Survival Analysis of Time-to-First Birth after Marriage among Women in Ethiopia: Application of Parametric Shared Frailty Model.

By:

Ayele Gebeyehu

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By

Ayele Gebeyehu

Advisor: Yehenew Getachew (PhD.)

Co-advisor: Dinberu Seyoum (PhD Candidate)

Jimma, Ethiopia

October, 2015

STATEMENT OF AUTHOR

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Jimma University, Jimma, Ethiopia

DEPARTMENT OF STATISTICS, SCHOOL OF GRADUATE STUDIES

JIMMA UNIVERSITY

As thesis research advisors, we her by certify that we have read the thesis prepared by Ayele Gebeyehu under our guidance, which is entitled "**Survival Analysis of Time-to-First Birth after Marriage among Women in Ethiopia: Application of Parametric Shared Frailty Model**", in its final form and have found that (1) its format, citations, and bibliographical style are consistent and acceptable and fulfill university and department style requirements; (2) its illustrative materials including tables and figures are in place; and (3) the final manuscript is satisfactory to the graduate committee and is ready for submission to the university library.

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DEDICATION

This thesis is dedicated to my family and to my beloved girlfriend Metadel Chanie!!!

ABSTRACT

Background: Marriage to first birth interval is important incidence in the life of women with increasing responsibilities. It plays a significant role in the future life of each woman and has a direct relationship with fertility. Ethiopia is the second most populous countries in sub-Saharan Africa next to Nigeria along with scarcity of resources. This study aimed to investigate the potential risk factors affecting time-to-first birth among married women in Ethiopia using parametric shared frailty model where regional states of the women were used as a clustering effect in the model since. Time-to-first birth and First birth interval (FBI) are used interchangeably in this document.

Methods: The data source for the analysis was the 2011 EDHS data. The study considered 7,925 women who went into marriage for the first time without a child or no pregnancy from eight regional states and two city administrations. The AFT and parametric gamma shared frailty models were employed with the help of R statistical package and STATA soft wares.

Results: The median survival time of first birth interval and the median age of women at first marriage were 30 months and 16 years respectively. The clustering effect was significant and log-normal gamma shared frailty model was preferred over weibull and log-logistic gamma shared frailty models based on AIC and graphical evidence. The result showed women's educational, age of women at marriage, contraceptive, place of residence, and employment status of women were significantly affect timing of first birth interval. Women who used contraceptive had prolonged time-to-first birth by the factor of ϕ=1.116 and women lived in urban had prolonged by the factor of ϕ=1.292 from their counterpart.

Conclusion: The result suggested that women from different region had different pattern in their timing of first birth interval. Women education, increasing age of women at marriage shorten timing of first birth but urban women, employed and contraceptive users had longer survival of time-to-first birth from their respective counterpart. Creating job opportunities, give awareness on family planning through use of contraceptive and the importance of elongating time-to-first birth for rural women are important avenues for rising time to first birth.

Key Words: Survival Data Analysis, Frailty, Acceleration Factor, Censored, Time-to-First Birth

LIST OF ACRONYMS

AIC	Akaike Information Criterion
AFT	Accelerated Failure Time
CSA	Central Statistical Agency
DHS	Demographic and Health Survey
EAs	Enumeration Areas
EDHS	Ethiopian Demographic and Health Survey
FBI	First Birth Interval
Pdf	probability density function
PH	Proportional Hazard
PO	Proportional Odds
SNNP	Southern Nations, Nationalities and Peoples
TFR	Total Fertility Rate
UN	United Nations

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

1.1 Background

The first visible outcome of the fertility process is the birth of the first child. The first birth marks a woman's transition into motherhood. It plays a significant role in the future life of each individual woman and has a direct relationship with fertility. The age at which child bearing begins influences the number of children a woman bears throughout her reproductive period in the absence of any active fertility control (Moultrie *et al*., 2012). For countries in sub-Saharan Africa, where contraceptive use is relatively low as compared with developed world, younger ages at first birth tend to boost the number of children a woman will have. However, even when family planning is widespread, the timing of first births can affect complete family size if contraception is used for spacing but not for limiting fertility (Ngalinda, 1998). Generally in the societies were the births are confined to marriage, reproduction starts from the onset of effective marriage and first birth interval following effective marriage depends on the demographic characteristic of women at the earlier stages of married life (Mukhlesur *et al*., 2013).

Fertility patterns in the world have changed dramatically over the last two decades since the international conference on population and development (ICPD) in 1994, producing a world with very diverse child bearing patterns (United Nations, 2014). Many countries in Asia were able to reduce their fertility through government policies. For instance, China and Vietnam have witnessed declines in their total fertility rate (TFR) due to stringent government policies that discourage early and arranged marriage (Lofstedt *et al*., 2005). However, the delayed fertility transition has been observed to be underway in the region with remarkable progress in African countries like South Africa, Botswana, and Zimbabwe (Bongaarts, 2008; Moultrie *et al*., 2012), fertility remains high in Africa by the standards of the rest of the world.

Fertility rates in sub Saharan Africa have been identified to exhibit a very unique demographic scenario in the world that sets it apart from other regions in the world. Contrary to the case of most regions like Europe, South America and Asia that have for long entered the fertility transition marked by a declined in their fertility rates in the 1950s and 1960s, sub-Saharan Africa is the only region in the world, where fertility decline has been rather slow and late (Ekane, 2013). According to Malmberg (2008), the current fertility rates in the sub-continent stand at the same level as that of Asia and South America towards the end of the 1970s. Most countries in Sub Saharan Africa are still experiencing relatively higher fertility rates. What can be discern from the information so far provided, is that sub-Saharan Africa is the sole region in the world that has not so far experienced any significant decline in its fertility rates. According to United Nations (2014) report, 45 out of 66 high fertility countries (more than 3.2 children per woman) are increasingly concentrated in sub-Saharan Africa.

Ethiopia is the second most populous countries in sub-Saharan Africa next to Nigeria with 94,351,001 population size and 29 years of doubling time (CSA,2013) along with the scarcity of resources. Uncontrolled fertility has adversely influenced the socio-economic, demographic and environmental development of the country. Poverty, war and famine, associated with low levels of education and health, a weak infrastructure, and low agricultural and industrial production have aggravated the problem of overpopulation (Ezra, 2001). When we look back at the history of Ethiopia population growth rate, there has been a steady increase since 1960. Based on 1984 census information, population growth rate was estimated at about 2.3% for the 1960-70 period, 2.5% for the 1970-80 period, and 2.8% for the 1980-85 period. Population projections compiled in 1988 by the CSA projected a 2.83 percent growth rate for 1985-90 and a 2.96%t growth rate for 1990-95. According to the 2007 Ethiopia population census, the annual population growth rate within 1994-2007 was estimated as 2.6%.
For the formulation of effective policy to motivate people for longer first birth interval after marriage, it is crucial to study the effect of various socio-economic and demographic factors which affect time-to-first birth. Having these, this research examined factors associated to time-to-first birth after marriage using parametric survival models. Survival analysis is a statistical method for data analysis where the response variable is the time to the occurrence of an event, time-to-first birth after marriage in this study.

In this study time-to-first marriage was clustered by the region. Hence, the effect of the region was assessed by introducing the frailty term in the survival model. The study used parametric gamma shared frailty model in determining the factors which affect the time-to-first birth after marriage. And, accelerated failure time (AFT) models also fitted using weibull, log-logistic and log-normal baseline distributions to compare and get the best model which fits the time-to-first birth data appropriately.

1.2. Statement of Problem

High fertility in Ethiopia remains the dominant factor dictating the future size, growth and composition of the population in the country. In order to reduce fertility and control population growth of the country, the factors that influence fertility should be clearly identified (Zhang, 2007). Experience of fertility transition countries also emphasizes the role of its determinant in fertility change (Bongaarts, 2011). Human fertility is a function of a variety of factors. The factor varies from place to place, depending on the specific conditions of the given area (Lindstrom & Kiros, 2001; Yohannes *et al*., 2004).

Total fertility rate can be lessened by increasing the age at marriage (Islam, 2009). But age at marriage is difficult to increase due to effect of strong social customs on it. The other option is to increase the length of time-to-first birth. If population control policies are formulated in a way that first birth interval is controlled, then higher order birth interval will be also controlled (Islam, 2009). For the formulation of effective policy to motivate people for longer time-to-first birth, it is necessary to study the effect of various socio-economic and demographic factors which affect time-to-first birth. A proper understanding of these factors are of paramount importance in tackling the problem of uncontrolled fertility, which covers the way for the improvement of the prevailing socioeconomic problems of the country.

Even though, several studies on time-to-first birth after marriage used different statistical models to explore its determinant factor, its evolution still needs to be studied. In the literature review, the use of survival analysis in the modeling the determinants of time-to-first birth were played important role. Kaplan-Meier, Cox proportional hazard model, and parametric survival models have been used which assumes the survival data of different observations are independent and identical of each other. This assumption does not hold in other situations, which are not common as originally thought. Yet, the concept of this model allows for modeling the risk of different groups; it does not control the risk factor for some relevant covariates that are often unobservable, or difficult to measure even unknown (Wienke, 2010). But the fertility rate is quite different and customs, culture and practice of people vary across regions. This implied that the existence of heterogeneity in the survival of time-to-first birth between different regions.

This research aimed to explore factors that affect time-to-first birth after marriage by using parametric shared frailty model. Frailty term was added to account the correlation which comes from the cluster, accounts unobservable random effect. In general, the motivation behind this study is to address the following major research questions:

- What are the key socio-economic and demographic predictors of time-to-first birth after marriage among women in Ethiopia?
- Which baseline distributional assumption among the weibull, log-logistic, and log-normal describes well time-to-first birth after marriage?
- Finally, the multivariable model will be fitted and interpreted using the selected appropriate model

1.3. Objective of the Study

1.3.1 General Objective

Modeling time- to-first birth after marriage among women in Ethiopia using different parametric shared frailty model approaches.

1.3.2 Specific Objectives

The specific objectives are:

- To identify factors associated with time-to-first birth after marriage for Ethiopian women.
- To estimate the survival time and compare the survival curves of time-to-first birth among different levels of covariates
- To assess the clustering (region) effect in determining the factors associated with time-to-first birth after marriage among women in Ethiopia
- To compare the performance of AFT and parametric frailty model in modeling time-to-first birth dataset.

1.4. Significance of the Study

The result of this study will provide information on time- to- first birth among women in Ethiopian and its determinant factors. Specifically;

- To provide information about the covariates or risk factors of time- to- first birth
- Provide information to government and concerned bodies in setting policies and strategies.
- Use as a stepping stone for further studies related to time-to- first birth.

2. LITERATURE REVIEW

2.1. Description of Fertility

Fertility refers to the actual reproductive performance of women and it is the most important component of population dynamics and plays a major role in changing the size and structure of the population of a given area over time (Ayanaw, 2008). Many theoretical approaches have been developed to explain variations in fertility. The most common measure of fertility is the total fertility rate that is defined as the average number of births that a woman would have if she survived to the end of her childbearing ages (Manda & Meyer, 2005). Each marriage increase the likelihood of more children as women in the right age of child bearing and this leads to high total fertility rate. Several indicators are used to measure fertility patterns, such as the first birth interval after marriage (Lloyd, 2005).

2.2. Time-to-First Birth after Marriage

The birth interval of the first child can be used as one of the indicators of fertility. Marriage to first birth is important incidence in the life of women with increasing responsibilities. The waiting time of a woman to first birth after marriage, can determine the happiness and or survival of her marriage. While delayed births could lead to contention, suspicions and even breakups of marriages, very early births, especially the unexpected and unwanted ones, could do same or even worse (Logubayom & Luguterah, 2013). According to Singh *et al*. (2006), among the various types of fertility data used, data on first birth interval have an upper hand over all other types of birth interval due to certain reasons. First, being the earliest and first event of the married life of a female, it hardly suffers from recall lapse; second, it is free from inconsistent fluctuation of breast feeding (Singh, 2007).

2.2.1. Risk Factors of Time-to-First Birth

Time-to-first birth after marriage is affected by a complex range of factors. Some of which are rooted in social and cultural norms, others in the reproductive histories and behaviors of individual women, utilization of reproductive health services and other personal factors. Group differences in reproductive behavior are usually explained from the characteristics and socio-cultural perspectives (United Nations, 1987). While the former attributes variations in fertility behavior to socio-economic and demographic differences among groups, the latter assigns a unique role to availabilities of required materials like contraceptive as key to making variations on birth intervals.

Time-to-first birth is associated with couple's personal characteristics like age at marriage, education, occupation, and place of residence but with the influence of social norms. Age of women at first birth is important determinant and it affects the growth of population. Early child bearing increases the women's reproductive span as compared to those similarly fecund women who bear child later. It also reduces age gap between the two generations (Kumar & Danabalan, 2006).

Zhenzhen (2000) found the reason of delay in first live birth for women who married in between 1980-92 for China. Urban women deliberately control the fertility by limiting the birth interval. Education, residence urban/rural, age at first marriage, marriage cohort played a significant role in the determination of marriage to first birth interval. The median of marriage to first birth interval for Chinese women is found to be two years.

Education of both spouses had not shown any substantial effect on the first birth interval in Taiwan. The college educated Taiwanese women had two months long birth interval than women who had completed only school education. Women with fifteen years marital duration had long birth interval than those who had less marital duration. Urban residents had wider interval than rural. The difference of interval between urban and rural women was four months and family planning program had not attained the desired results and prevalence rate in rural areas was low than urban. Contraceptive use had shown insignificant relationship with birth spacing (Stokes & Hsieh, 1983).

Islam (2009) had also investigated the determinants of first birth interval in rural Bangladesh. Respondent's age, age of women at marriage, family income and quality of care at clinic were found as significant determinants. For the same country, using Cox PH Model based on the Bangladesh Demographic and health survey (Bdhs, 2004), place of residence, region, women's education, husbands' education, access to media, women's work status, wealth index and contraceptive use were found to have significant effect on time-to-first birth while religion and husbands' education were not. And also the mean and median of first birth interval were 33 and 25 months respectively (Mukhlesur *et a*l., 2013). And Rabbi *et al*. (2013) also used Multivariate approach to determine significant factors of age at first birth. Accordingly, age of women at marriage, and place of residence (urban as reference) found to be negatively associated while mass media exposure, wealth index (poor as reference), work status of women were positively associated with first birth interval.

Research conducted in Pakistan using Cox Regression Model by considering the covariates: age of women at the first birth, age at marriage, ideal number of children (fertility intention), ideal number of boys (son preference), region (Punjab, Sindh, KPK, Baluchistan), education of both spouses, wealth index and occupation of both spouses was conducted to identify the potential covariates that affect time-to-first birth after marriage. This research revealed that women's age at marriage, education (illiterate) and wealth index (poorer) contribute significantly to first birth interval. But ideal number of children (fertility intention), ideal number of boys (son preference), and education status of both spouses were insignificant. The average value of marriage to first birth interval is found to be approximately 31 months or 2.7 years. (Kamal & Pervaiz, 2013).

Shayan *et al*. (2014) in Iran investigated prognostic factors of first birth interval after marriage using Cox PH and Parametric Survival Models. The result showed that age at marriage, level of women's education, and menstrual status had highly significant effects on the duration of birth interval after marriage but wealth index, both women's and husband educational levels were not significant. The mean and median of the first birth interval after marriage for Iranian women were found to be 31.2 and 25.2 months, respectively.

Hidayat *et al*. (2014) used Cox PH and Exponential distribution in modeling first birth interval after marriage and associated factors in Indonesia. The result showed that place of residence, mother's education, and age at marriage significantly affects the interval. But knowledge about contraception and work status of women found to be insignificant.

Nath *et al.* (2000) conduct study on the effect of status of women on first birth interval in Indian Urban society. Education of women, work status, participation in family decisions and age at marriage were taken as status variable along with socioeconomic variables (family income, family status and caste system). Among these factors, age of women at marriage, education status of women, family income and participation in family decision found to have significant effect on first birth interval. Caste system also had played insignificant contribution in the determination of time-to-first birth in India.

According to Gayawan and Adebayo (2013), by using Semi-parametric Survival modeling for age at first birth in Nigeria, by using DHS data (2008), 31% of women who had their first child before age 15 years ended up having 7 or more children, only 8.3% of those who had first birth after age 25 years ended with this number. The corresponding mean numbers of children for these women are 6.62 and 2.62 respectively, a difference of 4.0. The risk of bearing the first child is lower for women who attend secondary and higher education than those who have no education. In addition, working status of women and use of contraceptive methods were found to be significant in determining first birth.

