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Survival Analysis to Determine the Significant Factors Associated with Birth Interval of Women in Ethiopia: Based on 2011 Ethiopian Demographic and Health Survey Data

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Abstract: Longer intervals between consecutive births decrease the number of children a woman can have. This results in beneficial effects on population size and on the health status of mothers and children. The general objective of this study was to model the birth intervals of adult women age 15-49 years old in Ethiopia and to identify the variable that affects the length of birth intervals of women. The study utilizes the data extracted from the 2011 Ethiopian Demographic and Health Survey (EDHS). In this study cox proportional hazards and shared gamma frailty models were adopted for the analysis to identify important demographic and socioeconomic factors that may affect the length of birth intervals and to analyze correlated birth intervals respectively. The result of the two models revealed that mother's age, place of residence, mother education level, wealth index, mother age at first birth, childbirth order, survival status of the previous child, breast feeding status, and contraceptive use were found to have significant effect on the length of birth interval for Ethiopian women. The analysis with the frailty model shows that child birth order may not be an important covariate for analyzing birth intervals, especially when mother's age at first birth is already in the model. Moreover, shared gamma frailty model have resulted in a minimum AIC as compared to cox proportional hazard model without frailty term in the model, suggesting that shared gamma frailty model is the most powerful one in predicting the birth intervals of women among regional states of Ethiopia. Hence, the setting of correlated observations, the cox frailty models are recommended for providing statistically valid estimates of the effects of proximate determinants after adjusting for the background variables and unobserved random effects.

Keywords: Birth Interval, Cox PH Model, Frailty Model, Correlated, Time Event Data, Ethiopia

1. Introduction

Birth interval is the length of time between two successive live births. Longer time periods between births allow the next pregnancy and birth to be at full gestation and growth [1]. Births too close together are associated with schizophrenia in offspring and hinder the physiological ability of mothers and, thus, expose them to complications during and after pregnancy [2]. Short birth intervals (less than 24 months) increase maternal risks such as third trimester bleeding, toxemia, malnutrition, anemia, and maternal mortality [3]. It can lead to several serious outcomes for neonates as well, such as prematurity, low birth weight, stillbirth, neonatal mortality and adverse effect on intellectual ability, physical growth and development [4]. Beyond the health implications, shorter birth intervals accelerate population growth and undermining development efforts. Shorter birth interval is difficult for women to become productive members of society, by limiting their contribution to economic development. Moreover, when a newborn comes, it is likely that the family will invest more of its limited resources in the form of care to the newborn, while the other children will receive inadequate share of the resources [5]. On the other hand, optimal birth spacing (OBS) yields the greatest health, social, and economic benefits for the family.

The recent evidence showed that births should be spaced at three to five years apart to ensure maximum health benefits for mothers, newborns, and older children [6]. Additional to these direct health benefits for mother and child, birth spacing has social benefits such as increased savings, less stress on the mother and more time for the couple to engage in other activities [7]. Identification of the potential variables or covariates that correlate to the length of birth interval of women is very important for understanding the insights of birth spacing patterns, maternal and child health. The total number of births during a woman's whole reproductive period depends on the length of intervals between her births. The variations of fertility levels in a country can be attributed to the differences in the length of the reproductive life of women and differences in the length of time between births when women are exposed to the risk of conception. Analysis of those factors influencing the span and those affecting the spacing of fertility has proven useful, since in many cases they appear to vary quite substantially across populations [8]. In recent years, policy makers and planners have focused a great deal of attention on the birth interval and its determinants. Because the number of births a woman may have during her reproductive span depend on the spacing between the births and also there is significant link between birth spacing and maternal and child health [9]. Therefore, the spacing of births through a deliberately prolonged interval between births and a delay in child bearing following marriage could be logical alternative strategies for fertility control.

Ethiopia is one of the most densely populated countries in Africa with a projected population of 87.1 million with annual population growth rate of 2.6% [6]. According to Ethiopian demographic and health survey (2011), total fertility rate (TFR) was 4.8 which is substantially higher among rural women than among urban women where rural women give birth to nearly three more children during their reproductive years than urban women 5.5 and 2.6, respectively. Evidence shows that nearly two million people are added to the country's population each year. The country is characterized by a very high fertility, low life expectancy, high maternal and child mortality, poor nutritional status, high infant mortality, low per capital income, etc. [6]. Information on duration of birth intervals provide insight to birth spacing patterns which is the heart of reproductive health in general and family planning in particular. The Federal Ministry of Health (FMOH), reproductive health department and health bureaus of respective regions have made concerted effort to reduce fertility and promote the health of the women and their children. Women in Ethiopia however, still experience shorter birth intervals [10]. In the developing world most demographic surveys like World Fertility Survey and Demographic and Health Surveys, collect data that are clustered according to geographical regions due to sampling design. Mothers in a same cluster usually share certain unobserved characteristics and as a result birth intervals of the same cluster tend to be correlated. A lot of studies have been conducted on birth intervals in Ethiopia, but most of them either did not use data from whole region or did not consider heterogeneity due to sampling design in the analysis. This ignoring the dependencies among the observations, obtained from a cluster sampling scheme, can lead to incorrect standard errors of the estimates of the parameters of interest [11].

