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DETERMING RISK FACTORS TO TIME TO FIRST MARRIAGE AMONG WOMEN IN ETHIOPIA: APPLICATION OF PARAMETRIC SHARED FRAILTY MODEL

DESTAW TADILO

BAHIRDAR UNIVERSITY

COLLEGE OF SCIENCE

DEPARTMENT OF STATISTICS

DETERMING RISK FACTORS TO TIME TO FIRST MARRIAGE AMONG WOMEN IN ETHIOPIA: APPLICATION OF PARAMETRIC SHARED FRAILTY MODEL

BY: DESTAW TADILO

ADVISOR: DEREJE TESFAYE (ASSIS. PROF)

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BAHIRDAR, ETHIOPIA

DEPARTMENT OF STATISTICS, SCHOOL OF GRADUATE STUDIES
BAHIRDAR UNIVERSITY

This is to certify that the thesis prepared by Destaw Tadilo, entitled: The determinant factors to time to first marriage among women in Ethiopia: Application of parametric shared frailty model and summited in partial fulfillment of the requirements for the Degree of Master of Science in Statistics (Biostatistics) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

Advisor	Signature	Date
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Internal Examiner	Signature	Date
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External Examiner	Signature	Date
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Abstract

Background: Marriage is a significant and memorable event in one's life cycle as well as the most important foundation in the family formation process. Most studies are done on determinants of age at first marriage using logistic regression but the current study tried to model the survival time of age at first marriage by considering region as a frailty effect. The main objective of this study is to model time to age at first marriage amongst women in Ethiopia.

Methods: The data set in this study were obtained from Demography and Health survey conducted in Ethiopia in 2016 E.C. Women's work status, religion, place of residence, women education level, access to media, wealth index and desire for more children are variables which were considered as the potential determinant of time to age at first marriage in this study. In this study, we used models to account for the loss of independence that arises from the clustering of women in region of Ethiopia and also we used AIC and BIC to compare different parametric shared frailty models.

Results: Of all 15683 women aged 15-49, 11405 (72.72%) were married and the median & mean age at first marriage for women living in Ethiopia were 17 years and 17.25 years respectively, while the minimum and maximum age at first marriage observed were 10 years and 43 years respectively. Based on the result of selected model (Weibull-Inverse Gaussian shared frailty model), place of residence of women, religion of women, education level of women, access to media and desire for more children were significant at 5% level of significance. In contrast work status of women and wealth index were not significant at 5% level of significance. The clustering effect was significant for modeling time-to-age at first marriage dataset and there was heterogeneity among the regions on age at first marriage (θ=0.0463).

Conclusion: This study also showed that there was a clustering (frailty) effect on modeling time-to- age at first marriage among women living in Ethiopia due to the fact that heterogeneity in Region from which the women live in, assuming women living in the same Region share similar risk factors related to marriage.

Keywords: Time-to-age at First Marriage, Risk Factors, Heterogeneity, Frailty, Laplace transformations

List of Abbreviations

AFM	**Age at First Marriage**
AIC	**Akaike's Information Criteria**
AIDS	**Acquired immunodeficiency Syndrome**
CSA	**Central Statistical Agency**
DHS	**Demographic Health Survey**
EDHS	**Ethiopia Demographic Health Survey**
EM	**Expectation Maximization**
HIV	**Human Immunodeficiency Virus**
KM	**Kaplan Meier**
PH	**Proportional Hazard**
STDs	**Sexual Transmitted Diseases**
PS	**Positive Stable**
UNICEF	**United Nation Children's Fund**

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CHAPTER ONE

INTRODUCTION

1.1. Background

Marriage is a significant and memorable event in one's life cycle as well as the most important foundation in the family formation process. Age at marriage is the age at which individuals get married and this varies across communities and individuals (UNICEF., 2005). Age at first marriage is of particular interest because it marks the transition to adulthood in many societies; the point at which certain options in education, employment, and participation in society are foreclosed; and the beginning of regular socially acceptable time for sexual activity and childbearing. Marriage is not only the most predominant context for childbearing but also one of the most important determinants of fertility (Lesthaeghe, 1989). Moreover, age at first marriage of woman is an important factor for early childbearing, and early childbearing mother is at higher risk for poor prenatal outcomes such as gestational diabetes, gestational hypertension and preterm deliveries than the general population (Palacios et al., 2012). However, reproduction is not the only function of marriage.

Marriage marks the beginning of a new family unit with all the complicated statuses and the roles that the members of this unit are expected to play. For the society as a whole, marriage unites several individuals from different families and represents the creation of a production and consumption unit as well as one for the exchange of goods and services (Ikamari, 2005). Changes in marriage pattern, for instance delayed marriage, are believed to bring in the issues of dating, premarital sex, unwanted pregnancy, abortion, STDs and HIV/AIDS (Jones, 2007). Studies indicate that an increase in age at marriage leads to a rise in premarital sex and in absence of contraception which gives rise to unwanted pregnancies and a rise in adolescent fertility (Jones, 2007). On the one hand, women who marry early will have, on average; a longer period of exposure to the risk of pregnancy, often leading to higher fertility. On the other hand, societies with later age at first marriage have experienced decreased fertility rates while in traditional populations in Asia and Africa where age at first marriage is younger, high levels of fertility have been observed (Bongaarts and Potter, 2013). Due to its importance, various researchers believe that understanding variations in age at marriage helps in explaining differences in fertility across populations and fertility within individual populations over time (Economic, 1990); (EZEH and Dodoo, 2001).

Children born to young mothers are usually subject to elevated risks of morbidity and mortality (Zabin and Kiragu, 1998); (Ikamari, 2005). Some studies indicate that marrying at an early age in certain parts of the world leads to higher rates of divorce (Jones, 2005); (Lucas, 2017). Delayed age at marriage (or late marriage) directly affects completed fertility by reducing the number of years available for childbearing. Later marriage permits women to complete their education, build labor force skills, and develop career interests that compete with childbearing within marriage. These career interests may, in turn, motivate women to limit family size and/or widen the spacing of their children (Amin, 1996); (Jensen and Thornton, 2003).

Studies elsewhere have, however, identified a number of factors that seem to influence the timing of marriage (Jejeebhoy, 1995); marriage is nearly universal, age at marriage has a strong influence on a variety of social, economic and demographic factors. It is argued that by delaying marriage, women may stay in school longer, find more suitable mates, gain greater bargaining power and push the age of childbearing upward resulting in better child outcomes, fewer births and slower population growth. Unfortunately, despite the importance of age at first marriage in an individual's life history and its role in fertility and mortality transitions, most studies are done on determinants of early marriage using logistic regression but the current study tried to model the survival time of age at first marriage by considering region as a frailty effect. 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. Therefore, this study examines the effect of social, demographic and economic factors on the woman's age at first marriage.

In particular, the study aims at establishing the effects of some of the factors that have been indicated in studies elsewhere to be closely associated with the woman's age at first marriage. The goal is to determine the factors that are influencing age at first marriage in Ethiopia so as to manipulate these factors to increase age at marriage and thereby reduce fertility and population growth rates to manageable levels. Age at first marriage (AFM) has health implication on women and their under-five children.

Age at marriage is of particular interest because it marks the beginning of regular exposure to the risks of pregnancy and childbearing hence affecting fertility levels and population growth especially in countries with low contraceptive rate. Marriage forms the basis of family formation and, as such, is an important determinant of fertility by increasing or decreasing duration of exposure to the risk of childbearing. Therefore, age at first marriage (AFM) has a direct bearing on fertility behavior.

1.2. Statement of the problem

Age at early marriage is a health issue as well as a human right violation. A recent review show that girls who marry before the age of 18 were disproportionately affected by complicated pregnancies that may lead to maternal mortality and morbidity: girls aged 10–14 were five times more likely to die in pregnancy or childbirth than women aged 20– 24; girls aged 15–19 were twice as likely to die (Staff, 2011). A pregnancy too early in life before a girl's body is not fully mature is a major risk to both mother and baby. Also, they were more likely to experience complications of childbirth including obstetric fistula and hemorrhaging (Neal et al., 2018).

Mortality rates for babies born to mothers under age 20 were almost 75 percent higher than for children born to older mothers in Ethiopia. Teenage women were also twice as likely as older women to die due to complications during pregnancy and childbirth. Infants born from teenage mothers were more likely to suffer from low birth weight, and were at higher risk of dying in its first year by 60% compared with infants of mothers in their twenties (Nour, 2006). Age at first marriage had health implication for women and their under-five children (Adebowale et al., 2012). Many of the studies conducted used logistic regression analysis and Cox proportional hazard models to estimate the effect of covariates on the age at first marriage; which restricts attention to the events that occur within the shortest time observed and the correct inference based on Cox's models needs identically and independently distributed samples respectively.

Logistic regression does not account the censoring observations i.e., does not hold for time-to event data; however, survival analysis is more powerful than Logistic framework that takes censoring into considerations. But here we want to use different parametric shared frailty models since these models permit the analysts to account for the loss of independence that arises from the clustering of subjects in higher level units. Similarly, it allows researchers to make valid inferences when examining the effect of both subject characteristics and cluster characteristics on the risk of the occurrence of the outcome. Multilevel survival model used to model survival data when there are repeated measures on a subject, subjects nested within some other hierarchy, or some other reason to have both fixed and random effects (Crowther et al., 2014).

The current study focused on women aged 15-49 years, in the questionnaire designed for the survey, a question was asked from the respondents on age at first marriage (Quantitative). 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- age at first marriage between different regions.

This research aimed to explore factors that affect time-to-age at first 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-age at first marriage among women in Ethiopia?
- Which baseline distributional assumption among the Exponential, weibull, log-logistic, and log-normal describes well time-to- age at first marriage?
- Which frailty distribution among the Gama and inverse Gaussian distributions best describe the age at first marriage?
- Finally, the multivariable model was fitted and interpreted using the selected appropriate model.

1.3. Objective of the Study

1.3.1 General Objective

Determining factors that affect time- to-age at first marriage among women in Ethiopia using different parametric shared frailty model approaches.

1.3.2 Specific Objective

The specific objectives of this study are:-

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

1.4. Significance of the Study

The results are expected to give some knowledge about:-

- The determinants or risk factors of age at first marriage in Ethiopian women.
- The key socio-economic and demographic predictors of age at first marriage in Ethiopian women.
- Policy and strategies designation for government and other concerned bodies.
- More generally the study provides information on marriage in Ethiopian women by analyzing the impact of different covariates on survival of age at first marriage and the study will also add to the existing literature on the determinant of time to age at first marriage, that is, it provides an input for further study in Ethiopia.

1.5. Limitation of the study

- ✓ The reporting of age at first marriage might be inaccurate. This might arise from recall bias.
- ✓ The study also collected information on duration of marriage in an effort to minimize the effect of error reporting on age at first marriage.
- ✓ The cross-sectional nature of the data that could obscure the causal effect relationships of factors.

CHAPTER TWO

LITERATURE REVIEW

2.1. An Over view of Marriage

According to Demographic and Health Surveys (DHS), which provide much of the current country-level child marriage data, age at child marriage is most common in the world's poorest countries. The highest rates are in sub-Saharan Africa and South Asia as well as parts of Latin America and the Caribbean (Lloyd et al., 2005).

The 'economic theory of marriage' developed by (Schultz, 1974), argues that marriage is a function of economic benefits as individuals aim to maximize their own wellbeing and production through marriage. The author further notes that, uneducated and less educated women are easily trapped into marriage due to the perceived benefit from the potential husband's earnings whilst educated women are less likely to marry since they could maximize their preferences elsewhere in the market because of their personal qualities. (Raymo, 2003) who assessed the impact of schooling on marriage in Japan also argued that even though late marriage was commonly observed among educated girls, a strong inverse relationship existed between education and marriage. According to this study, educated girls tended to delay the timing of marriage due to employment opportunities. (Sibanda et al., 2003) documented delayed marriage in Addis Ababa though their findings did not indicate who postponed marriage and why the timing shifted to later ages.