Similar study in Nigeria using four parametric models whose various curves and estimates are compared with non-parametric values were considered, namely Inverse Gaussian, Log-logistic, Weibull and Burr Type XII. The best model appears to be Inverse Gaussian based on the Akaike Information Criterion. In this study the covariate, wealth index of the family, work status of women, education level of women and her partner, age at marriage of women and place of residence were considered. The risk of giving her first birth for women lived in rural, illiterate women, women without job was higher than their respective counterpart. But education level of husband had no contribution to the time of first birth after marriage. The mean and median waiting times to first birth after marriage by women in Nigeria are 28.8 and 20.0 months respectively (Amusan and Mohd, 2014).

Logubayom and Luguterah (2013) used Non-Parametric Survival Analysis technique and data from the 2008 Ghana Demographic and Health Survey (GDHS) to examine first birth interval after marriage. The study considered only women of childbearing age (15-49 years), who went into marriage without a child or a pregnancy. The result showed that region of residence, educational level of women, and wealth index of the family had significant effect while age at first marriage and age at first intercourse are not. And most women (74%) have their first birth within the first three years of marriage and some women have even after ten years in marriage and the estimated median time of first birth interval was 30 months. For the same country Gyimah(2003), using regression analysis, also reported that women who had short first birth interval tend to have a higher number of births than those whose first birth occur late regardless of their birth cohort.

Gurmu and Etana (2010), investigated Ethiopian Marriage to first birth interval Using Cox's proportional hazards model, which is significantly different for age of women at marriage, region, education of women, and marriage cohort in Ethiopia. Of the nine regional states, the study showed that Amhara region, where child marriage is commonly practiced, exhibits longer interval between marriage and first birth. For the same country, Ethiopia, Wondiber and Eshetu (2011), using AFT model with 2011 EDHS, reported that the median survival time of first birth for rural women was 29 months.

Wondiber and Eshetu (2012) also used AFT model to analyze the determinant of birth intervals in rural Ethiopia using 2011 EDHS. They reported that the time-to-first birth affected by region, educational level of the mother and wealth index of the family. According to their finding, the estimated median time of first birth was 29 months.

2.3. Survival Models

The origin of survival analysis goes back to the time when life tables were introduced. Life tables are one of the oldest statistical techniques and are extensively used by medical statisticians and by actuaries. Yet relatively little has been written about their formal statistical theory. Kaplan and Meier (1958) gave a comprehensive review of earlier work and many new results. Cox (1972) was largely concerned with the extension of the results of Kaplan and Meier to the comparison of life tables and more generally to the incorporation of regression like arguments into life table analysis.

Survival models have the capability of handling censored data. Cox (1972) and Cox and Oakes (1984) used survival analysis in modeling human lifetimes. Fergusson et al. (1984) used hazard functions to study the time to marital breakdown after the birth of child. Hazard functions had been also used in studies of time to shift in attentions in classroom (Felmlee *et. al*., 1983), in study of relapse of mental illness (Lavori et al., 1984), marital dissolutions (Morgan et al. 1988), and human lifetimes (Gross *et al*., 1975).

Proportional hazards modeling is the most frequently used type of the survival analysis modeling in many research areas, having been applied to topics such as smoking relapse (Stevens & Hollis,1989), affective disorders childhood family breakdown interruptions in conversation (Dress, 1986), and employee turnover (Morita *et al*., 1989), and in medical areas for identification of important covariates that have as significant impact on the response of the interested variables.

Cox (1972) introduced a semi parametric survival model. This model is based on the assumption that the survival times of distinct individuals are independent of each other. This assumption holds in many experimental settings and widely applicable. However; there are instances in which this assumption may be violated. For example, in many epidemiological studies, survival times are clustered into groups such as families or geographical units: some unmeasured /immeasurable characteristics shared by the members of that cluster, such as genetic information or common environmental exposures could influence time to the studied event. To account these factors, we should include the random effect terms in the standard Cox model (Clayton, 1978; Klein *et al*., 1992; Nielsen *et al*., 1992; Hastie & Tibshirani, 1993).

Frailty models are extensions of the PHs model which is best known as the Cox model (Cox, 1972), the most popular model in survival analysis. Frailty models are substantially promoted by its applications to multivariate survival data in a seminar paper by Clayton (1978) without using the notion frailty. Hougaard (1986) used several distributions for frailty including gamma, inverse Gaussian, positive stable distributions and claimed that these two distributions are relevant and mathematically tractable as a frailty distribution for heterogeneous populations. Flinn and Heckman (1982) used a lognormal distribution for frailty, whereas Vaupel *et al*. (1979) assumed that frailty is distributed across individuals as a gamma distribution. Recent research has addressed the problem of heterogeneity. Hougaard (1986) suggested the power variance function (PVF) distribution which includes gamma, inverse Gaussian, positive stable distributions as frailty model. Hedeker *et al*. (1996) discussed a frailty regression model for the analysis of correlated grouped time survival data. Frailty models have been applied to the analysis of event history data, including the study of age at time of death for individuals in terms of population (Zelterman, 1992), unemployment duration (McCall, 1994), pregnancy in women (Aalen, 1987) and migration (Lindstorm, 1996).

3. DATA AND METHODS

3.1. Data Source

The data for this study was extracted from the published reports of Ethiopian Demographic and Health Survey (EDHS, 2011) which is obtained from Central Statistical Agency (CSA) collected during rom 27 December 2010 to 3 June 2011. It is the third survey conducted in Ethiopia as part of the worldwide DHS project. The 2011 EDHS was designed to provide estimates for the health and demographic variables of interest for the following domains. Ethiopia as a whole; urban and rural areas (each as a separate domain); and 11 geographic administrative regions (9 regions and 2 city administrations), namely: Tigray, Affar, Amhara, Oromiya Somali, Benishangul-Gumuz, Souther Nations Nationalities and Peoples (SNNP), Gambela and Harari regional states and two city administrations, that is, Addis Ababa and Dire Dawa. The principal objective of the 2011 EDHS is to provide current and reliable data on fertility and family planning behavior, child mortality, adult and maternal mortality, children's nutritional status, use of maternal and child health services, knowledge of HIV/AIDS, and prevalence of HIV/AIDS and anemia.

3.2. Sampling Design

The 2007 Population and Housing Census, conducted by the CSA, provided the sampling frame from which the 2011 EDHS sample was drawn. Administratively, regions in Ethiopia are divided into zones, and zones, into administrative units, called weredas. Each wereda is further subdivided into the lowest administrative unit, called Kebele. And each kebele was subdivided into census enumeration areas (EAs) or clusters. The 2011 EDHS sample was selected using a stratified, two-stage cluster sampling design (CSA, 2011).

Clusters were the sampling units for the first stage. The sample included 624 clusters, 187 in urban areas and 437 in rural areas. Households comprised the second stage of sampling. In the second stage, a fixed number of 30 households were selected for each cluster. The 2011 EDHS used three questionnaires: the Household Questionnaire, the Woman's Questionnaire, and the Man's Questionnaire. These questionnaires were adapted from model survey instruments developed for the measure DHS project to reflect the population and health issues relevant to Ethiopia. In addition to English, the questionnaires were translated into three major local languages-Amharic, Oromiffa, and Tigrigna.

All women aged 15-49 were eligible for interview. In the interviewed households 16,515 eligible women were identified for individual interview. This study considered only women who went into marriage for the first time without a child or no pregnancy and whose records were complete. Thus, less than nine months of waiting time for first birth after marriage and having negative birth interval were excluded. In all, a total of 7,925 women from eight regions and two city administration were included in the study. This research did not consider Somali region because the data for Somali may not be totally representative of the region as a whole since some EAs are not interviewed due to drought and security problems (CSA, 2011). And the data were analyzed using the R-statistical packages (version 3.2.1) and STATA (version 11.0) soft wares.

3.3. Variables in the study

The response (dependent) and predictor variables used in the model for the estimation of parameters are defined as follows.

3.3.1. The Response Variable

The response variable is time-to-first birth among woman in Ethiopia, which is measured in months. For women who did not give birth the time was measured till the date of the interview (27 December 2010 to 3 June 2011).

3.3.2. Explanatory Variables

Several predictors were considered in this study to investigate the determinant factors of time- to- first birth. These are age of women at marriage, women education, husband's education, contraceptive use, and wealth index, place of residence, media exposure, and women employment status. These covariates are described together with their coding scheme in Table 1. Among these covariates only age at marriage is continuous the rest of them are categorical.

Table3.1: Description of independent variables used in the analysis

Variables	**Description**	**Categories**
age	Age of women at marriage	Measured in years
Women education	Women's level of education	0= No education;1= Primary; 2= Secondary & above
Husband education	Husband's level of education	0= No education;1= Primary; 2= Secondary and above
Wealth index	Household wealth index	0= Poor; 1=Meddle; 2=Rich)
Place of residence	Place of residence	0=Rural; 1=Urban)
Mass media	Access to mass media	0= No; 1= Yes
Employment status	Employment status of women	0= unemployed ; 1= Employed
Contraceptive	Use of Contraceptive	0 = Non-User, 1=User

Region of the women was considered as a clustering effect in frailty model.

3.4. Survival Analysis

Survival analysis is a collection of statistical procedures for data analysis for which the outcome variable of interest is time until an event occurs. By time, we mean years, months, weeks, or days from the beginning of follow-up of an individual until an event occurs; alternatively, time can refer to the age of an individual when an event occurs. By event, we mean death, disease incidence, relapse from remission, recovery (e.g., return to work) or any designated experience of interest that may happen to an individual. The problem of analyzing time-to-event data arises in several applied fields such as medicine, biology, public health, epidemiology, engineering, economics, sociology, demography and etc. The terms lifetime analysis, duration analysis, event-history analysis, failure-time analysis, reliability analysis, and transition analysis refer essentially to the same group of techniques although the emphases in certain modeling aspects could differ across disciplines (Aalen *et a*l., 2008).

The use of survival analysis, as opposed to the use of other statistical method, is most important when some subjects are lost to follow up or when the period of observation is finite certain patients may not experience the event of interest over the study period. In this latter case one cannot have complete information for such individuals. These incomplete observations are referred to as being censored. Most survival analyses consider a key analytical problem of censoring. In essence, censoring occurs when we have some information about individual survival time, but we do not know the survival time exactly.

In reality such event can occur due to the following reasons:

1. A person does not experience the event before the study ends
2. A person is lost to follow-up during the study period and
3. A person withdraws from the study for unknown/known reasons

There are three categories of censoring.

i) Right censoring: Survival time is said to be right censored when it is recorded from its beginning to a defined time before its end time. This type of censoring is commonly recognized survival analysis and also considered in this study. Let C denote the censoring time, that is, the time beyond which the study subject cannot be observed. The observed survival time is also referred to as follow up time. It starts at time 0 and continues until the event T or a censoring time C, whichever comes first. Let C_1, $C_{2\dots}$ C_n be a sample of censoring times. And T_1, T_2… T_n be event times. We observe a sample of couples, (y_1, δ_1), (y_2, δ_2), …, (y_n, δ_n), where for i=1,2,….n. (Cox,1984)

$$Y_i = \min(T_i, C_i) = \begin{cases} T_i , if\ T_i \le C_i \\ C_i , if\ \ T_i > C_i \end{cases}$$

$$\delta_i = I(T_i \le C_i) = \begin{cases} 1 , if\ T_i \le C_i \\ 0 , if\ \ T_i > C_i \end{cases}$$

ii) Left censoring: Survival time is said to be left censored if an individual develops an event of interest prior to the beginning of the study.

iii) Interval censoring: Survival time is said to be interval censored when it is only known that the event of interest occurs within an interval of time but the exact time of its occurrence is not known.

The presence of censoring complicates research design and statistical analysis. Thus, censoring creates some unusual problem in the analysis of data because such data cannot be handled properly by standard statistical methods. Researchers used different techniques to respond to the complication due to censoring unsatisfactorily. New developments in statistical theory accompanied by new development in statistical computing have changed how researchers can study such data.

An important assumption for methods presented in survival analysis studies for the analysis of censored survival data is that the individuals who are censored are at the same risk of subsequent failure as those who are still alive and uncensored. i.e. a subject whose survival time is censored at time C must be representative of all other individuals who have survived to that time. If this is the case, the censoring process is called non-informative. Statistically, if the censoring process is independent of the survival time, then we will have non-informative censoring. In this study, we assumed that the censoring is non-informative right censoring.

The response variable in survival analysis is survival time and is no longer limited to only time to death. It is a non-negative random variable used loosely for the time period from a starting time point to the occurrence of any event. In this study context, survival time is the length of time of first birth after marriage which is measured in months.

3.4.1. Survival Functions

The survivor function is defined to be the probability that the survival time of a randomly selected subject is greater than or equal to some specified time. Thus, it gives the probability that an individual surviving beyond a specified time. Let T be a continuous random variable associated with the survival times, t be the specified value of the random variable T and f (t) be the underlying probability density function of the survival time T. The cumulative distribution function F(t), which represents the probability that a subject selected at random will have a survival time less than some stated value t, is given by (Cox,1984);

$$F(t) = P(T < t) = \int_0^t f(u)du \text{ , where; } t \geq 0 \quad (1)$$

The survivor function S(t), is given by;

$$S(t) = P(T \geq t) = 1 - F(t), \qquad \text{where;} \quad t \geq 0 \quad (2)$$

From equations (1) and (2) the relationship between f (t) and S(t) can be derived as

$$f(t) = \frac{d}{dt}F(t) = \frac{d}{dt}\left(1 - S(t)\right) = \frac{-d}{dt}S(t) \geq 0 \tag{3}$$

Theoretically, as t ranges from 0 to infinity, the survivor function can be graphed as a smooth curve. Survivor functions have the characteristics that:

1. They are non-increasing
2. At time t = 0, S(0) = 1; that is, at the start of the study, since no one has experienced the event yet, the probability of surviving past time 0 is one and
3. At time $t \to \infty$, $S(\infty) \to 0$; that is, theoretically, if the study period increased without limit, eventually nobody would survive, so the survivor curve must eventually converge to zero.

3.4.2. Hazard Function

The hazard function h(t) gives the instantaneous potential for failing at time t, given the individual has survived up to time t. This is the conditional probability of experiencing the event of interest within a very small time interval of size Δt having survived up to time t. It is a measure of the probability of failure during a very small interval, assuming that the individual has survived at the beginning of the interval. In addition, it is not a probability as it does not lie between 0 and 1. The hazard function, $h(t) \geq 0$ is given as (Cox, 1984);

$$h(t) = \lim_{\Delta t \to 0} \frac{P\{an\ individual\ fails\ in\ the\ time\ interval\ (t, t+\Delta t) given\ survives\ untill\ time\ t\}}{\Delta t}$$

$$= \lim_{\Delta t \to 0} \frac{P(t \leq T \leq t + \Delta t \mid T \geq t)}{\Delta t}$$

By applying the theory of conditional probability and the relationship in equation (3), the hazard function can be expressed in terms of the underlying probability density function and the survivor function becomes:

$$h(t) = \frac{f(t)}{S(t)} = -\frac{d}{dt}\ln S(t). \tag{4}$$

The corresponding cumulative hazard function, H(t), is defined as:

$$H(t) = \int_0^t h(u)du = -\ln S(t), \tag{5}$$

Then;

$$S(t) = \exp(-H(t)) \ \text{ and } f(t) = h(t)S(t) \tag{6}$$

The survival function is most useful for comparing the survival progress of two or more groups while the hazard function gives a more useful description of the risk of failure at any time point.

3.4.3. Non-parametric Survival Methods

Nonparametric methods are often very easy and simple to understand as compared to parametric methods. Furthermore, nonparametric analyses are more widely used in situations where there is doubt about the exact form of distribution.

Survival data are conveniently summarized through estimates of the survival function and hazard function. The estimation of the survival distribution provides estimates of descriptive statistics such as the median survival time. These methods are said to be non-parametric methods since they require no assumptions about the distribution of survival time. Preliminary analysis of the data using non-parametric methods provides insight into the shape of the survival function for each group and get an idea of whether or not the groups are proportional, i.e., if the estimated survival functions for two groups are approximately parallel (do not cross). In order to compare the survival distribution of two or more groups, log-rank tests can be used

3.4.3.1. The Kaplan-Meier Estimator of Survival Function

The Kaplan-Meier (KM) estimator is the standard non parametric estimator of the survival function, S(t), proposed by Kaplan and Meier (1958) which is not based on the actual observed event and censoring times, but rather on the ordered in which events occur. It is also called the Product-Limit estimator. KM estimator incorporates information from all of the observations available, both censored and uncensored, by considering any point in time as a series of steps defined by the observed survival and censored times. When there is no censoring, the estimator is simply the sample proportion of observations with event times greater than t. The technique becomes a little more complicated but still manageable when censored times are included. Let ordered survival times are given by $0 \leq t_1 \leq t_2 \leq t_j \leq \infty$, then (Kaplan &Meier, 1958)

$$\hat{S}(t) = \begin{cases} 1, & if\ t < t_1 \\ \prod_{j:t_{j} \leq t} \left[1 - \frac{d_j}{r_j}\right], & \text{if } t \geq t_1 \end{cases} \quad (7)$$

Where; d_j is the observed number of events at time t_j and r_j is the number of individuals at risk at time t_j.