Frailty modelling approach accounts for this problem by specifying independence among observed data items conditional on a set of unobserved or latent variables. Whereas, the Cox proportional hazards model has no such term and dependence of the event times is not accounted for. Birth intervals can be considered as time to event data, where the intervals are either closed or open-ended depending on whether the interval is defined as the time between two successive births (closed interval) or the time between the birth of the youngest child and the interview date (open-ended interval). Considering open-ended intervals as censored and closed intervals as failure, Cox's proportional hazards model can be used to identify important factors for birth intervals provided the intervals are independent. The random effects models for time-to-event data, which are known as frailty models, can be used to analyze correlated birth intervals.

This study gives particularly a new approach to know the presence of unobserved factors (heterogeneity) with the help of observed prognostic factors. Various studies have been conducted to study the effects of prognostic factors incorporating frailty effect in different diseases like kidney transplant, waiting time to first pregnancy, genetic trait etc. However the application of frailty on birth interval is still an unexplored avenue. Different studies show that there are lots of researches on the analysis of correlated survival data have appeared recently in the demographic literature. [12] Studied frailty modeling for clustered survival data. [13] Assessed the determinants of inter birth interval among women's of child bearing age in Oromia region Ethiopia using multivariable logistic regression. [14] conducted duration and determinants of birth interval among women of child bearing age in Southern Ethiopia. [15]. applied parametric frailty and shared frailty models to waiting time to first pregnancy. [16] the Prognostic factors of first birth interval using the parametric survival models. [17] Tried to examine the covariates of birth intervals and the effect of increased birth intervals on current fertility level in Bangladesh using cox proportional hazards model. [18] Studied a multivariate proportional hazards model with a single random effect and estimation of their model using the method of expectation maximization algorithm. [11] Conducted a nested frailty model for modeling child mortality considering both family and community level clustering effect.

The main purpose of this study was to model the birth interval of adult women age 15-49 years old using cox proportional hazard and shared gamma frailty modelling approaches and then after to compare their performance to suggest an appropriate model for analyzing birth intervals of Ethiopian women.

The specific objectives of the study which should be accomplished to achieve the general objective was:

i. To identify the relative contribution of different potential risk factors to the change in birth intervals.
ii. To assess the unobserved heterogeneity in clusters for birth interval data.
iii. To compare Cox proportional hazard and shared gamma frailty models and thereby to show the benefits of taking into account the clustering of subjects within region using shared gamma frailty model.
iv. To investigate the unobserved heterogeneity by different covariate in Ethiopia.

2. Method

2.1. Data Source

This study used the data collected in the Ethiopian Demographic and Health Survey. The 2011 Ethiopia Demographic and Health Survey were conducted by the Central Statistical Agency (CSA) under the auspices of the support of the Ministry of Health from 27, December 2010 through June 2011 with a nationally representative sample of nearly 17,817 households. The sampling frame used for the 2011 EDHS was the Population and Hosing Census conducted by the Central Statistical Authority (CSA) in 2007 during the 2007 Population and Housing Census, each of the kebeles was sub divided in to convenient areas called census enumeration area (EAs). The 2011 EDHS sample was selected using a stratified, two stage cluster design and EAs were the sampling units for the first stage. For the 2011 EDHS, a representative sample of approximately 17,817 households from 624 clusters was selected. In the first stage, 624 clusters, 187 urban and 437 rural were selected from the list of enumeration areas based on sampling frame. In the second stage, a complete listing of households was carried out in each selected cluster. The analysis presented in this study on birth interval was based on the 10,847 women who have at least one birth over the five-year period of 2005–2011 are selected from the EDHS data.

2.1.1. Variables in the Study

Variables considered in this study were selected based on literature's which have been conducted at the global level. Potential determinant factors expected to be correlated with birth interval included as variables of the study.

2.1.2. Response Variable

In this study, birth interval is the response variable which is defined as the length of time between two successive live births measured in months.