Age at first marriage determines the age at first birth and at the long run influences the total number of children a woman bears throughout her reproductive period, in the absence of any active fertility control. Variation in age of entry into marriage explains the differences in fertility across populations (Nag and Singhal, 2013). Worldwide, more than 700 million women alive were married before their 18th birthday. More than one in three (about 250 million) entered into union before age 15. If there is no reduction in the practice of child marriage, up to 280 million girls alive are at risk of becoming brides by the time they turn 18. Child marriage among girls is most common in South Asia and sub-Saharan Africa (Unicef, 2014). Early or teenage marriage is very common in the northern part of Nigeria. Good percentage of Northern girls goes into first marriage as teenagers without formal education and any livelihood. Parents in this part of the country place more value on girls because of bride price, so they take good care of them from childhood till they are physically matured only to give them out in marriage as teenagers. This calls for urgent attention by individuals and the government. Early or teenage marriage has potentially harmful consequences both on individuals and the country at large. The young girls involved are deprived of basic human rights and ordinary life experiences other young people have (Singh and Samara, 1996),(Chukwu et al., 2018),(Isiugo-Abanihe, 1994). Many of them are forced to drop out of school. They are isolated from family, friends, and other sources of support. Their health is at risk because of early sexual activity and childbearing. One of the health risks is vesicovaginal fistula (a condition that does not allow the bladder to hold liquid, hence urine comes out as soon as it gets into the bladder) which is common in Northern Nigeria Countries with a high percentage of too early marriage are more likely to experience extreme and persistent poverty, and high levels of maternal and child mortality.

In sub-Saharan Africa, for example, 21 of 30 countries have seen an increase in the national age at marriage over the past several decades (Westoff, 2003). However, this increase in the age at marriage is occurring slowly and unevenly within countries. According to (UNICEF) figures, 66 percent of Bangladesh girls are married before the age of 18 and approximately a third of women were married by the age of 15 ; although the legal age at first marriage for females in Bangladesh is 18 years. The highest rates of child marriage are found in West Africa, in countries such as Niger, Chad, and Mali. However, in East Africa, the numbers of girls married in countries such as Ethiopia, Zambia, and Tanzania is also substantial. In rural Tanzania, median age at marriage is 18.5. The Demographic and Health Survey (DHS) for 1995 to 2003 shows that in Niger, 47 percent of women aged between 20 and 24 were married before the age of 15, and 87 percent before the age of 18, a total of 53 percent had also had a child before the age of 18.8 The 1992, 2000, and 2006/7 Namibia DHS report showed that mean age at marriage was 24 in 1992, 26.2 in 2000 and 28.6 in 2006/7. In Uganda, marriage is almost universal sooner or later, everyone marries, an early age at first marriage is observed for both males and females. According to the 1995, 2000/01 and 2006 Uganda Demographic and Health Surveys, the age at first marriage has been 17.5, 17.8 and 17.8 respectively and coupled with a low contraceptive prevalence rate of 24%, they have led to a high total fertility rate of 6.9. In the effort to increase the age at first marriage, Uganda has tried to intervene by setting the minimum legal age for a woman to get married at 18 years and through emphasis on educating the girl child through a number of educational reforms instituted since 1990. However, not all girls of school going age are enrolled in schools, there are high girl child dropout rates and entry into marriages at early ages is still high. According to the 2002 Uganda Population and Housing Census 6,308,849 girls marry below 16 years and this leads to low education attainment among women and unplanned pregnancies and high fertility.

In Ethiopia, although there remain distinctive ethnic differences in access to education, rural – urban migration and marriage practices (age at marriage and the prevalence of polygamy and 10 divorce), entry into marriage is near universal among all groups, with only 1 percent of men and women age 35 and above having never married (CSA, 2001:77). Marriage is of central importance to all aspects of life in Ethiopia; in one way or another, practically all essentials are organized, procured, and guaranteed through the institution of marriage (Weissleder, 1974). A strict sexual division of labor that makes the performance of tasks not of one's gender almost taboo provides a compelling pragmatic rationale for entry into marriage. For women, in particular, being single or in a household without a man is associated with marginalized social status, dependence on kin, and greater vulnerability (Pankhurst, 1992)Among the Amhara, who for centuries have been the most dominant cultural and political group, very early age at marriage is common. According to the 2005 Ethiopia DHS the median age at first marriage for women in the Amhara region ages 20-49 was 14.4 years compared to a median of 17.1 years among women in the Oromiya region (CSA, 2006). But generally acknowledged minimum age-at-first marriage in Ethiopia is currently 18 years (Erulkar and Muthengi, 2009) Parents view early marriage strategically because it provides a means to extend the family's social networks, which are a critical source of aid during times of crisis and household need. Because first marriages generally involve a bond between households, a bride's virginity is not simply a matter of honor; it has an economic value to parents and to the young women themselves (Pankhurst, 1992).

In societies, such as Ethiopia, where family networks function as mutual support groups, how well a young woman and man marries has long-term consequences for the families involved as well as for the bride and groom. According to (Dagne, 1994) the competition to find desirable partners for one's own children means that the earlier a marriage is arranged, the less parents have to worry about. At the same time, depletion of family resources associated with war, political turmoil and economic and environmental crisis has made it more difficult for families to secure a suitable husband for their daughters, and for young men to attain the economic independence desirable in a marriage partner. To the extent that marriage is delayed, individual autonomy in partner selection is likely to be greater for both men and women. Because grooms bring most of the assets into a marriage, their outcome in the marriage market is not as important in determining their future economic well-being as it is for brides (Fafchamps and Quisumbing, 2005). Marriages in many parts of Ethiopia can be divided into six types: ceremonial marriage (serg), religious marriage (k'urban), civil marriage (semanya), marriage proceeded by the provision of labor (k'ot'assir), paid labor marriage (gered or demoz), and marriage by abduction (t'ilf). The types of marriages differ in terms of the involvement of parents in the match; the level of formality, ceremony and expense; and expectations of labor exchanges (Pankhurst, 1992). Marriage by abduction and civil marriage are now the standard forms of marriage, although ceremonial marriage which involves considerable expense remains common in urban areas.

In rural areas arranged marriages are the norm whereas abduction marriage provides a socially acceptable way to circumvent the parents’ or the bride's disapproval of a match (Fafchamps and Quisumbing, 2002). While there are strong social and economic pressures on girls to comply with their parents’ desires, there are also opportunity costs and risks associated with early marriage and the early initiation of sexual intercourse, especially premarital sexual intercourse that does not lead to marriage. Very early age at first marriage and premarital first sex are associated with marital instability and divorce, multiple partners; poverty, and subsequent drift into prostitution or paid domestic work (Duncan, 1993).

2.2. Early Marriage and Health Consequence

Evidence from South Africa in a study by (Yamauchi, 2007) indicates that “education reduces the probability of early marriage but increases the probability of contracting HIV”. However, it can be argued that the correlation could be influenced by unobservable factors such as the culture and norms of the community under study. The findings may not hold in highly conservative societies, where pre-marital sex is frowned upon (Lindstrom et al., 2009). In a study on ‘education and health’ (Vogl, 2012) posits a positive link between parental education and a child’s health. The argument is that educated parents tend to be healthier than the less educated ones and therefore, are more likely to have healthier children. Therefore, one of the benefits of increasing the level of education is that, it assists in delaying a child's transition into an early marriage arrangement. By implication there is therefore, a benefit in a child avoiding early marriage by extending their stay in school. Early marriage increases the risk of divorce (Andersson, 1997) according to economic theories as they argue the partners do not spend enough time and energy for finding an optimal spouse and they do not possess the necessary emotional, educational and economic resources required for a marriage (Martin and Bumpass, 1989) The propensity to marry, the stability and duration of marriage have considerable implications for the organization of family life. The age at first marriage may also influence population growth, labour supply, consumption, wage rates, mortality, migration and to some extent fertility (Mensch et al., 2005). Women who marry early will have, on average; a longer period of exposure to the risk of pregnancy, often leading to higher completed fertility. Variation in age of entry into marriage helps explain differences in fertility across populations and also helps explain trends in fertility within individual populations over time ((Economic, 1990); (EZEH and Dodoo, 2001)).

Therefore, age at first marriage has a direct bearing on fertility behavior ((Davis and Blake, 1956);(Bongaarts, 1978).

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 and Cuzick, 1985); (Klein and Goel, 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 and Cuzick, 1985) 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 (Lindstrom, 1996).

CHAPTER THREE

DATA AND METHODS

3.1. Data Source

The data set in this study obtained from Ethiopian Demographic and Health Survey (EDHS) which was conducted by Central Statistical Agency (CSA) in 2016, which was the fourth comprehensive survey conducted as part of the worldwide. The 2016 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, Oromia, 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 2016 EDHS is to provide current and reliable data on marriage, 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 sampling frame used for the 2016 EDHS is the Ethiopia Population and Housing Census (PHC), which was conducted in 2007 by the Ethiopia Central Statistical Agency. The 2016 EDHS sample was stratified and selected in two stages. Each region was stratified into urban and rural areas, yielding 21 sampling strata. Samples of EAs were selected independently in each stratum in two stages.

In the first stage, a total of 645 EAs (202 in urban areas and 443 in rural areas) were selected with probability proportional to EA size (based on the 2007 PHC) and with independent selection in each sampling stratum. Households comprised the second stage of sampling.

In the second stage of selection, a fixed number of 28 households per cluster were selected with an equal probability systematic selection from the newly created household listing. All women age 15-49 and all men age 15-59 who were either permanent residents of the selected households or visitors who stayed in the household the night before the survey were eligible to be interviewed.

3.3. Variables in the study

3.3.1. Dependent variable

The dependent variable in this study is age at first marriage which is a continuous variable. It is measured as the length of time from birth until the age at first marriage which is measured in years. On a sample of all Ethiopian women aged 15-49, we retrospectively observe the timing to first marriage since birth. Hence we have to consider two things. First, all cases with no observed events are right censored. Therefore the women who had not yet experienced the event of interest resulting in right censoring of the data. There is no reason for this censoring pattern to be dependent on the survival times and we consider it uninformative. Second, in order to make censoring valid, we have to assume that all women marry before the age of 50.

3.3.2. Independent / predictor variables

The independent variables considered in this study are respondents work status, religion, region, type of residence, women education level, access to media, wealth index and desire of children.

Table 3.1: Description and categories of the predictor variables

Variables	Categories
Respondents Working status	0=Yes
	1=No
Religion	0=Orthodox
	1-Muslim
	2=Protestant
	3=Others
Residence	0=Rural
	1=Urban
Region	0=Tigray
	1=Afar
	2=Amhara
	3=Oromiya
	4=Somalia
	5=Benishangul Gumuz
	6=SNNPR
	7=Gambella
	8=Harer
	9= Adiss Abeba
	10= Dire Dewa
Women education level	0=No education
	1=Primary
	2=Secondary
	3=Higher
Access to media	0=Yes
	1=No
Wealth index	0=Poor
	1=Middle
	2=Rich
Desire of children	0=Yes
	1=No

3.4. Method of Data Analysis

3.4.1. Survival Analysis

Survival analysis consists of studies of the survival time of a subject (usually measured in days, weeks, months, or years), which is the time that elapses between the baseline and the moment an adverse event occurs, or the subject drops out of the trial. Sometimes the survival time is called a lifetime or an event time.

The survival times for subjects who dropped out of the trial (called dropouts or lost to follow up subjects*)* are right-censored (or, more simply, censored). The survival times of the subjects who remain in the trial until it ends are censored *as* well. This term applies to situations when it is known that the subject survived a certain length of time and was healthy, but the later health condition for this subject is not recorded. Censored survival times represent very important information and should be kept in the database. Retained censored survival times increase the overall survival rate of the subjects-that is, the percentage of people who are alive for a given period of time. For example, if a subject drops out after being in a study for 5 months, the subject is still included in calculation of the survival rate up to 5 months. Naturally, a higher survival rate implies a better treatment efficacy.

