Addis Ababa University

College of Natural and Computational Sciences

Department of Statistics

DETERMINANTS OF TIME TO SECOND BIRTH AMONG WOMEN OF REPRODUCTIVE AGE IN ETHIOPIA: AN APPLICATION OF PARAMETRIC SHARED FRAILTY MODEL

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This is to certify that the thesis prepared by Sintayehu Birhanu Arja, entitled: "***Determinants of Time to Second Birth among Women of Reproductive Age in Ethiopia: An Application of Parametric Shared Frailty Model***" submitted in partial fulfilment 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.

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This thesis has been submitted for examination with my approval as a university advisor.

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Abstract

Determinants of Time to Second Birth among Women of Reproductive Age in Ethiopia: An Application of Parametric Shared Frailty Model

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The term "birth interval" denotes the duration between the birth of one child and the subsequent birth. This study aimed to discern the factors influencing the second birth interval among women in Ethiopia, utilizing a parametric shared frailty model. Data was sourced from the 2019 Ethiopian Mini Demographic and Health Survey, comprising 5846 women aged 15-49 years. Both accelerated failure time and gamma shared frailty models were employed in this study, with the performance of fitted models compared using AIC. The findings revealed that 4,678 (80.02%) women experienced a second birth. The log-logistic gamma shared frailty model demonstrated the lowest AIC value and was consequently selected for final analysis. The analysis from the fitted log-logistic gamma shared frailty model highlighted the significance of clustering effects. Moreover, factors such as women's age, marital status, level of education, place of residence, age at first birth, contraceptive usage, and child survival status emerged as the most influential determinants of the second birth interval. Conversely, variables like wealth index and breastfeeding status were found to be insignificant covariates. Specifically, an increase in women's age correlated with a decrease in the time to the second birth, while factors such as marital status, level of education, rural residency, being aged 20-24 years at first birth, and contraceptive usage were associated with longer intervals between births. Government health policies and interventions aimed at enhancing maternal and child health programs should prioritize women's education, and efforts should be made to encourage and facilitate the use of contraceptive methods for family planning and birth spacing purposes.

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List of Abbreviations & Acronyms

AFT Accelerated Failure Time

AIC Akaike Information Criterion

CI Confidence Interval

CSA Central Statistical Agency

Df Degree of freedem

DHS Demographic and Health Surveys

EAs Enumeration Areas

EDHS Ethiopian Demographic and Health Survey

EMDHS Ethiopia Mini Demographic and Health Survey

EPHC Ethiopia Population and Housing Census

EPHI Ethiopian Public Health Institute

FMoH Federal Ministry of Health

HRs Hazard Ratios

KM Kaplan-Meier

LR Likelihood Ratio

MLE Maximum Likelihood Estimation

PH Proportional Hazard

SE Standard Error

WHO World Health Organization

Chapter 1

Introduction

1.1 Background of the Study

Population structures evolve due to fertility, mortality, and migration dynamics (Gu et al., 2021). Fertility stands out as a key determinant of population growth, significantly shaping both its size and composition (Yohannes et al., 2011). Identified as a primary driver of population growth, high fertility rates present concerns for countries worldwide due to their potential impact on economic, political, and social dimensions (Ayanaw, 2008; Götmark and Andersson, 2020). Moreover, high fertility imposes burdens on maternal and child health, amplifying risks and complications (Tessema et al., 2013).

Recognizing the health risks, the World Health Organization (WHO) recommends spacing births between three to five years to mitigate health hazards for both mothers and children. Birth interval, denoting the period between successive childbirths, carries significant implications for maternal and child well-being, as well as for population dynamics and family planning (Dhingra and Pingali, 2021; WHO, 2007).

Across countries and regions, birth intervals vary widely. Particularly in low- and middle-income nations like those in sub-Saharan Africa and South Asia, short birth intervals prevail due to diverse factors including cultural norms, limited access to family planning services, and insufficient awareness regarding birth spacing benefits. These shorter intervals heighten risks to maternal and child health, contributing to elevated rates of mortality, preterm births, and other adverse outcomes (Pimentel et al., 2020).

Evidence from Demographic and Health Surveys (DHS) highlights the positive impact of longer birth intervals on reducing infant and maternal mortality rates (Molitoris et al., 2019). Yet, millions of women in underdeveloped regions lack access to modern family planning methods, resulting in constrained birth spacing choices (Abdel-Fattah et al., 2007; WHO, 2007). Similarly, data from developing nations underscores that a significant proportion of births occur within short intervals following the preceding birth (Rutstein, 2005).

Optimal birth spacing correlates with enhanced maternal and child health outcomes. Adequate time between pregnancies allows for physical recovery, emotional bonding, and improved child growth and development (Conde-Agudelo et al., 2012).

Ethiopia, confronting rapid population growth despite governmental efforts to enhance maternal and child health, faces challenges posed by short birth intervals (Gebremedhin, 2022).

Understanding the determinants of birth intervals among Ethiopian women is pivotal for formulating targeted interventions and policies. Various factors including maternal age, parity, education, socio-economic status, healthcare access, cultural beliefs, and contraceptive utilization influence birth spacing (Faruk et al., 2023). While existing studies offer insights, further research is warranted to delve into the specific determinants within Ethiopia, empowering stakeholders to design effective interventions and bolster maternal and child health outcomes (Shifti et al., 2020b).

1.2 Statement of the Problem

The period between successive live births, carries considerable implications for both maternal and child health outcomes, as well as for population dynamics (Molitoris et al., 2019). Extensive research has demonstrated that the timing and spacing of births can significantly impact maternal physical and mental well-being, child development, and family dynamics (Kreyenfeld et al., 2017; Zhang and Emery, 2023).

Short birth intervals, prevalent particularly in many low- and middle-income nations, are linked with heightened risks of adverse health outcomes, encompassing maternal malnutrition, preterm births, low birth weight, and infant and maternal mortality (Belachew et al., 2023). Optimal birth spacing, conversely, correlates with reduced risks of maternal morbidity and mortality, enhanced child health and nutrition, and overall family welfare improvement (Conde-Agudelo et al., 2012; Rutstein and Winter, 2014). Longer birth intervals afford women adequate time for physical and emotional recovery from previous pregnancies, as well as access to family planning services, thereby yielding improved maternal and child health outcomes (Rodríguez-Almagro et al., 2019).

Ethiopia, characterized by its large population and diverse socio-cultural milieu, grapples with distinct challenges in maternal and child health alongside population growth. Elevated fertility rates and short birth intervals exacerbate maternal and child mortality rates, placing strain on the healthcare system and hindering socioeconomic progress (Assefa et al., 2019). Despite progress in enhancing reproductive health outcomes, including increased contraceptive utilization and declining fertility rates, there persists a necessity to comprehensively grasp the factors influencing birth intervals to address enduring gaps and formulate targeted interventions (Shifti et al., 2020a).

This study concentrates on the occurrence of second births due to its influence on demographic trends, maternal and child health outcomes, and family dynamics. Understanding the determinants of the second birth interval holds paramount importance in crafting effective interventions and policies aimed at promoting optimal reproductive health, enhancing maternal and child well-being, and aiding families in decision-making (Zhang and Emery, 2023).

Thus, this study is driven to examine the determinants of the second birth interval among Ethiopian women, considering various socio-demographic, economic, and reproductive health factors. The objective is to furnish evidence-based insights into the factors shaping birth intervals among Ethiopian women through the identification and analysis of these determinants. Consequently, the study aspires to address the following research questions:

- What is the median duration of the second birth interval among women in Ethiopia, and how does it differ across various demographic subgroups?
- What factors contribute to the length of the second birth interval among women in Ethiopia?
- Does the duration of the second birth interval vary within different clusters across Ethiopia?

1.3 Objectives of the Study

1.3.1 General Objective

The goal of this study was to pinpoint the factors influencing the duration of the second birth interval among women of childbearing age in Ethiopia.

1.3.2 Specific Objectives

This study is motivated to address the following specific objectives:

- To estimate the median second birth interval time in women of childbearing age in Ethiopia.
- To examine variations in birth interval times across different demographic subgroups.

1.4 Significance of the Study

Studying the second birth interval holds significant importance as it marks a crucial phase in family formation and fertility patterns, thereby impacting population growth, demographic shifts, and societal development. Consequently, the findings of this study stand to offer valuable insights into the determinants of the second birth interval among women in Ethiopia.

Specifically, this research contributes to the existing body of knowledge concerning birth spacing practices within the Ethiopian context. It sheds light on the cultural, social, and economic factors that influence birth intervals in Ethiopia, thereby enriching our understanding of reproductive behaviors in this setting. Moreover, by incorporating a larger sample size and encompassing diverse populations from various regions of Ethiopia, this study enhances the generalizability of its findings, thereby increasing their applicability to broader contexts.

Furthermore, the findings of this study hold practical implications for the development of evidence-based interventions and policies aimed at promoting optimal birth spacing practices in Ethiopia. By identifying the factors that influence the second birth interval, this research provides a foundation for the design and implementation of targeted strategies to improve maternal and child health outcomes and foster sustainable population growth.

Chapter 2

Literature Review

2.1 Operational Definitions

Second Birth Interval: The second birth interval denotes the time-frame between the birth of the first child and the conception of the second child (Afolabi et al., 2021; Afolabi and Palamuleni, 2022).

Short Birth Interval: A short birth interval is defined as an interval of less than 24 months between consecutive births. This classification aligns with the widely accepted categorization of birth intervals in existing literature (Gebrehiwot et al., 2019).

Timing of Birth Intervals: The timing of birth intervals refers to the sequential order of births within a woman's reproductive history. It categorizes birth intervals as first birth, second birth, third birth, and so forth, based on the sequence of pregnancies and deliveries (Casterline and Odden, 2016).

Spacing of Birth Intervals: The spacing of birth intervals pertains to the duration between successive births, typically measured in months or years. It can be categorized as short, medium, or long based on predetermined intervals, such as less than 24 months for short spacing, 24 to 47 months for medium spacing, and 48 months or more for long spacing (Gebrehiwot et al., 2019).

2.2 Empirical Literature Review on Birth Interval

Understanding the factors influencing birth intervals among Ethiopian women holds critical significance in addressing the challenges posed by high fertility rates and short birth intervals. These determinants encompass a wide array of individual, social, cultural, economic, and healthcare-related factors (Hailu and Gulte, 2016). Exploring these factors provides valuable insights into the intricate dynamics shaping birth spacing practices in Ethiopia. The following section delves into key determinants identified in the literature, which have implications for Ethiopian reproductive health programs and policies.

Maternal age emerges as a pivotal factor influencing birth intervals. Younger mothers often experience shorter birth intervals due to higher fertility rates and a desire to complete their desired family size earlier in life (Ajayi and Somefun, 2020; Pimentel et al., 2020). Factors such as early marriage and societal pressure for early childbearing also contribute to shorter birth intervals among younger mothers (Aleni et al., 2020). Conversely, older mothers tend to have longer birth intervals due to increased maternal age-related risks, a focus on providing quality care to existing children, the pursuit of educational or career aspirations, a desire for smaller family sizes, and potentially greater access to family planning resources (Finlay et al., 2017; Hailemeskel et al., 2020).

Parity, or the number of previous live births, is closely linked to birth intervals. Women with fewer children may opt for shorter birth intervals to complete their desired family size within a shorter time-frame, driven by cultural or personal preferences. Conversely, those with higher parity may choose longer birth intervals to ensure adequate care, resources, and attention to existing children, possibly influenced by considerations of the financial burden associated with raising multiple children simultaneously (Hajian-Tilaki et al., 2009; Singh et al., 2011).

Educational attainment significantly influences birth intervals, with higher levels of education associated with longer intervals (Abdel-Fattah et al., 2007; Belachew et al., 2023; Kamal and Pervaiz, 2012). Education empowers women by providing knowledge about family planning methods and reproductive health, enabling them to delay subsequent pregnancies to pursue educational and career opportunities (Barclay and Kolk, 2017). Additionally, education enhances decision-making power and access to resources necessary for effective family planning (Brown et al., 2015).

Socioeconomic factors, including income level, poverty, and household wealth, play a significant role in birth spacing. Women from lower socioeconomic backgrounds may face barriers to accessing healthcare and family planning resources, resulting in shorter birth intervals (Abdel-Fattah et al., 2007). Economic constraints may also influence preferences for longer birth intervals, driven by considerations of financial stability and the ability to support larger families. Conversely, women with higher socioeconomic status often have better access to healthcare services, including contraception, and may be more aware of the benefits of birth spacing for maternal and child health (Shifti et al., 2020b).

Access to high-quality healthcare services is crucial for birth interval determination. Adequate access to reproductive health services, such as antenatal care, skilled birth attendants, and contraception methods, enables informed decision-making about birth spacing (Yirgu et al., 2020). Access to healthcare facilities and trained providers ensures that women receive appropriate family planning counseling and have access to a variety of contraceptive options tailored to their needs. Limited access to healthcare services can lead to shorter birth intervals and increased maternal and child health risks (Muchie, 2017). Comprehensive reproductive health services, including prenatal and postnatal care, contribute to longer birth intervals and improved maternal and child health outcomes (Yirgu et al., 2020).

Cultural and social factors exert significant influence on birth intervals in Ethiopia. Birth spacing practices are shaped by societal expectations, gender roles, and community perceptions of family size and fertility preferences (Shifti et al., 2020b). Cultural practices and norms, such as early marriage and limited decision-making power for women, contribute to shorter birth intervals

(Gebrehiwot et al., 2019).

Religious beliefs also impact birth intervals, with some communities favoring larger family sizes due to cultural norms emphasizing fertility and the importance of having many children (Yohannes et al., 2011). Certain religious contexts may restrict or discourage contraceptive use, leading to shorter birth intervals (Obilor and Osita-Njoku, 2021). Understanding cultural and religious factors is crucial for designing interventions that align with the values and practices of different communities (Davidson et al., 2017).

Effective contraceptive use plays a vital role in birth interval determination. Access to and use of modern contraceptive methods enable women to plan and space pregnancies, resulting in longer intervals (Karra et al., 2022). Factors influencing contraceptive use include knowledge about methods, availability and affordability of contraceptives, cultural acceptability, misconceptions and myths, and personal preferences (Blackstone et al., 2017; Yohannes et al., 2011). Increased contraceptive awareness and use contribute significantly to longer birth intervals by providing women with means to avoid unintended pregnancies (De Jonge et al., 2014).