The Kaplan-Meier estimator, $\widehat{S}$(t) is a step function with jumps at the observed event times. The size of the jump at a certain event time t_j depends on the number of events observed at t_j, as well as on the pattern of the censored event times before t_j. The variance of the Product-Limit estimator is estimated by Greenwood‟s formula (Greenwood, 1920), and is given by;

$$Var(\widehat{S}(t)) = \left[\hat{S}(t)\right]^2 \sum_{j:t_j \le t} \frac{d_j}{r_j(r_j - d_j)};\ j= 1, 2, \ldots, r \quad (8)$$

Since the distribution of survival time tends to be positively skewed, the median is preferred for a summary measure. The median survival time is the time beyond which 50% of the individuals under study are expected to survive, i.e., the value of t_{50} at $\hat{S}(t_{50})$ = 0.5. The estimated median survival time is given by $t_{50} = \min\{t_i / \widehat{S}(t) < 0.5\}$, where t_i is the observed survival time for the i^{th} individual, i= 1,2,…, n. in general, the estimate of the p^{th} percentile is:

$$\hat{t}(p) = \min\{ t_i / \widehat{S}(t) < 1 - \frac{P}{100}\} \quad (9)$$

A confidence interval for the percentiles can be obtained using delta method (Hosmer & Lemeshaw, 1998). The variance estimator for the p^{th} percetile is given by:

$$Var[\widehat{S}(t_{(p)})] = \left(\frac{d\,\widehat{S}(t(p))}{dt(p)}\right)^2 var(t_{(p)}) = (-f(t_{(p)}))^2\, var(t_{(p)}) \quad (10)$$

The standard error of $t_{(p)}$ is given by:

$$SE(\hat{t}_{(p)}) = \frac{1}{f(\hat{t}(p))} SE\left[\widehat{S}(t(p))\right]$$

The standard error of $\hat{S}(t_{(p)})$ can be obtained by using Greenwoods formula

$$\hat{f}((\hat{t}(p)) = \frac{\hat{S}(\widehat{U}(p)) - \hat{S}\left(\hat{l}(p)\right)}{\hat{l}(p) - \widehat{U}(p)} \quad (11)$$

where,

$$\widehat{U}(p) = \max[S(t_j) \ge 1 - \frac{P}{100} + \delta]$$

$$\hat{l}(p) = \min\left[S(tj) \le 1 - \frac{P}{100} - \delta\right]$$

Where, t_j is the j^{th} ordered event time, j= 1,2,…, r.

Then, the 95% confidence interval for $t_{(p)}$ is given by:

$$\hat{t}_{(p)} \pm 1.96 * SE(\hat{t}_{(p)}) \quad (12)$$

3.4.3.2. Non parametric Comparison of Survival Functions

The simplest way of comparing the survival times obtained from two or more groups is to plot the Kaplan-Meier curves for these groups on the same graph. However, this graph does not allow us to say, with any confidence, whether or not there is a real difference between the groups. The observed difference may be a true difference, but equally, it could also be due merely to chance variation. Assessing whether or not there is a real difference between groups can only be done, with any degree of confidence, by utilizing statistical tests. Among the various non-parametric tests one can find in the statistical literature, the Mantel-Haenzel test, currently called the "log-rank" is the one commonly used non-parametric tests for comparison of two or more survival distributions. The log rank test statistic for comparing two groups is given by (Cox, 1984):

$$Q = \frac{\left[\sum_i^m w_i(d_{1i} - \hat{e}_{1i})\right]^2}{\sum_i^m w_i^2 \hat{V}_{1i}} \sim \chi^2_{k-1}, \quad (13)$$

Where: $\hat{e}_{1i} = \frac{n_{1i} d_i}{n_i}$ And $\hat{V}_{1i} = \frac{n_{1i} n_{0i} d_i (n_{1i} - d_i)}{n_i^2 (n_i - 1)}$

n_{oi} is the number at risk at observed survival time $t_{(i)}$ in group 0

n_{1i} is the number at risk at observed survival time $t_{(i)}$ in group 1

n_i is the total number of individuals or risk before time $t_{(i)}$

d_{1i} is the number of observed event in group 1

d_i is the total number of event at $t_{(i)}$

k is number of groups in each category

3.4.4. Cox PH Regression Model

The non-parametric method does not control for covariates and it requires categorical predictors. When we have several prognostic variables, we must use multivariate approaches. But we cannot use multiple linear regression or logistic regression because they cannot deal with censored observations. We need another method to model survival data with the presence of censoring. One very popular model in survival data is the Cox proportional hazards model.

The Cox proportional hazards (PH) regression model (introduced in a seminal paper by Cox, 1972), a broadly applicable and the most widely used method of survival analysis. Survival models are used to quantify the effect of one or more explanatory variables on failure time. This involves specification of a linear -like model for the log hazard. A parametric model based on the exponential distribution may be parameterized as follows:

$$\log h_i(t \mid x) = \alpha + \beta_1 x_{i1} + \beta_{21} x_{i2} + \cdots + \beta_k x_{ik}$$

Equivalently;

$$h_i(t \mid x) = \exp(\alpha + \beta_1 x_{i1} + \beta_{21} x_{i2} + \cdots + \beta_k x_{ik}) = \exp(\alpha)\exp(\beta' X)$$

In this case the constant α represents the log-baseline hazard since $\log h_i(t) = \alpha$ when all the x's are zero. The Cox PH model is a semi-parametric model where the baseline hazard $\alpha(t)$ is allowed to vary with time.

$$\log h_i(t \mid x) = \alpha(t) + \beta_1 x_{i1} + \beta_{21} x_{i2} + \cdots + \beta_k x_{ik}$$

$$h_i(t \mid x) = h_o(t)\exp(\beta_1 x_{i1} + \beta_{21} x_{i2} + \cdots + \beta_k x_{ik})$$

$$h_i(t \mid x) = h_o(t)\exp(X_i^T \beta) \quad (14)$$

Where , $h_o(t)$ is the baseline hazard function; $\mathbf{X}_i$ is a vector of covariates and $\boldsymbol{\beta}$ is a vector of parameters for fixed effects.

The corresponding survival function for Cox-PH model is given by:

$$S(t,X) = [S_o(t)]^{\exp\{\sum_{i=1}^{p} \beta_i X_i\}} \quad (15)$$

where, $S_o(t)$ is the baseline survival function.

In this model, no distributional assumption is made for the survival time; the only assumption is that the hazards ratio does not change over time (i.e., proportional hazards) that is why this model is also known as semi -parametric model. Even though the baseline hazard is not specified, we can still get a good estimate for regression coefficients β, hazard ratio, and adjusted hazard curves.

If all of the x's are zero the second part of equation(12) equals 1 so, $h_i(t) = h_o(t)$. For this reason the term $h_o(t)$ is called the baseline hazard function. With the Cox proportional hazards model the outcome is described in terms of the hazard ratio.

The measure of effect is called hazard ratio. The hazard ratio of two individuals with different covariates X and X^* is given by:

$$\widehat{HR} = \frac{h_o(t)\exp(\hat{\beta}'X)}{h_o(t)\exp(\hat{\beta}'X^*)} = \exp\{\sum \hat{\beta}'(X - X^*)\} \quad (16)$$

This hazard ratio is time-independent, which is why this is called the proportional hazards model. The parameter of the Cox proportional hazard model refers to the hazard ratio of one group in comparison to the other groups for categorical covariates and change in hazard ratio with a unit change of the covariate for the continuous variables when other covariates are fixed.

The change in hazard ratio for the continuous covariate is given by:

$$\frac{h_i(t,x_k+1\ )}{h_k(t,x_k\ )} = \exp(\beta_k). \quad (17)$$

Which represent change in the hazard when there is a unit change in the covarite while other covariates keeps constant.

For catagorical explanatory variable X with a levels, the model containes (a-1) dummy variables defind as D_i = 1, if x =i, and 0 otherwise for i= 1,2,…,a -1. Let $\beta_1, \beta_2, \dots, \beta_{a-1}$ denote the coefficient of the levels of dummy variables. The ratio of the hazard of two subjects, one with X at level j and other with k (j,k = 1,2,…, a-1), provided that the value of all other explanatory variables for this subject are the same, the hazard ratio between these two categories is given by:

$$\frac{h(t\ \vert D_j\ )}{h(t\ \vert D_k\ )} = \frac{\exp(\beta_j)}{\exp(\beta_k)} = \exp(\beta_j - \beta_k). \quad (18)$$

The quantity $\exp(\beta_j - \beta_k)$100% signifies the ratio of hazard function for subject at level j and k of covariates, given that the effect of other covariate keeps fixed.

3.4.4.1. Partial Likelihood Estimation for Cox PH Model

Fitting the Cox proportional hazards model, we estimate $h_o(t)$ and β. A more popular approach is proposed by Cox (1972) in which a partial likelihood function that does not depend on $h_o(t)$ is obtained for β. Partial likelihood is a technique developed to make inference about the regression parameters in the presence of nuisance parameters ($h_o(t)$) in the

Cox PH model. In this part, we construct the partial likelihood function based on the proportional hazards model.

The data in survival analysis based on the sample size n are denoted by the triplet (T_i,δ_i, X_i), i= 1, 2,…,n where T_i is the time at which the i^{th} individual experience the event (in this research context; give birth), δ_i = 1 if the event has occurred, $\delta_i = 0$ if censored, X_i is the vector of covariate or risk factors for the i^{th} individual.

We assume;

- Given X_i the life time and the censoring times are independent (non-informative censoring).
- $\tau_1 < \tau_1 < \ldots < \tau_D$ be the D ordered distinct event times
- We assume that there are no tied event times.

Let us define by;

- I_j is the identity of the individual who give birth at time τ_j
- V_j the time of the j^{th} failure at time τ_j and all information about censoring in $[\tau_{j-1}, \tau_j]$

The observable data (T_i,δ_i, X_i) is represented by {I_j} and {V_j}. Hence;

$$P(\text{Data}) = P(\{I_1,V_1,\ldots,I_D,V_D\})$$
$$= P(\{I_1,V_1\}) \text{ x } P(\{I_2,V_2\}/ \{I_1,V_1\}) \text{x}\ldots\text{x } P(\{I_D,V_D\}/\{ I_1,V_1,\ldots,I_{D-1},V_{D-1} \})$$
$$= \prod_{j=1}^{D} P(I_j \mid I_1, V_1, \ldots, I_{j-1}, V_{j-1}, V_j) \text{ x } P(V_j \mid \{I_1, V_1, \ldots, I_{j-1}, V_{j-1}\})$$

Due to the non-informative censoring, the second term does not add much information about the parametersβ.

Hence, we de fine the partial likelihood as;

$$L^{partial}(\beta) = \prod_{j=1}^{D} P(I_j \mid \{ I_1, V_1, \ldots, I_{j-1}, V_{j-1}, V_j\}) = \prod_{j=1}^{D} P(I_j \mid H_j)$$

Where, H_j is the "history" of the data, up to j th failure and including the failure time, but not the identity of the failing.

At each failure, we note that the quantity $P(I_j \mid H_j)$ is the conditional probability that a specific individual fails at time τ_j given all the individuals that had not fail before τ_j.

We denote by R(t) the set of all the individuals under study just prior to time t.

$P(I_j \mid H_j)$= P(individuals I_j fails ∣ one individual fails in R(τ_j))

$$= \frac{P(\text{individuals Ij fails } \mid \text{at risk at } \tau_j)}{\sum_{l \in R(\tau_j)} P(individual\ l\ fails\ \mid at\ risk\ at\ \tau_j)}$$

$$= \frac{\lambda(\tau_j \mid X_j) d\tau_j}{\sum_{l \in R(\tau_j)} \lambda(\tau_j \mid X_j) d\tau_j} = \frac{\lambda_o(\tau_j)\exp(\beta^T X_j)}{\sum_{l \in R(\tau_j)} \lambda_o(\tau_j)\exp(B^T X_l)} = \frac{\exp(\beta^T X_j)}{\sum_{l \in R(\tau_j)} \exp(B^T X_l)}$$

We get the partial likelihood;

$$L^{partial}(\beta) = \prod_{j=1}^{D} \frac{\exp(\beta^T X_j)}{\sum_{l \in R(\tau_j)} \exp(B^T X_l)}. \quad (19)$$

This is the partial likelihood defined by Cox. Note that, it does not depend on the underlying hazard function $h_o(.)$. Cox recommends treating this is as an ordinary likelihood for making inferences about β in the presence of the nuisance parameter $h_o(.)$.

The likelihood function in equation (15) can be expressed by;

$$L^{partial}(\beta) = \prod_{j=1}^{D} \left[\frac{\exp(\beta^T X_j)}{\sum_{l \in R(\tau_j)} \exp(B^T X_l)}\right]^{\delta_i} \quad (20)$$

The partial likelihood given by equation (16), although it describes only part of the data, could be regarded as a likelihood function allowing the estimation of β with standard procedures.

In general, large sample properties like normality and consistency of maximum likelihood estimators of β based on partial likelihood have been shown to be the same as those of any estimator from complete likelihood (Hosmer & Lemeshow, 1999).

3.4.5. Accelerated Failure Time Model

Although parametric models are very applicable to analyze survival data, there are relatively few probability distributions for the survival time that can be used with these models. In these situations, the accelerated failure time model (AFT) is an alternative to the PH model for the analysis of survival time data. Under AFT models we measured the direct effect of the explanatory variables on the survival time instead of hazard. This characteristic allows for an easier interpretation of the results because the parameters measure the effect of the correspondent covariate on the mean survival time.

The AFT model states that the survival function of an individual with covariate X at time t is the same as the survival function of an individual with a baseline survival function at a time t*exp(α'**X**), where α'= (α_1, α_2,…, α_p) is a vector of regression coefficients. In other words, the accelerated failure-time model is defined by the relationship (Klein & Moeschberger, 2003):

$$S(t \mid \mathbf{X}) = S_0\{t * \exp(\alpha'\mathbf{X})\}, \text{ for all X.} \quad (21)$$

Hereby we can consider on a log-scale of the AFT model with respect to time is given analogous to the classical linear regression approach. In this approach, the natural logarithm of the survival time Y =log (T) is modeled. This is the natural transformation made in linear models to convert positive variables to observations on the entire real line. A linear model is assumed for Y;

$$Y = \log(T) = \mu + \alpha' x + \sigma\varepsilon$$

where: α' = (α_1, α_2… α_p) is a vector of regression coefficients

μ = intercept

σ= is scale parameter and

ε = is the error distribution assumed to have a particular parametric distribution.

When we denote by S_0 the survival function when X = 0 then we find that

$$P(T > t \mid X) = P(Y > \log(t) \mid X)$$

$$= P\{\mu + \sigma\varepsilon > \log(t) - \alpha' X \mid X\}$$

$$= P\{\exp(\mu + \sigma\varepsilon) > t*\exp(-\alpha' X) \mid X\}$$

$$= S_o\{t*\exp(-\alpha' X)\}$$

The effect of the covariates on the survival function is that the time scale is changed by a factor $\exp(-\alpha' X)$, and We call this an acceleration factor.

We note that when

$\exp(-\alpha' X) > 1 \rightarrow$ the survival process accelerates.

$\exp(-\alpha' X) < 1 \rightarrow$ the survival process decelerates.

If X is an indicator variable, this is equivalent to

$\alpha > 1 \rightarrow$ Time shrinks

$\alpha < 1 \rightarrow$ Time accelerates

For each distribution of ε there is a corresponding distribution for T. The members of the AFT model considered in this study are the Weibull AFT, log- logistic AFT, and log-normal AFT models. The AFT models are named for the distribution of T rather than the distribution of log T.