2.1.3. Explanatory Variables

The explanatory variables which might determine the change in birth intervals of women were socio-economic, demographic, health and environmental factors. Several predictors are considered in this study to investigate the important relative contribution of different potential risk factors to the change in birth intervals.

Table 1. *Description of the variables and coding in the study*

Covariate/Factor	Covariate/Factor
Mother Age	Residence
1=15-19	1=Urban
2=20-24	2=Rural
3=25-29	Mother Education
4=30-34	1=No education
5=35-39	2=Primary
6=40-44	3=Secondary
7=45-49	4=Higher
Religion	Father education
1=Orthodox	1=No education
2=Catholic	2=Primary
3=Protestant	3=Secondary
4=Muslim	4=Higher
5=Others	
Mother Occupation	Father Occupation
1=Not working	1=Not working
2=Professionals	2=Professionals
3=Others	3=Others
Wealth index	Type of birth
1=Poor	1=Single birth
2=Middle	2=Multiple birth
3=Rich	
Marital Status	Child birth order
1=Single	1=1
2=Married	2=2 – 4
3=Widowed	3=5 – 7
4=Divorced	4=8+
5=Separated	
Mother age at 1st birth	Sex of child
1=<15	1=Male
2=15 – 20	2=Female
3=21 – 25	Breastfeeding status
4=>=26	1=No
	2=Yes
Survival status of index child	Contraceptive use
1=Dead	1=No
2=Alive	2=Yes

2.2. Methods of Statistical Analysis

2.2.1. Cox Proportional Hazard Model

This study is intended to model the birth interval of adult women's living in Ethiopia using survival modelling framework. Survival analysis is a statistical method for data analysis where the outcome variable of interest is the time to the occurrence of an event [19]. The Cox proportional hazards [20] model is now the most widely used for the analysis of survival data in the presence of covariates or prognostic factors. This is the most popular model for survival analysis because of its simplicity, and not being based on any assumptions about the survival distribution. This is a semi- parametric model for fitting survival data which describes the relation between the event incidence, as expressed by the hazard function and covariates that influence survival time.

Let t_{ijk} represent the birth interval corresponding to the kth child of the jth mother in the ith cluster and $Z_{ijk}=(Z_{ijk1}, Z_{ijk2}, Z_{ijkp})'$ is the associated p dimensional covariate vector (i=1,..., n; j=1,..., m_i; k=1,..., d_{ij}). The hazard function for the birth interval t_{ijk} can be modeled using.

Cox's proportional hazards model [20] as

$$h(t) = h_0(t)exp(\beta_1 z_1 + \beta_2 z_2 + \ldots.\beta_p z_p) \quad (1)$$

Where $h(t)$is the hazard function at time t with covariates with $Z = (Z_1, Z_2, \ldots \ldots.. Z_P)$ or it's is dependent on the number of regressors incorporated in the model, whose impact is measured by the size of the respective coefficients of the covariates. $h_0(t)$ is the arbitrary baseline hazard function that characterizes how the hazard function changes as a function of survival time or the value of the hazard if all the covariates are equal to zero. $\beta = (\beta 1, \beta 2, \ldots \ldots.. \beta p)$ is a column vector of p regression parameters associated with explanatory variables. In this model, no distributional assumption is made for the survival data, the only assumption is that the hazards ratio does not change over time (i.e., proportional hazards). If two individuals are compared that have covariate values Z and Z*, the ratio of their hazard rates at any time point simplifies to

$$\frac{h(t|Z)}{h(t|\, Z^*)} = \frac{h_0(t)exp(\beta' Z)}{h_0(t)exp(\beta' Z^*)} = \exp\left(\beta'(Z - Z^*)\right) \quad (2)$$

This ratio is constant or proportional throughout the study, that is, Equation (2) does not depend on t. The regression coefficients in the proportional hazards Cox model, which are the unknown parameters in the model, can be estimated using the method of maximum likelihood. In Cox proportional hazards model we can estimate the vector of parameters β_1 s without having any assumptions about the baseline hazard $h_0(t)$.

2.2.2. Frailty Model

The concept of frailty provides a suitable way to introduce random effects in the model to account for association and unobserved heterogeneity. In statistical terms, a frailty model is a random effect model for time-to-event data, where the random effect (the frailty) has a multiplicative effect on the baseline hazard function [21]. Frailty models are the extensions of the proportional hazards model which is best known as the Cox model [20] the most popular model in survival analysis. Normally, in most clinical application, survival analysis implicitly assumes a homogeneous population of individuals to be studied. This means that all individuals sampled in that study are subject in principle under the same risk (e.g., risk of death, risk of disease recurrence). In many applications, the study population cannot be assumed to be homogeneous, but must be considered as a heterogeneous sample i.e., a mixture of individuals with different hazards. For example, in many cases it is impossible to measure all relevant covariates related to the disease of interest, sometimes because of economic reasons, sometimes the importance of some covariates is still unknown.