Partner characteristics and involvement also influence birth intervals. Supportive partners who participate in reproductive decision-making and family planning discussions are crucial in promoting longer intervals (Abdel-Fattah et al., 2007). Shared responsibility for contraception and support for birth spacing decisions enhance family planning effectiveness (Kudeva et al., 2020).

Breastfeeding affects birth intervals, with exclusive breastfeeding acting as a natural contraceptive method that suppresses ovulation and delays fertility return (Kamal and Pervaiz, 2012; Kemi and Olurotimi, 2011). Extended breastfeeding duration's may result in longer intervals. However, breast-feeding's contraceptive effectiveness can vary based on factors such as duration, frequency, introduction of complementary foods, and individual fertility patterns (Mulugeta et al., 2022).

Regional and contextual factors also shape birth intervals. Variations in access to healthcare services, socioeconomic conditions, cultural norms, and geographic location can influence birth spacing practices in Ethiopia. Rural areas may have limited healthcare access and lower education levels, contributing to shorter intervals (Shifti et al., 2020a; Yohannes et al., 2011). Cultural diversity and regional customary practices further influence birth spacing decisions (Ajayi and Somefun, 2020).

A study conducted by Bayleyegne and Asfaw (2020) aimed to model birth intervals among adult women aged 15 to 49 in Ethiopia, utilizing data from the 2011 Ethiopian Demographic and Health Survey (EDHS). Employing Cox proportional hazards and shared gamma frailty models, the analysis identified significant demographic and socioeconomic factors influencing birth interval length. The results from both models highlighted the significance of factors such as maternal age, place of residence, maternal education level, wealth index, maternal age at first birth, birth order, previous child's survival status, breastfeeding status, and contraceptive use on the duration of birth intervals for Ethiopian women.

Similarly, Fagbamigbe (2020) conducted a study on the timing of second childbirth, revealing that contraceptive use, higher wealth quintile, employment status, urban residence, higher education levels among women and their spouses, and survival of the first child were protective factors for the second birth interval of women in Nigeria.

In a study by Fufa and Tolessa (2021) focusing on potential risk factors influencing women's birth intervals in rural Ethiopia using data from the 2016 EDHS, contraception use, age, marital status, religion, breastfeeding status, and women's educational level emerged as statistically significant factors affecting the timing between successive childbirths. Analysis using the Weibull inverse Gaussian model confirmed the statistical significance of contraception use, marital status, age, breastfeeding, religion, and educational level.

Mustefa and Belay (2021) investigated successive birth intervals and found marital status, religion, women's education level, husband's education level, age at first birth, and family wealth index to be significant factors influencing birth intervals among women in Ethiopia.

Furthermore, Wondiber and Eshetu (2012) examined factors influencing birth intervals in rural Ethiopia using data from the 2011 EDHS. Their findings revealed variations in the time between successive births based on region, religion, and education level. The median length of birth intervals in rural Ethiopian communities was reported as 28 months, with more than 75% of births occurring within three years.

Lastly, Tesfaye et al. (2015) analyzed determinants of birth interval in four disadvantaged regions of Ethiopia based on EDHS 2011 data. Their findings indicated that educated women, wealthy women, those adhering to the Orthodox religion, urban residents, women from the Benishangul-Gumuz region, and those whose index child survived tend to have longer birth intervals.

Chapter 3

Data and Methodology

3.1 Source of Data

The data for this study originates from the 2019 Ethiopia Mini Demographic and Health Survey (EMDHS-2019), a collaborative effort between the Ethiopian Public Health Institute (EPHI), the Central Statistical Agency (CSA), and the Federal Ministry of Health (FMoH). Serving as the second Mini Demographic and Health Survey, its primary objective was to generate reliable estimates of key demographic and health indicators nationally, as well as for urban and rural areas, and each of the country's geographical regions, including Tigray, Afar, Amhara, Oromia, Somali, Benishangul-Gumuz, Southern Nations, Nationalities, and Peoples' Region (SNNPR), Gambella, and Harari regional states, alongside the two city administrations, Addis Ababa and Dire Dawa. The survey was conducted as a population-based cross-sectional study spanning from March 21 to June 28, 2019, covering all regions across the country.

The sampling framework employed for the 2019 EMDHS comprised all census Enumeration Areas (EAs) established for the 2019 Ethiopia Population and Housing Census (EPHC) prepared by the CSA. The survey's sample design utilized a two-stage stratified sampling method. Initially, 305 EAs (212 in rural areas and 93 in urban areas) were selected with probability proportional to EA size. Subsequently, 30 households were systematically chosen from each cluster using equal probability systematic selection, along with an additional equal probability systematic selection from the newly established household listing. To ensure survey precision across regions, sample allocation was conducted, resulting in the selection of 25 EAs from eight regions (including two city administrations) and 35 EAs from the three largest regions: Amhara, Oromia, and SNNPR (EPHI and ICF., 2021).

Inclusion and Exclusion Criteria

The study will encompass women aged 15 to 49 years who had experienced at least one childbirth at the time of the survey. Conversely, women who had not given birth will be excluded from the study.

3.2 Variables of the Study

3.2.1 Response Variable

The response variable in this study was the second birth interval, which measures the duration between the first and second childbirths and is treated as a continuous variable. The survival time of the second birth interval can be regarded as time-to-event data, where the occurrence of the second birth is considered an event. For observations where the second birth has not yet occurred, the censoring indicator (status) is denoted as 0, while for those where the event (second birth) has occurred, the status is denoted as 1.

3.2.2 Independent Variables

This study examines various covariates to explore the significant determinants of the second birth interval. The covariates, along with their categories and coding scheme, are detailed in Table 3.1.

Table 3.1: Description and categories of the independent variables

Covariates	Categories with code values	Covariates	Categories with code values
Region	1 = Tigray 2 = Afar 3 = Amhara 4 = Oromia 5 = Somali 6 =Benishangul Gumuz 7 = SNNPR[d] 8 = Gambella 9 = Harari 10 = Addis Ababa 11 = Dire Dawa	Education	1 = No education 2 = Primary 3 = Secondary & Above
		Wealth Index	1 = Poor 2 = Middle 3 = Rich
		Age at first birth	1 = < 20 years 2 = 20–24 years 3 = $\geq$ 25 years
		Residence	1 = Urban 2 = Rural
Age	1 = 15-19 2 = 20-24 3 = 25-29 4 = 30-34 5 = 35-39 6 = 40-44 7 = 45-49	Religion	1 = Orthodox 2 = Protestant 3 = Muslim 4 = Others[a]
		Marital Status[b]	1 = Married 2 = Widowed 3 = Divorced
Contraceptive use	1 = No 2 = Yes	Breastfeeding status	1 = No 2 = Yes
Sex of child[c]	1 = Male 2 = Female	Survival status of child[c]	1 = Dead 2 = Alive

[a] Catholic, traditional and other religion followers, [b] Married and living with a partner are considered as married, widowed, and never in union (single) consider as widowed, and divorced and separated are considered divorced.
[c]Both the sex of the child and survival status of a child used for first birth, & [d]SNNPR is the former region of Ethiopia

3.3 Method of Data Analysis

3.3.1 Survival Analysis

Survival analysis is a statistical approach used to analyze time-to-event data, where the event of interest could be death, failure, relapse, or any other specific occurrence. Within this framework, some observations may have unknown survival times, a situation referred to as censored observation. Censoring is a distinctive aspect of survival analysis, denoting instances where information regarding individual survival times is partial or incomplete, lacking precise details about the event occurrence.

3.3.1.1 Survivor Function

The survival function; denoted as $S(t)$ is used to ascertain the probability that a woman "survives" beyond a specified time t before experiencing a second birth, given a random variable T representing the survival time. Mathematically, it is expressed as:

$$S(t) = P(T > t) = 1 - F(t) = \int_{t}^{\infty} f(u)\,du, t \geq 0 \tag{1}$$

Where $f(t)$ and $F(t)$ are the probability density and the cumulative density functions respectively of a given distribution.

3.3.1.2 Hazard Function

The hazard function denoted by $h(t)$, is a measure of the risk of the event happening at any point in time. It is the instantaneous potential per unit of time to have a second birth, given that the individual had survival (i.e. not had an event) up to time t (Kleinbaum and Klein, 2011). It is given by:

$$h(t) = \frac{f(t)}{S(t)}, F(t) = -\frac{d}{dt} lnS(t) \tag{2}$$

The cumulative hazard function H(t), is given by:

$$H(t) = \int_{0}^{t} h(u)\,du = lnS(t) \tag{3}$$

3.3.1.3 Kaplan-Meier Estimates

The Kaplan-Meier (KM) estimator is the standard non parametric estimator of the survival function, $S(t)$ proposed by Kaplan and Meier (1958) (Dudley et al., 2016). In this study on a second birth interval, the Kaplan-Meier estimator can be used to estimate the survival probability or the proportion of individuals who have not given birth again (event of interest) at different time points. The KM estimator takes into account censored observations, which occur when individuals have not experienced the event by the end of the study period or are lost to follow-up. By estimating the survival probabilities over time. The KM estimator of survival function, $\hat{S}(t)$ is given by:

$$\hat{S}(t) = \prod_{t(i) \leq t} \frac{(n_i - d_i)}{n_i} = \prod_{t(i) \leq t} \left(1 - \frac{d_i}{n_i}\right) \tag{4}$$

In the context of this study, this formula can be used to estimate the probability of not having another birth (surviving without a second birth) at a given time t, where $\hat{S}(t)$ represents the estimated survival probability at time t, d_i is the number of women who had a second birth at time t, and n_i is the number of women at risk (who have not had a second birth or experienced censoring) just before time t.

3.3.1.4 Log-Rank Test

The log-rank test is a nonparametric test used to compare the survival functions of two or more groups (Grafféo et al., 2016). In this study, a log-rank test is used to compare the birth interval distributions between different groups or assess the impact of covariates on the second birth interval. The log-rank test determines whether there are significant differences in the survival probabilities (proportions of individuals without a second birth) between the groups over time. The mathematical expression for the log-rank test statistic is given by:

$$\chi^2 = \sum \left[\frac{(O_1 - E_1)^2}{V_1} + \frac{(O_2 - E_2)^2}{V_2} + ... + \frac{(O_k - E_k)^2}{V_k} \right] \tag{5}$$

Within the context of this study, this formula can be used to calculate the log-rank test statistic, where $O_1, O_2, ..., O_k$ represent the observed number of individuals with second birth in each group, $E_1, E_2, ..., E_K$ represent the expected number of individuals under the assumption of no difference, and $V_1, V_2, ..., V_K$ are the variances of these expected numbers. By conducting the log-rank test, we can assess whether there are significant variations in the second birth interval between different groups.

3.3.2 Cox Proportional Hazard Model

The Cox Proportional Hazard (PH) model, also referred to as Cox regression, serves as a widely utilized semi-parametric regression model within survival analysis. It explores the association between covariates and the hazard function, which reflects the instantaneous risk of experiencing the event of interest at any given time (Zhang, 2016). In this investigation concerning the second birth interval, the Cox PH model can be employed to scrutinize the relationship between the lengths of second birth intervals and the covariates under examination. By utilizing the Cox PH model, we can estimate Hazard Ratios (HRs) and evaluate the influence of covariates on the second birth interval while accommodating potential non-proportional hazards. The Cox PH model is represented as:

$$h(t|X) = h_0(t)exp(\beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p) \tag{6}$$

Where $h(t|X)$ represents the hazard function at time t given the covariate values $X = (X_1, X_2, ..., X_p), h_0(t)$ is the baseline hazard function, and $\beta = (\beta_1, \beta_2, ..., \beta_p)$ are the coefficients representing the effects of the covariates. By estimating the HRs associated with the covariates, we can assess how different factors influence the survival time of the second birth interval, considering the effects of other covariates.

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

$$S(t,x) = [S_0(t)]^{exp\sum_{i=0}^{p}\beta_i X_i} \tag{7}$$

Where, $S_0(t)$ is the baseline survival function.

3.3.2.1 Parameter Estimation in Cox PH Model

Full maximum likelihood requires that we maximize with respect to the unknown parameter of interest β, and unspecified baseline hazard and survival functions. This indicates that unless we explicitly specify the baseline hazard, $h(t)$ we cannot obtain the maximum likelihood estimators for the full likelihood. However Cox (1972) introduced the partial likelihood method as the procedure to estimate the regression coefficients of the PH model. Assuming that there are no tied event times, to estimate the regression parameter $\beta^{'}$s by maximizing the partial likelihood given by:

$$L(\beta) = \prod_{i=0}^{n} \left[\frac{exp(X_i^T \beta)}{\sum_{j\varepsilon R(t_i)} exp(X_i^T \beta)} \right]^{\delta_i} ; i = 1,2,...,n; j = 1,2,...,m \tag{8}$$

Where $R(t_i) = j : t_j \geq t_i$, denotes the risk set at time t_i, n represents the number of individuals in the data set, and m the observed survival times, δ_i is an indicator variable whose value is equal to one when the event occurs or equal to zero when the event is censored.

3.3.2.2 Checking Proportionality Assumption

The Cox proportional hazards model assumes proportional hazards, where the hazard ratio remains constant over time. One common method to test this assumption is examining Schoenfeld residuals (Xue et al., 2013). These residuals compare observed and expected covariate values at each event time. Graphical assessments, like Schoenfeld residuals versus time plots, help detect departures from proportional hazards. Additional methods include log-minus-log survival plots (Kuitunen et al., 2021).

3.3.3 Accelerated Failure Time Models

The Accelerated Failure Time (AFT) model is an alternative model if the proportionality assumption of the Cox PH model does not hold. An AFT survival model is an alternative approach to analyzing survival data, where the focus is on modeling the underlying distribution of the survival times rather than the hazard function (Majeed, 2020). AFT models assume a specific distribution for the time between births, such as exponential, Weibull, log-logistic or log-normal. These models allow us to investigate the relationship between second birth interval lengths and covariates of interest, assuming a linear relationship. By utilizing AFT models, we can estimate the effects of covariates on the log-transformed the second birth interval lengths and understand how different factors influence the survival time of second birth interval. The AFT model mathematically is given by:

$$log(T_i) = \alpha + \beta_1 X_1 + ... + \beta_p X_p + \sigma \varepsilon_i \tag{9}$$

Where $log(T_i)$ represents the logarithm of the second birth interval length, $X_1, X_2, ..., X_p$ are the covariates, α is the intercept, $\beta_1, \beta_2, ...\beta_p$ are the coefficients representing the effects of the covariates, σ is the scale parameter, and ε_i is the error term assumed to follow a specific distribution. By fitting this model, one can estimate the effects of covariates on the log-transformed second birth interval lengths and gain insights into how these covariates impact the timing and spacing of births.