This model can be related to the accelerated failure-time model representation (15) as in. The survival function of T_i can be expressed by (Klein & Moeschberger, 2003)

$$S_i(t) = P(T_i \geq t)$$
$$= P(\log(T_i) \geq \log(t))$$
$$= P(Y_i \geq \log(t))$$
$$= P(\mu + \alpha' x + \sigma\varepsilon \geq \log(t))$$
$$= P\left(\varepsilon_i \geq \frac{logy-\mu-\alpha' x}{\sigma}\right) = S_{\varepsilon_i}\left(\frac{logt-(\mu+\alpha' x)}{\sigma}\right) \quad (22)$$

3.4.5.1. Weibull Accelerated Failure Time model

The Weibull distribution (including the exponential distribution as a special case) as shown above can also be parameterized as an AFT model, and they are the only family of distributions to have this property. The results of fitting a Weibull model can therefore be interpreted in either framework (Klein & Moeschberger, 2003). Then the Weibull distribution is very flexible model for time-to-event data. It has a hazard rate which is monotone increasing, decreasing, or constant.

From equation (15), the AFT representation of the survival and hazard function of the Weibull model is given by:

$$S_{\varepsilon_i}(t) = \exp\left(-exp\left(\frac{logt-(\mu+\alpha' x)}{\sigma}\right)\right) = \exp\left(-exp\left(\frac{-(\mu+\alpha' x)}{\sigma}t^{\frac{1}{\sigma}}\right)\right) \quad (23)$$

$$h_i(t) = \frac{1}{\sigma}t^{\frac{1}{\sigma}-1}\exp\left(\frac{-\mu-\alpha' x}{\sigma}\right) \quad (24)$$

3.4.5.2. Log-logistic Accelerated Failure Time model

The log-logistic distribution has a fairly flexible functional form, it is one of the parametric survival time models in which the hazard rate may be decreasing, increasing, as well as hump-shaped that is it initially increases and then decreases. In cases where one comes across to censored data, using log-logistic distribution is mathematically more advantageous than other distributions. According to the study of Gupta *et* al. (1999), the log-logistic distribution is proved to be suitable in analyzing survival data conducted by Cox (1972), Cox and Oakes (1984), Bennet (1983) and O'Quigley and Stare (1982).

The cumulative distribution function can be written in closed form is particularly useful for analysis of survival data with censoring (Bennett, 1983). The log-logistic distribution is very similar in shape to the log-normal distribution, but is more suitable for use in the analysis of survival data. The log-logistic model has two parameters λ and ρ, where λ is the scale parameter and ρ is the shape parameter.

Its pdf is given by (Bennett, 1983);

$$f(t) = \frac{\lambda\rho t^{\rho-1}}{(1+\lambda t^{\rho})^2} \quad (25)$$

The corresponding survival and hazard functions are given by;

$$S(t) = \frac{1}{1+\lambda t^{\rho}} \quad (26)$$

$$h(t) = \frac{\lambda\rho t^{\rho-1}}{1+\lambda t^{\rho}}, \quad (27)$$

Where; $\lambda \in R, \rho > 0$

When $\rho \leq 1$, the hazard rate decreases monotonically and when $\rho > 1$, it increases from zero to its maximum point and then decreases to zero. Suppose that the survival times have lo-logistic distribution with parameter λ and ρ, under the AFT model, the hazard function for the ith individual is

$$h_i(t/x)= h_o\big(texp(-\alpha' x_i)\big)\exp(-\alpha' x_i)= \frac{\rho\exp((\lambda)\text{t}\exp(-\alpha' x_i)}{1+\exp(\lambda)\{\text{t}\exp(-\alpha' x_i\}^{\rho}} \quad (28)$$

The log-logistic AFT model with a covariate x may be written as;

Y= logT= $\mu + \alpha' x_i + \sigma\varepsilon$, where; $\alpha' = (\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_p)$; ε has standard logistic distribution. The survival with covariate x is given as follows:

$$S_T(t/x) = \frac{1}{1+\lambda\exp(\beta' x)t^{\rho}} = \frac{1}{1+\exp(log\lambda+\beta' x)} \quad (29)$$

$$h_T(t/x)= \frac{\rho t^{\rho-1}\lambda\exp(\alpha' x)}{1+\lambda\exp(\alpha' x)t^{\rho}} = \frac{\rho t^{\rho-1}\lambda\exp(\alpha' x)}{1+\exp(log\lambda+ \alpha' x)} \quad (30)$$

To interprete the factor $\exp(\beta' x)$ for log-logistic model, one can notice that the odds of survival beyond time t for log-logistic model is given by $\frac{S_T(t)}{1-S_T(t)}$.

We can see that the log-logistic distribution has the proportional odds (PO) property. So this model is also a proportional odds model, in which the odds of an individual surviving beyond time t are expressed as

$$\frac{S_T(t)}{1-S_T(t)} = \exp(-\alpha' x)\, \frac{S_0(t)}{1-S_0(t)} \tag{31}$$

The factor exp($-\alpha' x$) is an estimate of how much the baseline odds of survival at any time changes when individual has covariate x. And exp($\alpha' x$) is the relative odds of experiencing the event for an individual with covariate x relative to an individual with the baseline characteristics. As this representation of log-logistic regression is as accelerated failure time model with a log logistic baseline survival function, then the log logistic model is the only parametric model with both a proportional odds and an accelerated failure-time representation. If T_i has a log-logistic distribution, then ε_i has a logistic distribution. The survival function of logistic distribution is given by (Collett, 2003)

$$S_{\varepsilon_i}(\varepsilon) = \frac{1}{1+\exp(\varepsilon)} \tag{32}$$

Then, the AFT representation of log-logistic survival function is given by

$$S_t(t) = \left[1 + t^{\frac{1}{\sigma}} \exp\left(\frac{-\mu-\alpha' x}{\sigma}\right)\right]^{-1} \tag{33}$$

And the associated hazard function for the i^th individual is given by

$$h_t(t) = \frac{1}{\sigma t}\left[1 + t^{\frac{-1}{\sigma}} \exp\left(\frac{-\mu-\alpha' x}{\sigma}\right)\right]^{-1} \tag{34}$$

If the plot of $\log\left[\frac{1-S(t)}{S(t)}\right]$ against log(t) is linear , the log-logistic distribution is appropriate for the given data set.

3.4.5.3. Log-normal Accelerated Failure Time Model

If the survival times are assumed to have a log-normal distribution, the baseline survival function and hazard function are given by (Collett, 2003):

$$S_o(t) = 1-\Phi\left(\frac{\log t-\mu}{\sigma}\right), \qquad h_o(t) = \frac{\phi\left(\frac{\log t}{\sigma}\right)}{\left[1-\emptyset\left(\frac{\log t}{\sigma}\right)\right]\sigma t}, \tag{35}$$

Where μ and μ are parameters, $\phi(x)$ is the probability density function of and $\phi(x)$ is the cumulative density function of the standard distribution. The survival function for the i^th individual is

$$S_i(t) = S_o(t/\eta_i) = S_o(t * \exp(\mu + \alpha' x_i)) = 1-\phi\left(\frac{\log t-\alpha' x_i-\mu}{\sigma}\right) \tag{36}$$

Where η_i= exp($\alpha_1 x_1$+ $\alpha_2 x_2$…+$\alpha_p x_p$). Therefore the log survival time for the ith individual has normal (μ+ $\alpha' x_i, \sigma$). The log normal distribution has the AFT propoerty. In a two group study: we can easily get

$\phi^{-1}[1 - S(t)] = \frac{1}{\phi}(logt - \alpha' x_i - \mu)$, where x_i is the value of a categorical variable which takes the value 0 in one group and 1 in the other group. This implies that the plot $\phi^{-1}[1 - S(t)]$ against log (t) will be linear if the lo-normal distribution is appropriate for the given data set.

3.4.5.4. Parameter Estimation

Parameters of AFT models can be estimated by maximum likelihood method. The likelihood of n observed survival times, t_1, t_2, $t_{3\ldots}$ t_n, the likelihood function for right censored data is given by:

$$L(\alpha, \mu, \sigma) = \prod_{j=1}^{n} f_i(t_i)^{\delta_i} \ *S_i(t_i)^{1-\delta_i} \tag{37}$$

Where $f_j(t_j)$ the density function of the i^{th} individual at time t_i , $S_i(t_i)$ is the survival function of the i^{th} individual at time t_i, δ_i is indicator variable. The logarithm of the above equation yields;

$$\log L(\alpha, \mu, \sigma) = \sum_{j=1}^{n}\{-\delta_i log(\delta t_i + \delta_i log f_i(x_i) + (1-\delta_i) log S_i(W_i))\} \tag{38}$$

Where, $W_j = \left\{logt_i - \frac{\mu + \alpha_{1i}x_i + \cdots + \alpha_{pi}x_{pi}}{\delta}\right\}$, Z= $\{z_{ji}\}$ is vector of covariates for the j^{th} subject. The maximum likelihood parameters estimates are found by using Newton-Raphson procedure which can be done by software.

3.4.6. Shared Frailty Model

Many statistical models and methods proposed to model failure time data assume that the observations are statistically independent of each other. However, this does not hold in many applications. The concept of frailty provides a suitable way to introduce random effects in the model to account for association and unobserved heterogeneity. In its simplest form, a frailty is an unobserved random factor that modifies multiplicatively the hazard function of an individual or a group or cluster of individuals.

An individual is said to be frail if he or she is much more susceptible (exposed or infected) to adverse events than others. Vaupel *et al*. (1979) introduced the term frailty to indicate that different individuals are at risk even though on the surface they may appear to be quite similar with respect to the measurable such as age, gender, weight, etc. They used the term frailty to represent an unobservable random effect shared by subjects with similar (unmeasured) risks in the analysis of mortality rates. A random effect describes excess risk or frailty for distinct categories, such as individual or families, over and above any measured covariates. Thus random effect or frailty models have been introduced into the statistical literature in an attempt to account for the existence of unmeasured attributes such as genotype that do introduce heterogeneity into a study population. It is recognized that individuals in the in the same group (cluster) are more similar than individuals in different cluster because they share similar genes, environment, custom, and culture, etc. Thus, frailty or random effect model try to account for correlations within groups (Prentice *et al*., 1981)

The assumption of a shared frailty model is that all individuals in cluster share the same frailty Z_i, and this is why the model is called the shared frailty model. It was introduced by Clayton (1978) and extensively studied in Hougaard (2000), Therneau and Grambsch (2000), and Duchateau *et al.* (2007). Shared-frailty models are appropriate when we wish to model the frailties as being specific to groups of subjects, such as subjects within families, kebeles, regions, etc. Here a shared frailty model may be used to model the degree of correlation within groups; i.e., the subjects within a group are correlated because they share the same common frailty.

Conditional on the frailty, the survival times in cluster i ($1 \leq i \leq n$) are assumed to be independent. And the proportional hazard frailty model assumes (wienke, 2010);

$$h_{ij}(t \mid X_{ij},U_i) = \exp(\beta' X_{ij}+u_i)h_o(t) = Z_i h_o(t)\exp(\beta' X_{ij}) \qquad (39)$$

An alternative when the proportional hazard assumption fails the accelerated failure time frailty model is used and given as:

$$h_{ij}(t \mid X_{ij},U_i) = \exp(\beta' X_{ij}+u_i)h_o(\exp(\beta' X_{ij}+u_i)t) = Z_i h_o(Z_i\exp(\beta' X_{ij})t)\exp(\beta' X_{ij})$$

Where, $h_o(t)$ is the baseline hazard function, $Z_i = \exp(u_i)$, β is a vector of parameters to be estimated, X is a vector of observed covariates. The frailties Z_i are assumed to be identically and independently distributed random variables with common density function, $f(z, \theta)$, where θ is the parameter of the frailty distribution. The variability of Z_i determines the degree of heterogeneity among the groups. In empirical applications, the observed survival data are used to estimate the parameters of the distribution of frailty f(z, θ), and to actually predict the individual frailties. Since Z multiplies the hazard function, it has to be non-negative. Another constraint is further needed for identifiability reasons, more specifically; the mean of Z is typically restricted to unity in order to separate the baseline hazard from the overall level of the random frailties .

3.4.6.1. The Gamma Frailty Distribution

The gamma distribution has been widely applied as a mixture distribution for example (Greenwood &Yule, 1920; Hougaard, 2000). From a computational point of view, it fit very well into survival models, because it is easy to derive the formulas for any number of events. This is due to the simplicity of the derivatives of the Laplace transform. The gamma frailty distribution has been widely used in parametric modeling of intra-cluster dependency because of its simple interpretation, flexibility and mathematical tractability (Vaupel *et al*., 1979; Clayton, 1978; Oakes, 1982). To make the model identifiable, we restrict that expectation of the frailty equals one and variance be finite, so that only one parameter needs to be estimated. Thus, the distribution of frailty Z is the one parameter gamma distribution. Under the restriction, the corresponding density function and Laplace transformation of gamma distribution is given by (Gutierrez, 2002):

$$f_z(z) = \frac{Z_i^{\left(\frac{1}{\theta}\right)-1}}{\theta^{\frac{1}{\theta}}\Gamma(\frac{1}{\theta})}\exp(\frac{-Z_i}{\theta}) \text{ , } \theta > 0 \qquad (40)$$

Where Γ(.) is the gamma function, it corresponds to a Gamma distribution Gam(μ, θ) with μ fixed to 1 for identifyability and its variance is θ. The associated Laplace transform is:-

$$L(u) = \left(1 + \frac{u}{\theta}\right)^{-\theta} \text{ , } \theta > 0 \qquad (41)$$

Note that if θ > 0, there is heterogeneity. So the large values of θ reflect a greater degree of heterogeneity among groups and a stronger association within groups. The conditional survival and hazard function of the gamma frailty distribution is given by (Gutierrez, 2002):

$$S_\theta(t) = [1 - \theta \ln(S(t))]^{-\frac{1}{\theta}} \qquad (42)$$

$$h_\theta(t) = h(t)[1 - \theta \ln(S(t))]^{-1} \qquad (43)$$

Where S(t) and h(t) are the survival and the hazard functions of the baseline distributions. For the Gamma distribution, the Kendall's Tau (Hougaard, 2000), which measures the association between any two event times from the same cluster in the multivariate case. It is an overall measure of dependence and independent of transformations on the time scale and the frailty model used. The associations within group members are measured by Kendall's, which is given by:-

$$\tau = \frac{\theta}{\theta+2} \in (0,1) \qquad (44)$$

3.4.6.2. Parameter Estimation

Estimation of the frailty model can be parametric or semi-parametric. In the former case, a parametric density is assumed for the event times, resulting in a parametric baseline hazard function. Estimation is then conducted by maximizing the marginal log-likelihood (Munda et al., 2012). In the second case, the baseline hazard is left unspecified and more complex techniques are available to approach that situation (Abrahantes & Duchateau, 2007). Even though semi-parametric estimation offers more flexibility, the parametric estimation will be more powerful if the form of the baseline hazard is somehow known in advance (Munda *et al*., 2012).

For right-censored clustered survival data, the observation for subject $j \in J_i = \{1, \ldots, n_i\}$ from cluster i $I = \{1, \ldots,s\}$ is the couple $(y_{ij}\ \delta_{ij})$, where $y_{ij} = \min(t_{ij}, c_{ij})$ is the minimum between the survival time t_{ij} and the censoring time c_{ij} , and where $\delta_{ij} = I(t_{ij} \leq c_{ij})$ is the event indicator. When covariate information are been collected the observation will be $(y_{ij}, \delta_{ij}, X_{ij})$, where X_{ij} denote the vector of covariates for the j^{th} observation in the i^{th} cluster. In the parametric setting, estimation is based on the marginal likelihood in which the frailties have been integrated out by averaging the conditional likelihood with respect to the frailty distribution. Under assumptions of non-informative right -censoring and of independence between the censoring time and the survival time random variables, given the covariate information, the marginal log-likelihood of the observed data can be written as (Gutierrez, 2002):

$$l_{marg}(\psi, \beta, \theta; Z, X)$$
$$= \prod_{i=1}^{s}\left[\left(\prod_{j=1}^{ni}\left(h_o(y_{ij})\exp(X_{ij}^T\beta)\right)^{\delta_{ij}}\right)X\int_0^\infty Z_i^{di}\, exp\left(-Z_i\sum_{j=1}^{ni} h_o\,(y_{ij}\exp(X_{ij}^T\beta))\right)f(Z_i)dz_i\right]$$
$$= \prod_{i=1}^{s}\left[\left(\prod_{j=1}^{ni}\left(h_o(y_{ij})\exp(X_{ij}^T\beta)\right)^{\delta_{ij}}\right)X(-1)^{di}L^{(di)}\left(\sum_{j=1}^{ni} H_o\,(y_{ij})\exp(X_{ij}^T\beta)]\right)\right]$$

Taking the logarithm, the marginal likelihood is:

$$l_{marg}(\psi, \beta, \theta; z, X) = \sum_{i=1}^{s}\{[\sum_{j=1}^{n_i} \delta_{ij}(\log(h_o(y_{ij})) + X_{ij}^T \beta)] + \log[(-1)^{di} L^{(d)}([\sum_{j=1}^{ni} H_o(y_{ij})\exp(X_{ij}^T\beta)]\} \quad (45)$$

Where: $d_i = \sum_{j=1}^{ni} \delta_{ij}$ is the number of events in the i-th cluster, and $L^{(q)}(.)$ is the q^{th} derivative of the Laplace transform of the frailty distribution defined as:

$$L(s) = E[\exp(-Zs)] = \int_0^\infty \exp(-Z_i s)\, f(Z_i) dz_i, \quad s \geq 0, \quad (46)$$

Where ψ represents a vector of parameters of the baseline hazard function, β the vector of regression coefficients and θ the variance of the random effect. Estimates of ψ, β, θ are obtained by maximizing the marginal log-likelihood (31); this can be done if one is able to compute higher order derivatives $L^{(q)}(.)$ of the Laplace transform up to q = max{d1, …, ds}.