This consideration is true for all regression models, not only survival models. If it is known that some factor is important, it makes sense to try to obtain the individual values, but if it is not possible, the standard is to ignore the presence of such variables and lead to an increase in the variability of the response compared to the case, when the variables are included. In the survival data case, however, the increased variability implies a change in the form of the hazard function. Shared frailty model is a conditional model in which frailty is common to all subjects in a cluster. The shared frailty 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, the given frailty, all event times in a cluster are independent. The shared frailty concept is one of the important approaches in multivariate survival modelling and is relevant to event times of related individuals, similar organs and repeated measurements. Individuals in a cluster are assumed to share the same frailty. That is why this model is known as shared frailty model. To adjust regional level heterogeneity, clusters are considered as random for the following frailty model for the conditional hazard function given the random cluster effect.

$$h_{ij}\left(t \middle| U_i, z_{ij}\right) = h_o(t) U_i \exp(\beta' z_{ij}) \quad (3)$$

Where Ui is the random effect for the ith cluster exp (Ui) is known as frailty. The model of the equation (3) is known as shared frailty model because all the mothers in a specific cluster share the same frailty and the frailty exp (Ui) acts multiplicatively on the baseline hazard function h0 (.). The frailty model can be considered as a generalization of the Cox's proportional hazards model, i.e. frailty model reduces to Cox's proportional hazards model with ui=0 or exp (ui)=1. For complete specification of the frailty model (3), the distribution for the frailty term or random effect needs to be specified. Estimation of the frailty model can be parametric or semi-parametric. In the former case, a parametric density is assumed for the event times, resulting in a parametric baseline hazard function. Estimation is then conducted by maximizing the marginal log-likelihood [15]. In the second case, the baseline hazard is left unspecified and more complex techniques are available to approach that [22, 23]. Even though semi-parametric estimation offers more flexibility, the parametric estimation will be more powerful if the form of the baseline hazard is somehow known in advance [15].

For reasons of convenience, analysts often choose parametric representations of frailty models that are mathematically tractable. [24] Used several distributions for frailty including gamma, inverse Gaussian, positive stable distributions and claimed that these two distributions are relevant and mathematically tractable as a frailty distribution for heterogeneous populations. [25] Used a lognormal distribution for frailty, whereas [26] assumed that frailty is distributed across individuals as a gamma distribution. In this study we used the gamma distribution which is the main frailty distributions widely used in the literature because of its simplicity and mathematical tractability. From an analytical and computational view gamma is a very convenient distribution.

3. Result

3.1. Descriptive Analysis of Birth Interval Data in Ethiopia

Birth interval is defined as the length of time between two successive live births of a mother and it can be classified as either a closed or an open interval. A closed birth interval is the one that corresponds to the length of time between two successive live births and on the other hand, an open interval is the length of time between the birth of the youngest child and the date of interview, so there is an open interval for each woman selected in the study. In this study, the data consists of 10,847 women of which about 65% were closed interval and the rest of were open interval. Birth interval data can be considered as survival data with open intervals as censored observations and closed intervals as the complete observations. In this study cox proportional hazards model and shared frailty model were considered for examining the effects of different demographic and socioeconomic factors on the birth intervals. In both models, the same set of covariates were used and we implemented the models in statistical software R, a public domain software and Stata software for computing proportional hazards models and shared frailty model.

Table 2. *Distribution of important socioeconomic, demographic and biological characteristics for the change of birth interval of women in Ethiopia.*