In what follows, each uncensored observation is termed "married," regardless of whether a marriage or a different adverse event has occurred. Denote by T the random variable representing the survival time of a subject. Let f(t), $t \geq 0$, denote the probability density function (pdf) of T , and let F(t) = P(T ≤ t) = $\int_0^t f(x)\,dx$, $t \geq 0$, be the cumulative distribution function (cdf) of T. The distribution of T is called the survival time distribution (or the lifetime distribution). The objective of survival analysis is to estimate and model the following functions: The survival function, S(t), defined as the probability that a subject survives up to time *t:*

$S(t) = P(T>t) = \int_t^\infty f(x)\,dx = 1-F(t)$, t>0 … … … … … . . (3.1)

The hazard function, h(t), defined as the following ratio:

$h(t) = \frac{f(t)}{s(t)}$, $t \geq 0$… … … … … … … … … … … … … … … … … … … (3.2)

It is interpreted as an instantaneous death rate, since the probability that the event occurs within small time interval [t, t+dt), given that the subject survived up to time t, $t \geq 0$, is equal to

$P(T<t+dt/ T>t) = \frac{P(t<T< t+dt)}{P(T>t)} = \frac{f(t)}{s(t)} dt$ =h(t)dt … … … … …. … (3.3)

The cumulative hazard function, H(t), defined by

$$H(t) = \int_0^t h(x)\,dx, \ t \geq 0 \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

3.4.2. Non-Parametric Survival Analysis

Non-parametric survival analyses are more widely used in situations where there is doubt about the exact form of distribution. In survival analysis, the 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. The Kaplan-Meier, Nelson-Aalen and Life Tables are the most widely used to estimate the survival and hazard functions (Collett, 2015)

3.4.3. Estimation of Survival functions by the Kaplan-Meier Method

A widely used method for estimation of the survival function is the Kaplan Meier method. This method produces the Kaplan-Meir estimator, a nonparametric estimator, which does not assume any known algebraic form of the estimated survival function. The Kaplan-Meier estimator is also referred to as the KM estimator or the product-limit estimator. Suppose k distinct survival times are observed. Arranged in increasing order, they are t1 < t2 < ... < tk .

At time t_i, there are n_i subjects who are said to be at risk-that is, they survived up to this time (not including it) and were not censored. Denote by di the number of subjects who have an event at time ti. To simplify notation, let to = 0 and do = 0. Then the Kaplan-Meier estimator of the survival function S (t) is:

$$\hat{S}(t) = \prod_{i:ti\leq t}\left(\frac{ni-di}{ni}\right) = \prod_{i:ti\leq t}\left(1-\frac{di}{ni}\right), \ t \geq 0 \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.5)$$

3.4.4. The Kaplan-Meier Survival Curve

The Kaplan-Meier survival curve is the plot of the Kaplan-Meier estimator of the survival function S(t) against time t. This curve is a step-function that decreases at the times of events. The censored times are usually marked by a cross (x).

3.4.5. Median Survival Times

The median survival is the time at which fractional survival equals 50%.Use of the Kaplan-Meier estimator is not restricted to estimating survival probabilities for given times t. It may also be used to estimate fractiles such as the median survival time. Consider the p^{th} fractile t(p) of the cumulative distribution function F(t) = 1-S(t), and assume that F(t) has positive density f (t)=F′(t)=-S′(t) in a neighborhood of t(p). Then t(p) is uniquely determined by the relation F(t(p))= p, or equivalently, S(t(p))=1-p. The Kaplan-Meier estimator is a step function and hence does not necessarily attain the value 1- p. Therefore a similar relation cannot be used to define the estimator t(p) of p^{th} fractile. Rather we define t(p) to be the smallest value of t for which $\hat{S}$(t) ≤ 1- p, that is, the time t where $\hat{S}$(t) jumps from a value greater than 1- p to a value less than or equal to 1- p. Hence the median survival times (t(0.5)) to be the smallest value of t for which $\hat{S}$(t) ≤ 0.5, that is, the time t where $\hat{S}$(t) jumps from a value greater than 0.5 to a value less than or equal to 0.5.

3.5. 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 al., 2008).

Multilevel survival analysis is the statistical technique that can apply for clustered (grouped) survival times. Researchers often encounter grouped or multilevel data like individuals are nested within families, and families are nested within neighborhoods. In our study also encountered such kinds of data. For instance women aged 15-49 nested with in region. Analyzing such data requires special treatment because most multivariate models assume that observations are independent, and grouped data clearly violate this assumption. Statisticians and biomedical researchers identified adverse consequences of applying the Cox regression to grouped survival times ((Andersen and Gill, 1982); (Prentice et al., 1981)). They noted that when the independent assumption of the Cox model is violated, the tests of statistical significance are biased and in ways that cannot be predicted beforehand (Wei et al., 1989). Mixed effects cox regression models, mixed effect piecewise exponential survival models and discrete time survival models with mixed effects are the statistical models for multilevel survival analysis. Hence in this study we concentrate on parametric shared frailty models and discrete time survival models with mixed effects.

3.5.1. 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 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, 1986), (Therneau and Grambsch, 2000) and (Duchateau and Janssen, 2004). 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.

3.5.2. Mixed Effects Cox regression Models

Mixed effects cox regression models are used to model survival data when there are repeated measures on an individual, individuals nested within some other hierarchy, or some other reason to have both fixed and random effects. Mixed effect model allow the model to have multiple random effects, whereas frailty models allow model with only random intercept (Crowther et al., 2014). That is why they say parametric shared frailty model is a special case of mixed effects cox regression models. Moreover, parametric shared frailty model is a special case of mixed effects cox regression models due to the fact that as it assume a parametric distribution for baseline hazard function and it consider shared frailty as cluster-specific random effects. Suppose individuals are nested in one of G groups or clusters. A mixed effects cox regression model can be formulated as:-

$$h_i(t) = h_0(t)exp(x_i\beta + \alpha_j) \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \quad (3.6)$$

Where α_j denotes the random effects associated with the j[th] cluster. (Rabe-Hesketh and Skrondal, 2008) use the term 'shared frailty' to denote the exponential of the random effect: exp(α_j). The random effect can be thought of as a random intercept that modifies the linear predictor, while the shared frailty term has a multiplicative effect on the baseline hazard function:

$$h_i(t) = h_0(t)\exp(\alpha_j)exp(x_i\beta + \alpha_j) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.7)$$

3.6. Modeling Frailty and Shared Frailty Model

Expanding proportional hazards model to include a random effect, called a frailty, allows for modeling association between individual failure times within a group. The frailty approach is a statistical modeling concept which aims to account for heterogeneity, caused by unmeasured covariates. In statistical terms, a frailty model is a random effect model for time-to-event data, where the random effect (the frailty) has a multiplicative effect on the baseline hazard function (Wienke, 2010). (Vaupel et al., 1979) used the frailty approach to derive the individual hazard function based on the population hazard function obtained from life tables. The shared frailty approach assumes that all failure times in a cluster are conditionally independent given the frailties. The value of the frailty term is constant over time and common to all individuals in the cluster, and thus it is responsible for creating dependence between event times in a cluster. This dependence is always positive in shared frailty models.

A frailty acts multiplicatively on the hazard function and the model that incorporates this random effect into the hazard function is called the frailty model. There are two different, but related, connotations of frailty. First, frailty is the missing covariates that are not known to us and consequently they are unobservable. More specifically, let *Z* denote the covariate vector that is known to us and w denote the covariate vector that is unknown.

The hazard function for a given individual is

$h(t/z)$ =$h_0(t)\exp(\beta z+\varphi w)$ … … … … … … … (3.8)

, Where ψ is the regression coefficient of unknown covariates. To simplify Eq. (3.8), let u = exp(ψw), then the hazard function has the form

$h(t/z)$ = h_0(t) u$\exp(\beta z)$ … … … … … … … … … … … … … (3.9), Where *u* is a random variable assumed to have a one-dimensional distribution q. In Eq. (3.9), the frailty *u* represents the total effect on failure of the covariates not measured when collecting information on individuals. Equation (3.9) is known as the frailty model.

(Clayton, 1978) suggested the other connotation of the frailty when individuals in a study are divided into distinct groups. Here, the frailty denotes unobservable common covariates shared by members in a group, and the frailty model handles the dependence generated by those common covariates. For example, for a study including husband and wife, each couple shares common environmental factors; for menozygotic twins study, twins share a common genotype as well as common environmental factors. Specifically, suppose there are *G* groups with *ni* individuals in the *i* th group; *Zij* is the observable covariate vector for the j^{th} individual in the i^{th} group. Let *wi* be the unobservable covariates for the i^{th} group and ψ be its regression coefficient.

The hazard function of the *j* th individual in the i^{th} group is:

$h_{ij}(t/z_{ij})$ = h_0(t) $\exp(\beta z_{ij} + \varphi w_i)$ i= 1, …, G, j= 1, …, n_i .. … … … (3.10)

Replacing exp*(ψwi)* by ui , which is the frailty of the i^{th} group, the hazard function incorporating frailty reduces to

$h_{ij}(t/z_{ij})$ = h_0(t) $u_i$exp(βz_{ij}) i= 1,…, G, j= 1, …, n_i. . … … … … (3.11)

Here it is assumed that u_1, . . . ,u_G are random variables with the common probability density function q. The model (3.11) can be considered as a random effects model with two sources of variation. There is a group variation, described by the random variable u with the probability density function q.

Secondly, there is the individual variation described by the hazard function $h_0(t)$ exp(βZij). In (3.11), members in a group share the same frailty, so the frailty model under this circumstance is known as the shared frailty model. Also, in this model, groups with a large value of the frailty will experience the failure at earlier times than groups with small values of the frailty (Hougaard, 2012).

3.7. Inference for the Shared Frailty Model

As in most contexts, provided that one trusts the model (3.10), maximum likelihood method is the method of choice. To derive the general form of the likelihood function, it is assumed that the common factor causes dependence between individuals in a given group, and conditional on that, all individuals within the group are independent. Thus, for one group of n individuals, the conditional joint survival distribution of failure times T_1,T_2, . . . ,T_n is given by

$P(T_1>t_1,\ldots,T_n>t_n/u)= P(T_1>t_1/u)P(T_2>t_2/u)\ldots P(T_n>t_n/u)$

$=\exp\left\{-u\sum_{j=1}^{n}H_0(t_j)\,exp(\beta z_j)\right\}$… … … … … … … … 3.12

Note that we omit the group index i in Eq. (3.12). The above joint conditional survival distribution holds for any group. Integrating the frailty out, we get the joint survival function for this group expressed as

$S(t_1, t_2, \ldots, t_n) = P(t_1>t_1, T_2>t_2,\ldots,Tn>t_n) = \int_0^\infty P(t1>t1, T2>t2, \ldots, Tn>tn/u)\; q(u)du = \int_0^\infty \exp\left\{-u\sum_{j=1}^{n}H_0(t_j)\,exp(\beta z_j)\right\}\; q(u)du = LP\left\{\sum_{j=1}^{n}H_0(t_j)\,exp(\beta z_j)\right\}$ … … … … … .3.13

where LP is the Laplace transform of the density function q and $H_0(t) = \int_0^t h_0(u)du$. From Eq. (3.13) it is clear that the joint survival function for one group is the Laplace transform of the frailty density function q with parameter $\sum_{j=1}^{n}H_0(t_j)\,exp(\beta z_j)$. In principle, any distribution on the positive numbers can be applied as a frailty distribution. In this paper, we concentrate on the gamma, the inverse Gaussian and the positive stable distributions.

