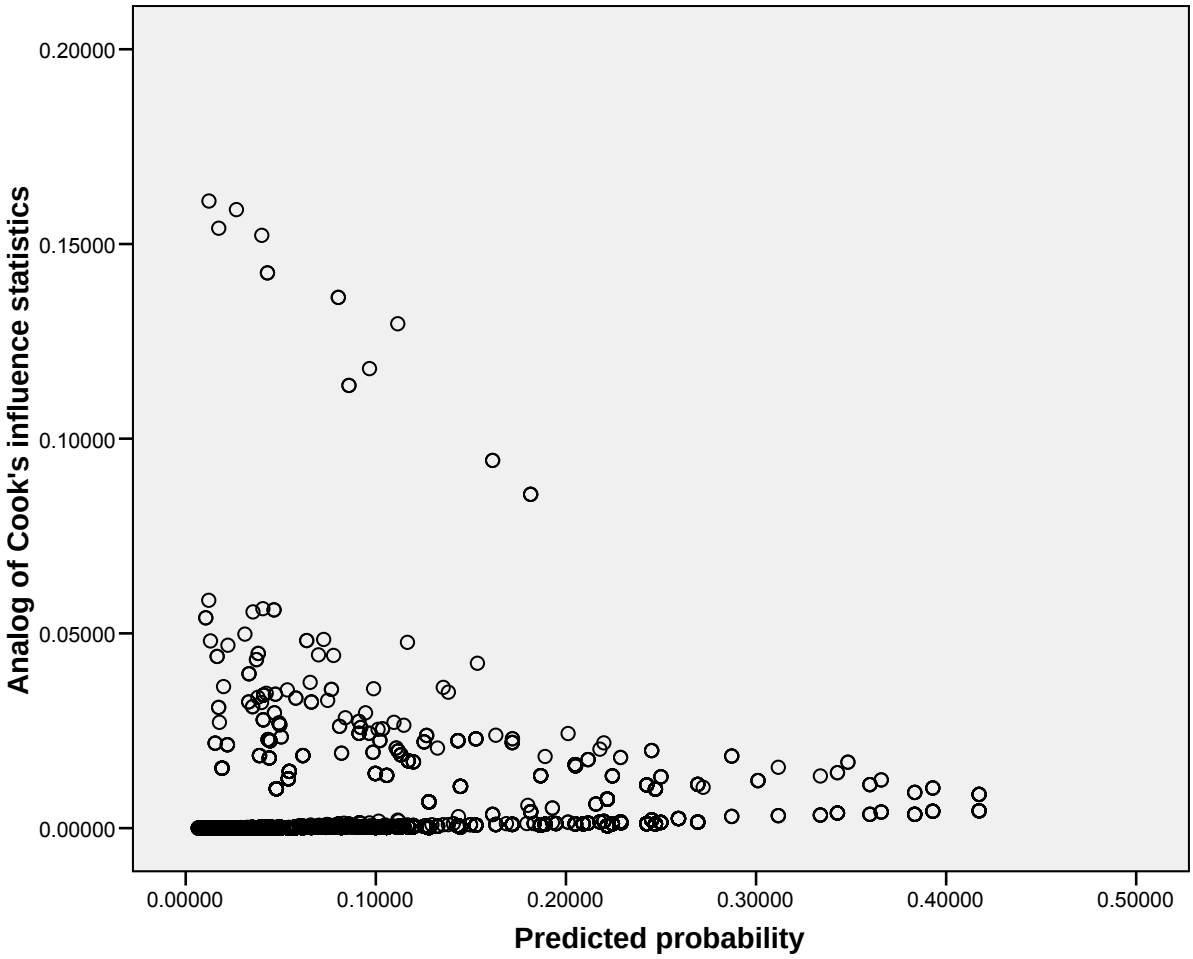
Iteration		-2 Log likelihood	Coefficients
			Constant
Step 0	1	4309.669	-1.720
	2	3861.789	-2.356