Covariate	Category	Event (%)	Censored	Total
Mother age	15 – 19	94 (22.5)	323	417
	20 – 24	879 (52.7)	790	1669
	25 – 29	2122 (79.1)	533	2655
	30 – 34	1754 (91.2)	170	1924
	35 – 39	1744 (94.2)	108	1852
	45 – 49	1215 (95.7)	54	1269
	45 – 49	1028 (96.9)	33	1061
Religion	Orthodox	3206 (76.3)	994	4200
	Muslim	3698 (84.7)	669	4367
	Protestant	1658 (84.3)	308	1966
	Catholic	104 (84.6)	19	123
	Others	107 (93.0)	8	115
Residence	Urban	1875 (68.2)	874	2749
	Rural	6961 (86.0)	1137	8098
Mother Education	No education	6368 (89.1)	776	7144
	Primary	1990 (70.2)	844	2834
	Secondary and above	303 (55.3)	245	548
		175 (54.5)	146	321
Father Education	No education	4625 (85.7)	769	5394
	Primary	2874 (79.4)	747	3621
	Secondary and above	1337 (73.0)	495	1832
Mother Occupation	Not working	4262 (82.0)	936	5198
	Professionals	100 (58.8)	70	170
	Others	4474 (81.7)	1005	5479
Father Occupation	Not working	203 (77.2)	60	263
	Professionals	504 (75.9)	160	664
	Others	8129 (81.9)	1792	9921
Wealth index	Poor	4024 (87.1)	596	4620
	Middle	1407 (86.2)	226	1633
	Rich	3405 (74.1)	1189	4594
Marital Status	Single	24 (24.2)	75	99
	Married	7654 (83.4)	1519	9173
	Widowed	946 (88.7)	63	559
	Divorced	468 (65.7)	244	712
	Separated	194 (63.8)	110	304
Mother age at 1st birth	<=15	1875 (90.4)	200	2075
	16-20	4774 (81.6)	1075	5849
	21-25	1751 (75.8)	558	2309
	>=26	436 (71.0)	178	614
Type of birth	Single birth	8680 (81.2)	2011	10691
	Multiple birth	156 (100.0)	0	156
Child Birth Order	1	0 (0.0)	2011	0

Covariate	Category	Event (%)	Censored	Total
	2-4	4520 (100.0)	0	4520
	5-7	2856 (100.0)	0	2856
	8 and above	1460 (100.0)	0	1460
Sex of child	Male	4478 (81.2)	1034	5512
	Female	4358 (81.7)	977	5335
Survival Status of the index child	Alive	8270 (81.3)	1903	10173
	Dead	4931 (80.8)	1172	6103
Breastfeeding status	Yes	3905 (82.3)	839	4744
	No	6729 (82.3)	1456	8185
Contraceptive use	Yes	1311 (75.4)	428	1739
	No	6729 (82.3)	1456	8185

When we look at the mothers' age, 3.8% (417) of the mother are found in the range of 15-19 years, is the minimum number of women founded whereas, the maximum number of women found in the age group of 25-29 years which is 24.5% (2655). Women's place of residence is categorized as rural and urban in which 74.7% (8098) are found in rural settings while 25.3% (2749) are found in urban settings.

Regarding to educational attainments of both mothers and fathers, 65.9% (7144) mothers and 49.7% (5394) fathers have no any kind of formal education, 26.1% (2834) mothers and 33.4% (3621) fathers have at least primary level education and 5.1% (548) mothers and 16.9% (1832) fathers from the sample have a formal educational level of at least secondary. About 42.6% (4620) of the household's wealth indexes were classified as poor while 15.1% (1633) had medium income and 42.4% (4594) were rich. And also the output show that 19.1% (2075) of the mothers had first birth before the age of 16 years. Whereas 53.9% (5849), 21.3% (2309), 5.7% (614) of the mothers had first birth at the age range of 16-20 years, 21-25 years and above 25 years respectively. The survival status of the index child at the time of the occurrence of the next birth was computed using data on age at the death of the index child and date of birth of the next child. Accordingly, women who experienced the death of the previous child at the birth of the next child are considered as women who lost the index child and grouped under the 'dead' category.

Those women whose child was alive proceeding to the next child are classified under the 'alive' category of the variable survival status of the index child's. The percentage distribution for women who lost their first child is 6.2% and women whose first child was alive at the birth of the second child accounted for 93.8%. Status of breast feeding of the last child is categorized into two groups. The first group includes those women whose last child not breastfed and the second group includes women whose last child breastfed. 56.3% of women not breast fed their last child while 43.7% of women breastfed their last child. Women who have ever used any one of the family planning methods are classified as 'yes' while those women who had never practiced any family planning methods are grouped under 'no' category. The number of women who use contraceptive methods are 16.0% (1739) where as 75.5% (8185) does not use any contraceptive methods.