From Eq. (3.13) one can derive the likelihood function for one group as follows:

If the failure time is observed for the j^{th} individual at time *tj*, its probability is given by $P(T_j=t_j, T1>t1, T_2>t_2,\ldots)= -\frac{\partial S(t_1,\ldots,t_n)}{\partial t_j} = -h_0(t)\exp(\beta z_{ij})\ LP^{(1)}\left(\sum_{j=1}^{n} H_0(t_j)\, exp(\beta z_j)\right)\ldots\ldots$ … … … … … … … … 3.14 ,where *LP(1)(s)* denotes the first derivative of *LP(s)* with respect to s. Let $D. = \sum \delta_j$, the total number of failures in the group, and θ be the parameter of the frailty distribution. Then, using Eq. (3.14), the likelihood for one group is given by

$= (-1)^{D\cdot}\left\{\prod_{j=0}^{n} h_0(t_j)^{\delta_j}\exp(\beta\delta_j z_{ij})\right\}(LP)^{D\cdot}\left(\sum_{j=1}^{n} H_0(t_j)\, exp(\beta z_j)\right)\ldots\ldots\ldots 3.15$

The likelihood function for all individuals is constructed by multiplying the group likelihoods together. Specifically, if Di denotes the number of failures in the i th group, and $D = \sum_{i=0}^{G} Di$, then the likelihood function is given by

$=(-1)^{D_i\cdot}\left\{\prod_{j=0}^{n} h_0(t_{ij})^{\delta_{ij}}\exp(\beta\delta_{ij} z_{ij})\right\}(LP)^{D_i\cdot}\left(\sum_{j=1}^{n} H_0(t_{ij})\, exp(\beta z_{ij})\right)\ldots\ldots\ldots\ldots 3.16$

If we assume a parametric form for h_0, we can handle the estimation in the usual way by differentiating the log likelihood function. If a parametric form is not assumed for h_0, there are several estimation methods like full conditional approach and EM algorithm available to handle this semi-parametric model.

3.7.1. The Gamma Frailty Model

(Clayton, 1978) proposed the gamma distribution for the frailty. Since then, the gamma frailty model has been used extensively because the derivatives of its Laplace transformation are quite simple. From a computational and analytical point of view, it fits very well to failure data. It is widely used due to mathematical tractability (Wienke, 2010).

The density function of the frailty is

$q(u)=\frac{u^{\frac{1}{\theta}-1}}{\Gamma(1/\theta)\theta^{\frac{1}{\theta}}}\exp\left(\frac{-u}{\theta}\right)\ldots\ldots\ldots\ldots\ldots 3.17$

Where $\theta>0$ and u>0 indicates that individuals in group are frail, whereas u<0 indicates that individuals are strong and have lower risk. The corresponding Laplace transform is given by;

$LP(s) = (1+\theta s)^{\frac{-1}{\theta}}$. Usually, we use the one-parameter gamma distribution denoted by Gamma *(θ)*. Thus the mean of the frailty is 1, which is the desired property of the frailty distribution; the variance is θ, which reflects the degree of dependence in the data. Large θ indicates strong dependence. The conditional survival function of the gamma frailty distribution is given by: (Gutierrez et al., 2001).

$S(\theta) = [1 - \ln\{s(t)\}]^{\frac{-1}{\theta}}$, θ > 0 … … … … … … … … … … … … … … … 3.18

The conditional hazard function of the gamma frailty distribution is given by: (Gutierrez, 2002)

$h_\theta(t)=h(t)\,[1 - \ln\{s(t)\}]^{-1}$ … … … … … … … … 3.19 , where S (t) and h(t) are the survival and the hazard functions of the baseline distributions. The gamma model has predictive hazard ratios which are time invariant (Fine et al., 2003). For the Gamma distribution, the Kendall's Tau (Hougaard, 2012), measures the association between any two event times from the same cluster in the multivariate case and given by:-

$\tau = \frac{\theta}{\theta + 2}$, where τϵ (0,1) … … … … … … … … … … … 3.20

One can derive the likelihood function as follows. The p^{th} derivative of the Laplace transform is

$LP^{(p)}(S)=(-1)^p\theta^p(1+\theta s)^{\frac{-1}{\theta - p}}\frac{\Gamma\frac{1}{\theta+p}}{\Gamma}(\frac{1}{\theta})$ … … … … … … … … … … . … . . 3.21

Following Eq. (3.16), the likelihood for all individuals is given by

$=(-1)^D \prod_{i=1}^{G} \theta^{D_i} \frac{\Gamma(\frac{1}{\theta}+D_i)}{\Gamma(\frac{1}{\theta})} \{\prod_{j=1}^{ni} h_0(t_{ij})^{\delta_{ij}} \exp(\delta_{ij}\beta z_{ij})\} \quad *\{1+\theta\sum_{j=1}^{ni} H_0(t_{ij})\exp(\beta z_{ij})\}^{\frac{-1}{\theta}-D_i}$

… … … … … … … … … … … …3.22

For gamma frailty model the marginal hazards are not proportional over time.

3.7.2. Inverse Gaussian Frailty Model

Similar to the gamma frailty model, simple closed-form expressions exist for the unconditional survival and hazard functions, this makes the model attractive. The probability density function of an inverse Gaussian shared distributed random variable with parameter θ > 0 is given by

$f_u(u) = (\frac{1}{2\pi\theta})^{\frac{1}{2}}\, u^{\frac{-3}{2}} \exp\left[-\frac{(u-1)^2}{2\theta u}\right]$, θ > 0, u > 0 … … … … … … … 3.23

For identifiability, we assume u has expected value equal to one and variance j.

The Laplace transformation of the inverse Gaussian distribution is:-

$LP(s) = \exp\left[\frac{1-(1+2\theta s)^{\frac{1}{2}}}{\theta}\right]$, θ > 0, s > 0 … … … … … … … … … … … … 3.24

For the inverse Gaussian frailty distribution the conditional survival function is given by: (Gutierrez et al., 2001).

$S_\theta(t) = \exp\left[\frac{1}{\theta}(1 - [1 - 2\theta \ln\{s(t)\}]^{\frac{1}{2}})\right]$, θ > 0 … … … … … … … …3.25

For the inverse Gaussian frailty distribution the conditional hazard function is given by: (Gutierrez et al., 2001).

$h_0(t) = h(t)\,[1 - 2\theta \ln\{s(t)\}]^{\frac{-1}{2}})$ $\quad , \theta > 0$ … … … … … … … 3.26

Where S (t) and h(t) are the survival and the hazard functions of the baseline distributions. With multivariate data, an Inverse Gaussian distributed frailty yields a Kendall's Tau given by:-

$\tau = \frac{1}{2} - \frac{1}{\theta} + 2\frac{\exp(\frac{2}{\theta})}{\theta^2}\int_{\frac{2}{\theta}}^{\infty}\frac{\exp(-u)}{u}du$ where $\tau \epsilon \frac{(0,1)}{2}$

3.8. Baseline Hazard Distribution for Parametric Frailty Models

3.8.1. Baseline Exponential Distribution

The exponential distribution, with only one unknown parameter and it is the simplest of all life distribution models. In the exponential model, the conditional probability is constant over time. In other words, the main feature of exponential distribution is that the instantaneous hazard doesn't vary over time. Modeling the dependency of the hazard rate on covariates entails constructing a model that ensures a non-negative hazard rate (or non-negative expected duration time).The exponential PH model is a special case of the Weibull model when $\gamma = 1$.

The hazard function under this model is to assume that it is constant over time.

Table 3.2: Baseline Exponential distribution for survival and hazard functions

f(t)	S(t)	h(t)	H(t)	Parameter space
λexp(-λt)	exp(-λt)	Λ	λ t	λ>0

3.8.2. Baseline Weibull Distribution

Weibull distribution is one of the parametric distributions which are used for the analysis of life time data and mostly used in literature for modeling life time data (Ibrahim et al., 2014) and (Yu, 2006). The Weibull distribution is more general and flexible than the exponential distribution and allows for hazard rates that are non-constant but monotonic. It is a two parameter model (λ and γ), where λ is the scale parameter and γ is the shape parameter because it determines whether the hazard is increasing, decreasing, or constant over time i.e., the hazard rate increases when, $\gamma > 1$ and decreases when $\gamma < 1$ as time goes on. When $\gamma = 1$, the hazard rate remains constant, which is the special case of exponential.

Table 3.3: Baseline Weibull distribution for Survival and Hazard functions

f(t)	S(t)	h(t)	H(t)	Parameter space
$\gamma\lambda t^{\gamma-1}$exp(-$\lambda t^{\gamma}$)	exp(-λt^{γ})	$\gamma\lambda t^{\gamma-1}$	$\gamma\lambda t^{\gamma}$	λ,γ >0

3.8.3. Baseline Log-Logistic Distribution

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 is the scale parameter and γ is the shape parameter which is denoted by log L (γ, λ). The distribution imposes the following functional forms on the density, survival, hazard and cumulative hazard function:

Table 3.4: Baseline Log-logistic distribution for Survival and Hazard functions

f(t)	S(t)	h(t)	H(t)	Parameter space
$\frac{\gamma\lambda t^{\gamma-1}}{(1+\lambda t^{\gamma})^2}$	$\frac{1}{1+\lambda t^{\gamma}}$	$\frac{\gamma\lambda t^{\gamma-1}}{1+\lambda t^{\gamma}}$	$\ln\left[1+\left(\frac{t}{\lambda}\right)^{\gamma}\right]$	λ∈ R,γ >0

By specifying one of the four functions f (t), S(t), h(t) or H(t) specifies the other three functions of the above baselines. The parameter λ is reparameterized in terms of predictor variables and the regression parameters. Typically for parametric models, the shape parameter γ is held fixed.

3.8.4. Baseline Log normal distribution

Lognormal distribution plays an important role in probabilistic design because negative values of engineering phenomena are sometimes physically impossible. Typical uses of lognormal distribution are found in descriptions of fatigue failure, failure rates, and other phenomena involving a large range of data. A random variables, T, is said to have a lognormal distribution with parameters μ and δ, if logT has a normal distribution with μ and variance σ^2 . The probability density function of T is given by:

$$f(t) = \frac{1}{\delta\sqrt{2\pi}} t^{-1}\exp\{(-logt - \mu)^2) \,/\, 2\sigma^2\}$$

The survivor function of lognormal distribution is $S(t) = 1 - \phi\left(\frac{logt-\mu}{\delta}\right)$

Where ϕ. Is the standard normal distribution function given by

$$\phi(z) = \frac{1}{2\pi}\int_{-\infty}^{z} \exp(^{-u^2}/_{2})\, du$$

And the hazard function is h(t) = $\frac{\phi(\frac{logt}{\delta})}{[1-\phi(\frac{logt}{\delta})]\delta t}$

3.9. Comparisons of Models

Model comparison and selection are among the most common problems of statistical practice, with numerous procedures for choosing among a set of models (Kadane and Lazar, 2004) and (Lahiri, 2001). There are several methods of model selection. The most commonly used methods include information criteria. One of the most commonly used model selection criteria is Akaike Information Criterion (AIC). A data-driven model selection method such as an adapted version of Akaike's information criterion AIC (Akaike, 1974) is used to find the truncation point of the series. In some circumstances, it might be useful to easily obtain AIC value for a series of candidate models (Munda et al., 2012). In this study, we used the AIC criteria to compare two different multilevel survival models. The model with the smallest AIC value is considered a better fit.