3.3.3.1 Weibull AFT Model

The Weibull distribution (including the exponential distribution as a special case when the shape parameter is equal to one) is a very flexible model for time-to-event data. It has a hazard rate that is monotone increasing, decreasing, or constant (Klein and Moeschberger, 2011). It is a two-parameter mode (λ and ρ) where λ is the scale parameter and ρ is the shape parameter because it determines whether the hazard is increasing, decreasing, or constant over time. The pdf is given by: $f(t) = \lambda \rho t^{\rho-1} exp(-\lambda t^{\rho})$,where; $\lambda, \rho > 0$ and the corresponding survival and hazard functions are given as;

$$S(t,\lambda,\rho) = exp(-\lambda t^{\rho})\, and\, h(t,\lambda,\rho) = \lambda \rho t^{\rho-1} \tag{10}$$

The AFT representation of the survival and hazard function of the Weibull model is given by:

$$S_i(t) = exp\left(-exp\left(\frac{-\mu + (\beta' x_i)}{\sigma}\frac{1}{\sigma t}\right)\right)\, and\, h_i(t) = \frac{1}{\sigma} t^{\frac{1}{\sigma}-1} exp\left(\frac{-\mu - \beta' x_i}{\sigma}\right) \tag{11}$$

3.3.3.2 Log-logistic AFT Model

The log-logistic distribution has a fairly flexible functional form, it is one of the parametric survival time models in which the hazard rate may be decreasing, increasing, as well as hump-shaped that is it initially increases and then decreases. It has two parameters λ and ρ, where, λ is the scale parameter and ρ is the shape parameter. Its pdf is given by:

$$f(t) = \frac{\lambda \rho t^{\rho-1}}{(1+\lambda t^{\rho})^2} \tag{12}$$

Under the AFT model, the corresponding survival and hazard functions are given by:

$$S(t,\lambda,\rho) = \frac{1}{1+\lambda t^{\rho}} \, and \, h(t,\lambda,\rho) = \frac{\lambda\rho t^{\rho-1}}{1+\lambda t^{\rho}}, \lambda,\rho > 0 \tag{13}$$

If T_i has a log-logistic distribution, then ε_i has a logistic distribution. The survival function of logistic distribution is given by (Collett, 2003).

$$S_{\varepsilon_i}(\varepsilon) = \frac{1}{1+exp(\varepsilon)} \tag{14}$$

Then, the AFT representation of log-logistic survival and hazard functions are given by:

$$S_i(t) = \left[1+t^{\frac{1}{\sigma}} exp\left(\frac{-\mu-\beta' x_i}{\sigma}\right)\right]^{-1} \; and \; h_i(t) = \frac{1}{\sigma t}\left[1+t^{\frac{-1}{\sigma}} exp\left(\frac{-\mu-\beta' x_i}{\sigma}\right)\right]^{-1} \tag{15}$$

3.3.3.3 Log-normal AFT Model

If the survival times are assumed to have a log-normal distribution, the baseline survival function and hazard function respectively are given by: Simply assuming that $\varepsilon \sim N(0,1)$

$$S_0(t) = 1-\Phi\left(\frac{logt-\mu}{\sigma}\right) \; and \; h_0(t) = \frac{\phi(\frac{logt}{\sigma})}{1-\phi(\frac{logt}{\sigma})\sigma t} \tag{16}$$

Where μ and σ are parameters, $\phi(x)$ is the pdf and $\Phi(x)$ is the cumulative density function of the standard distribution. The survival function of the i^{th} individual is:

$$S_i(t) = 1-\Phi\left(\frac{logt-\beta' x_i-\mu)}{\sigma}\right) \tag{17}$$

3.3.3.4 Parameter Estimation in AFT Model

The parameters of accelerated failure time models are estimated using the Maximum Likelihood Estimation (MLE) method. The likelihood of the n observed survival time $t_1, t_2 ..., t_n$, is given by:

$$L(\alpha,\mu,\sigma) = \prod_{j=0}^{n} [f_i(t_i)]^{\delta_i}[S_i(t_i)]^{1-\delta_i} \tag{18}$$

Where $f_i(t_i)$ the density function of the i^{th} individual at time t_i, S_i is the survival function of the i^{th} individual at time t_i, δ_i is an indicator variable. The maximum likelihood parameters estimates are found by using the Newton-Raphson procedure which can be done by software.

3.3.4 Frailty Model

The Frailty model is a statistical model commonly used in survival analysis to account for unobserved heterogeneity or clustering within a population. It allows for the examination of individual-specific or group-specific random effects, referred to as frailties, that capture the unmeasured or latent factors influencing survival outcomes (Balan and Putter, 2020). Frailty models are hazard models having a multiplicative frailty factor (Hanagal, 2011). In the context of examining the unobserved heterogeneity of mothers due to the cluster they belong to; the frailty model can be employed to investigate how the cluster of the mother influences the survival time or event of interest (time to second birth).

3.3.5 Shared Frailty Models

The shared frailty model is a conditional independence model in which frailty is common to all subjects in a cluster. This model is responsible for creating dependence between event times. It is also known as a mixture model because the frailties in each cluster are assumed to be random. It assumes that, given the frailty, all event times in a cluster are independent. The assumption is that the cluster of the mother represents a shared characteristic that affects the survival outcomes of mothers within that cluster. The model can be specified as follows:

$$h_{ij}(t) = h_0(t)exp(\beta^T X_{ij} + \gamma_i) = h(t)Z_i exp(\beta^T X_{ij}) \tag{19}$$

In this equation, $h_{ij}(t)$ represents the hazard function for the j^{th} individual from the i^{th} cluster at time t; $h_0(t)$ is the baseline hazard, $\beta^{'}$s are the fixed effects vector of dimension p, X_{ij} is the vector of covariates for the j^{th} individual in the i^{th} cluster, and $Z_i = exp(\gamma_i)$ is the frailty term or random effect for the i^{th} cluster.

By including the frailty term Z_i, the model accounts for the correlation or clustering of survival outcomes within clusters. It allows for the estimation of the group-specific random effects, which capture the differences in survival outcomes among mothers from different clusters. These random effects are assumed to follow a specific distribution, such as a gamma distribution.

3.3.5.1 Shared Gamma Frailty Model

The gamma frailty model belongs to the power variance function family (Hougaard, 1986) and can be expressed in terms of its Laplace transform from which properties such as mean and variance are easily derived (Duchateau and Janssen, 2008). The gamma distribution $\Gamma(k, \lambda)$ has been widely applied as a frailty distribution. The two parameter gamma density function is given by:-

$$f_z(Z) = \frac{k^{\lambda} z^{\lambda-1} e^{-kz}}{\Gamma(\lambda)} \tag{20}$$

with $\lambda > 0$ as the shape parameter and $k > 0$ as the scale parameter. The Laplace transform is:

$$L(s) = \int_0^\infty e^{-zs} f_z(Z) dz = k^\lambda (s+k)^{-\lambda} \tag{21}$$

In frailty modeling the typical choice of the parameters of the gamma distribution is $k = \lambda$, using θ as notation for the variance of Z, we have $E(Z) = 1$ and $var(Z) = \theta - \frac{1}{k}$. This distribution with parameters $(\frac{1}{\theta}, \frac{1}{\theta})$ is called a one-parameter gamma distribution with variance parameter θ. With the assumption $k = \lambda$ (necessary for identify-ability reasons), the two-parameter gamma distribution turns to a one-parameter distribution $\Gamma(\frac{1}{\theta}, \frac{1}{\theta})$. The conditional survival and hazard functions of the Gamma frailty distribution are given by: (Gutierrez, 2002).

$$S_\theta(t) = [(1 - \theta lnS(t))]^{\frac{-1}{\theta}} \, and \, h_\theta(t) = h(t)[(1 - \theta lnS(t))]^{-1} \tag{22}$$

The variance θ of the frailty term represents the heterogeneity among clusters while the mean is constrained to be 1 in order to make the average hazard identifiable. A larger variance indicates a stronger association within groups. The associations within group members are measured by Kendall's Tau (Hougaard, 1986), which is given by: $\tau = \theta/(\theta + 2), where\, \tau \varepsilon (0, 1)$

3.3.5.2 Parameter Estimation in Frailty Model

Estimation of the frailty model can be either parametric or semi-parametric. In the parametric approach, a specific parametric density is assumed for the event times, leading to a parametric baseline hazard function. Estimation involves maximizing the marginal log-likelihood (Munda et al., 2012). Conversely, in the semi-parametric approach, the baseline hazard remains unspecified, allowing for more complex techniques to be employed. Although semi-parametric estimation offers greater flexibility, parametric estimation may be more powerful if the form of the baseline hazard is known in advance (Munda et al., 2012). In the parametric setting, estimation is based on the marginal likelihood, obtained by integrating the frailties by averaging the conditional likelihood with respect to the frailty distribution. Assuming right-censoring and independence between the censoring time and survival time of random variables, given covariate information, the marginal log-likelihood of the observed data can be expressed as:

$$l_{marg}(\psi, \beta, \theta; z, x) = \sum_{i=1}^{s} \left[\sum_{j=1}^{n_i} \left[\delta_{ij}(log(h_0(y_{ij})) + x_{ij}^T \beta \right] + log \left[(-1)^{d_i} L^{(d)} (\sum_{j=1}^{n_i} H_0(y_{ij} exp(x_{ij}^T \beta)) \right] \right] \tag{23}$$

Where ψ represents a vector of parameters of the baseline hazard function, β the vector of regression coefficients, θ the variance of the random effect, x_{ij} denote the vector of covariates for the j^{th} observation in the i^{th} cluster, $y_{ij} = min(t_{ij}, c_{ij})$ is the minimum between the survival time t_{ij} and the censoring time c_{ij}, $\delta_{ij} = I(t_{ij} \leq c_{ij})$ is the event indicator, $d_i = \sum_{j=1}^{n_i} \delta_{ij}$ is the number of events in the i^{th} cluster. Estimates of ψ, β, θ are obtained by maximizing the marginal log-likelihood.

3.3.6 Variable Selection

Finding a subset of the available inputs that correctly predicts the response variables is done via variable selection. One of the most important steps in the modeling process is choosing appropriate variables to include modeling method. The most common methods of selecting a subset of covariates are purposeful selection, step-wise (forward selection and backward elimination), and best sub-set selections (Hosmer and Lemeshow, 1999).

3.3.7 Model Selection

For model selection, various methods can be employed, such as information criteria that balance model fit and complexity (Mac Nally et al., 2018). Akaike Information Criterion (AIC) is a statistical method that can estimate the quality of models by comparing different possible parameters of models (Akaike, 1974). AIC is a likelihood-based measure for model fit, and in general, it is written as:- $AIC = -2logL + 2P$ where $logL$ is the log likelihood of a model that will compare with the other models and P is the number of parameters in the model. This study used the AIC criteria to compare survival analysis model accelerated failure time model and parametric shared frailty model. The model with the smallest AIC value is considered a better fit.

3.3.8 Model Diagnosis

3.3.8.1 Graphical Method

The graphical method can be used whether or not the distribution fits the observed data. For instance, in the case of the Weibull baseline hazard function, the plot of $log[-log\hat{S}(t)]$ versus $log(t)$ is used, where $\hat{S}(t)$ is the Kaplan-Meier survival estimate. The Log-logistic assumption can be graphically evaluated by plotting $log((1-\hat{S}(t))/\hat{S}(t))$ versus $log(t)$. If the distribution of the survival function is log-logistic, then the resulting plot should be a straight line. For the model with the log-normal baseline, the plot of $\phi^{-1}[1-\hat{S}(t)]$ versus t is used. This plot should be linear and go through the origin (Klein, 1992).

3.3.8.2 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 (Cox and Snell, 1968). The Cox–Snell residual for the i^{th} individual with observed t_i, r_{ci}, is defined as:

$$r_{ci} = \hat{H}(\frac{t_i}{x_i}) = -log[\hat{S}\frac{t_i}{x_i}] \tag{24}$$

Where t_i is the observed survival time for individual i, $\hat{H}(t_i)$ is the cumulative hazard function of the fitted model, x_i is the covariate values for individual i, and $\hat{S}(t_i)$ is the estimated survival function on the fitted model. The corresponding form of residual-based particular AFT model can be obtained. For example, under the Weibull AFT model since $S_{\varepsilon i}(\varepsilon) = exp(-exp(\varepsilon))$, the Cox-Snell residual is then given by:

$$r_{ci} = -log\hat{S}(t) = -logS_{\varepsilon i}(r_{si}) = exp(r_{si}) \tag{25}$$

where r_{si} is standard residual given by:

$$r_{si} = \frac{logt - \mu - \beta_i X_i}{\sigma} \tag{26}$$

Similarly, with the log-logistic AFT model, since $S_{\varepsilon i}(\varepsilon) = (1 - exp(\varepsilon))^{-1}$, the Cox-Snell residual is then given as: $r_{ci} = log[1 + exp(r_{si})]$ Also under the log-normal AFT model, $S_{\varepsilon}(\varepsilon) = 1 - \phi(\varepsilon)$ hence the Cox-Snell residual becomes, $r_{ci} = log[1 - \phi(r_{si})]$ If the fitted model is appropriate, the plot of $log(-logS(r_{ci}))$ versus $logr_{ci}$ is a straight line with the unit slope through the origin.

Chapter 4

Results and Discussion

4.1 Descriptive Statistics

Table 4.1 presents the descriptive statistics of the study findings. Among reproductive-aged women, 4,678 (80.02%) had a second birth. The age group with the highest number of women was 25-29 years (24.8%), while the lowest was 15-19 years (4.24%), with only 20.16% experiencing a second birth. Oromia had the highest number of women (12.11%), while Addis Ababa had the lowest (6.40%). The Somali region had the highest proportion of second births (90.93%), followed by SNNPR (87.26%). Muslim women comprised the majority (42.76%), with 83.08% having a second birth, compared to 74.6% of Orthodox followers.