3.2. Results of the Cox Proportional Hazard Model

In order to identify the relative contribution of different potential risk factors to the change in birth intervals, we first used univariate analysis to check all the risk factors before proceeding to more complicated models. The likelihood ratio test is considered in each univariate Cox PH model. Variables are identified as significant using 0.2 - 0.25 significance level in the univariate model. We then fit the full multivariate Cox PH model including all the potential risk factors. The fit of the Multivariate Cox's Proportional Hazards Model Table 3 shows that the covariates mother age, place of residence, mother education level, wealth index, mother age at first birth, child birth order, survival status of the previous child, breast feeding status and contraceptive use have significant effects on the likelihood of birth at 5% level of significance. Place of residence is one of the crucial socioeconomic variables in affecting birth interval length. The estimated covariate coefficient $\hat{\beta}$ =0.123 for place of residence (reference group being urban) indicator implies that the hazards ratio is exp ($\hat{\beta}$)=1.131. This shows women who residences in rural places were 1.131 times more likely to have subsequent birth compared with women who resides in urban places. The implication of 95% confidence interval is that the hazard ratio can get as low as 1.037 and as high as 1.234. Mother's education is found to be a very important covariate for birth interval as the analysis shows that highly educated mothers have significantly smaller likelihood of birth compared to illiterate and primary educated mothers, and there is a significant difference in likelihood of birth among women with at least secondary or higher education. Taking no education as reference group we have the coefficients $\hat{\beta}$ =-0.182, -0.809 and -1.162 for primary, secondary and higher education level respectively. These figures imply that the hazard ratios for these categories are 0.834, 0.445 and 0.313 for primary, secondary and higher education level respectively. The hazard of primary and secondary education level women to have subsequent birth after the index child was reduced by 16.6% and 24.6% compared to those with no formal education.

The multivariable cox proportional hazard model results in Table 3 show that the socioeconomic factor wealth status has significant effect on birth intervals. And the time ratio of the birth interval for mid-range and rich households compared with poor ones are 1.108 and 1.233, respectively, and are significant because, the p-value corresponding to middle and rich groups of mothers are 0.008 and 0.000, respectively. Age of women at birth of the first child was significant predictor of birth interval. Women aged 16 -20 years were 1.4% less likely to have a subsequent birth compared to those aged less than or equal to 15 years (HR=0.986, 95% CI: 0.953, 1.020). Likewise, women aged 21-25 and above 25 years were 14.3% (HR=0.857, 95% CI: 0.811, 0.905) and 27.9% (HR=0.721, 95% CI: 0.630, 0.826) less likely to have a subsequent birth respectively. As women get older and older there is a consistent decrements in the probability of having subsequent births.

Table 3. *Multivariable Cox PH Model for birth interval dataset, 2011 EDHS.*

Covariate (Reference)	Coef (β)	Std. Err.	P-value	HR	95%CIfor exp (β)
Mother age (15 -19)					
20 – 24	1.483	0.116	0.000	4.405	(3.511, 5.526)
25 – 29	1.116	0.059	0.000	3.052	(2.719, 3.425)
30 – 34	0.716	0.049	0.000	2.047	(1.859, 2.253)
35 – 39	0.489	0.046	0.000	1.631	(1.491, 1.784)
40 – 44	0.254	0.043	0.000	1.289	(1.185, 1.401)
45 – 49	0.031	0.044	0.476	1.032	(0.947, 1.123)
Religion (Orthodox)					
Muslim	-0.501	0.411	0.223	0.606	(0.271, 1.357)
Catholic	-0.270	0.422	0.523	0.763	(0.334, 1.747)
Protestant	-0.340	0.411	0.409	0.712	(0.318, 1.595)
Others	-0.343	0.411	0.405	0.710	(0.317, 1.590)
Residence (Urban)					
Rural	0.123	0.044	0.005	1.131	(1.037, 1.234)
Mother Education (No Edu.)					
Primary	-0.182	0.089	0.040	0.834	(0.700, 0.992)
Secondary	-0.809	0.227	0.000	0.754	(0.485, 0.894)
Higher and above	-1.162	0.144	0.012	0.313	(0.123, 0.479)
Father Education (No Edu.)					
Primary	0.102	0.156	0.511	1.108	(0.816, 1.503)
Secondary	-0.058	0.151	0.700	0.943	(0.701, 1.269)
Higher and above	-0.066	0.179	0.713	0.936	(0.659, 1.330)
Mother Occupation (Not working)					
Professionals	-0.103	0.030	0.349	0.902	(0.850, 0.957)
Others	-0.061	0.035	0.656	0.941	(0.879, 1.007)
Father Occupation (Not working)					
Professionals	0.210	0.094	0.255	1.233	(0.026, 1.483)
Others	0.230	0.094	0.420	1.259	(0.047, 1.514)
Wealth index (Poor)					
Middle	-0.102	0.156	0.018	1.108	(1.016, 1.503)
Rich	-0.210	0.094	0.002	1.233	(1.026, 1.483)
Marital Status (Single)					
Married	0.195	0.218	0.372	1.215	(0.792, 1.864)
Widowed	-0.011	0.074	0.886	0.989	(0.855, 1.144)
Divorced	-0.006	0.086	0.946	0.994	(0.840, 1.177)
Separated	-0.128	0.087	0.140	0.880	(0.742, 1.043)
Mother age at 1st birth (<=15)					
16-20	-0.014	0.017	0.001	0.986	(0.903, 0.989)
21-25	-0.155	0.028	0.012	0.857	(0.811, 0.905)
>=26	-0.327	0.069	0.016	0.721	(0.630, 0.826)
Type of birth (Single)					
Multiple birth	0.151	0.082	0.066	1.163	(0.990, 1.366)
Child Birth Order (1)					
2-4	0.650	0.040	0.000	0.522	(0.483, 0.565)
5-7	-0.333	0.035	0.031	0.717	(0.669, 0.767)
8 and above	-0.139	0.123	0.026	0.870	(0.684, 0.906)
Survival Status of the index child (Dead)					
Alive	-0.244	0.084	0.000	0.784	(0.664, 0.925)
Breastfeeding status (No)					
Yes	-0.012	0.004	0.000	0.940	(0.9802, 0.997)
Contraceptive use (No)					
Yes	-0.090	0.051	0.016	0.914	(0.627, 0.986)