3.10. Model Diagnostics

3.10.1. Evaluation of the Baseline Parameters

The graphical methods can be used to check if a parametric distribution fits the observed data or not. The model with the Weibull baseline has a property that the log (-log (ŝ(t))) is linear with the log of time, where ŝ(t) = exp (-λt^{γ}). Hence, log (-log (ŝ(t))) =log λ + γlog(t). The intercept and slope of the line will be rough estimate of log λ and γ respectively. This property allows a graphical evaluation of the appropriateness of a Weibull model by plotting log (-log (ŝ(t))) versus log (t) where ŝ(t) is Kaplan-Meier survival estimate (Dätwyler and Stucki, 2011). The appropriateness of the model with the exponential baseline can graphically be evaluated by plotting –log (ŝ(t))versus t where ŝ(t)is Kaplan-Meier survival estimate. This plot should be linear and goes through the origin (Klein, 1992). Because for exponential distribution, ŝ(t) = exp(-λt) , and hence, -log (ŝ(t))= λt is linear with time.

The appropriateness of the model with the log logistic baseline can graphically be evaluated by plotting log (1 - ŝ(t)/ ŝ(t))versus log (t), where ŝ(t) is Kaplan-Meier survival estimate. The log-failure odd versus log time of the log-logistic model is linear with slope λ then the survival time follows a log-logistic distribution.

Where the failure odds of log-logistic survival model can be computed as:

$$(1 - S(t))/S(t) = \frac{\frac{\lambda t^{\gamma}}{1+\lambda t^{\gamma}}}{\frac{1}{1+\lambda t^{\gamma}}}$$

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

$\log((1-S(t))/S(t))=\log(\lambda t^{\gamma}) = \log(\lambda) + \gamma\log(t)$, which is the liner function of log(t). (Dätwyler and Stucki, 2011)

3.10.2. The Cox-Snell Residuals

The Cox-Snell residuals method can be applied to any parametric model and the residual plots can be used to check the goodness of fit of the model. 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 and Moeschberger, 2003).

The Cox-Snell residual for the jth individual with observed survival time tj is given by rj = $\widehat{H}(T_j/x_j) = -\log \hat{S}(T_j/x_j)$, where $\widehat{H}$and $\hat{S}$are the estimated values of the cumulative hazard and survivor function of the j^{th} subject at time t*j* respectively. 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 unity and zero intercept. If yes, the fitted model is adequate. In general, Cox-Snell residual that provides a check of the overall fits of the model (Cox and Snell, 1968).

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Descriptive Statistics

From all 15,683 women aged 15-49; 11,405 (72.72%) were married and the median & mean age at first marriage for women living in Ethiopia were 17 years and 17.25 years respectively, while the minimum and maximum age at first marriage observed were 10 years and 43 years respectively. The Percentage of married women aged 15-49 was highest for those living in Oromia region (12.82%), followed by those living in Amhara region (11.81%), while the lowest for those living in Harari region(5.95%) when compared to those living in other regions. The mean age at first marriage is highest in Addis Ababa (20.70 years) and lowest in Amhara (15.88 years). Similarly, the median age at first marriage is highest in Addis Ababa (20 years) and lowest in Amhara (15years).

The percentage of women aged 15-49 who were ever married was higher for those residing in the rural area(72.09%) than those residing in urban area(27.91%). The median age and mean age at first marriage among women aged 15-49 is 18 years and 18.73 years respectively for those living in urban area, which is higher than those living in rural area (median=16 years, mean=16.68 years).

Concerning to educational level of women, percentage of women aged 15-49 who were married was highest for uneducated women (41.48%), while the lowest for those women having higher education (4.04%) relative to women having other level of education. The median age at first marriage is highest among women aged 15-49 is for those women achieving higher education (median= 21 years), while the lowest for those having no education (median=16). And the mean age at first marriage among women aged 15-49 is the highest for those achieving higher education (mean=21.29), while the lowest for those having no education which is 16.63 years.

The result revealed that the percentage of women aged 15-49 who were married was highest for those women with Muslim religion (30.89%), while the lowest for Catholic religion followers (0.42%) when compared to other religions in Ethiopia. The mean age at first marriage is highest for those protestant followers (17.35years), whereas the lowest for those women Muslim followers (17.01years). The median age at first marriage is similar as well as highest (17 years) for those women except Muslim followers, while the lowest for those women with Muslim religion (16 years).

Regarding to wealth index, the percentage of ever married women aged 15-49 were highest for poor women (31.62%), followed by rich women (31.33%), while the lowest for those having middle income (9.77%). The median age at first marriage is highest for those rich women (17 years), while similar as well as the lowest for those poor women and having middle income (16 years). And the mean age at first marriage is highest for the wealthier (18.04 years), while the lowest as well as similar for those poor women and having middle income (16 years).

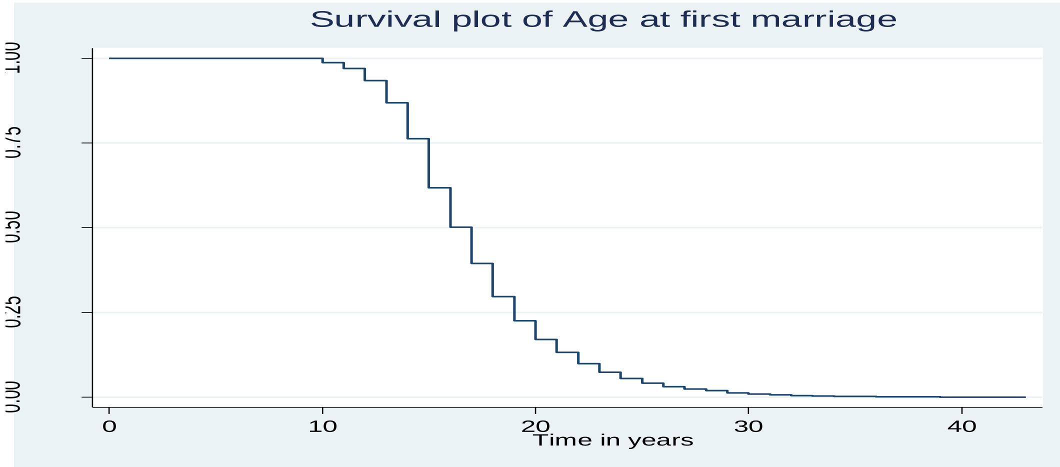
The percentage of women aged 15-49 who were married were higher for those who have not access to media(43.03%) than those having access to media(29.69%).The median age and mean age at first marriage for women age 15-49 (17 and 18 years) respectively is higher among those having better access to media than for those women not accessed.

Finally, with regard to work status of women, the percentage of women aged 15-49 who were first married were higher (46.48%) for those who have not work than those having work (26.24%). The median age and mean age at first marriage (17 and 17.60 years) respectively is higher for those working women than those are not working (Table 4.1 in Appendix).

4.2. Non-parametric Survival Analysis

4.2.1. The Kaplan- Meier Estimate of Time-to-age at first marriage

Non-parametric survival analysis is very important to visualize the survival of time-to-age at first marriage 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 marriage data set.



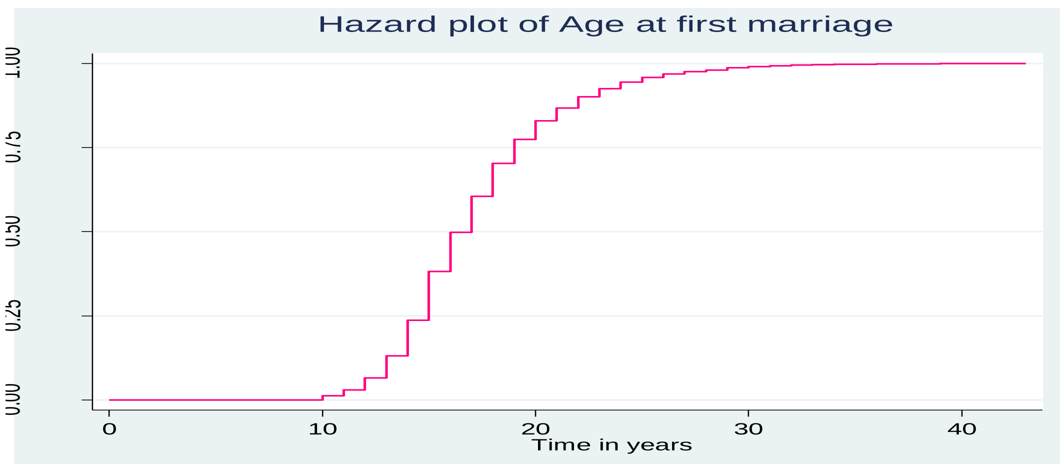


Figure 4.1: The K-M plots of Survival and hazard functions of age at first marriage.

A plot of the KM curves to the survival and hazard experience of time- to-age at first marriage 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 got first marriage early.

4.2.2 The Kaplan-Meier (KM) Survival Curve for Different Groups

The Kaplan-Meier estimate of the survival curve is the best description of times to event of a group of subjects using all the data currently available. . Survival time distribution for time-to-age at first marriage is estimated for each group using the K-M method and in order to compare the survival curves of two or more groups**.** The resulting KM survival curve based on EDHS

2016 dataset is shown in the Appendix. Note that in this plot survival time is being measured in years.

4.2.2.1 Survival probability of time (in years) by women's residence

Survival probability by women's residence VS time (in years) shown in figure 4.2 in the Appendix. This curve starts at one and continues horizontally until age at first marriage happened at 10 years; at this time, it then drops down for both women residing in urban and rural with slightly higher age at first marriage for those living in urban relative to those living rural. The longest survival time (age at first marriage) is for women who in fact married at 43 years.

4.2.2.2 Survival probability of time (in years) by women's religion

The graph of survival probability by women's religion VS time (in years) displayed in figure 4.3 in Appendix show that, those women with orthodox, protestant, Catholic Muslim and other religion seems to be overlapped. 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 getting first marriage for women's religion is the same.

4.2.2.3 Survival probability of time (in years) by women's educational attainment

Figure (4.4, in the appendix) shows the K-M plot of time-to-first marriage by level of women's education. From this plot we can observe that the risk of getting first 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 age at first marriage for women having no education is below others. The differences that are displayed in survival curve emphasize that the risk of getting first marriage for educated women is lower than uneducated.

4.2.2.4 Survival probability of time (in years) by access to media

The curves that survival probability by access to media VS time (in years) shows that the risk of getting first marriage for women have better access to media is lower than those are not(figure 4.5 in Appendix).

4.2.2.5 Survival probability of time (in years) by wealth index

From the plot that survival probability by wealth index VS time (in years) in figure 4.6 in Appendix shows that, the risk of getting first marriage for wealthier women is higher than others.

Here the curve for poor and middle seems to be overlapped. But it seems as there is least gap among curves.

4.2.2.6 Survival probability of time (in years) by women desire more children

Figure 4.7 in Appendix indicates that survival probability by women desire more children VS time (in years). From the figure we see that, the risk of getting first marriage for women desire more children is higher than women who don't no.

4.2.2.7 Survival probability of time (in years) by women's working status

Figure 4.8 in Appendix indicates that survival probability by women's working status VS time (in years). This curve starts at one and continues horizontally until age at first marriage happened at 10 years; at this time, it then drops down for both women having work and not working with slightly higher age at first marriage for those having work relative to those do not have work.

4.3. Statistical Model for Survival Analysis

The statistical models that we consider in this study were especial case of mixed effect cox regression model (Parametric shared frailty model). First let us try to see multivariable survival analysis using parametric shared frailty model with model comparison among various parametric shared frailty models and then finally we intend to compare between one best selected model among various parametric shared frailty models for EDHS 2016 dataset. As a result the elaboration or justification of the study for the latter case should be based on the final selected model.

4.3.1 Multivariable Analysis and Model Comparisons for Parametric shared frailty model

The multivariable survival analysis in this part of the study was done by assuming the exponential, weibull, log-logistic and lognormal distributions for the baseline hazard function; and the gamma and inverse Gaussian frailty distributions. It was performed using the covariates; residence, education level of women, religion, work status of women, access to media of women, desire for more children and wealth index of household. In this study, we used the AIC and BIC criteria to compare various candidates of parametric shared frailty models. The model with the smallest AIC and BIC value is considered a better fit.