3.4.7. Model Development

The methods of selecting a subset of covariates in a PHs regression model are essentially similar to those used in any other regression models. The most common methods are purposeful selection, step-wise (forward selection and backward elimination) and best sub-set selections. Survival analysis using Cox regression method begins with a thorough univariate analysis of the association between survival time and all important covariates (Hosmer and Lemeshow, 1999).

Recommendable procedure in selecting variables in the study

According to Hosmer and Lemeshow (1998), it is recommended to follow the steps given below.

1. Include all variables that are significant in the univariate analysis at relaxed level and also any other variables which are presumed to be clinically important to fit the initial multivariable model.
2. The variables that appear to be important from step one are then fitted together in a model. In the presence of certain variables others may cease to be important. As a result, backward elimination is used to omit non-significant variables from the model. Once a variable has been dropped, the effect of omitting each of the remaining variables in turn should be examined.
3. Variables, that were not important on their own, and so were not under consideration in step 2, may become important in the presence of others. These variables are therefore added to the model from step 2, with forward selection method. This process may result in terms in the model determined at step 2 ceasing to be significant.

3.4.8. Model Selection

For comparing models that are not nested, the Akaike's information criterion (AIC) is used which is defined as:

$$\text{AIC} = -2\text{LogL}+2(k+c+1), \quad (47)$$

Where k is the number of covariates and c the number of model specific distributional parameters. This thesis used the AIC to compare various candidates of non- nested parametric models. The preferred model is the one with the lowest value of the AIC.

3.4.9. Model Diagnosis

3.4.9.1. Checking the Adequacy of Parametric Baselines

The graphical methods can be used to check if a parametric distribution fits the observed data. Model with the weibull baseline has a property that the log (-log(S(t)) is linear with the log of time, where $S(t) = \exp(-\lambda t^{\rho})$. Hence, $\log(-\log(S(t))) = \log(\lambda) + \rho\log(t)$. This property allows a graphical evaluation of the appropriateness of a Weibull model by plotting $\log(-\log(\hat{S}(t)))$ versus log(t) where $\hat{S}(t)$ is Kaplan-Meier survival estimate (Datwyler and Stucki, 2009). The log-failure odd versus log time of the log-logistic model is linear. Where the failure odds of log-logistic survival model can be computed as:

$$\frac{1-s(t)}{s(t)} = \frac{\frac{\lambda t^{\rho}}{1+\lambda t^{\rho}}}{\frac{1}{1+\lambda t^{\rho}}} = \lambda t^{\rho}. \quad (48)$$

Therefore, the log-failure odds can be written as:

$$\text{Log}\left(\frac{1-S(t)}{S(t)}\right) = \log(\lambda t^{\rho}) = \log(\lambda) + \rho\log(t). \quad (49)$$

Therefore, the appropriateness of model with the log-logistic baseline can graphically be evaluated by plotting $\log(\frac{\hat{S}(t)}{1-\hat{S}(t)})$ versus log(time) where $\hat{S}(t)$ is Kaplan-Meier survival estimate (Datwyler and Stucki, 2009). If the plot is straight line, log-logistic distribution fitted the given dataset well. If the plot $\phi^{-1}[1-S(t)]$ against log (t) is linear, the lo-normal distribution is appropriate for the given data set.

3.4.9.2. The Quantile - Quantile Plot

A quantile-quantile or q-q plot is made to check if the accelerated failure time model provides an adequate fit to the data. The plot is based on the fact that, for the accelerated failure-time model,

$$S_1(t) = S_0(\phi t) \quad (50)$$

Where S_0 and S_1 are the survival functions in the two groups and ϕ is the acceleration factor. Let t_{op} and t_{1p} be the p^{th} percentiles of groups 0 and 1, respectively, that is:

$$t_{kp}=s_k^{-1}(1\text{-}p),\ k=0,1. \quad (51)$$

Using the relation $S_1(t) = S_0(\phi\ t)$, we must have $s_o(t_{op}) = 1\text{-}p = s_1(t_{1p}) = s_o(\phi\ t_{1p})$ for all t. If the accelerated failure time model holds, $t_{op} = \phi\ t_{1p.}$ To check this assumption we compute the Kaplan–Meier estimators of the two groups and estimate the percentiles t_{1p}, t_{0p}, for various values of p. If we plot the estimated percentile in group 0 versus the estimated percentile in group 1 (i.e., plot the points t_{1p}, t_{0p} for various values of p), the graph should be a straight line through the origin, if the accelerated failure time model holds. If the curve is linear, a crude estimate of the acceleration factor ϕ is given by the slope of the line (Klein, 1992).

3.4.9.3. Using Residual Plots

For the parametric regression problem, analogs of the semi parametric residual plots can be made with a redefinition of the various residuals to incorporate the parametric form of the baseline hazard rates (Klein, 2003). The first such residual is the Cox–Snell residual that provides a check of the overall fit of the model. The Cox–Snell residual, r_j, is defined by:

$$r_j = \widehat{H}(T_j \mid X_j) \quad (52)$$

where $\widehat{H}$ is the cumulative hazard function of the fitted model. If the model fits the data, then the r_j's should have a standard (λ =1) exponential distribution, so that a hazard plot of r_j versus the Nelson–Aalen estimator of the cumulative hazard of the r_j's should be a straight line with slope 1.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

A total of 7925 women who got the first marriage were included in this study from eight regional states and two cities administrative. The time interval between the first marriage and first birth was an interest of this research paper. Of total women, 5,966 (75.3%) of them gave birth while 1959 (24.7%) of them did not give birth until the end of the interview. Different covariates characteristics are displayed in Table 4.1. Out of 7925 women, 5969(75.3 %) were lived in rural while 1956 (24.7%) of them lived in urban. Wealth index of the family was categorized as poor, middle income and rich. It is reported that 3310 (41.8%), 1260 (15.9%) and 3355 (42.3%) of women were poor, middle, and rich households respectively. More than half of the women (63%) have not had job. 8.3% of the total women attained secondary and above education while 64.4% of them were uneducated. Of the total women, 3220 (40.6%) were Orthodox, 2925 (36.9%) Muslim, 1535 (19.4 %) Protestant, and 245 (3.1%) of them were from other religion followers. Furthermore, 5901 (74.5%) of the women had the experience of using contraceptive methods while 2024 (25.5%) of them had no any experience of using contraceptive. With regard to exposure to mass media, 4585 (57.9%) of the women had no any access of mass media and 3340 (42.1%) of them had access of mass media.

Table 4.1: Baseline covariates characteristics with their time-to-event status

			Status	
Variable	**Categories**	**Frequency**	**Censored**	**Event**
Place of Residence	Rural	5969 (75.3%)	1155 (19.4%)	4814 (80.6%)
	Urban	1956 (24.7%)	804 (41.1%)	1152 (58.9%)
Wealth Index of Family	Poor	3310 (41.8%)	608 (18.4%)	2702 (81.6%)
	Middle	1260 (15.9%)	244 (19.4%)	1016 (80.6%)
	Rich	3355 (42.3%)	1107 (33%)	2248 (67%)
Contraceptive Use	Use	5901(74.5%)	1514 (25.7%)	4387 (74.3%)
	Not Use	2024 (25.5%)	445 (22%)	1579 (78%)
Employment status of Women	Yes	2935 (37.0%)	966 (32.9%)	1969 (67.1%)
	No	4990 (63%)	993 (19.9%)	3997 (80.1%)
Religion	Muslim	2925 (36.9%)	579 (19.8%)	2346 (80.2%)

	Orthodox	3220 (40.6%)	1017 (31.6%)	2203 (64.4%)
	Protestant	1535 (19.4%)	312 (20.3%)	1223 (70.7%)
	Other	245 (3.1%)	51 (20.8)	194 (79.2%)
Mass Media	No	4585(57.9%)	986 (21.5%)	3599 (78.5%)
	Yes	3340 (42.1%)	973 (29.1%)	2367 (70.9%)
Women's' Education level	No education	5108 (64.4%)	1169 (22.9%)	3939 (77.1%)
	Primary	2159(27.2%)	507 (23.5%)	1652 (76.5%)
	Seco& above	658 (8.3%)	283 (43%)	375 (57%)
Husband's Education level	No education	3857 (48.7%)	939 (24.3%)	2918 (75.6%)
	Primary	2855(36.0%)	569 (19.9%)	2286 (80.1%)
	Seco& above	1213(15.3%)	451 (37.2%)	762 (62.8%)
Over All			**1,959(24.7%)**	**5,966 (75.3%)**

Of women who were included in the study, 3857 (48.7%) of them were illiterate (no education), 2855(36.0%)of the husbands had attended primary education and the remaining 1213(15.3%) were secondary and higher education level. The minimum age of women at first marriage was 7 years old and the maximum of 41 years with mean and standard deviations 17.14 years and 3.825 respectively. The median age of women at first marriage was 16 years.

As shown in figure 4.1, about 548(6.9%) of them were from the capital city Addis Ababa and 718 (9.1%) from Affar, 1166 (14.7%) from Amhara, 684 (8.6%) from Benishangul-Gumuz, 516(6.5%) from Dire Dawa, 636 (8.0%) from Gambela, 543 (6.9%) from Harari. 1203 (15.2%) from Oromiya, 1092 (13.8%) from SNNP and the rest 819 (10.3%) of them were from Tigray region. According to table 4.3, the maximum percentage of women having their secondary and above education were from Addis Ababa (36.5% of them) while only 2.3% of women from Amhara region attained secondary and above education. Only 9.3% of women from Affar region and 40% of women from Addis Ababa attained primary education and most of the women (82.6% of them) from Affar region have no educational background.

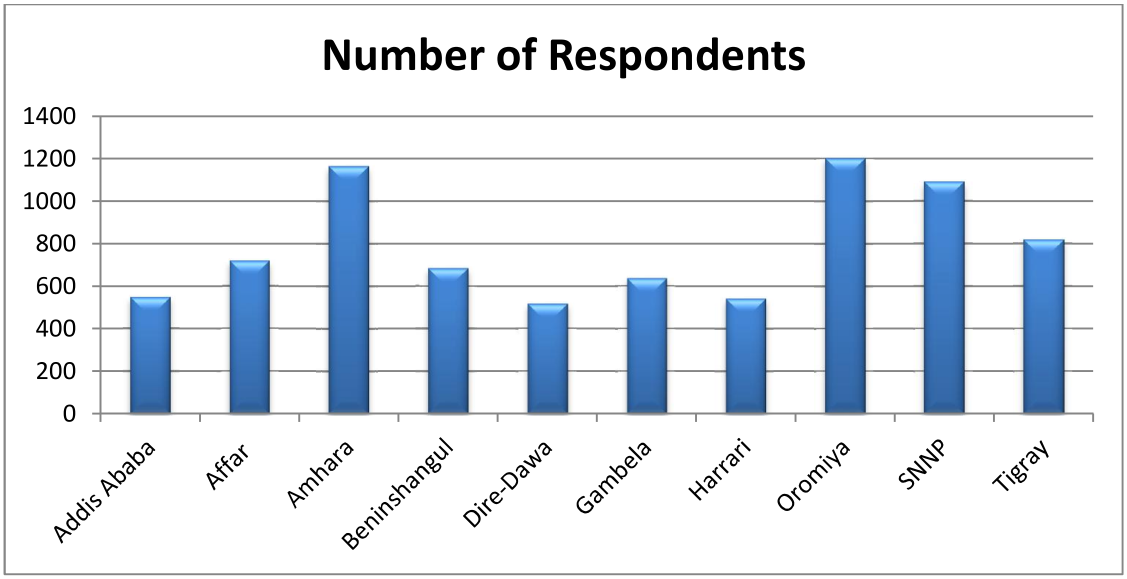

Figure 4.1: Bar chart of frequencies and Percentages of respondent by region

4.2. Non-parametric Survival Analysis

4.2.1. The Kaplan- Meier Estimate of Time-to-First Birth

Non-parametric survival analysis is very important to visualize the survival of time-to-first birth of women in Ethiopia under different levels of the covariate. Moreover, it gives information on the shape of the survival and hazard functions of first birth interval data set. Survival time distributions for time-to-first birth is estimated for each group using the K-M method and in order to compare the survival curves of two or more groups, log-rank test has been employed. The estimated median time and 95% confidence interval for time-to-first birth with different covariates characteristics are summarized in Table 4.3 in the appendix.

The median survival time of time- to-first birth for women from rural, 29 months (with 95% CI, [28.08, 29.92]) is less than that of from urban, 35 months with its 95% CI [32.67, 37.33]. The median survival time of time- to- first birth for contraceptive user was greater than non-users with 31 and 28 months respectively. Women who had job have the median survival time of 33 months which was greater than jobless women (29 months). The median time of FBI for illiterate (no education) women was 33 months which is greater than women having primary (25 months) and secondary and above education (30 months). The overall median survival time of first birth after marriage for Ethiopian women is 30 months (with 95% CI; 29.16, 30.84). The median survival time and the corresponding 95% confidence interval for the rest categorical variables are listed in Table 4.3 in the appendix.

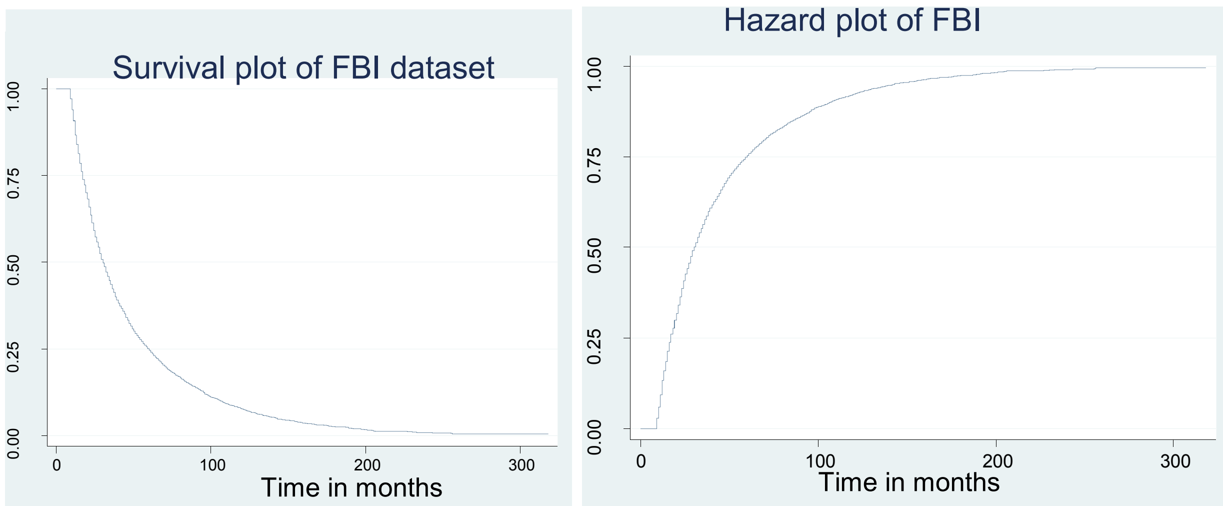

Figure 4.2: The K-M plots of Survival and hazard functions of FBI after marriage.

Plots of the KM curves to the survival and hazard experience of time- to- first birth is shown in figure 4.1. The survival plot decreases at increasing rate at the beginning and decreases at decreasing rate latter. This implies that most of the women gave first birth soon after marriage.