Most women were married (86.88%), with 81.91% experiencing a second birth. Among divorced women (8.36%), 39% did not have a second birth. Women from poor households (42.47%) had a higher proportion of second births (86.59%) compared to those from rich households (71.82%). A majority of women had no education (54.33%), with 91% having a second birth, while only 14.69% of those with secondary and above education. Rural women (71.81%) had a higher percentage of second births (84.11%) compared to urban women. Most women had their first birth before age 20 (73.45%), with 63.33% of those above 25 having a second birth. Non-contraceptive users had a higher proportion of births (82.09%) compared to contraceptive users. Breastfeeding was common (37.55%), with 79.56% having a second birth. Additionally, 52.34% of births were male, and 11.7% of women had lost a child, with 79.14% having a second child alive.

Table 4.1: Summary results of covariates of second birth interval among women in Ethiopia (EMDHS-2019)

Covariates	**Categories**	**Total (%)**	**Number of women who had second birth (%)**	**Number of women who had no second birth (%)**
Age	15-19	248(4.24)	50(20.16)	198(79.84)
	20-24	871(14.9)	432(49.6)	439(50.4)
	25-29	1450(24.8)	1139(78.55)	311(21.45)
	30-34	1088(18.61)	985(90.53)	103(9.47)
	35-39	982(16.8)	922(93.53)	60(6.11)
	40-44	687(11.75)	652(94.91)	35(5.09)
	45-49	520(8.89)	498(95.77)	22(4.23)

Covariates	Categories	Total (%)	Number of women who had second birth (%)	Number of women who had no second birth (%)
Region	Tigray	504(8.62)	386(76.59)	118(23.41)
	Afar	500(8.55)	410(82)	90(18)
	Amhara	643(11)	518(80.56)	125(19.44)
	Oromia	708(12.11)	594(83.9)	114(16.1)
	Somale	430(7.36)	391(90.93)	39(9.07)
	Benishangul-Gumuz	523(8.95)	425(81.26)	98(18.74)
	SNNPR	690(11.8)	606(87.26)	84(12.17)
	Gambela	529(9.05)	414(78.26)	115(21.74)
	Harari	476(8.14)	366(76.89)	110(23.11)
	Addis Ababa	374(6.4)	230(61.5)	144(38.5)
	Dire Dawa	469(8.02)	338(72.07)	131(27.93)
Religion	Orthodox	2063(35.29)	1539(74.6)	524(25.4)
	Protestant	1165(19.93)	959(82.32)	206(17.68)
	Muslim	2500(42.76)	2077(83.08)	423(16.92)
	Others	118(2.02)	103(87.29)	15(12.71)
Marital Status	Married	5079(86.88)	4160(81.91)	919(18.09)
	Widowed	278(4.76)	218(78.42)	60(21.58)
	Divorced	489(8.36)	300(61)	189(39)
Wealth Index	Poor	2483(42.47)	2150(86.59)	333(13.41)
	Middle	893(15.28)	754(84)	139(16)
	Rich	2470(42.25)	1774(71.82)	696(28.18)
Education	No education	3176(54.33)	2893(91)	283(9)
	Primary	1811(30.98)	1280(70.68)	531(29.32)
	Secondary & above	859(14.69)	505(58.79)	354(41.21)
Residence	Urban	1648(28.19)	1147(69.6)	501(30.4)
	Rural	4198(71.81)	3531(84.11)	667(15.89)
Age at first birth	<20 years	4294(73.45)	3637(84.7)	657(15.3)
	20–24 years	1072(18.34)	737(68.75)	335(31.25)
	≥25 years	480(8.21)	304(63.33)	176(36.67)
Contraceptive use	No	3953(67.62)	3245(82.09)	708(17.91)
	Yes	1893(32.38)	1433(75.7)	460(24.3)
Breastfeeding status	No	3651(62.45)	2963(81.16)	688(18.84)
	Yes	2195(37.55)	1715(78.13)	480(21.87)
Sex of Child	Male	3060(52.34)	2453(80.16)	607(19.84)
	Female	2786(47.66)	2225(79.86)	561(20.14)
Survival status of child	Dead	564(9.65)	498(88.2)	66(11.7)
	Alive	5282(90.35)	4180(79.14)	1102(20.86)

4.1.1 Kaplan-Meier Estimate of Second Birth Interval

The overall median survival time of the second birth interval for Ethiopian women is 36 months (95% CI: 35, 37). However, the median survival time varies across different characteristics of women. For rural women, the median survival time is 33 months (95% CI: 32, 34), while for urban women, it is 50 months (95% CI: 47, 55) (Figure 4.2). In terms of income, women with high (rich) income have a median survival time of 45 months, compared to 31 months for those with poor income and 35 months for those with middle income. Additionally, the median survival time for women with no education is 30 months, whereas for those with primary education, it is 44 months, and for those with secondary education and above, it is 69 months. Detailed median survival times and corresponding 95% confidence intervals for other categorical variables can be found in Table A.1 in Appendix A.

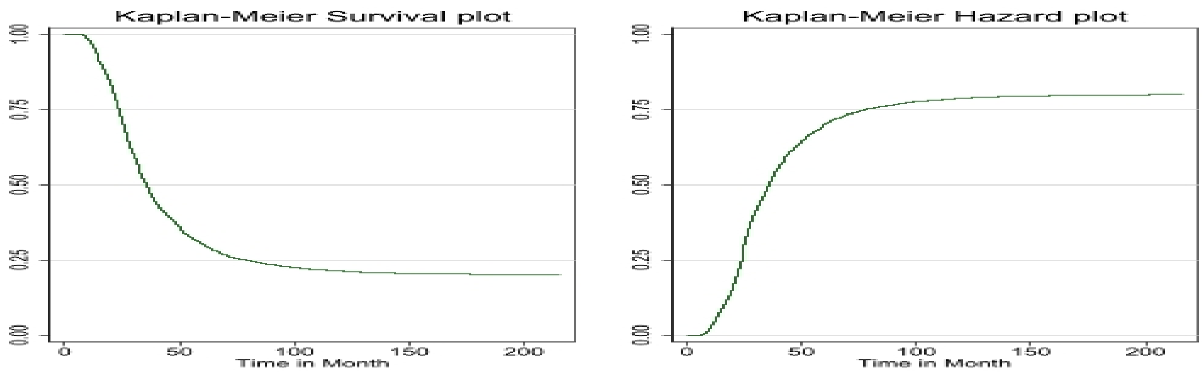

Figure 4.1: The K-M plot for survival and hazard functions of second birth interval among women in Ethiopia.

Figure 4.1 presents Kaplan-Meier curves illustrating the survival and hazard experiences of the second birth interval. On the horizontal axis, the survival time (in months) is depicted, while the vertical axis represents the probability of survival. Additionally, for Kaplan-Meier estimates, the horizontal axis denotes the survival time (in months), and the vertical axis indicates the cumulative hazard. The curves indicate that the survival rate of the second birth interval for women tends to increase as the duration in months progresses.

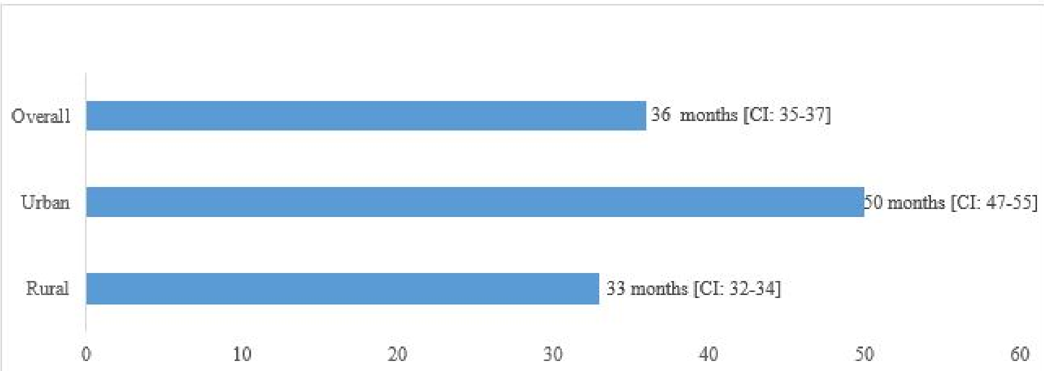

Figure 4.2: Median birth interval by place of residence.

4.1.2 Kaplan-Meier Survival Function of Different Groups

Kaplan-Meier Curve by Women's Age and Region

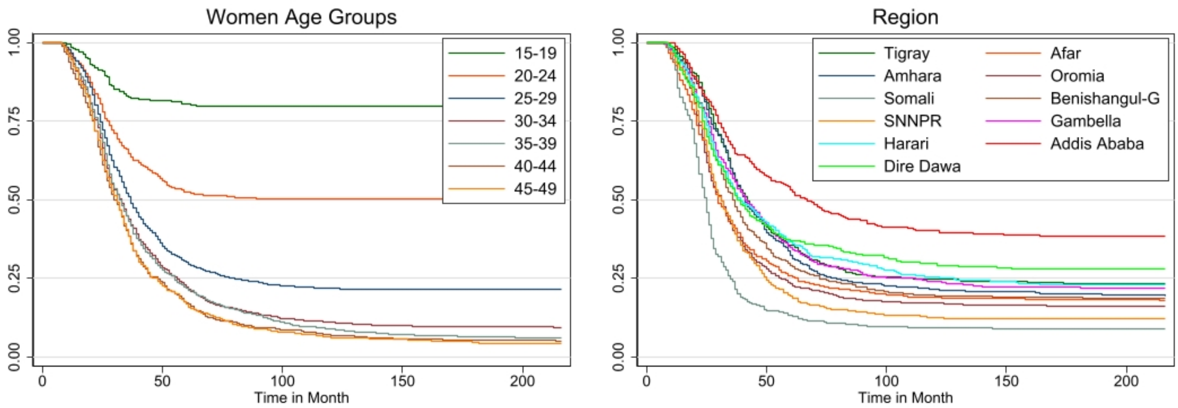

Figure 4.3: Plot of Kaplan-Meier Estimates by women age group and region.

Figure 4.3 illustrates the time to the second birth using non-parametric Kaplan-Meier analyses, segmented by women's age group and region. The analysis reveals that women in the age group 45-49 tend to have a shorter duration before their second childbirth compared to other age groups. Specifically, it is estimated that 25% of women in this age group would have had a second birth within 22 months. In contrast, women aged 20-24 have a longer estimated time of 27 months for the same proportion. Additionally, women living in the Somali region exhibit a shorter duration before their second childbirth compared to those residing in Addis Ababa.

Kaplan-Meier Curve by Women Religion and Marital Status

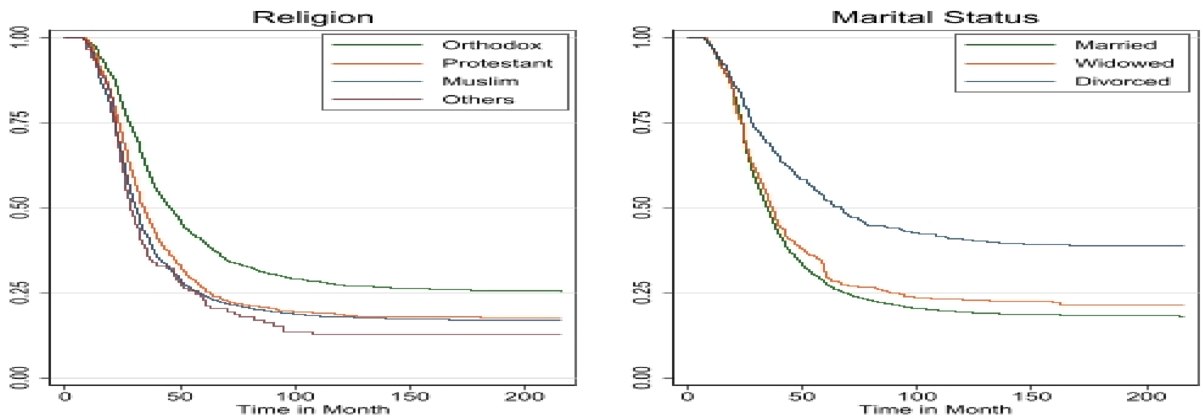

Figure 4.4: Plot of Kaplan-Meier Estimates by women religion and marital status.

Figure 4.4 illustrates the time to the second birth using non-parametric Kaplan-Meier analyses, segmented by women's religion and marital status. The analysis reveals that women who follow others religions tend to have a shorter duration before their second childbirth compared to Orthodox followers. Specifically, it is estimated that 25% of women in others religions would have had a second birth within 22 months. In contrast, women who follow Orthodox have a longer estimated time of 28 months for the same proportion. Additionally, married women tend to have a shorter duration before their second childbirth compared to divorced and widowed.

Kaplan-Meier Curve by Wealth Index and Education Level

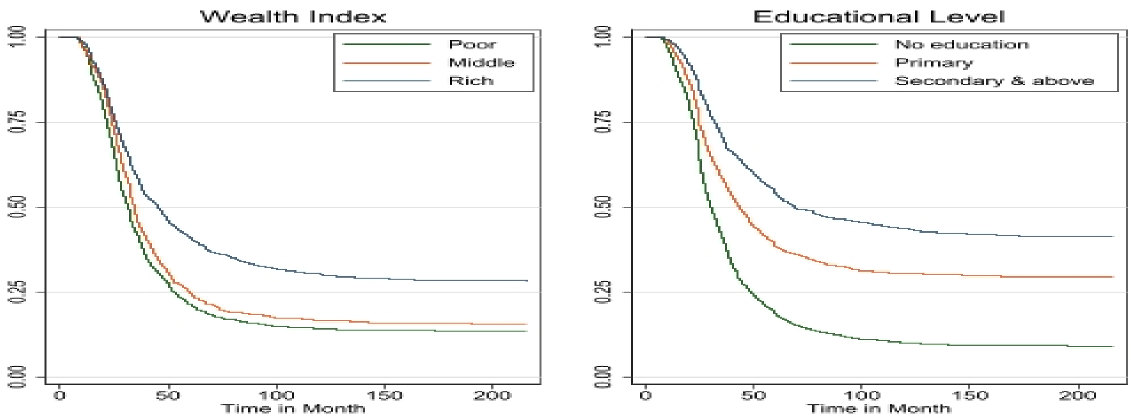

Figure 4.5: Plot of Kaplan-Meier Estimates by wealth index and education.