The analysis shows that birth order of a child is another important covariate for birth interval, where the likelihood of birth increases as the order increases, i.e. likelihood of births is significantly lower in earlier births compared to the later births. The time ratio of women who breastfeed their children to have subsequent birth after the index child was reduced by

6% as compared to those did not breastfeed their children. With regard to contraceptive use, women who use any of the contraceptive methods to have subsequent birth after the index child was reduced by 8.6% as compared to those did not use any of the contraceptive methods. Survival status of the index child is also found to be an important covariate for the likelihood of birth. It is found from the analysis that mothers who have lost their last child are more likely to have the next child earlier than the mothers who have not lost their child. Based on this, women with child loss experience are less likely to use contraception and more likely to discontinue if they are already using contraception.

3.3. Results of Shared Gamma Frailty Model

In our data set mothers are clustered into geographical regions. It is recognized that individuals in the same community are more similar than the individuals in different communities because they shared similar (possibly unmeasured) environmental exposures. In cox proportional hazard with frailty models same to cox proportional hazard without frailty done, first univariable analysis were done for all variables to select variables at 0.02 -0.25 level of significance, then variables significant at 25% were considered to fit in multivariable analysis to identify the significant variables associated with the birth interval accounting frailty in the model. The results Cox PH with gamma frailty model was obtained on Table 4. And the result show that the heterogeneity parameter θ is estimated to be 0.0191 (se: 0.0087) and the likelihood-ratio test of, H0=0 is rejected with p- value (< 0.000), meaning that the correlation within geographical location or within region cannot be ignored. In other word since its p-value=0.000, there is a significant frailty effect, implies correlation within region cannot be ignored or the gamma frailty models indicating that frailty variable (region) is very highly significantly related to the timing of birth interval.

Thus, there is much evidence pointing towards a population that is indicating heterogeneity. The results reveal that after accounting for heterogeneity and other confounders in the data, women who reside in rural places were 1.256 times more likely to have subsequent birth compared with women whore sides in urban places. The time ratio of primary or secondary education level women to have subsequent birth after the index child was reduced by 9.41% and 14.7% respectively as compared to those with no formal education after accounting for heterogeneity and other confounders in the data. The hazard of women whose previous children alive to have subsequent birth is reduced by 18.5% as compared to the time ratio for those children dead after accounting and controlling for other factors. The time ratio of women who breastfeed their child to have subsequent birth after the index child was reduced by 22.7% as compared to those do not breastfeed after accounting for heterogeneity and other confounders in the data. After accounting for heterogeneity and other factors, regarding to contraceptive use, women who use any of the contraceptive methods to have subsequent birth after the index child was reduced by 6.2% as compared to those did not use any of the contraceptive methods.