4.2.2. Survival of Time-to-First Birth for Different Groups of Women

4.2.2.1. Survival of Time- to-First Birth by Place of Residence

The survival plot for time-to-first birth by place of residence is shown in figure 4.2. The plot indicates that the risk of giving first birth after marriage is similar for both women lived in rural and urban at the beginning of the marriage. However, the difference becomes visible at the middle of the curve and comes closer at the end. At the middle point of the curve, the survival plot birth of first child for women those lived in rural is below that of urban women. This implied that the risk of giving first birth after marriage for rural women is higher than urban women. The result of the log rank test (Table 4.5 in Appendix) also revealed the some idea (p= 2.78e-11) means this difference is statistically significant.

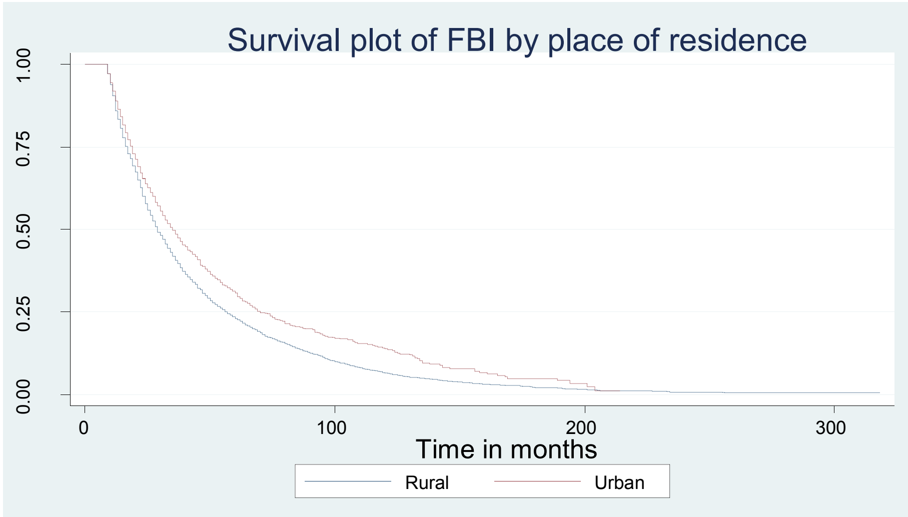

Figure 4.3: K-M plot of survival of time-to-first birth by place of residence

4.2.2.2. Survival of Time-to-First Birth by Access to Media

The survival plot of time- to- first birth by access to mass media is shown by figure 4.3 (in the appendix). As it can be observed from the plot, the survival curve for both groups is overlapped from the beginning to the end. This implied that the risk of giving first birth for women who had access to mass media and who didn't have access is the same. The log rank test (Table 4.6 in Appendix II) also revealed that mass media had no significant association to time- to- first birth after marriage (p = 0.25).

4.2.2.3. Survival of Time- to-First Birth by Contraceptive Use

The survival plot of time- to- first birth contraceptive is given in figure 4.4. This plot showed that the risk of giving first birth after marriage is similar for both groups (contraceptive user and non-user) at the first few months after marriage. But the difference becomes visible at the middle of the curve and becomes similar at the end of the curve. At the middle point of the curve, the survival plot birth of first child for women who did not use contraceptive is below that of the users. This implied that the risk of giving birth for contraceptive user is lower than that of who didn't use contraceptive. The result of the log rank test (Table 4.7 in Appendix II) also support the significance of this difference (p= 5.74e-09).

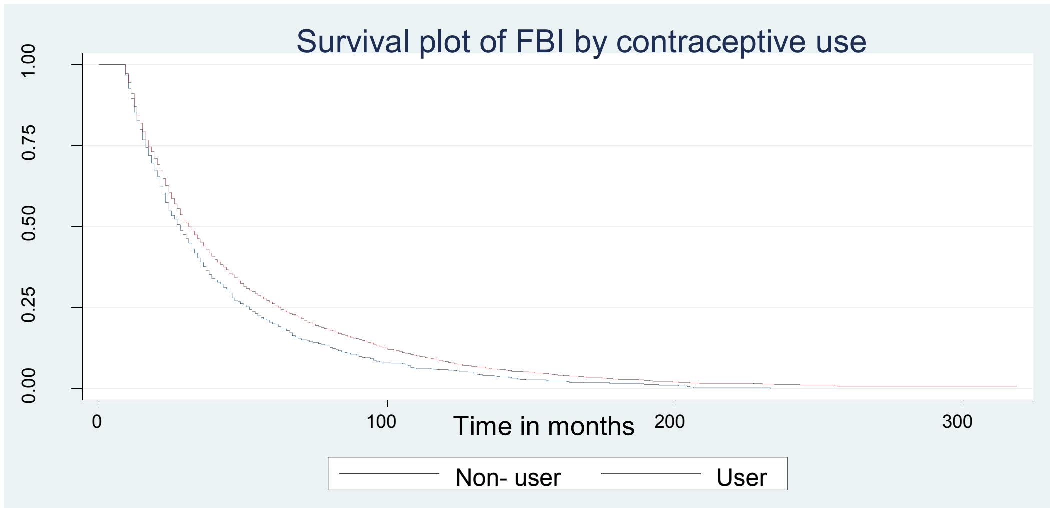

Figure 4.4: K-M plot of survival of time-to-first birth by contraceptive use

4.2.2.4. Survival of Time-to-First Birth by Wealth Index of the Family

The survival plot of time- to- first birth by wealth index of the family is shown in figure 4.5 (in the appendix). This plot suggested that the risk of giving first birth after marriage is similar for all groups (poor, middle, and rich) at the beginning and at the end of the plot. But a little beat difference is observed at the middle of the curve. At the middle point of the curve, the survival plot birth of first child for middle income family is below that of the poor and rich family. This implied that the risk of giving birth for middle income family higher than poor and rich family. The result of the log rank test (Table 4.8 in Appendix II) also significant (p= 0.048) means this difference is significant at 5% level of significance.

4.2.2.5. Survival of Time- to-First Birth by Level of Women Education

Figure (4.6, in the appendix) shows the K-M plot of time-to-first birth by level of women's education. From this plot we can observe that the risk of giving first birth after marriage is similar for all groups at the beginning and at the end of the plot. But the difference becomes visible at the middle of the curve. At the middle point of the curve, the survival plot birth of first child for women having primary education is below others. The differences that are displayed in survival curve emphasize that the survival of time-to-first birth for educated women is shorter than uneducated. The result of the log rank test (Table 4.9 in Appendix II) revealed the difference is significant (p= 0.000) at 5% level of significance.

4.2.2.6. Survival of Time-to-First Birth by Husband's Education Level

Figure (4.7, in the appendix) showed the K-M plot of time- to first birth by level of Husband's level education. From this plot we can observe that the risk of giving first birth after marriage is similar at the beginning and at the end of the plot. This implied that the risk of giving first birth after marriage for women who have husband with primary education is higher than the others. The result of the log rank test (Table 4.10 in Appendix II) also revealed that difference is significant at 5% level of significance (p= 0.036).

4.2.2.7. Survival of Time-to-First Birth by Women's Employment Status

The survival plot of time-to-first birth by women's employment status is given above (figure 4.6). From this plot we can observe that the risk of giving first birth after marriage is similar for both groups (jobless women & women having job) at the two extremes. But the difference becomes visible at the middle of the curve. At the middle point of the curve, the survival plot birth of first child for unemployed women below that its counterpart. This implied that the risk of giving first birth among jobless women was higher than that of employee women. The result of the log rank test (Table 4.11 in Appendix II) also supported the existence of significant difference (p= 2.59e-10).

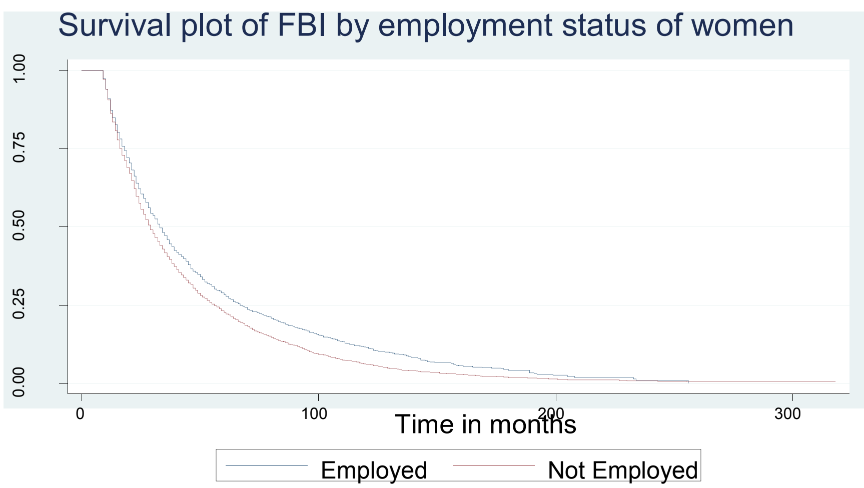

Figure 4.8: K-M plot of survival of time-to-first birth by employment status of women

4.3. Accelerated Failure Time Model Results

4.3.1. Univariable Analysis

This study used univariate analysis in order to see the effect of each covariate on time-to-first birth before proceeding to the multivariable analysis. The univariate analyses was fitted for every covariate by AFT models using different baseline distributions i.e. weibull, log-logistic, and log-normal. In all univariate analysis of AFT models, age of women at ffirst marriage, place of residence, wealth index of the family, education level of both spouses, contraceptive, and employment status of women were significantly associated with first birth interval after marriage while access to media was not significant at 10% level of significance. The summary of univariate analysis is given in Table 4.12 in the appendix. Hence, based on the univariate analysis, except access to mass media all explanatory variables are candidate predictors for further analysis.

4.3.2. Multivariable AFT Analysis

For time-to-first birth data, multivariable AFT models of weibull, log-logistic, and log-normal distribution were fitted by including all the covariates those are significant in the univariate analysis at 10% level of significance. To compare the efficiency of different models, the AIC was used. It is the most common applicable criterion to select model. Based on AIC, a model having the minimum AIC value was preferred. Accordingly, Log-normal AFT model (AIC = 24485.05) found to be the best for the time-to-first birth data set from the given alternatives when we include all the covariate those are significant in the univariate analysis.

Covariates which become insignificant in the multivariate analysis were removed from the model by using backward elimination technique. Accordingly, wealth index of the family and husband level of education were excluded. And finally, the effect of interactions terms were also tested and found to be statistically insignificant in multivariable log-normal AFT model at 5% level of significance. The final model kept the main effect of the covariate age of women at first marriage, place of residence, use of contraceptive, women's level of education and employment status of women. All AFT models and the corresponding AIC values are displayed in Table 4.13.

Table 4.13: Comparison of AFT models using AIC criteria for Time-to-First Birth data

Baseline Distribution	AIC
Weibull	25,656.12
Log- logistic	24,502.30
Log- normal	24,485.05

AIC=Akaike's information criteria

The output of the final log-normal AFT model is presented in Table 4.14. Increasing age of women at marriage and women's level of education (uneducated as reference) statistically significantly shorten time-to-first birth and place of residence (rural as reference category), use of contraceptive (Non-users as reference), and employment status of women (unemployed women as reference) prolong the survival time for time-to-first birth after marriage among married women in Ethiopian.

Table 4.14: Summary result the final Log-Normal AFT model

Covariate	Categories	Estimate($\hat{\beta}$)	ϕ	95%CI	SE($\hat{\beta}$)	P-value
Age		-0.07	0.93	[0.925, 0.934]	0.002	2.22e-204*
Place of	Rural	Ref				
Residence	Urban	0.26	1.30	[1.201, 1.373]	0. 030	2.14e-13*
Employment	Not employed	Ref				
Status	Employed	0.09	1.09	[1.057, 1.134]	0.018	8.71e-07*
Contraceptive	Non-Use	Ref				
	User	0.17	1.19	[1.139, 1.346]	0.021	2.66e-14*
Women	No education	Ref				
Education	Primary	-0.20	0.81	[0.779, 0.848]	0.022	2.69e-13*
	Seco& above	-0.02	0.98	[0.89, 1.070]	0.045	0.0570
Scale= 0.73						

ϕ Indicates Acceleration factor; significant at 5% level; 95%CI: 95% confidence interval for acceleration factor; SE($\hat{\beta}$): standard error for $\hat{\beta}$; Ref. Reference*

Under the log-normal AFT model, when the effect of other factor keep fixed, the estimated acceleration factor for women from urban is estimated to be 1.30 with 95% confidence interval [1.201, 1.373]. The confidence interval for the acceleration factor did not include one and P-value is very small (P= 2.14e-13). This indicates women from urban have prolonged survival of time-to-first birth than rural women. The acceleration factor for age at marriage was 0.93 (with 95% CI: 0.925, 0.934 and P= 2.22e-204) which indicates that as women's age at marriage increases the survival of time-to-first birth decreased. In other word, a one year increase in women's age at marriage decreases time-to-first birth by 7%. The acceleration factor for employed women was 1.09 (with 95% CI: 1.057, 1.134) by using unemployed women as reference category. This result suggested that employed women had longer survival of time-to-first birth than unemployed women (P=8.71e-07). The acceleration factors for women attending primary education and secondary & above are estimated to be 0.81 and 0.98 (with 95% CI: 0.779, 0.848; 0.89, 1.070) respectively by using uneducated women as reference category. This implied that uneducated women have longer survival of time-to-first birth, however the difference is not significant for women attending secondary & above level education and uneducated women (P=0.057). And the use of contraceptive prolong the survival of time-to-first birth by the factor of 1.19 (with 95% CI: 1.139, 1.346 and P=2.66e-14) when the non-users are used as reference category at 5% level of significance.

4.4. Parametric Shared Frailty Model Results

In the previous section (section 4.3), three AFT models were fitted and compared to analyze the survival of time-to-first birth after marriage to identify baseline distribution and associated risk factors. And the log-normal AFT model was selected based on AIC value. The main focus of this study is to investigate risk factors associated with the survival of time-to-first birth using parametric shared frailty model.

For the data on time-to-first birth, the three parametric baseline distribution with Gamma frailty distribution were fitted by using regional states of the women as frailty term. The effect of random component (frailty) was significant for both log-normal gamma shared frailty and log-logistic gamma shared frailty models but it was not significant for weibull-gamma shared frailty model. The AIC value for all parametric frailty models is summarized in table 4.15. The log-normal gamma shared frailty model had the smallest AIC value (13641.69) than weibull-gamma and log-logistic gamma shared frailty models. This indicates log-normal gamma shared frailty model is more efficient model to describe time-to-first birth dataset.

Table4.15: Comparison of shared gamma frailty model with different baseline

Baseline Distribution	Frailty Distribution	AIC Value
Weibull	Gamma	14587.83
Log-logistic	Gamma	13981.74
Log-normal	Gamma	13641.69

AIC=Akaike's information criteria

4.4.1. Log-normal Gamma Frailty Model Result

This model is the same as the log-normal AFT model discussed in the previous section, except that a frailty component has been included. The frailty in this model is assumed to follow a gamma distribution with mean 1 and variance equal to theta (θ). The estimated value of theta (θ) is 0.78. A variance of zero (θ = 0) would indicate that the frailty component does not contribute to the model. A likelihood ratio test for the hypothesis θ = 0 is shown in at the bottom of table 4.16 below and indicates a chi-square value of 1307.52 with one degree of freedom resulted a highly significant P-value of 0.000. This implied that the frailty component had significant contribution to the model. And the associated Kendall's tau (τ), which measures dependence within clusters (region), is estimated to be 0.28. The estimated value of the shape parameter in the log-normal-gamma frailty model is 3.185 (ρ =3.185). This value showed the shape of hazard function is uni-modal because the value is greater than unity implies it increases up to its maximum point and then decreases.

From table 4.16 the confidence intervals of the acceleration factor for all significant categorical covariates do not include one at 5% level of significance. This showed that they are significant factors for determining the survival of time-to-first birth among women in Ethiopian. However, from the covariate women's level of education secondary and above education is not significant by taking no education as reference (P-value = 0.259, ϕ = 0.956, 95% CI= 0.885, 1.033). The estimated coefficient of the parameters for women's age at marriage, women's educational levels are negative. The negative sign implies that decreasing logged of survival time and hence, shorter expected survival of time-to-first birth after marriage.