Table 4.2: AIC value and test of unobserved heterogeneity for multivariable parametric shared frailty models, EDHS 2016

Baseline Distribution	Shared Frailty model	AIC	BIC	Theta(θ)	P-value
Exponential	Gamma	23335.38	21347.09	0.0042	0.005
	Inverse-Gaussian	23213.67	20876.56	0.0065	0.005
Weibull	Gamma	3938.43	3820.97	0.0239	0.000
	Inverse-Gaussian	2191.38	2073.91	0.04633	0.000
Log-Logistic	Gamma	3868.80	3751.33	0.01826	0.000
	Inverse-Gaussian	3877.31	3759.85	0.01102	0.000
Lognormal	Gamma	3799.63	3726.28	0.01892	0.001
	Inverse-Gaussian	3797.68	3724.25	0.02005	0.001

P-value= P-value for Likelihood-ratio test of theta=0, θ =theta (variance of random terms),

Based on Table 4.2 the variance of the random effect (θ=0.04633) was highest and significant for Weibull-Inverse-Gaussian shared frailty model than the other models. And the AIC and BIC values of the Weibull-Inverse-Gaussian shared frailty model (2191.377, 2073.91) respectively, was the minimum among all the other AIC and BIC values of the parametric shared frailty models. This indicates that it was relatively the most efficient model to describe these dataset.

Table 4.3: Multivariable analysis using the Weibull- Inverse Gaussian shared frailty model, EDHS 2016

Covariates	Coef.	Std. Err.	Z	Φ	P>|z|	[95% Conf. Interval for Φ]	
Constant	2.86356	.0090242	317.32	17.5238	<0.001	17.21658	17.8365
Residence							
Urban(ref)							
Rural	-.0699977	.0065564	-10.68	0.932396	<0.001	0.920491	0.944455
Religion							
Orthodox(ref)							
Catholic	.0050433	.0272536	0.19	1.005056	0.853	0.952779	1.060202
Protestant	.0277478	.0060454	4.59	1.028136	<0.001	1.016026	1.040391
Muslim	.0071301	.0048467	1.47	1.007156	0.141	0.997634	1.016768
Others	.0343618	.0191914	1.79	1.034959	0.073	0.996753	1.07463
Womeneducation alattaint							
No education (ref)							
Primary	0.095049	.0051366	9.24	1.099713	<0.001	1.013022	1.113154
Secondary	.0973622	.0082839	11.75	1.10226	<0.001	1.084508	1.120302
Higher	.1813872	.0104981	17.28	1.198879	<0.001	1.174463	1.223803
Accessetomedia							
No(ref)							
Yes	.0922026	.0053125	0.04	1.096587	<0.001	1.010251	1.139541
Wealth							
Poor(ref)							
Middle	.0041044	.0064807	0.63	1.004113	0.527	0.991439	1.016948
Rich	.0117206	.0061216	1.91	1.01179	0.056	0.999723	1.024002
Desire of children							
Yes(ref)							
No	-.0298461	.0043912	-6.80	0.970595	<0.001	0.962277	0.978984
Working status							
No(ref)							
Yes	-.0060608	.0044929	-1.35	0.993958	0.177	0.985243	1.002749
	θ=0.04633	γ =0.149					
	τ = 0.0342						
	LR test of theta=0: chibar2(01) = 1997.73			Prob >= chibar2 = 0.000			

Coef= coefficient, S.e= standard error, ϕ = acceleration factor, 95% CI=Confidence Interval for acceleration factor, LCL=lower class limit, UCL= upper class limit, Chi-sq= Chi-square, Ref=Reference, θ = variance of the random effect, λ = scale parameter, γ = shape parameter, τ = Kendall's Tau.

Based on Gamma – Inverse Gaussian shared frailty model, covariates such that place of residence of women, categories of religion of women, education level of women, access to media and desire of more children were significant at 5% level of significance. In contrast work status of women and wealth index of household were not significant at 5% level of significance.

Acceleration factor of place of residence was 0.932 (95% CI: (0.920, 0.944)) for women who resided in rural. Women resided in rural area of Ethiopia have married early than those resided in urban area of Ethiopia (ϕ=0.932). Acceleration factor of access of media was 1.097 (95% CI:

(1.010, 1.140)) for women who had any access of media. Women who had not any access of media have married early than those who had any access of media (ϕ=1.097).

Acceleration factor of desire more children was .972 (95% CI: (0.962, 0.979)) for women who no desire more children. Women who desire more children have married early than those who did not desire more children.

Regarding to education level of women, the results obtained clearly showed that education has a statistically significant and strong delaying effect on marriage. The effect remained robust in the presence of a number of controls. A lower risk of getting married early among educated women may be due to waiting time for schooling, finding a match and for getting white collar jobs. Acceleration factor of education level was 1.099, 1.102 & 1.199 (95% CI: (1.0130, 1.113), (1.085, 1.120) and (1.174, 1.224) for women who attend primary school, secondary school and higher education respectively. Women who hadn't education have married early than those who attended at least primary.

Acceleration factor of religion was 1.028 (95% CI: (1.016, 1.040)) for women who are follower of protestant. Women who follow orthodox have married early than those who follow protestant.

The value of the shape parameter in the Weibull–Inverse-Gaussian shared frailty model was (γ =0.149). This indicates that non monotonic hazard rates, specifically initially increasing and then decreasing rates. The variability (heterogeneity) in the population of clusters (Region) estimated by this Weibull–Inverse-Gaussian shared frailty model was θ =0.0463, and the dependence within region was about τ = 3.4%.

4.4. Model Diagnostics

4.4.1 The Cox-Snell Residuals

The Cox-Snell residuals together with their cumulative hazard function were obtained by fitting the exponential, Weibull ,log-logistic model and lognormal models to our dataset, via maximum likelihood estimation (Figure 4.9). The plots indicate that the Weibull , Log-logistic model and lognormal models seems to fit the data well even if it is better fitted by weibull relative to others. But the exponential model fits poorly relative to others. These results are consistent with our previous results (in table 4.2) based on Akaike's information criterion. The plots of Cox-

Snell residuals VS estimated cumulative hazard function were nearest to the line through the origin for all models.

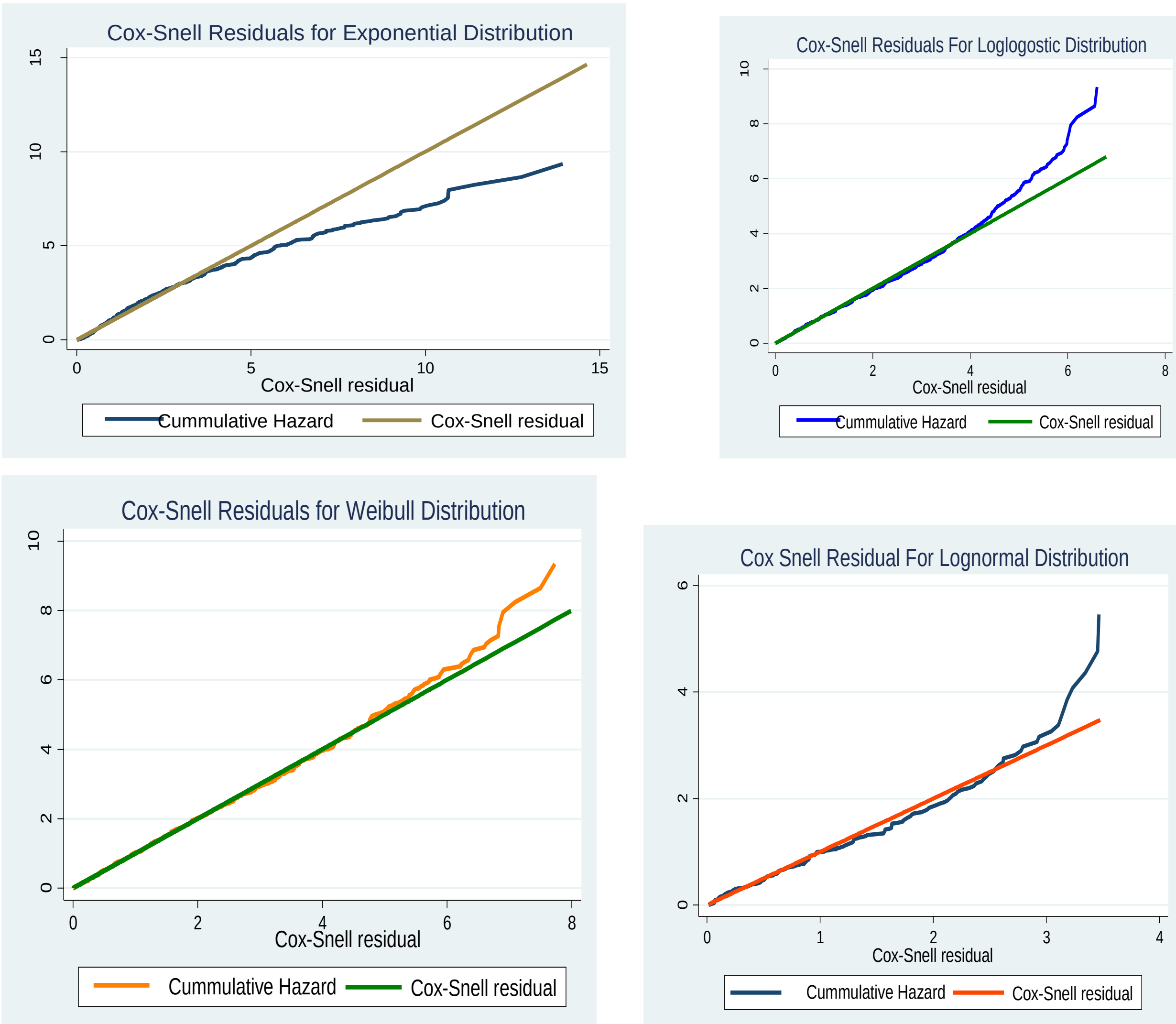


Figure 4.9: Cox–Snell residuals to evaluate model fit of Exponential, Weibull, Log-logistic and Lognormal model

4.5. Discussion

The main goal of the study was determining factors of time-to- age at first marriage among women in Ethiopia using parametric shared frailty models by considering four baseline distributions: Exponential, Weibull, log-logistic, and log-normal distributions and two shared frailty model: gamma and Inverse-Gaussian frailty. Covariate which were included in the study were residence, religion, woman's educational level, wealth index, access to mass media, desire of children, and working status of the respondent and the outcome variable of interest was the survival of time-to-age at first marriage measured in years.

The estimated median age of women at marriage was 17 years. Which is almost similar with the (Tessema et al., 2015) reported that about 60.6% of Ethiopian women were married before the age of 18 years using 2011 EDHS.

The results of this study suggested that place of residences was significant predictive factor for age at first marriage in Ethiopian women. This shows that women who lived in urban areas are more survived on age at first marriage than women who lived in rural areas. This might be due to the fact that rural areas tend to have institutional and normative structures such as the kinship and extended family that promote early marriage and childbearing, but women in urban areas need to develop skills, gain resources, and achieve maturity to manage an independent household and thus they have to delay marriage. Rural inhabitants have usually no access for maternal health and family planning programs as compared to urban residents (Woldemicael, 2008) which may result in early married as compared to urban. This finding is supported by in Nigeria by (Thomas, 2010), (Stokes and Hsieh, 1983) in Taiwanese women. They reported that rural women had got married earlier than urban women when the effect of other covariate held fixed.

This study also showed that women with primary, secondary and above education have faster transition to first marriage 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 age at first marriage. According to (Tessema et al., 2015) in Ethiopia age at marriage for educated women was greater than uneducated in Ethiopia which has a direct effect on age at first marriage. Moreover, education increases marital stability through secured financial resources (Ikamari, 2005). This is also more survived on age at first marriage. 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 (Gurmu and Etana, 2013) in Ethiopia,(Suwal, 2001) in Nepal, (Logubayom and Luguterah, 2013) and (Somo-Aina and Gayawan, 2019)in Ghana.