Figure 4.5 illustrates the time to the second birth using non-parametric Kaplan-Meier analyses, segmented by wealth index and women's education level. The analysis reveals that women in the poor (low-income) wealth index tend to have a shorter duration before their second childbirth compared to women in the rich (high-income) wealth index. Specifically, it is estimated that 25% of women in this wealth index would have had a second birth within 22 months. In contrast, women with high incomes have a longer estimated time of 26 months for the same proportion. Additionally, women with no education exhibit a shorter duration before their second childbirth compared to secondary & above education levels.

Kaplan-Meier Curve by Place of Residence and Age at First Birth

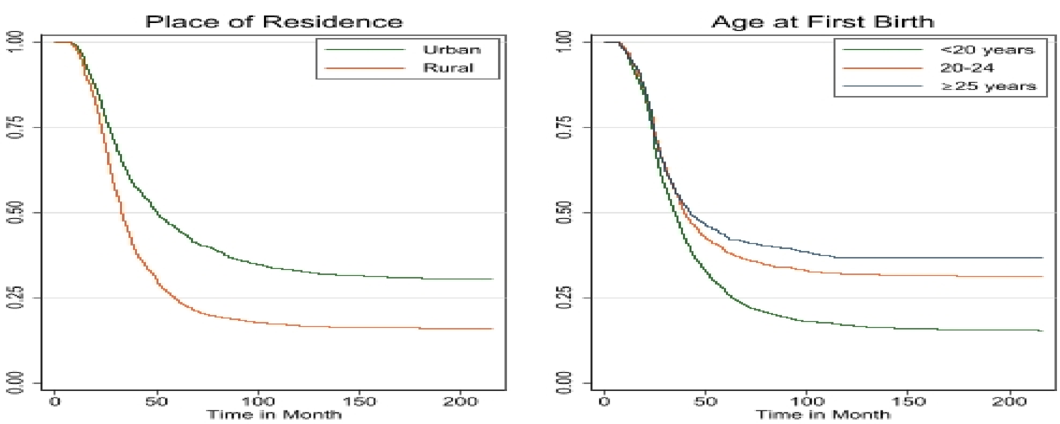

Figure 4.6: Plot of Kaplan-Meier Estimates b6 place of residence and women age at first birth.

Figure 4.6 illustrates the time to the second birth using non-parametric Kaplan-Meier analyses, segmented by place of residence and women age at first birth. The analysis reveals that women with the age at first birth of less than 20 years tend to have a shorter duration before their second childbirth compared to the age between 20-24 years and greater than 25 years. Specifically, it is estimated that 25% of women in this age at first birth would have had a second birth within 23 months. In contrast, women aged at first birth between 20-24 years have a longer estimated time of 25 months for the same proportion. Additionally, women living in rural areas exhibit a shorter duration before their second childbirth compared to those residing in urban areas.

Kaplan-Meier Curve by Breastfeeding Status and Contraceptive Use

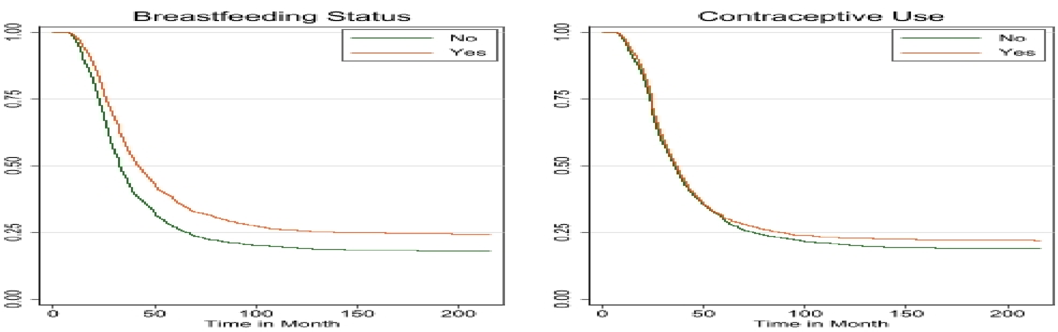

Figure 4.7: Plot of Kaplan-Meier Estimates by breastfeeding status and contraceptive use.

Figure 4.7 illustrates the time to the second birth using non-parametric Kaplan-Meier analyses, segmented by breastfeeding status and contraceptive use. The analysis reveals that women non-contraceptive users tend to have a shorter duration before their second childbirth compared to contraceptive users. Specifically, it is estimated that 25% of women would have had a second birth within 23 months. In contrast, contraceptive users have a longer estimated time of 26 months for the same proportion. Additionally, women who breastfeed their child tend to have a longer duration before their second childbirth, it is estimated that 25% of women would have had a second birth within 24 months. In contrast, women who do not breastfeed, have a shorter estimated time of 23 months for the same proportion.

Kaplan-Meier Curve by Sex of Child and Survival Status of Child

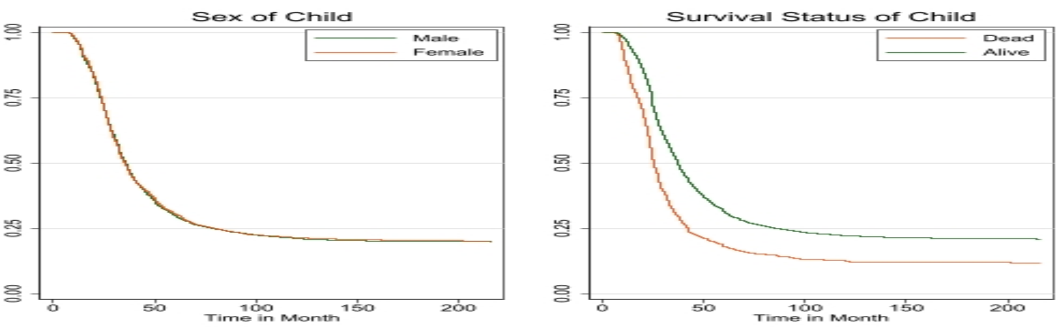

Figure 4.8: Plot of Kaplan-Meier Estimates by sex of child and survival status of child.

Figure 4.8 illustrates the time to the second birth using non-parametric Kaplan-Meier analyses, segmented by sex of the child and survival status of the child. The analysis reveals that women whose child has died tend to have a shorter duration before their second childbirth compared to those alive. Specifically, it is estimated that 25% of women whose child has died would have had a second birth within 17 months. In contrast, women whose child is alive have a longer estimated time of 24 months for the same proportion. Additionally, first birth sex is overlapped from the beginning to the end.

4.1.3 Log-rank test for Survival Curves

The Log-rank test was conducted to assess the significance of differences observed in the Kaplan-Meier estimates of survivor functions across various categories of covariates. Employed at a significance level of 5%, the test validated distinctions in the survival time for each covariate. The null hypothesis tested whether there were no differences in the probabilities of an event occurring at any given time point. Below is a summary of the corresponding log-rank test results evaluating the equality of survival curves for the covariates. The log-rank test results (Table 4.2) indicate statistically significant differences in the failure time (occurrence of second birth) across various categories including women's age group, region, religion, marital status, wealth index, women's education, place of residence, women's age at first birth, contraceptive use, breastfeeding status, and survival status of the child. This suggests variations in the probabilities of an event occurring at any given time point during the study period. However, the sex of the child did not show statistically significant differences in experiencing the event.

Table 4.2: Result of the log-rank test for each categorical variable

Covariate	Df	Chi-Square	p-value
Age	6	884.20	<.0001
Region	10	333.06	<.0001
Religion	3	155.89	<.0001
Marital Status	2	104.25	<.0001
Wealth Index	2	242.17	<.0001
Education	2	624.48	<.0001
Residence	1	193.68	<.0001
Age at first birth	2	138.47	<.0001
Contraceptive use	1	70.66	<.0001
Breastfeeding status	1	5.49	0.0191
Sex of child	1	0.06	0.7992
Survival status of child	1	108.74	<.0001

4.2 Proportional Hazard Assumption Checking

Test of proportional hazard assumption by Schoenfeld residual

The Schoenfeld residual is one of the methods that are used to check the PH assumption. The result showed that the PH assumption is violated for women's age group, religion, marital status, women's education, place of residence, women's age at first birth, contraceptive use, breastfeeding status, and survival status of the child, hence it was observed that each covariate has p-value of <0.05 and all of the covariates simultaneously (GLOBAL test) has a p-value <0.05, implying that the proportionality assumption is not fulfilled.

Test of proportional hazard assumption by graphical method

We also used the - (log (-log (survival))) versus survival time plot to check the PH assumption for all the categorical variables included in the model. The result presented in Appendix A Figure A.1 shows that the graphs for the six categorical variables display lines that are not parallel implying that the proportional-hazards assumption among categorical variable such as women's age, region, wealth index, religion, marital status and age at first birth has been violated. When the proportional hazards assumption is not satisfied, the Cox proportional hazards model would not be suitable.

4.3 Accelerated Failure Time Model Results

Since the proportional assumption is not satisfied, the accelerated failure time model is an alternative model for the analysis of this data. We fitted the data using an acceleration failure time model with Weibull, Lognormal, and Log-logistic as a baseline distribution.

4.3.1 Model Comparison for AFT Models

We utilized the Akaike Information Criterion (AIC) to compare the three models. The preferred model is the one with the lowest AIC value. As per Table 4.3, the log-logistic model (AIC: 14870.63) exhibits the smallest AIC value, indicating that the log-logistic accelerated failure time model provides the best fit for describing the second birth interval data among the candidate accelerated failure time models.

Table 4.3: Comparison of AFT models using AIC criteria

Baseline Distribution	AIC
Weibull AFT	15665.52
Log-normal AFT	14923.11
Log-logistic AFT	**14870.63**

In the AFT model, the sign of the coefficient indicates how a covariate affects the logged survival time. A positive coefficient increases the logged survival time and, consequently, the expected duration, while a negative coefficient decreases the logged survival time and, therefore, the expected duration. Thus, from Table B.4 in Appendix B, marital status (married), wealth index (poor), women's educational level (no education), age at first birth (less than 20 years), contraceptive non-use, and child survival status (dead) have positive coefficients (accelerated factor greater than one ($\phi > 1$) indicating an extension of the time to second birth) and increase the logged survival time. Conversely, women in the age group (15-19), belonging to the Orthodox religion, residing in urban areas, and not breastfeeding exhibit negative coefficients (accelerated factor less than one ($\phi < 1$) indicating a shortened time to second birth) and decrease the logged survival time.

4.4 Parametric Gamma Shared Frailty Model Results

In the sections above, AFT models with Weibull, log-normal and log-logistic baseline distributions were fitted for the second birth interval data. Additionally, gamma-shared frailty models with Weibull, lognormal, and log-logistic parametric baseline distributions were fitted using cluster/enumeration areas as a frailty term. From Table B.5 and B.6 in Appendix B and Table 4.5, the frailty term is highly significant (p = 0.000) for all gamma shared frailty models (Weibull gamma shared frailty, lognormal gamma shared frailty, and log-logistic gamma shared frailty). Among these models, Table 4.4 shows that the log-logistic gamma shared frailty model had a smaller AIC value (14549.96) than the lognormal (14814.25) and Weibull (15556.79) gamma shared frailty models. This indicates that the log-logistic gamma shared frailty model was the appropriate model to describe the second birth interval dataset.

Table 4.4: AIC value of Shared Gamma Frailty Models

Models	AIC
Weibull Gamma Shared Frailty	15556.79
Log-normal Gamma Shared Frailty	14814.25
Log-logistic Gamma Shared Frailty	**14549.96**

The result of the log-logistic gamma shared frailty model is given below in Table 4.5. From this result, the frailty term $\theta = 0.785$ indicates that there is heterogeneity between clusters and strong association among individuals in the same cluster. Kendall's tau (τ) is used to measure the dependence within the clusters. From the results of this study, the value of Kendall's tau (τ) for the log-logistic gamma frailty is 0.282. From this evidence, we can conclude that, on average, there is a positive correlation between second birth intervals within clusters. The shape parameter (λ = 3.115) was greater than one indicating that the shape of the hazard function is unimodal which means it increases up to sometime and then decreases. Considering religion, all categories had an acceleration factor of less than one indicating that Protestant, Muslim, and other followers had a shortened time to second birth. In the covariate wealth index, high income had an acceleration factor less than one, and middle income had an acceleration factor greater than one indicating that high income shortens the time to the second birth and middle income extends the time to the second birth. The acceleration factor of the covariate's marital status, educational level, place of residence, women's age at first birth, contraceptive use, and survival status of a child was greater than one. This implied that these covariates extend the time to the second birth. The acceleration factor of breast-feeding status and women's age group (in all categories) were less than one indicating that these covariates shortened the time to the second birth.

Table 4.5: Result of final log-logistic gamma shared frailty model

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Age	15-19	**Ref.**				
	20-24	-1.870	0.077	0.154	[0.133, 0.179]	0.000
	25-29	-2.113	0.075	0.121	[0.104, 0.140]	0.000
	30-34	-2.210	0.077	0.110	[0.094, 0.127]	0.000
	35-39	-2.219	0.078	0.109	[0.093, 0.127]	0.000
	40-44	-2.278	0.080	0.103	[0.088, 0.120]	0.000
	45-49	-2.238	0.083	0.107	[0.091, 0.126]	0.000
Religion	Orthodox	**Ref.**				
	Protestant	-0.096	0.036	0.909	[0.847, 0.975]	0.008
	Muslim	-0.184	0.032	0.832	[0.781, 0.886]	0.000
	Others	-0.193	0.074	0.825	[0.713, 0.954]	0.009
Marital Status	Married	**Ref.**				
	Widowed	0.105	0.049	1.110	[1.008, 1.223]	0.034
	Divorced	0.188	0.045	1.207	[1.105, 1.319]	0.000
Wealth Index	Poor	**Ref.**				
	Middle	0.008	0.031	1.008	[0.950, 1.070]	0.787
	Rich	-0.032	0.030	0.969	[0.913, 1.027]	0.288
Education	No education	**Ref.**				
	Primary	0.067	0.025	1.070	[1.018, 1.124]	0.007
	Secondary & above	0.196	0.042	1.216	[1.120, 1.321]	0.000
Residence	Urban	**Ref.**				
	Rural	0.129	0.040	1.138	[1.052, 1.230]	0.001
Age at first birth	<20 years	**Ref.**				
	20–24 years	0.093	0.029	1.097	[1.037, 1.161]	0.001
	$\geq$ 25 years	0.083	0.043	1.087	[0.999, 1.183]	0.053
Contraceptive use	No	**Ref.**				
	Yes	0.049	0.024	1.050	[1.002, 1.102]	0.043
Breastfeeding status	No	**Ref.**				
	Yes	-0.012	0.023	0.988	[0.945, 1.033]	0.587
Survival status of child	Dead	**Ref.**				
	Alive	0.260	0.034	1.297	[1.214, 1.385]	0.000

θ = 0.785, k = 0.321, AIC = 14549.96, τ = 0.282, λ = 3.115, LR test of θ = 0: chibar2(01) = 322.67 Prob >= chibar2 = 0.000

θ = variance of the random effect, τ = Kendall's Tau, λ = shape parameter, k = scale parameter, LR = likelihood ratio, prob=probability, chibar2 (01) = Chi-square distribution with 0 and 1 Df.