The age of women at marriage was statistically significant to determine time-to-first birth after marriage of Ethiopian women. The acceleration factor and its 95% Confidence interval was 0.927

and (0.922, 0.932) respectively yielding significant P-value of 0.000. Additionally, confidence interval did not include one which indicates age of women at first marriage was statistically significantly important factors for the survival of time-to-first birth. Accordingly, as age of women at first marriage increases, the survival of time-to-first birth becomes short. The acceleration factor for women who are lived in urban area was 1.292 times greater than those who are lived in rural area (rural as reference; ϕ: 1.292, 95%CI: 1.231, 1.357; P-value= 0.000), this indicates urban women have prolonged time-to-first birth than rural women. The acceleration factor and its 95% confidence interval of employed women was 1.080 and (1.042, 1.120) respectively (unemployed as reference category). The confidence interval did not include one and p-value was very small (P= 0.000) indicating that employment status of women was significant factor to determine the survival time of time-to-first birth at 5% level of significance. This showed that the timing of first birth for employed women was longer than unemployed women. The acceleration factor and its 95% confidence interval for women who use contraceptive were 1.116 and (1.072, 1.162) respectively. This showed that use of contraceptive prolong the survival of time-to-first birth when non-users taken as reference category at 5% level of significance. The acceleration factor of women's primary education level was estimated to be 0.828 with 95% confidence interval (0.796, 0.862) and secondary and above 0.956 with 95% confidence interval (0.885, 1.033) when the uneducated women taken as reference. This indicates educated women had short survival of time-to-first birth than uneducated women even if there is no significant difference between women attends secondary and above level of education and uneducated women.

Table 4.16: Results of final log- normal gamma frailty model

Covariate	**Category**	**Estimate($\widehat{\beta}$)**	**SE($\widehat{\beta}$)**	**ϕ**	**95% CI**	**P-value**
Age		-0.08	0.0027	0.927	[0.922, 0.932]	0.000*
Place of	Rural	Ref.				
Residence	Urban	0.26	0.0250	1.292	[1.231, 1.357]	0.000*
Employment	Unemployed	Ref.				
Status	Employed	0. 08	0.0180	1.080	[1.042, 1.120]	0.000*
Contraceptive	Non- User	Ref.				
	User	0.11	0.0206	1.116	[1.072, 1.162]	0.000*
Women	Noeducation	Ref				
education	Primary	-0.19	0.0204	0.828	[0.796, 0.862]	0.000*
	Sec&above	-0.05	0.0395	0.956	[0.885, 1.033]	0.259
θ= 0.78	λ = 2.541				likelihood=-6813.8	
τ = 0.28	ρ = 3.185				AIC = 13641.69	
Likelihood-ratio test of θ = 0: chi-square = 1307.52 P-value = 0.000*						

*SE($\widehat{\beta}$)= standard error of $\widehat{\beta}$; ϕ=acceleration factor ; 95 % CI= 95% confidence interval for acceleration factor; * = significant at 5% level; Ref. =Reference.* AIC= Akaike's Information Criteria

4.5. Comparison of Log-normal AFT and Log-normal- Gamma Frailty Model

From table 4.19, we can observe that the results from the Log-normal AFT and Log-normal-Gamma frailty model are quite similar but not identical. In this study, in order to compare the efficiency of the models the AIC was used. From the Table 4.19, we can see that the log-normal-gamma shared frailty model has a minimum AIC (13641.69) than log-normal AFT (AIC = 24,485.05), indicating that log- normal- gamma frailty model fitted the survival of time-to-first birth data better than the log-normal AFT model which did not take in to account the clustering effect. When we look at the estimated value of coefficients of the covariate, they are altered with the inclusion of the frailty component and the confidence interval for the acceleration factor is a little beat narrower for log-normal gamma frailty model. Furthermore, the variance of random effect (frailty) was significant at 5% level of significance which indicates that the parametric shared frailty model fit the given dataset better than AFT model. In general log-normal gamma shared frailty model is preferred over Log-normal AFT for modeling of time-to-first birth dataset.

Table 4.19: Comparison of Log-normal AFT and Log-normal- Gamma Frailty model

Covariate	Category	Log- normal AFT $\widehat{\beta}$	ϕ	95%CI	Lognormal–Gamma Frailty $\widehat{\beta}$	ϕ	95%CI
Age		-0.07	0.93	[0.92, 0.94]	-0.08	0.92	[0.91, 0.93]
Place of Residence	Rural	Ref.			Ref.		
	Urban	0.26	1.30	[1.20, 1.37]	0.26	1.29	[1.23, 1.36]
Employment Status	Unemployed	Ref.			Ref.		
	Employed	0.09	1.09	[1.06, 1.13]	0. 08	1.08	[1.04, 1.12]
Contraceptive	Not Use	Ref.					
	User	0.17	1.19	[1.14, 1.35]	0.11	1.12	[1.07, 1.16]
Women Education	No education	Ref.					
	Primary	-0.21	0.81	[0.78, 0.85]	-0.19	0.83	[0.80, 0.86]
	Sec & above	-0.02	0.98	[0.89, 1.07]	-0.05	0.96	[0.89, 1.03]
AIC=24,485.05					AIC =13641.69		
Log-likelihood= -12235.525					Log-likelihood = -6813.845		

Estimate ($\widehat{\boldsymbol{\beta}}$) = estimated value of $\widehat{\boldsymbol{\beta}}$; ϕ= acceleration factor; 95 % CI= 95% confidence interval for acceleration factor; Ref. = Reference; AIC= Akake's Information Criteria.

4.6. Model Diagnostics

4.6.1. Checking Adequacy of Parametric Baselines using Graphical Methods

After the model has been fitted, it is desirable to determine whether a fitted parametric model adequately describes the data or not. Therefore, the appropriateness of model with weibull baseline can be graphically evaluated by plotting log (-log(S(t)) versus log(time), the log logistic baseline by plotting $\log(\frac{\hat{S}(t)}{1-\hat{S}(t)})$ versus log(time) and the log-normal baseline by plotting $\phi^{-1}[1 - S(t)]$ against log (t). If the plot is linear, the given baseline distribution is appropriate for the given dataset. Accordingly, their respective plots are given in figure 4.7 below and the plot for the log-normal baseline distribution make straight line better than weibull and log-logistic baseline distribution. This evidence also strengthens the decision made by AIC value that log-normal baseline distribution is appropriate for the given dataset.

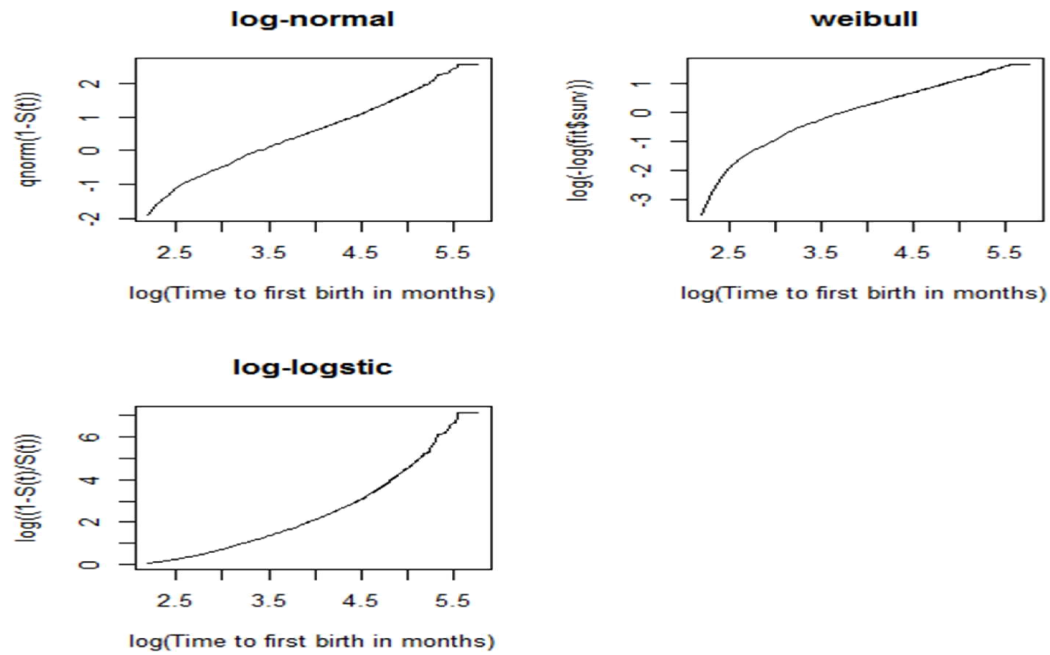

Figure 4.9: Graphs of Weibull, Log-logistic, and Log-normal baseline distributions for time-to-first birth data set.

4.6.2. Cox- Snell residuals plots

The Cox-Snell residuals are one way to investigate how well the model fits the data. The plot for fitted model of residuals for log-normal to our data via maximum likelihood estimation with cumulative hazard functions is given in figure 4.8 below. If the model fit s the data, the plot of cumulative hazard function of residuals against Cox-Snell residuals should be approximately a straight line with slope 1. The plot makes straight lines through the origin for log-normal baseline distribution suggesting that it is appropriate for time-to-first birth data set.

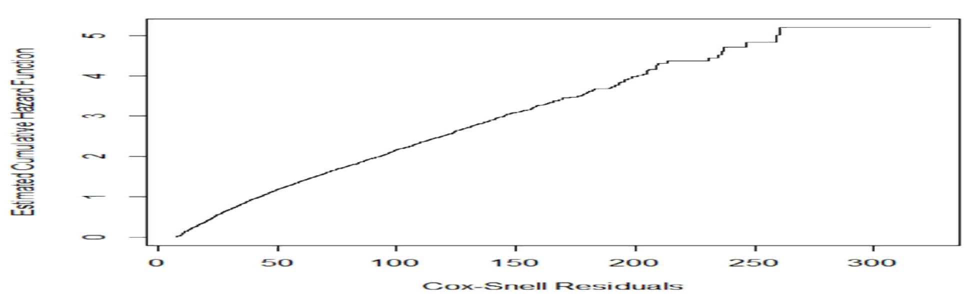

Figure 4.10: Cox- Snell residuals plots of log-normal baseline distributon for time- to- first birth data.

4.6.3. Quantile-Quantile Plot

A quantile-quantile or q-q plot is made to check if the AFT provided an adequate fit to the data using by two different groups of population. We shall graphically check the adequacy of the model by comparing the significantly different groups of women by place of residence, contraceptive use and employment status. The figures appear to be approximately linear for all covariates place of residence, contraceptive and employment status of women as shown in figure 4.9. Therefore the accelerated failure time appears to be the best to describe time-to-first birth data set.

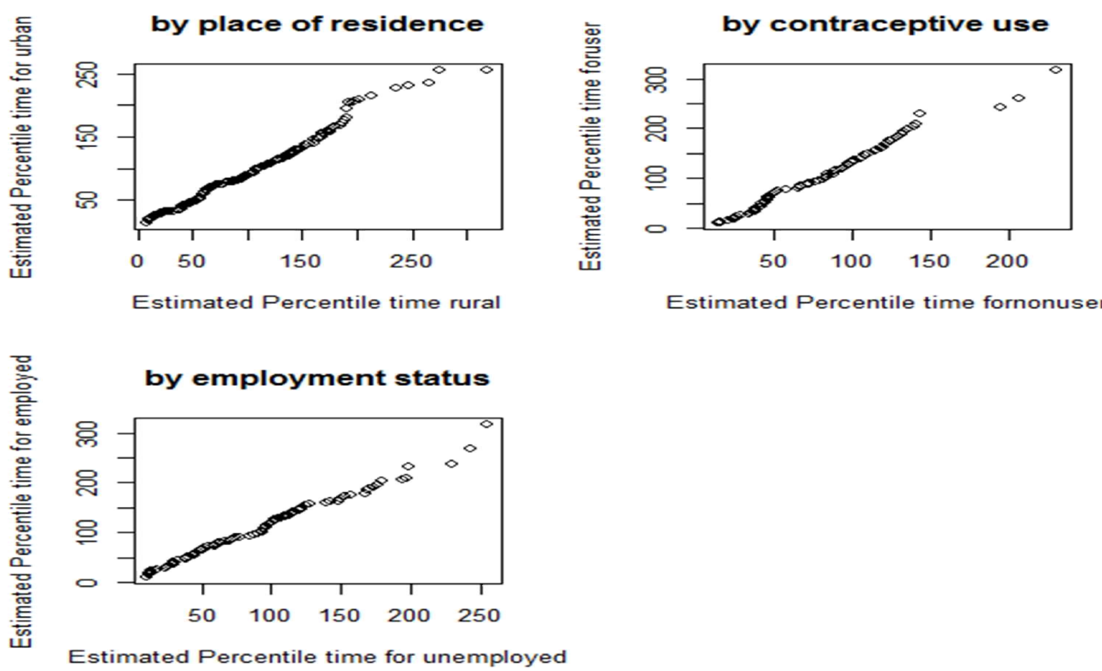

Figure 4.11: Quantile- Quantile plot to check the adequacy of the accelerated failure time model

4.7. Discussion

The main goal of the study was modeling the determinants of time-to-first birth after marriage among women in Ethiopia using AFT and parametric shared frailty models by considering three baseline distributions: Weibull, log-logistic, and log-normal distributions and gamma frailty. Covariate which were included in the study were woman's educational level, wealth index of the family, access to mass media, place of residence, husband's educational level, employment status of women, contraceptive, and age of women at first marriage and the outcome variable of interest was the survival of time-to-first birth after marriage measured in months.

The univariate analysis (in Appendix, Table 4.6) revealed that woman's educational level, wealth index of the family, place of residence, husband's educational level, employment status of women, contraceptive, and age of women at marriage were significantly associated with time to first birth after marriage but access to mass media was not significant at 10% level of significance. All significant covariates in univariate analysis were included in all multivariable analysis of AFT model and comparison was done within the models using AIC criteria where the model having minimum AIC value is selected to be the best (Munda, 2012). Log-normal AFT model was found to be the best over Weibull and Log-logistic AFT models based on AIC value and graphical evidence (figure 4.7). wealth index of the family and husband's educational level had no significant association to the survival of time-to-first birth while the covariates women's educational level, place of residence, employment status of women, contraceptive, and age of women at marriage were significantly associated with timing of first birth interval after marriage.

After analyzing the given data set by using log-normal AFT model, parametric shared frailty models by assuming gamma distribution for the frailty term were fitted by considering weibull, log-logistic and log-normal baseline distributions. Log-normal gamma shared frailty model was selected over weibull-gamma and log-logistic gamma shared frailty models based on AIC values. The aim of frailty model is not only to account heterogeneity subjects among different regions but also to measure the dependence or correlation within the same region. Gamma distribution is selected for the frailty term due to its mathematical tractability and flexibility of hazard function (Vaupel *et al*., 1979; Clayton & Cuzick, 1978). The clustering effect were significant (p-value= 0.000) in log-normal-gamma shared frailty model. This showed that there was heterogeneity between the regions on the timing of first birth after marriage. Finally the two models, log-normal AFT and log-normal gamma shared frailty, were compared, the results from the AFT and frailty model were quite similar to each other but some improvement was observed on the parameter estimates due to the inclusion of frailty term. Log-normal-gamma frailty model fitted the survival of time-to-first birth data better than log-normal AFT model (Table 4.19).

The findings of this study revealed that increasing age of women at marriage and women's education level significantly shorten the time-to-first birth while place of residence, contraceptive, and employment status of women accelerates time-to-first birth after marriage among women in Ethiopian. The estimated median age of women at marriage was 16 years. Which is almost similar with the Bedasa *et al*. (2015) reported that about 60.6% of Ethiopian women were married before the age of 18 years using 2011 EDHS.

The estimated median survival time of first birth after marriage of Ethiopian women is found to be 30 months with 95% confidence interval [29.16, 30.84]. This finding is almost similar with Wondiber and Eshetu (2011) using 2005 EDHS. They reported that the median time of first birth interval for rural women was 29 months. This estimate is exactly identical to Ghanaian women (Logubayom & Luguterah, 2013). But the median time of first birth interval for countries were 20 months for Nigerian (Amusan and Mohd, 2014), 25.2 months for Iranian (Shayan *et al*., 2014) and 25 months for Bangladesh women (Mukhlesure *et al*., 2013) which is shorter than the medina time of first birth interval in Ethiopia. This difference may be due to the practice of early marriage in Ethiopia which had potential to elongate timing of first birth.