And also a study conducted in Ethiopian regions by (Erulkar, 2013) investigated the factors associated with marriage and the result suggested that educational attainments of women had significant effect on marriage and women who were not educated were married earlier than educated. And the study conducted by (Agaba et al., 2010) in Uganda, educational attainments of women had significant effect on marriage. Our finding is supported by these studies since our study revealed that educational level of women had a significant effect on time to age at first marriage at 5% level of significance.

Access to mass media was found to have a significant effect on age at first marriage. The findings of this study showed that women who had no access of media were married at earlier age than those who had access of media. This finding had consistent with (Zahangir and Kamal, 2011),(Zahangir et al., 2008). Religion of women was found to have a significant effect on age at first marriage in our study. The result showed that women who follow protestant religion had prolonged time to age at first marriage than those who follow orthodox religion. This finding is consistent with (Hoq, 2013). The results of this study suggested that desire for more children was significant predictive factor for age at first marriage in Ethiopian women. This shows that women who desire more children were married at earlier age than those who were not desire. This is consistent with (Ezeh et al., 2009).

In this study work status of women was not a significant factor in determining time to age at first marriage among women living in Ethiopia. This is not consistent with the finding of (Shapiro and Tambashe, 2001) , (Zahangir et al., 2008) and (Kamal, 2011), they revealed that work status of women have significant effect on age at first marriage. With regards to wealth index was insignificant in determining time to age at first marriage among women. This is not similar with the study conducted by (Kamal, 2011).

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The main objective of this study was to model time-to- age at first marriage among women living in Ethiopia using appropriate shared frailty model by comparing different parametric survival models. To model the determinants of time-to-age at first marriage, different parametric shared frailty models by using different baseline distributions were applied. The comparison different parametric shared frailty models for the dataset was performed using the AIC and BIC criteria, where a model with minimum AIC and BIC is accepted to be the best. Accordingly, the Weibull-Inverse-Gaussian frailty model which has smallest AIC and BIC value was the most appropriate model to describe the dataset.

This study also showed that there was a clustering (frailty) effect on modeling time-to- age at first marriage among women living in Ethiopia due to the fact that heterogeneity in Region from which the women live in, assuming women living in the same Region share similar risk factors related to marriage. Therefore, it was important considering the clustering effect in modeling the hazard function. This study also revealed that, of all 15683 women age 15-49, 11045(72.27%) were married and the median & mean age at first marriage for women living in Ethiopia were 17 years and 17.25 years respectively, while the minimum and maximum age at first marriage observed were 10 years and 43 years respectively.

The median age of women at first marriage was 17 years. It is lowest for Amhara region, while highest for Addis Ababa administration city when compared to other regions in Ethiopia. The dataset was also best described by the weibull baseline as compared to the exponential, log-logistic and lognormal hazard functions. According to the cumulative hazard plots for the Cox-Snell residuals of the exponential, weibull, log-logistic and the lognormal models, the plot was more approached to the line in case of the weibull model, indicating that the weibull was relatively best. The determinant factors considered were residence of women, educational level of women, religion of women, work status of women, access to mass media, wealth index of household and desire of more children.

Analysis using the best model, Weibull-Inverse-Gaussian shared frailty model showed that residence of women, educational level of women, religion of women, access to media and desire for more children were the most significance factors for the time-to-age at first marriage. Women residing in urban part of Ethiopia had prolonged age at first marriage as compared to those residing in rural part of Ethiopia. Concerning educational level of women, women having better education had prolonged age at first marriage than illiterate women. With regards to religion of women, protestant follower women had prolonged age at first marriage compared to those who follow orthodox religion. In case of desire for more children women no desire more children had prolonged age at first marriage as compared to women desire for more children.

5.2 Recommendation

This study has implications for policies and programs that seek to increase women's age at first marriage. It is crucial to continue improving girls and young women access to education in the region, as this is important avenue for raising the women's age at first marriage. Awareness has to be given for the society on age at marriage. The education sector can play an effective role in this regard and the awareness need to follow the ordinance of the legal age of marriage because it is the most determinants of health for women and child borne.

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

- Awareness about the impact of early marriage should be given for rural women through health workers, health extensions or any other concerned bodies.
- Moreover, it is advisable to target young women, particularly those with no or little education including primary school girls, with information on reproductive health and to provide them to avoid ultimately early age marriage.
- And it is advisable to target young women, particularly those with no or little education, with information on reproductive health and to provide them with basic life skills to enable them to avoid early marriage.
- Religious leaders can also play an important role to delay age at first marriage among women in Ethiopia.

- Further studies should be conducted in each region of Ethiopia and identify other factors that are not identified in this study for instance culture of the society. Based on that study, regional governments should take actions to avoid early marriage.

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APPENDIX

Table 4.1:Descriptive summary for women age at first marriage by categories of covariates.

Covariates	Category	No. of Women (PerceSntage)	No. of Women ever married (Percentage)	Mean (Year)	Median (year)
Region	Tigray	1,682(10.72)	1,239 (10.86)	16.62	16
	Afar	1,128(7.19)	962(8.43)	16.26	16
	Amhara	1,719(10.96)	1,347 (11.81)	15.88	15
	Oromia	1,892(12.06)	1,462 (12.82)	17.14	16
	Somali	1,391(8.87)	1,089(9.55)	17.58	17
	Benishangul gumez	1,126(7.18)	886 (7.77)	16.69	16
	SNNRP	1,849(11.79)	1,293 (11.34)	17.45	17
	Gambela	1,035(6.60)	829 (7.27)	16.97	16
	Harari	906 (5.78)	679 (5.95)	17.84	17
	Addis Abeba	1,824(11.63)	867(7.60)	20.70	20
	Diredewa	1,131(7.21)	752 (6.59)	17.87	17
Residence	Urban	5,348 (34.10)	3,183(27.91)	18.73	18
	Rural	10,335(65.90)	8,222 (72.09)	16.68	16
Religion	Orthodox	6,413(40.89)	4,366(38.28)	17.40	17
	Catholic	91(0.58)	66(0.58)	17.42	17
	Protestant	2,814(17.94)	1,991(17.46)	17.52	17
	Muslim	6,209(39.59)	4,845 (42.48)	17.01	16
	Others	156(0.99)	137(1.20)	17.35	17
Educational attainment	No education	7,033 (44.84)	6,506(57.05)	16.63	16
	Primary	5,213(33.24)	3,209(28.14)	17.07	17
	Secondary	2,238 (14.27)	1,057(9.27)	19.20	19
	Higher	1,199(7.65)	633(5.55)	21.29	21
access to media	Yes	7,346(46.840	4,656(40.82)	18.00	17
	No	8,337(53.16)	6,749(59.18)	16.74	16
Wealth	Poor	5,940(37.88)	4,959(43.48)	16.65	16
	Middle	2,002(12.77)	1,532(13.43)	16.65	16
	Rich	7,741(49.36)	4,914(43.09)	18.04	17
Desire for more Children	Yes	11,420(72.82)	7,375 (64.66)	17.54	17
	No	4,263(27.18)	4,030(35.34)	16.73	16
Respondent currently working	No	10,011(63.83)	7,289(63.91)	17.05	16
	Yes	5,672 (36.17)	4,116(36.09)	17.60	17