4.4.1 Interpretation of Log-logistic Gamma Shared Frailty Model

From the log-logistic gamma shared frailty model in Table 4.5, the estimated coefficients for women's age group, religion, high-income (rich) wealth index, and breast-feeding status were negative. This negative sign suggests a decrease in the logged level of survival time compared to the reference category. Controlling for other covariates, the acceleration factors and their 95% confidence intervals for women's age groups 20-24, 25-29, 30-34, 35-39, 40-44, and 45-49 were 0.154 (0.133, 0.179), 0.121 (0.104, 0.140), 0.110 (0.094, 0.127), 0.109 (0.093, 0.127), 0.103 (0.088, 0.120), and 0.107 (0.091, 0.126), respectively, at a 5% level of significance when the 15-20 age group is taken as the reference category. None of these confidence intervals include one, indicating that the age group of the women was a statistically significant factor for the second birth interval when using the 15-20 age group as a reference category.

The acceleration factors for women of Protestant, Muslim, and other religions were 0.909, 0.832, and 0.825, with 95% confidence intervals of (0.847, 0.975), (0.781, 0.886), and (0.713, 0.954), respectively, at a 5% level of significance when Orthodox religion is taken as the reference. This suggests that women of all other religions had a shorter time to second birth compared to women who followed the Orthodox religion.

The acceleration factors for widowed and divorced women were 1.110 and 1.207, with 95% confidence intervals of (1.008, 1.223) and (1.105, 1.319), respectively, at a 5% level of significance when married women were taken as the reference category. The acceleration factor for women who lived in rural areas was 1.138, and its 95% confidence interval of (1.052, 1.230) does not include one. This suggests that rural women had an extended time to second birth by a factor of 1.138 at the 5% level of significance compared with urban residence women.

The acceleration factors for women's age at first birth between 20-24 years and greater than 25 years were estimated to be 1.097 with a 95% confidence interval of (1.037, 1.161) and 1.087 with a 95% confidence interval of (0.999, 1.183), respectively, when age less than 20 years at first birth is taken as the reference. This indicates that a woman's age at first birth greater than 20 years had extended the time to second birth compared to a woman's age less than 20 years at first birth, although there was no significant difference between age greater than 25 years at first birth and age less than 20 years at first birth.

The acceleration factors for women's educational level who attended primary and secondary & above were 1.070 and 1.216 with 95% confidence intervals of (1.018, 1.124) and (1.120, 1.321), respectively, at a 5% level of significance when uneducated women are taken as the reference. This suggests that educated women extended the time to second birth compared to uneducated women. The estimated coefficient for contraceptive use by women was 0.049, indicating extended time to second birth for contraceptive users. Hence, the time to second birth for contraceptive-user women was extended by a factor of 1.050 compared to the reference category (no) at the 5% level of significance.

The acceleration factor for women who were breastfed was 0.988, and its 95% confidence interval of (0.945, 1.033) when not breastfed is taken as the reference and is not significant. The acceleration factor for the status of the child when the first child is alive was 1.297, and its 95% confidence interval of (1.214, 1.385) does not include one. This indicates that the survival of the first child significantly increases the transition time to the second birth.

The acceleration factors for middle-income and rich households compared with poor ones are 1.008 and 0.969, respectively, and are not significant. This is because the p-values corresponding to middle and rich groups of women are 0.787 and 0.288, respectively, which are not significant.

4.5 Model Diagnosis

4.5.1 Diagnostic Plots of the Parametric Baselines

To check the adequacy of our baseline distribution, Weibull evaluated by plotting $log(-log\hat{S}(t))$ versus $log(t)$ i.e. the logarithm cumulative hazard function with the logarithm of time of the study, log-logistic graphically evaluated by plotting $log((1-\hat{S}(t))/\hat{S}(t))$ versus $log(t)$ i.e. log of failure odd versus logarithm of study time and the log-normal baseline by plotting $\phi^{-1}(1-\hat{S}(t))$ against $log(t)$. From Figure 4.9 the plot of log-logistic is approximately straight line than the other plots. This implied that the log-logistic is a better baseline distribution. This evidence supports the decision made based on the AIC value that log-logistic baseline distribution is appropriate for the given dataset.

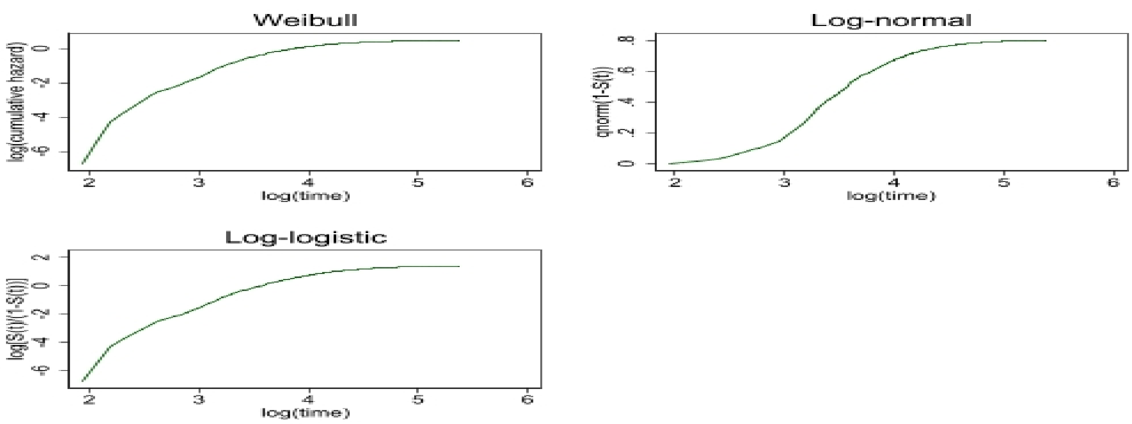

Figure 4.9: Graphs of Weibull, Log-normal, and Log-logistic baseline distributions

4.5.2 Cox-Snell Residual Plots

The Cox-Snell residuals are one way to investigate how well the model fits the data. In this case we used the Cox-Snell residuals to check the overall goodness of fit for Weibull, log-normal and log-logistic parametric baselines. From Figure 4.10 the plot shows that the line related to the Cox-Snell residuals of the log-logistic models were nearest to the line through the origin, again indicating that this model describes the second birth interval data well.

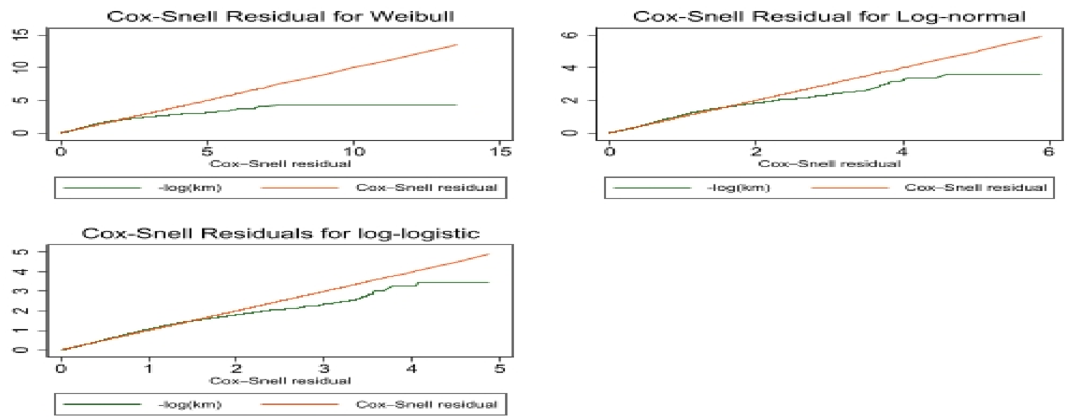

Figure 4.10: Cox-Snell residual plots for Weibull, Log-normal and Log-logistic AFT model

4.6 Discussion

The findings of this study revealed that women's educational level significantly influenced the second birth interval, extending the time to second birth by factors of 1.071 and 1.216 for those with primary and secondary & above education, respectively, compared to uneducated women. This aligns with previous studies in Bangladesh (Ahammed et al., 2019) and Ethiopia (Ayanaw, 2008; Hailu and Gulte, 2016), indicating that higher education delays second childbirth.

Similarly, the religion of women significantly impacted the second birth interval in Ethiopia, with Muslims, Protestants, and others experiencing shorter times to second birth compared to Orthodox followers. This corroborates findings from previous research by Tesfaye et al. (2015) and Ayanaw (2008).

Additionally, the study highlights the significant impact of rural residence, with rural women having longer second birth intervals than thier urban counterparts. This finding is consistent with prior studies (Ahammed et al., 2019; Fagbamigbe, 2020; Tesfaye et al., 2015; Yohannes et al., 2011), suggesting urban women are more likely to have a second birth sooner than rural women.

Moreover, older age at first birth was associated with extended second birth intervals, as older women were more inclined to delay second childbirth. This finding mirrors previous research (Fagbamigbe, 2020; Hailu and Gulte, 2016), which noted that older women tend to delay subsequent births.

Marital status emerged as a significant factor, with women in relationships (married) more likely to have a second birth compared to widowed or divorced women. This finding aligns with studies in Nigeria (Fagbamigbe, 2020), suggesting that married women have increased exposure to pregnancy and childbirth.

Furthermore, contraceptive use significantly extended the time to the second birth, with contraceptive users having longer intervals compared to non-users. This finding is consistent with previous research (Fagbamigbe, 2020; Towriss and Timæus, 2018), indicating that contraceptive use reduces the risk of subsequent births.

Unexpectedly, older age was associated with shorter second birth intervals, indicating a decline in second births as women age. This contradicts findings from Pakistan (Kamal and Pervaiz, 2012) but suggests a complex relationship between age and birth intervals.

Additionally, child loss was found to positively impact child spacing, with a higher risk of subsequent birth following infant or child mortality. This finding supports previous studies in Ethiopia (Bayleyegne and Asfaw, 2020) and elsewhere (Ramesh, 2006), highlighting the influence of child mortality on birth intervals.

Interestingly, wealth index and breastfeeding status were not significantly associated with the second birth interval in Ethiopian women, contrary to previous findings (Bayleyegne and Asfaw, 2020; Fufa and Tolessa, 2021; Mustefa and Belay, 2021).

Chapter 5

Conclusion and Recommendations

5.1 Conclusions

The main aim of this study was to uncover the determinants influencing the second birth interval among Ethiopian women. Among the total participants, 4678 (80.02%) had experienced a second birth, while 1168 (19.98%) had not. The median second birth interval was 36 months. Various parametric shared frailty and AFT models were employed, with the log-logistic gamma shared frailty model proving most suitable for the dataset. The presence of a frailty effect indicated heterogeneity among clusters in Ethiopia, necessitating frailty models.

Results from the log-logistic gamma shared frailty models identified women's age, religion, marital status, education level, place of residence, age at first birth, contraceptive use, and child survival status as significant factors influencing the second birth interval. Notably, older age and Protestant, Muslim, and others religious affiliations correlated with a shorter time to second birth, while being widowed or divorced, higher education, rural residence, being aged 20-24 years at first birth, and contraceptive use were associated with a longer interval. However, ages over 25 years at first birth did not show statistical significance.

5.2 Recommendations

Based on the findings of this study, the following recommendations are proposed:

- Government health policies and interventions aimed at enhancing maternal and child health programs should prioritize women's education.
- Efforts should be made to encourage and facilitate the use of contraceptive methods for family planning and birth spacing purposes.
- Infrastructure and accessible healthcare services in rural areas need to be expanded to ensure equitable access to maternal and child health services.
- Further research should be conducted in Ethiopia to identify additional factors influencing the second birth interval that may not have been captured in this study.

Limitation of the Study

One limitation of this study is the exclusion of certain variables, including women's employment status, as well as the employment status and educational level of husbands/partners, and women's age at marriage. These variables were not incorporated into the study due to non-responses from participants.

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Appendix A

Results of median survival time, univariable analysis using Weibull, log-normal, and log-logistic AFT models of second birth interval dataset.