Marriage at older age significantly associated to short time interval for the first birth. This result is consistent with Gurmu and Etana (2010) in Ethiopia, Yang (2001 as cited in Woldemicael, 2008) in China, Rabbi *et al.* (2013) in Bangladesh, and Shayan *et a*l. (2014) in Iran. They reported that women whose marriage was delayed had shown short first birth interval as compared to those who married early. The reason may be older women need to give birth soon after marriage to have the desired number of children before the end of their reproductive life and women who gets early marriage use contraceptive to elongate time-to-first birth until it becomes physically mentally matured. In addition, Sub fecundity due to immature age of women at marriage is another cause of long first birth interval (Dommaraju, 2008). But some contradictory results were also observed such as in Pakistan, younger women had shorter FBI as compared to older women (Kamal & Pervaiz, 2013)

The results of this study suggested that place of residences was significant predictive factor for time-to-first birth after marriage of Ethiopian women. Women who lived in urban areas had longer first birth interval than women who lived in rural areas. Rural inhabitants have usually no access for maternal health and family planning programs as compared to urban residents (Woldemicael, 2008) which may result in short interval for rural women as compared to urban. This finding is supported by Rabbi *et al*. (2013) in Bangladesh, Amusan and Mohd (2014) in Nigeria, Stokes & Hsieh (1983) in Taiwanese women. They reported that rural women had short first birth interval than urban women when the effect of other covariate held fixed. Another important finding of this study was that employment status of the women had a significant effect on time-to-first birth after marriage where time-to-first birth for employed women is longer than unemployed women. This is due to that employed women are busy to give child at early age of marriage. This is consistent with Islam (2009) in Bangladesh and Hidayat *et al.* (2014) in Indonesia.

The use of contraceptive also had significant association to time-to-first birth where women those used contraceptive had long first birth interval than the non-users. This is due to contraceptive service which helped them to protect early and unwanted pregnancy in marriage life of the couples. This result is consistent with Amusan and Mohd (2014) and Gayawan and Adebayo (2013) in Nigeria. But contradicting result is also obtained by Hidayat *et al.* (2014) in Indonesian and Islam (2009) in Bangladesh. They reported that contraceptive users have distinctly short time-to-first birth than non-users.

This study also showed that women with primary, secondary and above education have faster transition to first birth than illiterate women. Women's education is considered to be an essential component of reproductive behavior. When women spend a longer time at school, this is likely to significantly affect both age at marriage and the duration between marriage and the first birth. According to Bedasa *et al*. (2015) age at marriage for educated women was greater than uneducated in Ethiopia which has a direct effect on time-to-first birth. Moreover, education increases marital stability through secured financial resources (Ikamari, 2005). This is also believed to shorten time-to-first birth. At the time of entry to marital life, they are emotionally prepared, biologically mature, and financially secured to have a child. This finding is consistent with Wondiber and Eshetu (2012) in Ethiopia, Suwal (2001) in Nepal, Logubayom and Luguterah (2013) and Gayawan and Adebayo (2013) in Ghana, Gurmu & Etana (2010) in Ethiopia.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

This study was used a time-to-first birth dataset among married woman in Ethiopia which was obtained from central statistics agency with an aim of modeling the determinant of time-to-fist birth after marriage by using parametric shared frailty model. Out of the total 7925 women, about 75.3% were gave their first birth after marriage while 24.7% of them were not gave first birth until the end of interview. The estimated median time of first birth interval and the median age of women at first marriage were 30 months and 16 years respectively.

To model the determinants of time-to-first birth, different parametric shared frailty and AFT models by using different baseline distributions were applied. Among this using AIC, log-normal gamma shared frailty model is better fitted to time-to-first birth dataset than other parametric shared frailty and AFT models. There was a frailty (clustering) effect on the time-to-first birth that arises due to differences in distribution of timing of first birth interval among regions of Ethiopia. This indicates the presence of heterogeneity and necessitates the frailty models.

The result of Log-normal AFT and Log-normal-gamma frailty models showed that place of residence, age of women at marriage, use of contraceptive, level of women's education, and employment status of women were found significant predictors to time-to-first birth among married women in Ethiopia. Among these significant predictors, level of women's education and increasing age of women at first marriage shorten time-to-first birth while place of residence, use of contraceptive, and employment status of women prolong timing of first birth interval after marriage. From the category of women's level of education, secondary and above was not statistically significant.

Goodness of the fit of baseline distribution by means of graphical method and Cox-Snell residuals plots in figure 4.9 and 4.10 revealed that log-normal distribution is better when compared to Weibull and log-logistic baseline distributions to explain time-to-first birth dataset.

5.2. Recommendations

Based on the study findings, the following recommendations are made for policy makers and the community at large.

- Delay in marriage cannot be effective unless it follows delay in marriage to first birth interval. It is crucial to continue familiarizing couples with the concept of using family planning methods (contraceptives) to increase length of time to first birth.

- Awareness about the importance of elongating time-to-first birth after marriage should be given for rural women through health workers, health extensions or any other concerned bodies.

- Creating job opportunities for women contributes a lot to fertility reduction through elongating timing of first birth.

- Further studies should be conducted in each region of Ethiopia and identify other factors that are not identified in this study. Based on that study, regional governments should take actions to elongate time-to-first birth after marriage to reduce TFR.

Limitations of the Study

This thesis is not done without limitation. It did not consider Somali region because the data for Somali may not be totally representative of the region as a whole since some EAs are not interviewed due to drought and security problems.

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APPENDIX

Table 4.3: Frequencies and Percentages of women's education level by region

Region	Women's Level of Education			Total
	No Education	Primary	Secondary & above	
Addis Ababa	129(23.5%)	219 (40%)	200 (36.5%)	548
Affar	629 (87.6%)	65 (9.1%)	24(3.3%)	718
Amhara	961 (82.4%)	178 (15.3%)	27 (2.3%)	1166
Benishangul Gumuz	501 (732%)	160 (23.4%)	23 (3.4%)	684
Dire Dawa	303 (58.7%)	147 (28.5%)	66 (12.8%)	516
Gambela	308 (48.4%)	280 (44.0%)	48(7.5%)	636
Harrari	257 (47.3%)	165 (30.4%)	121 (22.3%)	543
Oromiya	778 (64.7%)	366 (30.4%)	59 (4.9%)	1203
SNNP	689 (63.1%)	365 (33.4%)	38 (3.5%)	1092
Tigray	553 (67.5%)	214 (26.1%)	52 (6.3%)	819
Total	**5108 (64.5%)**	**2159 (27.2%)**	**658 (8.3%)**	**7925 (100%)**

Table 4.2: Summary of quantitative variables

Variable	Minimum	Maximum	Mean	median	Std.Deviation
Age	7	41	17.14	16	3.825
FBI	9	318	35.91	30	31.812

Std.Deviation: standard deviation, Age measured in years and FBI measured in months

Table 4.3: Median time of first birth after marriage and confidence interval by levels of covariates

Variables	category	First Birth Interval	
		Median (in months)	95% CI
Place of Residence	Rural	29	[28.08, 29.92]
	Urban	35	[32.67, 37.33]
Wealth Index	Poor	30	[28.78, 31.22]
	Middle	28	[26.10, 29.90]
	Rich	32	[30.53, 33.47]

Contraceptive	User	31	[29.95, 32.65]
	Non-User	28	[26.53, 29.47]
Employment Status	Employed	33	[31.46, 34.54]
	Unemployed	29	[28.01, 29.10]
Mass Media	No	29	[27.76, 30.24]
	Yes	31	[29.85, 32.25]
Women Education	No education	33	[31.80, 34.22]
	Primary	25	[23.78, 26.22]
	Secondary&above	31	[27.82, 34.18]
Husband Education	No Education	35	[33.50, 36.50]
	Primary	26	[24.10, 27.01]
	Secondary & above	30	[27.90, 32.10]

95% CI: 95% Confidence interval for Median

Table 4.5: The log rank test for of survival curves of FBI after marriage by place of residence.

Covariate	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
Place of residence					
Rural	5969	4814	4601	9.83	44.3
Urban	1956	1152	1365	33.15	44.3

Chisq= 44.3 on 1 degrees of freedom, p= 2.78e-11

Table 4.6: The log rank test for of survival curves of FBI after marriage by mass media

Covariate	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
Mass Media					
No	4585	3599	3643	0.521	1.38
Yes	3340	2367	2323	0.817	1.38

Chisq= 1.4 on 1 degrees of freedom, p= 0.24

Table 4.7: The log rank test for of survival curves of FBI after marriage by contraceptive use

Covariate	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
contraceptive Status					
Non- User	2024	1579	1392	25.19	33.9
User	5901	4387	4574	7.66	33.9

Chisq= 33.9 on 1 degrees of freedom, p= 5.74e-09

Table 4.8: The log rank test for of survival curves of FBI after marriage by wealth index.

Covariate	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
Wealth index					
Poor	3310	2702	2639	1.49	2.76
Middle	1260	1016	926	8.72	10.62
Rich	3355	2248	2401	9.70	16.72

Chisq= 20.5 on 2 degrees of freedom, p= 3.53e-05

Table 4.9: The log rank test for of survival curves of FBI after marriage by women education level.

Covariate	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
Women education					
No education	5108	3939	4248	22.47	81.46
Primary	2159	1652	1342	71.54	95.87
Secondary& above	658	375	376	0.002	0.002

Chisq= 97.8 on 2 degrees of freedom, p= 0

Table 4.10: The log rank test for of survival curves of FBI after marriage by Husband education level.

Covariate	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
Women education					
No education	3857	2918	3332	51.54	121.93
Primary	2855	2286	1887	84.47	128.04
Secondary& above	1213	762	747	0.31	0.37

Chisq= 142 on 2 degrees of freedom, p= 0

Table 4.11: The log rank test for of survival curves of FBI after marriage Employment status of women.

Covariate	N	Observed	Expected	(O-E)^2/E	(O-E)^2/V
Employment Status					
Employment	2935	1969	2201	24.5	40
Not Employment	4990	3997	3765	14.3	40

Chisq= 40 on 1 degrees of freedom, p= 2.59e-10

Table 4.12: Univariate AFT analysis for time to first birth modeling using different baseline hazard functions

Covariates	Baseline Distributions		
	Weibull	Log- logistic	Log-normal
	$\hat{\beta}$ (95% CI ϕ)	$\hat{\beta}$ (95% CI ϕ)	$\hat{\beta}$ (95% CI ϕ)
Age	-0.07* (0.93, 0.94)	-0.08* (0.91, 0.93)	-0.07* (0.93, 0.94)
Mass Media			
No	Ref	Ref	Ref
Yes	-0.04 (0.93, 1.04)	-0.04 (0.93, 1.04)	-0.04 (0.93, 1.04)
Place of Residence			
Rural	Ref	Ref	Ref
Urban	0.15* (1.16, 1.21)	0.14* (1.10, 1.20)	0.13* (1.09, 1.19)
Wealth Index			
Middle	Ref	Ref	Ref
Poor	0.06* (1.00, 1.13)	0.07* (1.01, 1.14)	0.06* (1.00, 1.13)
Rich	0.12* (1.13, 1.23)	0.10* (1.04, 1.17)	0.10* (1.04, 1.17)
Employment Status			
Unemployed	Ref	Ref	Ref
Employed	0.14* (1.19, 1.26)	0.11* (1.12, 1.21)	0.10* (1.11, 1.19)
Women Education			
No education	Ref	Ref	Ref
Primary	-0.26* (0.75, 0.78)	-0.24* (0.74, 0.81)	-0.22* (0.77, 0.83)
Secondary&above	-0.11* (0.76, 0.98)	-0.08* (0.85, 1.00)	-0.08* (0.85, 1.00)
Husband education			
No education	Ref	Ref	Ref

Primary	-0.29* (0.70, 0.76)	-0.26* (0.74, 0.78)	-0.25* (0.75, 0.80)
Secondary&above	-0.17* (0.76, 0.83)	-0.16* (0.80, 0.89)	-0.15* (0.81, 0.91)
Contraceptive			
Non- User	Ref	Ref	Ref
User	0.16* (1.12, 1.30)	0.12* (1.18, 1.16)	0.11 * (1.07, 1.16)

95% CI ϕ: 95% confidence interval for acceleration factor, **Indicates significant at 10% level of significance, Ref= reference*

Table 4.17: Results of multivariate Weibull-Gamma frailty model

Covariate	Category	Estimate($\hat{\beta}$)	SE($\hat{\beta}$)	ϕ	P-value
Age		-0.07	0.31690	0.93	3.93e-208*
Place of	Rural	Ref.			
Residence	Urban	0.31	0.03161	1.36	1.55e-22*
Employment	Unemployed	Ref.			
Status	Employed	0.14	0.02004	1.15	1.16e-12*
Contraceptive	Non- User	Ref.			
	User	0.23	0.02182	1.26	6.53e-26*
Women	Noeducation	Ref			
education	Primary	-0.26	0.02211	0.77	1.56e-32*
	Sec&above	-0.07	0.04532	0.93	0.108
θ= 0.985	AIC = 14587.83				
τ = 0.329					
Likelihood-ratio test of θ = 0: chi-square = 1.63	P-value = 0.89				

SE($\hat{\beta}$)=standard error of $\hat{\beta}$; ϕ=acceleration factor;=significant at5% level;Ref. =Reference.*
AIC= Akaike's Information Criteria

Table 4.18: Results of multivariate log-logistic Gamma frailty model

Covariate	Category	Estimate($\widehat{\beta}$)	SE($\widehat{\beta}$)	ϕ	P-value
Age		0.07	0.31690	0.93	2.14e-47*
Place of Residence	Rural	Ref.			
	Urban	0.26	0.02854	1.30	1.64e-20*
Employment Status	Unemployed	Ref.			
	Employed	0.11	0.01890	1.12	1.67e-09*
Contraceptive	Non- User	Ref.			
	User	0.17	0.02080	1.19	1.50e-15*
Women education	Noeducation	Ref			
	Primary	-0.20	0.02101	0.82	1.20e-21*
	Sec&above	-0.01	0.04101	0.99	0.927
θ= 0.416	AIC = 13981.74				
τ = 0.134					
Likelihood-ratio test of θ = 0: chi-square = 1013			P-value = 0.000*		

*SE($\widehat{\beta}$)=standard error of $\widehat{\beta}$; ϕ=acceleration factor; * = significant at 5% level; Ref. =Reference.*
AIC= Akaike's Information Criteria

Table: summary of test of pairwise interaction effect

Covariate	$-2LL_2 - (-2LL_1)$	Decision
Age*pr	0.48	Do not reject Ho
Age*employmentstat	1.89	Do not reject Ho
Age*contracep	1.07	Do not reject Ho
Age*womeneduc	2.01	Do not reject Ho
Pr*employmentsttat	2.83	Do not reject Ho
Pr*contracep	2.05	Do not reject Ho
Pr*womeneduc	1.96	Do not reject Ho
Employmentstat*womeneduc	2.67	Do not reject Ho

Employmentstat*contracep	0.75	Do not reject Ho
Womeneduc*contracep	2.12	Do not reject Ho

$-2LL_2$ = with main effect only; $-2LL_1$ = main and interaction effect; Ho= the coefficient of interaction effect is zero.

Figure 4.5: K-M plots for survival of time- to- first birth after marriage by access to mass media and By wealth index of the family

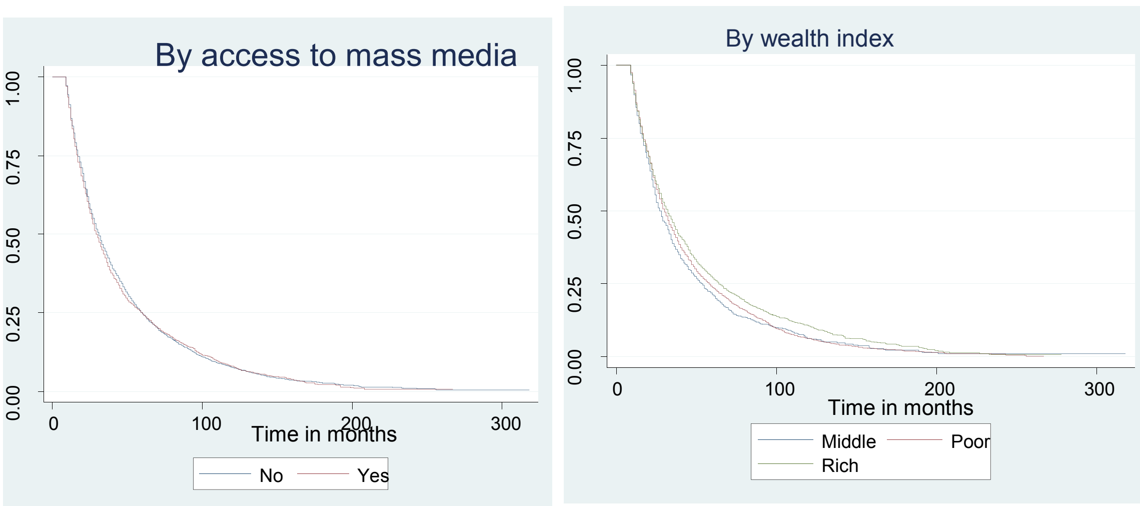

Figure 4.6: K-M plots for survival of time- to- first birth after marriage by *women and Husband education* level