	3	3833.914	-2.566
	4	3833.696	-2.587
	5	3833.696	-2.587

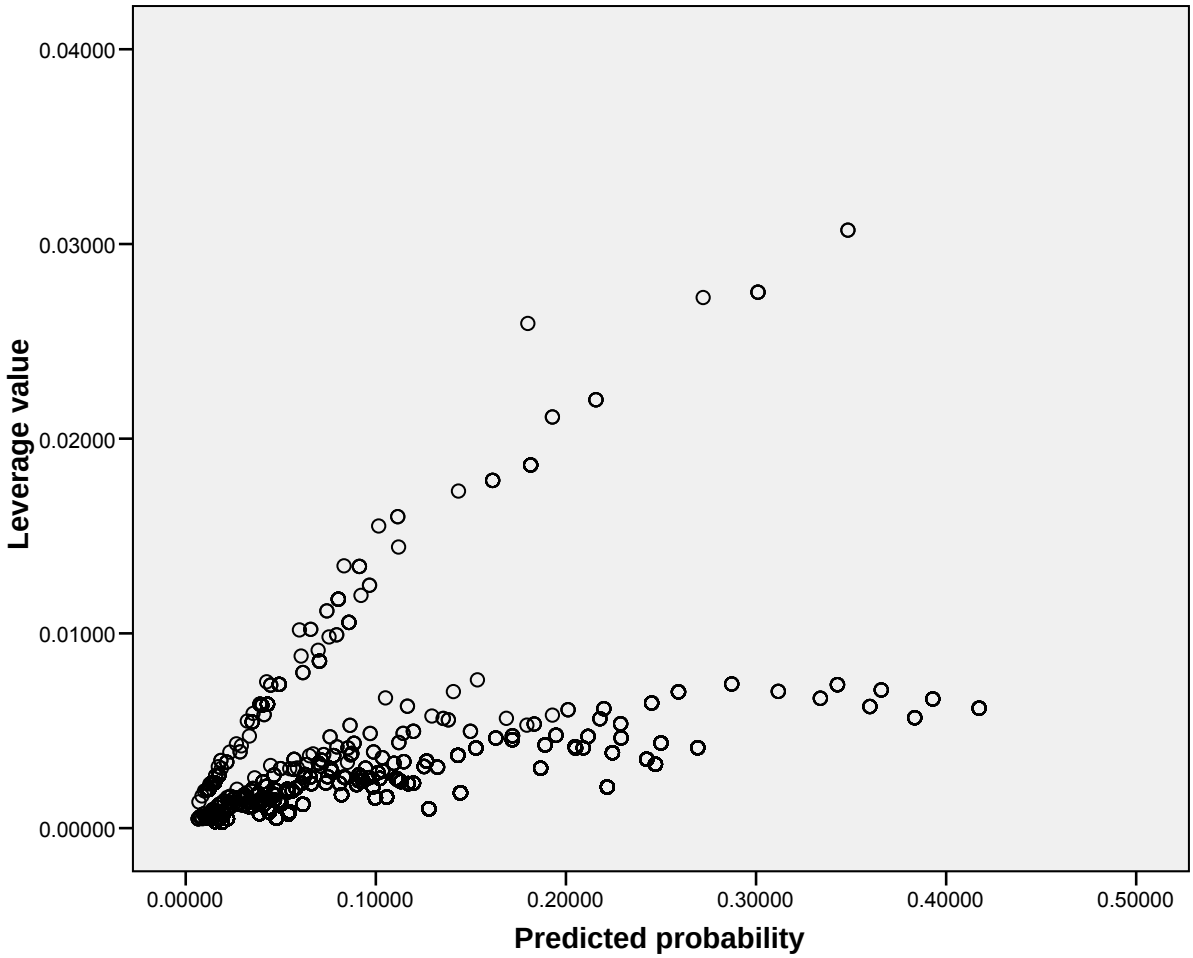
a. Constant is included in the model.