Table A.1: Median time of second birth interval and confidence interval by levels of covariates

Covariate	Categories	SBI Mst	SBI 95% CI	Covariate	Categories	SBI Mst	SBI 95% CI
Region	Tigray	42	[38, 47]	Wealth Index	Poor	31	[30, 32]
	Afar	30	[28, 33]		Middle	35	[33, 36]
	Amhara	41	[39, 44]		Rich	45	[42, 47]
	Oromia	31	[29, 33]	Residence	Urban	50	[47, 55]
	Somali	25	[23, 26]		Rural	33	[32, 34]
	Benishangul Gumuz	36	[33, 39]	Age	25-29	37	[35, 38]
	SNNPR	31	[29, 33]		30-34	33	[31, 34]
	Gambella	41	[38, 47]		35-39	32	[31, 34]
	Harari	39	[36, 46]		40-44	30	[28, 33]
	Addis Ababa	67	[57, 81]		45-49	31	[29, 33]
	Dire Dawa	38	[35, 43]	Age at first birth	<20 years	35	[34, 36]
Religion	Orthodox	46	[43, 48]		20–24 years	39	[37, 43]
	Protestant	35	[33, 36]		$\geq$25 years	42	[37, 53]
	Muslim	30	[29, 32]	Contraceptive use	No	33	[32, 34]
	Others	28	[26, 33]		Yes	42	[40, 44]
Education	No education	30	[30, 31]	Breastfeeding status	No	36	[34, 37]
	Primary	44	[41, 46]		Yes	36	[35, 38]
	Secondary & above	69	[62, 86]	Sex of child	Male	35	[35, 37]
Marital Status	Married	35	[34, 36]		Female	36	[34, 37]
	Widowed	37	[33, 40]	Survival status of child	Dead	26	[24, 27]
	Divorced	67	[57, 77]		Alive	37	[36, 38]

SBI: Second Birth Interval; **Mst**: Median survival time

Table A.2: Weibull AFT model Univariable Analysis

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Age	15-19	**Ref.**				
	20-24	-1.387	0.130	0.250	[0.193, 0.323]	0.000
	25-29	-2.544	0.127	0.079	[0.061, 0.101]	0.000
	30-34	-2.876	0.128	0.056	[0.044, 0.072]	0.000
	35-39	-3.003	0.129	0.050	[0.039, 0.064]	0.000
	40-44	-3.072	0.131	0.046	[0.036, 0.060]	0.000
	45-49	-3.147	0.133	0.043	[0.033, 0.056]	0.000

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
	Tigray	**Ref.**				
	Afar	0.018	0.073	1.018	[0.883, 1.173]	0.807
	Amhara	0.134	0.059	1.144	[1.019, 1.284]	0.023
	Oromia	-0.060	0.064	0.941	[0.830, 1.068]	0.348
	Somali	-0.352	0.073	0.703	[0.609, 0.812]	0.000
Region	Benishangul-Gumuz	0.038	0.066	1.039	[0.913, 1.182]	0.560
	SNNPR	-0.072	0.068	0.930	[0.815, 1.062]	0.284
	Gambella	0.136	0.069	1.146	[1.001, 1.311]	0.049
	Harari	-0.030	0.072	0.971	[0.843, 1.118]	0.681
	Addis Ababa	0.059	0.081	1.061	[0.906, 1.243]	0.461
	Dire Dawa	-0.011	0.072	0.989	[0.858, 1.140]	0.881
	Orthodox	**Ref.**				
Religion	Protestant	-0.266	0.047	0.767	[0.699, 0.841]	0.000
	Muslim	-0.226	0.040	0.798	[0.738, 0.863]	0.000
	Others	-0.364	0.093	0.695	[0.579, 0.834]	0.000
	Married	**Ref.**				
Marital Status	Widowed	0.298	0.063	1.347	[1.191, 1.524]	0.000
	Divorced	0.481	0.054	1.618	[1.456, 1.800]	0.000
	Poor	**Ref.**				
Wealth Index	Middle	0.060	0.039	1.062	[0.984, 1.145]	0.122
	Rich	0.152	0.038	1.165	[1.082, 1.254]	0.000
	No education	**Ref.**				
Education	Primary	0.116	0.033	1.123	[1.053, 1.199]	0.000
	Secondary & above	0.389	0.050	1.476	[1.339, 1.627]	0.000
Residence	Urban	**Ref.**				
	Rural	-0.226	0.042	0.798	[0.735, 0.866]	0.000
Age at first birth	<20 years	**Ref.**				
	20–24 years	0.570	0.036	1.767	[1.646, 1.898]	0.000
	$\geq$ 25 years	0.947	0.054	2.578	[2.321, 2.864]	0.000
Contraceptive use	No	**Ref.**				
	Yes	0.048	0.030	1.050	[0.989, 1.114]	0.110
Breastfeeding status	No	**Ref.**				
	Yes	-0.322	0.029	0.725	[0.685, 0.767]	0.000
Sex of child	Male	**Ref.**				
	Female	-0.032	0.026	0.969	[0.922, 1.019]	0.216
Survival status of child	Dead	**Ref.**				
	Alive	0.221	0.042	1.247	[1.148, 1.355]	0.000

Table A.3: Log-normal AFT model Univariable Analysis

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
	15-19	**Ref.**				
	20-24	-1.132	0.082	0.322	[0.274, 0.379]	0.000
	25-29	-1.883	0.080	0.152	[0.130, 0.178]	0.000
Age	30-34	-2.156	0.082	0.116	[0.099, 0.136]	0.000
	35-39	-2.238	0.084	0.107	[0.091, 0.126]	0.000
	40-44	-2.342	0.087	0.096	[0.081, 0.114]	0.000
	45-49	-2.397	0.090	0.091	[0.076, 0.109]	0.000

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Region	Tigray	**Ref.**				
	Afar	-0.112	0.072	0.894	[0.776, 1.029]	0.119
	Amhara	0.116	0.058	1.123	[1.002, 1.258]	0.046
	Oromia	-0.078	0.063	0.925	[0.817, 1.047]	0.215
	Somali	-0.362	0.074	0.696	[0.602, 0.805]	0.000
	Benishangul-Gumuz	0.049	0.065	1.050	[0.926, 1.192]	0.446
	SNNPR	-0.079	0.066	0.924	[0.812, 1.051]	0.230
	Gambella	0.087	0.069	1.090	[0.953, 1.248]	0.207
	Harari	-0.032	0.070	0.969	[0.844, 1.111]	0.648
	Addis Ababa	0.008	0.075	1.008	[0.870, 1.167]	0.917
	Dire Dawa	-0.025	0.071	0.975	[0.849, 1.120]	0.724
Religion	Orthodox	**Ref.**				
	Protestant	-0.261	0.046	0.770	[0.703, 0.843]	0.000
	Muslim	-0.255	0.040	0.775	[0.717, 0.837]	0.000
	Others	-0.375	0.095	0.687	[0.570, 0.828]	0.000
Marital Status	Married	**Ref.**				
	Widowed	0.268	0.062	1.308	[1.159, 1.476]	0.000
	Divorced	0.421	0.049	1.523	[1.384, 1.677]	0.000
Wealth Index	Poor	**Ref.**				
	Middle	0.026	0.039	1.027	[0.951, 1.108]	0.499
	Rich	0.125	0.037	1.133	[1.055, 1.217]	0.001
Education	No education	**Ref.**				
	Primary	0.136	0.032	1.145	[1.076, 1.219]	0.000
	Secondary & above	0.343	0.046	1.410	[1.288, 1.542]	0.000
Residence	Urban	**Ref.**				
	Rural	-0.161	0.039	0.851	[0.788, 0.92]	0.000
Age at first birth	<20 years	**Ref.**				
	20–24 years	0.413	0.034	1.511	[1.413, 1.616]	0.000
	$\geq$ 25 years	0.638	0.050	1.893	[1.718, 2.087]	0.000
Contraceptive use	No	**Ref.**				
	Yes	0.068	0.030	1.071	[1.01, 1.135]	0.021
Breastfeeding status	No	**Ref.**				
	Yes	-0.197	0.029	0.821	[0.776, 0.869]	0.000
Sex of child	Male	**Ref.**				
	Female	-0.003	0.025	0.997	[0.949, 1.048]	0.915
Survival status of child	Dead	**Ref.**				
	Alive	0.246	0.043	1.279	[1.176, 1.392]	0.000

Table A.4: Log-logistic AFT model Univariable Analysis

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Age	15-19	**Ref.**				
	20-24	-1.462	0.099	0.232	[0.191, 0.281]	0.000
	25-29	-2.280	0.094	0.102	[0.085, 0.123]	0.000
	30-34	-2.516	0.096	0.081	[0.067, 0.097]	0.000
	35-39	-2.573	0.097	0.076	[0.063, 0.092]	0.000
	40-44	-2.678	0.100	0.069	[0.057, 0.084]	0.000
	45-49	-2.731	0.102	0.065	[0.053, 0.080]	0.000

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Region	Tigray	**Ref.**				
	Afar	-0.112	0.071	0.894	[0.778, 1.029]	0.118
	Amhara	0.120	0.056	1.128	[1.011, 1.258]	0.031
	Oromia	-0.085	0.061	0.918	[0.815, 1.036]	0.165
	Somali	-0.355	0.072	0.701	[0.609, 0.808]	0.000
	Benishangul-Gumuz	0.047	0.063	1.048	[0.927, 1.185]	0.454
	SNNPR	-0.073	0.064	0.930	[0.821, 1.053]	0.254
	Gambella	0.088	0.067	1.092	[0.957, 1.246]	0.193
	Harari	-0.011	0.069	0.989	[0.864, 1.132]	0.869
	Addis Ababa	0.040	0.078	1.040	[0.894, 1.211]	0.610
	Dire Dawa	-0.039	0.070	0.961	[0.838, 1.104]	0.576
Religion	Orthodox	**Ref.**				
	Protestant	-0.273	0.045	0.761	[0.697, 0.832]	0.000
	Muslim	-0.259	0.039	0.772	[0.714, 0.834]	0.000
	Others	-0.381	0.092	0.683	[0.570, 0.819]	0.000
Marital Status	Married	**Ref.**				
	Widowed	0.230	0.060	1.258	[1.118, 1.416]	0.000
	Divorced	0.445	0.051	1.561	[1.413, 1.724]	0.000
Wealth Index	Poor	**Ref.**				
	Middle	0.016	0.037	1.016	[0.944, 1.093]	0.677
	Rich	0.099	0.035	1.104	[1.030, 1.183]	0.005
Education	No education	**Ref.**				
	Primary	0.127	0.031	1.135	[1.068, 1.206]	0.000
	Secondary & above	0.391	0.048	1.478	[1.347, 1.623]	0.000
Residence	Urban	**Ref.**				
	Rural	-0.178	0.039	0.837	[0.776, 0.904]	0.000
Age at first birth	<20 years	**Ref.**				
	20–24 years	0.352	0.034	1.422	[1.330, 1.521]	0.000
	$\geq$ 25 years	0.584	0.053	1.793	[1.617, 1.988]	0.000
Contraceptive use	No	**Ref.**				
	Yes	0.085	0.029	1.089	[1.029, 1.153]	0.003
Breastfeeding status	No	**Ref.**				
	Yes	-0.178	0.028	0.837	[0.792, 0.884]	0.000
Sex of child	Male	**Ref.**				
	Female	-0.008	0.025	0.992	[0.945, 1.041]	0.741
Survival status of child	Dead	**Ref.**				
	Alive	0.247	0.041	1.280	[1.181, 1.388]	0.000

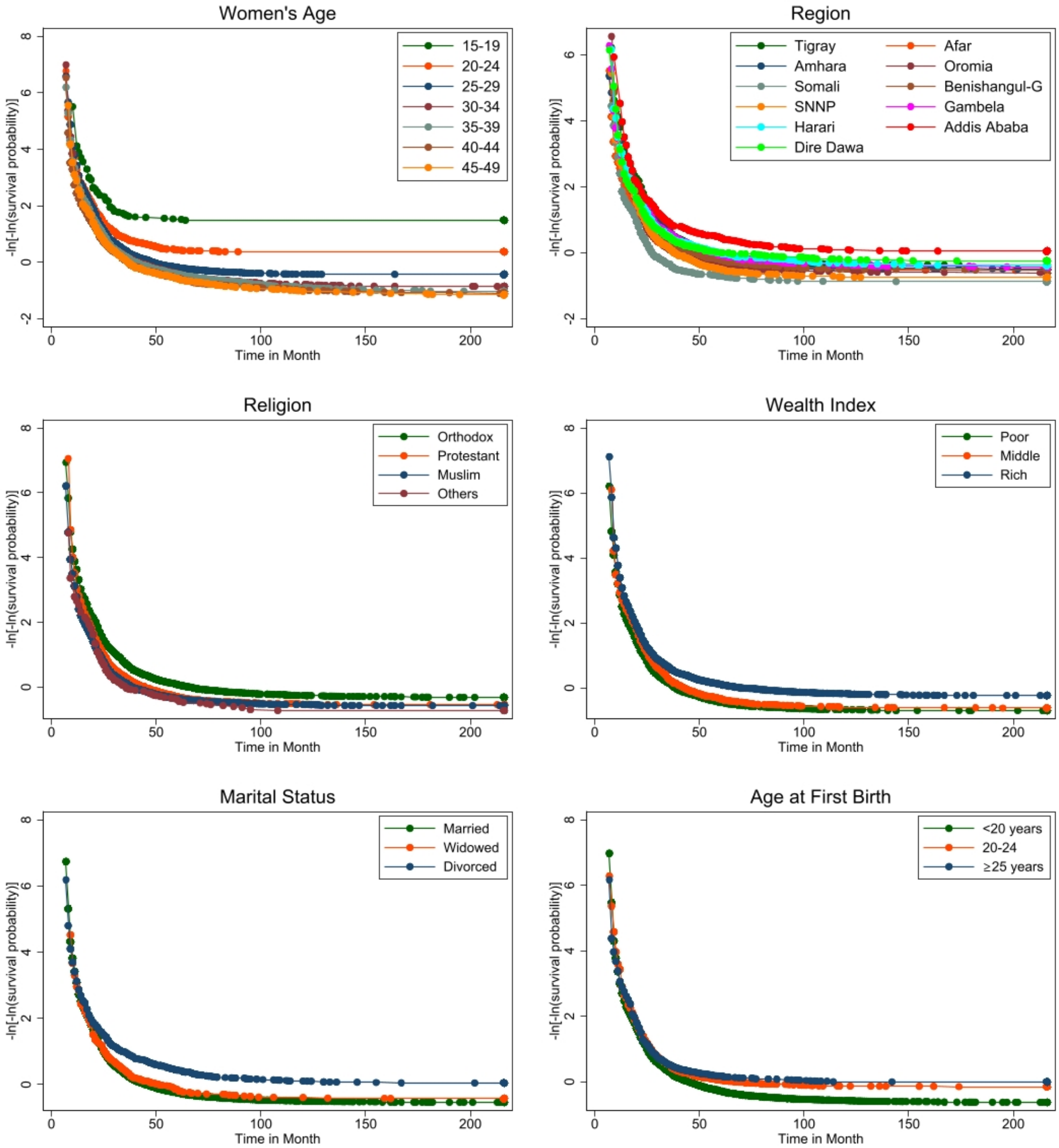

Figure A.1: Plot of –log(-log(survival)) versus time to assess the proportionality assumption for age, region, wealth index, religion, marital status and age at first birth.