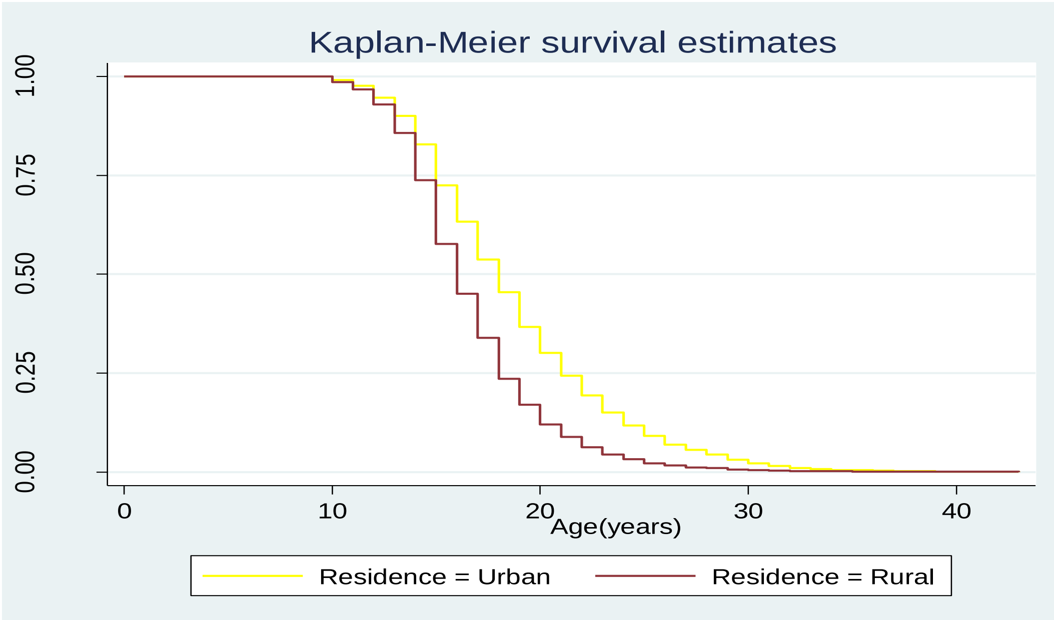

Figure 4.2: Survival function estimate of AFM grouped by Place of residence

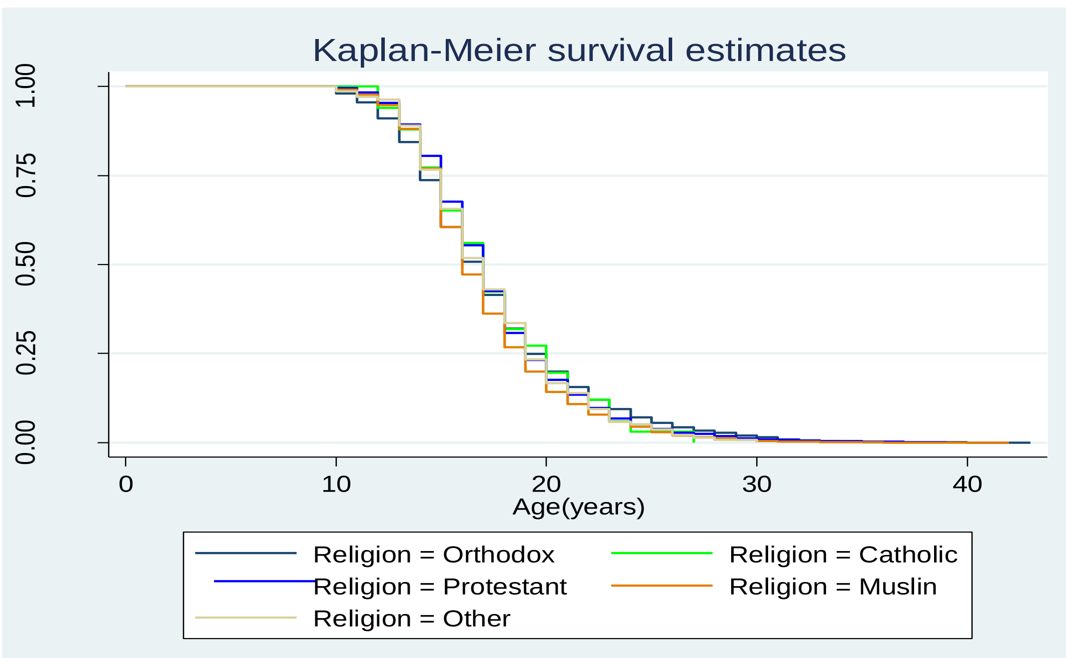

Figure 4.3: Survival function estimate of AFM grouped by Religion

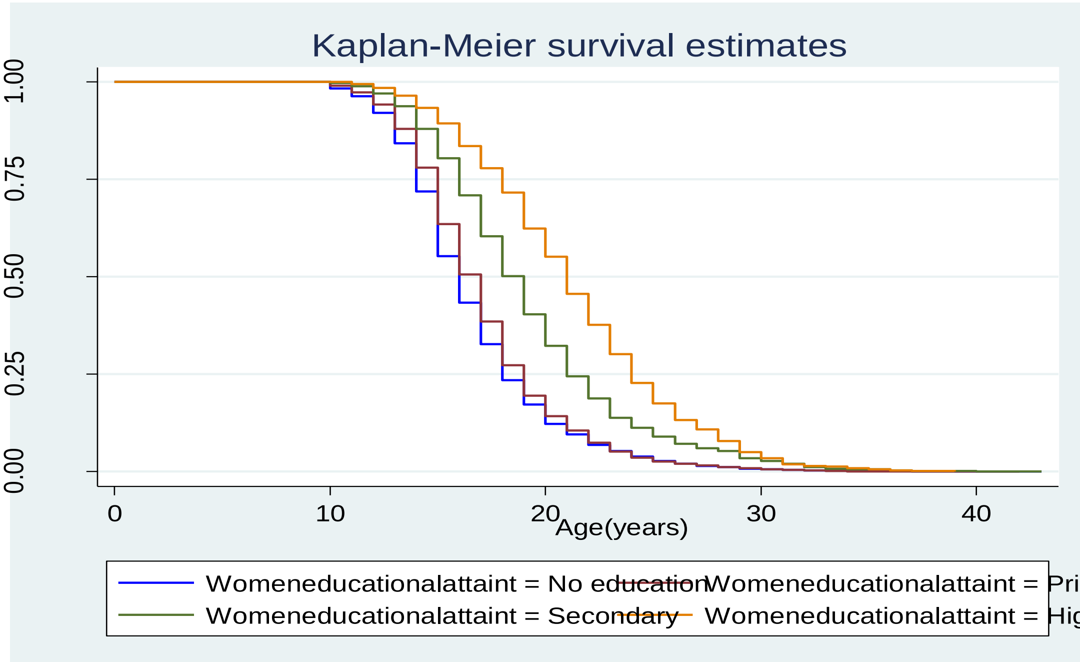

Figure 4.4: Survival function estimate of AFM stratified by women educational attainment

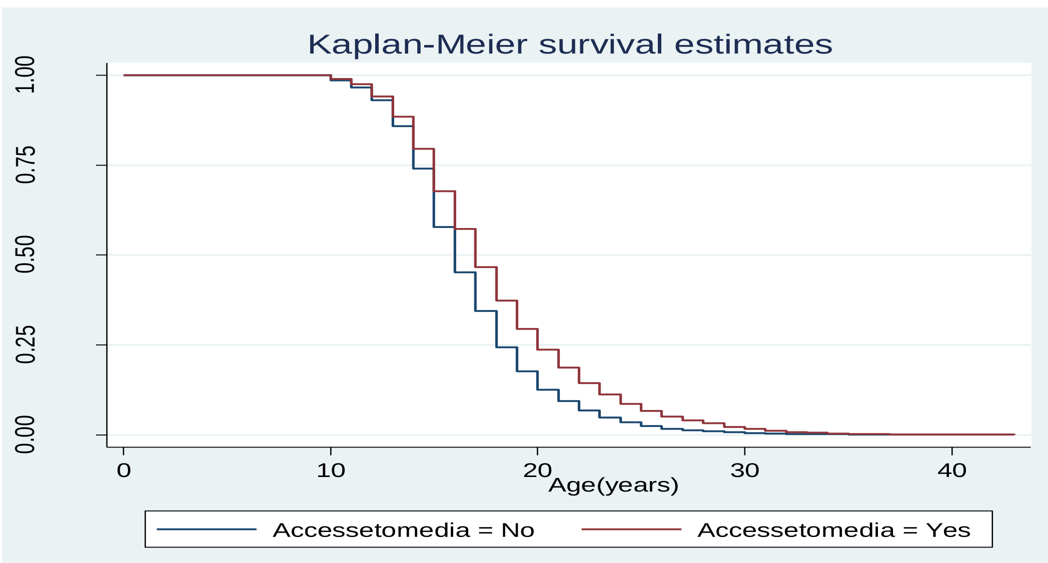

Figure 4.5: Survival function estimate of AFM stratified by Access to media

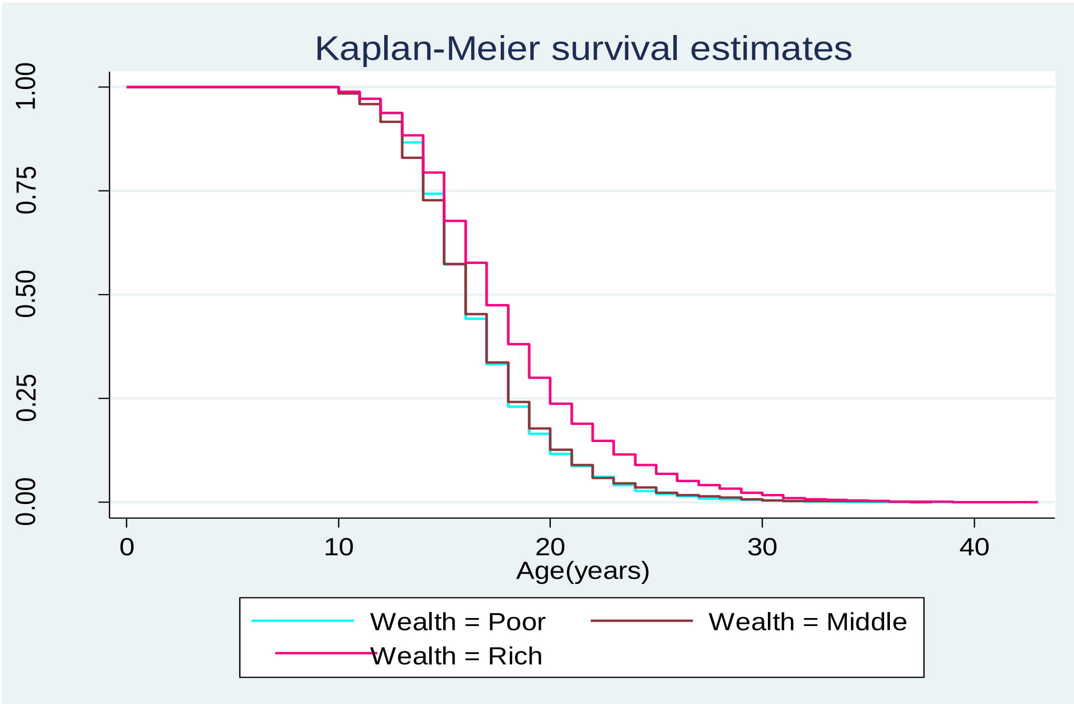

Figure 4.6: Survival function estimate of AFM stratified by wealth

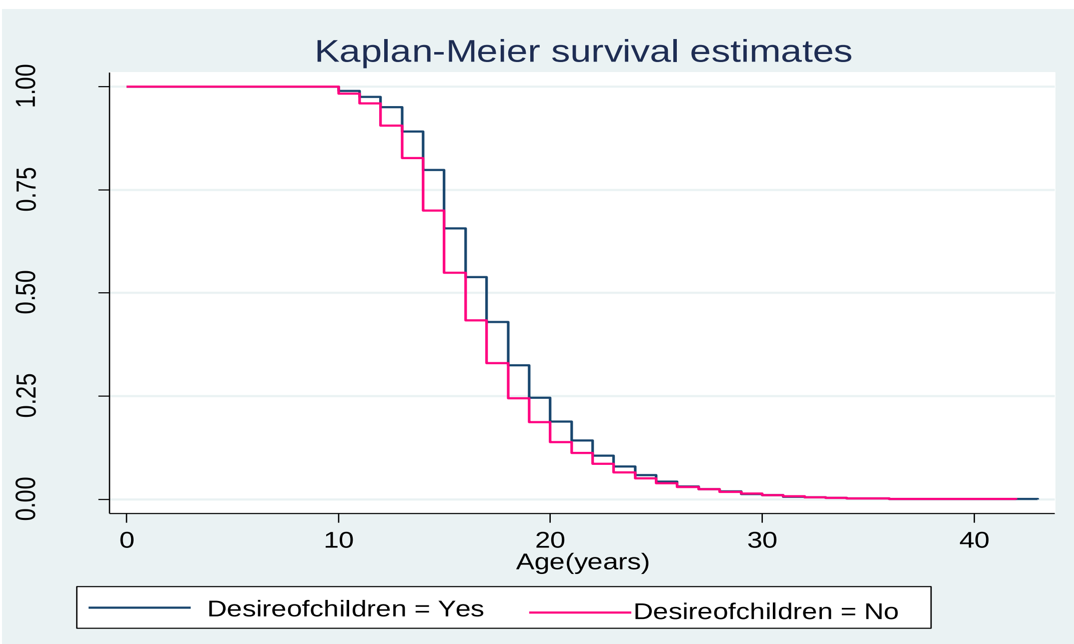

Figure 4.7: Survival function estimate of AFM stratified by desire of children

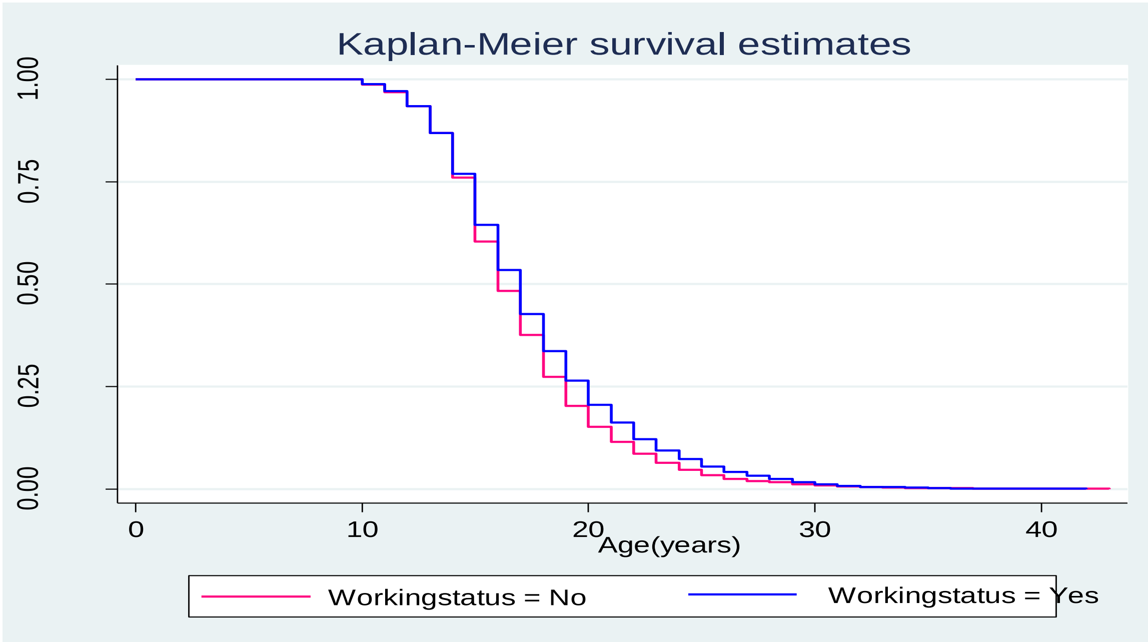

Figure 4.8: Survival function estimate of AFM stratified by working status