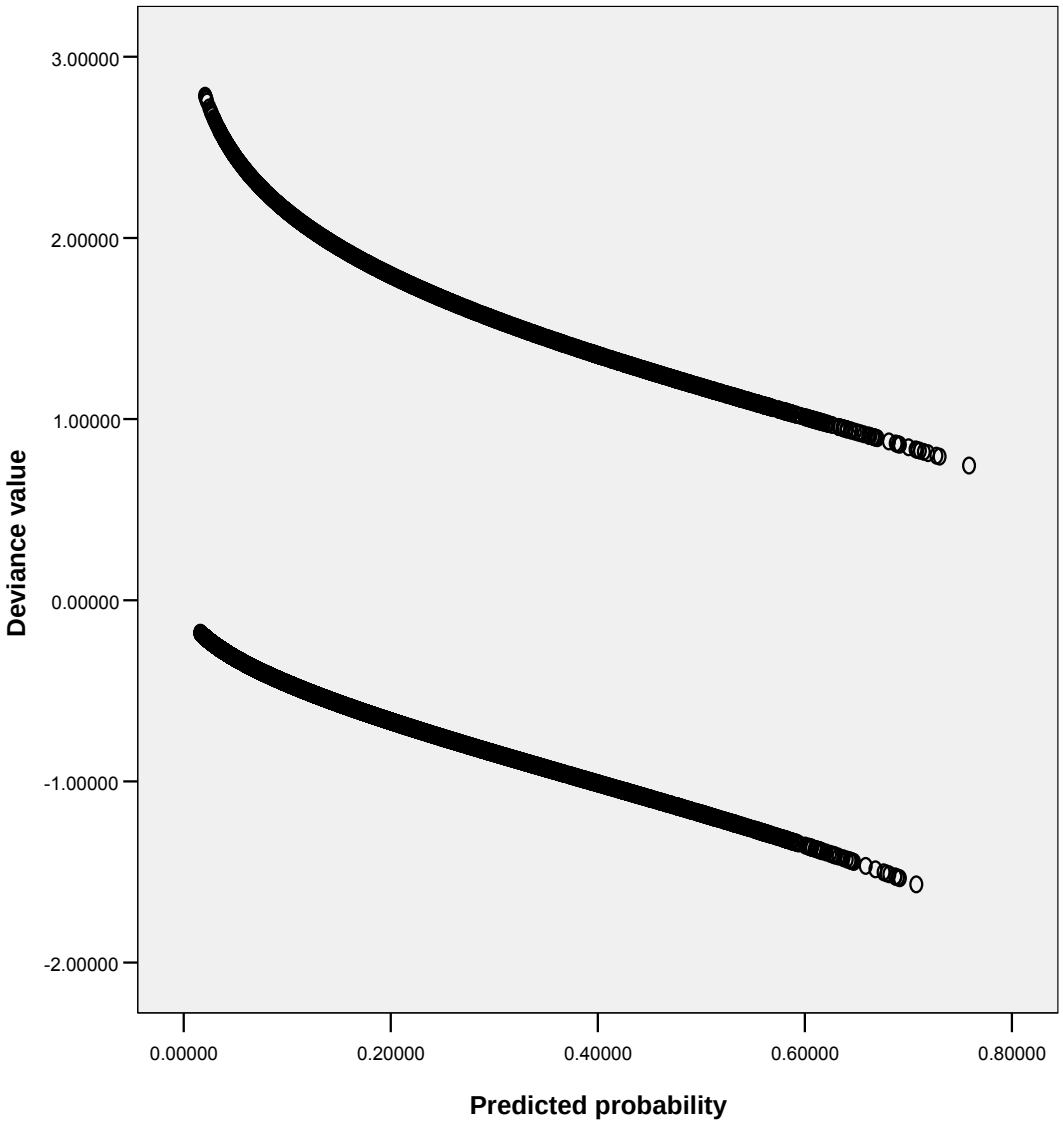
b. Initial -2 Log Likelihood: 3833.696

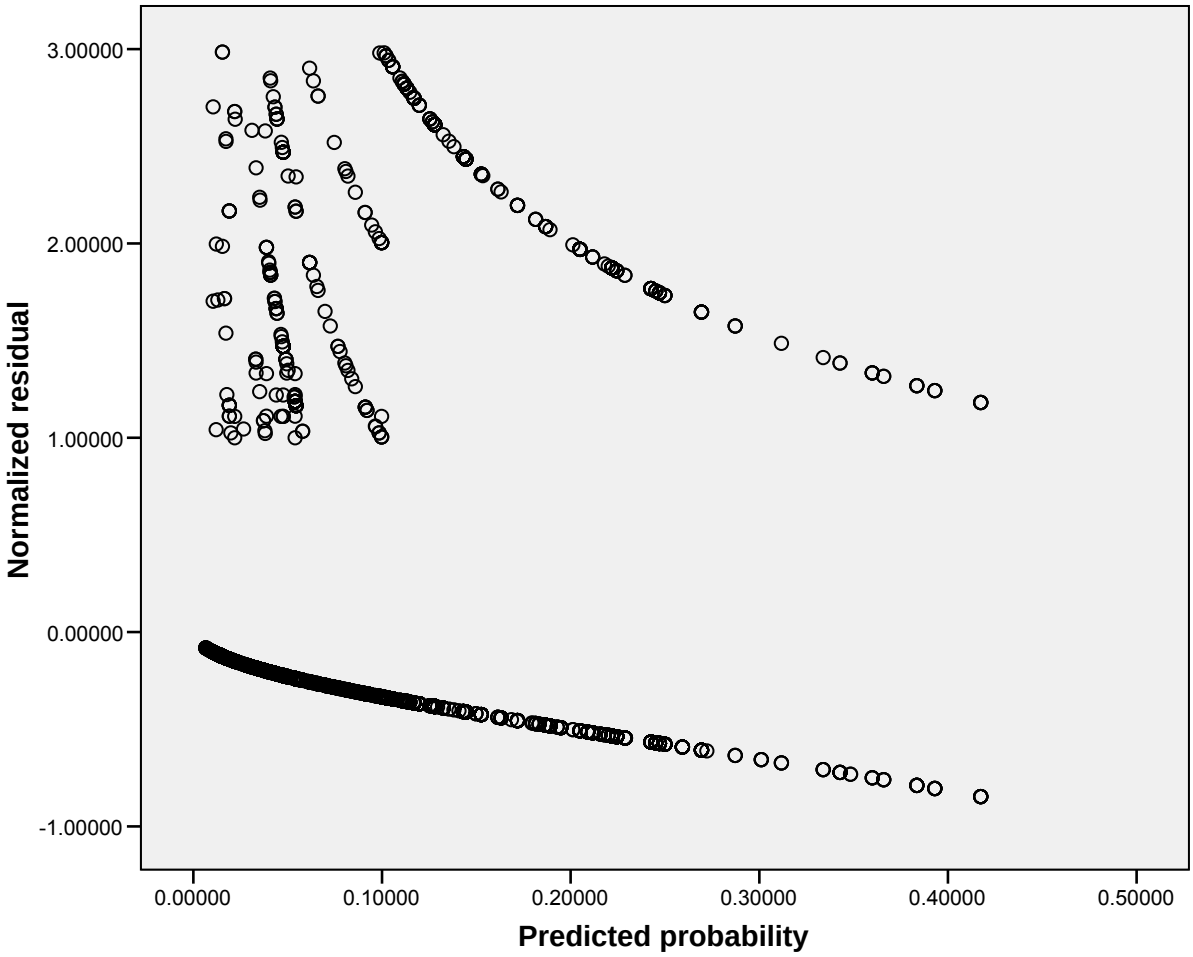
c. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Scatter plot for diagnostics checking




0.04000
0.03000
0.02000
0.01000
0.00000
Leverage value
0.00000
0.10000
0.20000
0.30000
0.40000
0.50000
Predicted probability


3.00000
2.00000
1.00000
0.00000
-1.00000
-2.00000
Deviance value
0.00000
0.20000
0.40000
0.60000
0.80000
Predicted probability


3.00000
2.00000
1.00000
0.00000
-1.00000
Normalized residual
0.00000
0.10000
0.20000
0.30000
0.40000
0.50000
Predicted probability