Appendix B

Results of multivariable analysis using Cox PH model, Weibull, log-normal, log-logistic AFT models, Weibull gamma shared frailty and lognormal gamma shared frailty models of second birth interval dataset.

Table B.1: Cox PH model Multivariable Analysis

Covariates	Categories	Coef.	SE(Coef.)	Wald	P-value	[95% CI]
Age	15-19	**Ref.**				
	20-24	1.395	0.150	9.301	0.000	[1.101, 1.689]
	25-29	2.287	0.146	15.642	0.000	[2, 2.573]
	30-34	2.557	0.147	17.373	0.000	[2.269, 2.846]
	35-39	2.620	0.148	17.666	0.000	[2.329, 2.911]
	40-44	2.702	0.150	17.966	0.000	[2.407, 2.996]
	45-49	2.755	0.153	18.039	0.000	[2.455, 3.054]
Religion	Orthodox	**Ref.**				
	Protestant	0.324	0.042	7.712	0.000	[0.241, 0.406]
	Muslim	0.361	0.035	10.180	0.000	[0.292, 0.431]
	Others	0.409	0.103	3.973	0.000	[0.207, 0.611]
Marital Status	Married	**Ref.**				
	Widowed	-0.297	0.072	-4.125	0.000	[-0.438, -0.156]
	Divorced	-0.473	0.062	-7.634	0.000	[-0.594, -0.351]
Wealth Index	Poor	**Ref.**				
	Middle	-0.066	0.044	-1.520	0.128	[-0.152, 0.019]
	Rich	-0.119	0.042	-2.872	0.004	[-0.201, -0.038]
Education	No education	**Ref.**				
	Primary	-0.135	0.038	-3.573	0.002	[-0.209, -0.061]
	Secondary & above	-0.386	0.057	-6.826	0.000	[-0.497, -0.275]
Residence	Urban	**Ref.**				
	Rural	0.190	0.044	4.318	0.000	[0.104, 0.276]
Age at first birth	<20 years	**Ref.**				
	20–24 years	-0.391	0.041	-9.438	0.000	[-0.472, -0.310]
	$\geq$ 25 years	-0.660	0.062	-10.710	0.000	[-0.781, -0.539]
Contraceptive use	No	**Ref.**				
	Yes	-0.104	0.034	-3.055	0.002	[-0.171, -0.037]
Breastfeeding status	No	**Ref.**				
	Yes	0.236	0.033	7.052	0.000	[0.170, 0.301]
Survival status of child	Dead	**Ref.**				
	Alive	-0.330	0.049	-6.799	0.000	[-0.425, -0.235]

Table B.2: Weibull AFT model Multivariable Analysis

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Age	15-19	**Ref.**				
	20-24	-1.402	0.132	0.246	[0.190, 0.319]	0.000
	25-29	-2.550	0.128	0.078	[0.061, 0.100]	0.000
	30-34	-2.890	0.129	0.056	[0.043, 0.072]	0.000
	35-39	-3.010	0.130	0.049	[0.038, 0.064]	0.000
	40-44	-3.091	0.132	0.045	[0.035, 0.059]	0.000
	45-49	-3.157	0.134	0.043	[0.033, 0.055]	0.000
Religion	Orthodox	**Ref.**				
	Protestant	-0.316	0.037	0.729	[0.678, 0.784]	0.000
	Muslim	-0.313	0.031	0.731	[0.688, 0.777]	0.000
	Others	-0.397	0.090	0.672	[0.564, 0.801]	0.000
Marital Status	Married	**Ref.**				
	Widowed	0.345	0.063	1.412	[1.248, 1.596]	0.000
	Divorced	0.507	0.054	1.661	[1.494, 1.847]	0.000
Wealth Index	Poor	**Ref.**				
	Middle	0.087	0.038	1.091	[1.012, 1.176]	0.022
	Rich	0.171	0.037	1.187	[1.105, 1.276]	0.000
Education	No education	**Ref.**				
	Primary	0.131	0.033	1.141	[1.069, 1.217]	0.000
	Secondary & above	0.403	0.049	1.496	[1.358, 1.648]	0.000
Residence	Urban	**Ref.**				
	Rural	-0.214	0.039	0.808	[0.749, 0.871]	0.000
Age at first birth	<20 years	**Ref.**				
	20–24 years	0.558	0.036	1.747	[1.626, 1.876]	0.000
	$\geq$ 25 years	0.943	0.054	2.569	[2.312, 2.854]	0.000
Contraceptive use	No	**Ref.**				
	Yes	0.067	0.030	1.069	[1.008, 1.134]	0.025
Breastfeeding status	No	**Ref.**				
	Yes	-0.321	0.029	0.725	[0.685, 0.768]	0.000
Survival status of child	Dead	**Ref.**				
	Alive	0.210	0.042	1.234	[1.135, 1.341]	0.000

Coef. = Coefficient, **95% CI for ϕ** = 95% Confidence Interval (CI) for acceleration factor, **Ref.** = Reference

Table B.3: Log-normal AFT model Multivariable Analysis

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Age	15-19	**Ref.**				
	20-24	-1.126	0.082	0.324	[0.276, 0.381]	0.000
	25-29	-1.876	0.080	0.153	[0.131, 0.179]	0.000
	30-34	-2.147	0.082	0.117	[0.099, 0.137]	0.000
	35-39	-2.224	0.084	0.108	[0.092, 0.128]	0.000
	40-44	-2.329	0.087	0.097	[0.082, 0.115]	0.000
	45-49	-2.368	0.090	0.094	[0.078, 0.112]	0.000

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Religion	Orthodox	**Ref.**				
	Protestant	-0.314	0.036	0.730	[0.680, 0.784]	0.000
	Muslim	-0.365	0.031	0.695	[0.654, 0.738]	0.000
	Others	-0.399	0.091	0.671	[0.561, 0.802]	0.000
Marital Status	Married	**Ref.**				
	Widowed	0.291	0.062	1.338	[1.185, 1.509]	0.000
	Divorced	0.443	0.049	1.557	[1.414, 1.714]	0.000
Wealth Index	Poor	**Ref.**				
	Middle	0.059	0.039	1.061	[0.984, 1.144]	0.125
	Rich	0.154	0.035	1.167	[1.089, 1.250]	0.000
Education	No education	**Ref.**				
	Primary	0.157	0.032	1.169	[1.099, 1.244]	0.000
	Secondary & above	0.366	0.045	1.442	[1.320, 1.575]	0.000
Residence	Urban	**Ref.**				
	Rural	-0.142	0.036	0.868	[0.808, 0.932]	0.000
Age at first birth	<20 years	**Ref.**				
	20–24 years	0.398	0.034	1.489	[1.392, 1.593]	0.000
	$\geq$ 25 years	0.616	0.049	1.851	[1.680, 2.040]	0.000
Contraceptive use	No	**Ref.**				
	Yes	0.086	0.029	1.090	[1.029, 1.154]	0.004
Breastfeeding status	No	**Ref.**				
	Yes	-0.187	0.029	0.829	[0.784, 0.878]	0.000
Survival status of child	Dead	**Ref.**				
	Alive	0.238	0.043	1.269	[1.166, 1.381]	0.000

Table B.4: Log-logistic AFT model Multivariable Analysis

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Age	15-19	**Ref.**				
	20-24	-1.469	0.100	0.230	[0.189, 0.280]	0.000
	25-29	-2.285	0.095	0.102	[0.085, 0.122]	0.000
	30-34	-2.517	0.096	0.081	[0.067, 0.097]	0.000
	35-39	-2.569	0.097	0.077	[0.063, 0.093]	0.000
	40-44	-2.676	0.100	0.069	[0.057, 0.084]	0.000
	45-49	-2.714	0.103	0.066	[0.054, 0.081]	0.000
Religion	Orthodox	**Ref.**				
	Protestant	-0.331	0.035	0.718	[0.671, 0.770]	0.000
	Muslim	-0.374	0.030	0.688	[0.649, 0.730]	0.000
	Others	-0.411	0.088	0.663	[0.557, 0.788]	0.000
Marital Status	Married	**Ref.**				
	Widowed	0.255	0.060	1.290	[1.146, 1.452]	0.000
	Divorced	0.468	0.051	1.596	[1.444, 1.764]	0.000
Wealth Index	Poor	**Ref.**				
	Middle	0.048	0.037	1.049	[0.975, 1.128]	0.198
	Rich	0.130	0.034	1.139	[1.065, 1.217]	0.000
Education	No education	**Ref.**				
	Primary	0.146	0.031	1.158	[1.089, 1.230]	0.000
	Secondary & above	0.412	0.047	1.510	[1.377, 1.655]	0.000

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Residence	Urban	**Ref.**				
	Rural	-0.160	0.036	0.852	[0.794, 0.915]	0.000
Age at first birth	<20 years	**Ref.**				
	20–24 years	0.338	0.034	1.402	[1.311, 1.500]	0.000
	$\geq$ 25 years	0.558	0.053	1.748	[1.576, 1.938]	0.000
Contraceptive use	No	**Ref.**				
	Yes	0.103	0.029	1.108	[1.047, 1.173]	0.025
Breastfeeding status	No	**Ref.**				
	Yes	-0.169	0.028	0.845	[0.799, 0.893]	0.000
Survival status of child	Dead	**Ref.**				
	Alive	0.240	0.041	1.271	[1.172, 1.378]	0.000

Table B.5: Multivariable analysis of Weibull gamma shared frailty model

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
Age	15-19	**Ref.**				
	20-24	-1.405	0.127	0.245	[0.191, 0.315]	0.000
	25-29	-2.538	0.123	0.079	[0.062, 0.101]	0.000
	30-34	-2.871	0.124	0.057	[0.044, 0.072]	0.000
	35-39	-3.001	0.125	0.050	[0.039, 0.064]	0.000
	40-44	-3.067	0.127	0.047	[0.036, 0.060]	0.000
	45-49	-3.152	0.129	0.043	[0.033, 0.055]	0.000
Religion	Orthodox	**Ref.**				
	Protestant	-0.252	0.047	0.778	[0.709, 0.852]	0.000
	Muslim	-0.286	0.039	0.751	[0.696, 0.812]	0.000
	Others	-0.311	0.100	0.733	[0.603, 0.891]	0.002
Marital Status	Married	**Ref.**				
	Widowed	0.326	0.063	1.385	[1.224, 1.567]	0.000
	Divorced	0.489	0.054	1.631	[1.468, 1.812]	0.000
Wealth Index	Poor	**Ref.**				
	Middle	0.070	0.040	1.073	[0.992, 1.161]	0.080
	Rich	0.120	0.041	1.127	[1.040, 1.223]	0.004
Education	No education	**Ref.**				
	Primary	0.111	0.034	1.118	[1.046, 1.194]	0.001
	Secondary & above	0.407	0.051	1.503	[1.360, 1.661]	0.000
Age at first birth	<20 years	**Ref.**				
	20–24 years	0.541	0.036	1.717	[1.600, 1.843]	0.000
	$\geq$ 25 years	0.920	0.053	2.509	[2.261, 2.785]	0.000
Residence	Urban	**Ref.**				
	Rural	-0.252	0.051	0.777	[0.704, 0.858]	0.000
Contraceptive use	No	**Ref.**				
	Yes	0.020	0.031	1.020	[0.961, 1.083]	0.517
Breastfeeding status	No	**Ref.**				
	Yes	-0.285	0.029	0.752	[0.711, 0.797]	0.000
Survival status of child	Dead	**Ref.**				
	Alive	0.214	0.042	1.239	[1.140, 1.346]	0.000

θ = 0.083, k = 0.839, AIC = 15556.79, τ = 0.039, λ = 1.192,
LR test of theta = 0: chibar2(01) = 110.73, Prob >= chibar2 = 0.000

Table B.6: Multivariable analysis of log-normal gamma shared frailty model

Covariates	Categories	Coef.	SE(Coef.)	ϕ	[95% CI for ϕ]	P-value
	15-19	**Ref.**				
	20-24	-1.159	0.079	0.314	[0.269, 0.366]	0.000
	25-29	-1.867	0.077	0.155	[0.133, 0.180]	0.000
Age	30-34	-2.108	0.079	0.121	[0.104, 0.142]	0.000
	35-39	-2.191	0.081	0.112	[0.095, 0.131]	0.000
	40-44	-2.275	0.084	0.103	[0.087, 0.121]	0.000
	45-49	-2.310	0.087	0.099	[0.084, 0.118]	0.000
	Orthodox	**Ref.**				
Religion	Protestant	-0.096	-0.236	0.044	[0.725, 0.860]	0.000
	Muslim	-0.184	-0.345	0.037	[0.658, 0.762]	0.000
	Others	-0.193	-0.320	0.096	[0.601, 0.877]	0.001
	Married	**Ref.**				
Marital Status	Widowed	0.256	0.061	1.292	[1.146, 1.456]	0.000
	Divorced	0.397	0.049	1.487	[1.350, 1.638]	0.000
	Poor	**Ref.**				
Wealth Index	Middle	0.048	0.039	1.049	[0.972, 1.132]	0.220
	Rich	0.089	0.039	1.093	[1.013, 1.179]	0.022
	No education	**Ref.**				
Education	Primary	0.127	0.032	1.135	[1.067, 1.208]	0.000
	Secondary & above	0.345	0.047	1.411	[1.288, 1.547]	0.000
Residence	Urban	**Ref.**				
	Rural	-0.063	0.049	0.939	[0.854, 1.033]	0.194
Age at first birth	<20 years	**Ref.**				
	20–24 years	0.364	0.034	1.439	[1.346, 1.538]	0.000
	$\geq$ 25 years	0.541	0.050	1.717	[1.557, 1.895]	0.000
Contraceptive use	No	**Ref.**				
	Yes	0.048	0.030	1.050	[0.990, 1.113]	0.104
Breastfeeding status	No	**Ref.**				
	Yes	-0.145	0.028	0.865	[0.818, 0.914]	0.000
Survival status of child	Dead	**Ref.**				
	Alive	0.237	0.042	1.267	[1.167, 1.376]	0.000

θ = 0.1, k = 0.896, AIC = 14814.15, τ = 0.048, λ = 1.116, LR test of θ = 0: chibar2(01) = 110.87
Prob > = chibar2 = 0.000