Table 4. *Multivariable Shared Gamma Frailty Model for Birth Interval Dataset, 2011 EDHS.*

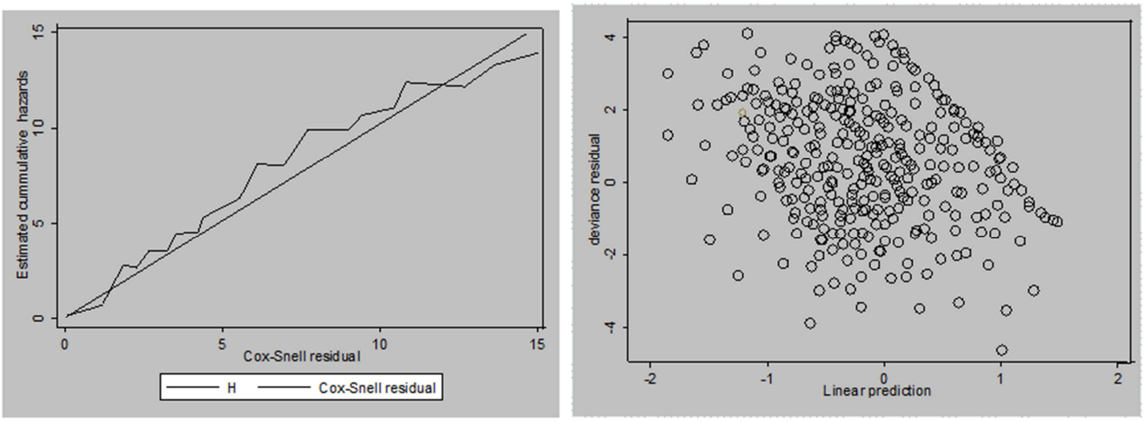
Covariate (Reference)	Coef (β)	Std. Err.	P-value	HR	95% CI for $exp(\beta)$
Mother age (15 -19)					
20 - 24	-0.373	0.075	0.001	0.689	(0.556, 0.854)
25 – 29	-0.772	0.049	0.000	0.462	(0.375, 0.569)
30 – 34	-0.999	0.039	0.000	0.368	(0.298, 0.456)
35 – 39	-1.234	0.032	0.000	0.291	(0.234, 0.361)
40 – 44	-1.457	0.026	0.000	0.233	(0.187, 0.291)
45 -49	-1.491	0.026	0.000	0.225	(0.179, 0.283)
Residence (Urban)					
Rural	0.228	0.048	0.000	1.256	(1.166, 1.354)
Mother Education (No Edu.)					
Primary	-0.099	0.026	0.001	0.906	(0.856, 0. 957)
Secondary	-0.159	0.056	0.015	0.853	(0. 750, 0. 969)
Higher and above	-0.128	0.089	0.009	0.880	(0.402, 0.546)
Father Education (No Edu.)					
Primary	-0.069	0.022	0.054	0.933	(0.890, 1.177)
Secondary	-0.304	0.026	0.674	0.738	(0.689, 1.090)
Higher and above	-0.233	0.139	0.188	0.792	(0.561, 1.106)
Mother Occupation (Not working)					
Professionals	0.003	0.130	0.981	1.003	(0.778, 1.094)
Others	-0.038	0.023	0.105	0.963	(0.919, 1.208)
FatherOccupation (Not working)					
Professionals	-0.251	0.073	0.118	0.778	(0.647, 1.135)
Others	-0.276	0.062	0.301	0.759	(0.635, 1.039)
Wealth index (Poor)					
Middle	-0.049	0.030	0.013	0.952	(0.795, 0.984)
Rich	-0.053	0.029	0.001	0.948	(0.693, 0.976)
Marital Status (Single)					
Married	-0.179	0.172	0.385	0.836	(0.558, 1.252)
Widowed	-0.172	0.178	0.416	0.842	(0.557, 1.273)
Divorced	-0.297	0.156	0.158	0.743	(0.491, 1.122)

Covariate (Reference)	Coef (β)	Std. Err.	P-value	HR	95% CI for $exp(\beta)$
Separated	-0.160	0.185	0.461	0.852	(0.556, 1.305)
Mother age at 1st birth (<=15)					
16-20	-0.090	0.018	0.000	0.914	(0.883, 0.946)
21-25	-0.326	0.023	0.001	0.722	(0.690, 0.755)
>=26	-0.511	0.048	0.024	0.600	(0.546, 0.658)
Type of birth (Single)					
Multiple birth	-0.146	0.070	0.073	0.864	(0.736, 1.014)
Child Birth Order (1)					
2-4	0.102	0.156	0.511	1.108	(0.816, 1.503)
5-7	0.155	0.047	0.456	1.168	(0.080, 1.263)
8 and above	0.123	0.044	0.005	1.131	(1.037, 1.234)
Survival Status of the index child (Dead)					
Alive	-0.205	0.037	0.000	0.815	(0.745, 0.890)
Breastfeeding status (No)					
Yes	-0.257	0.019	0.000	0.773	(0.735, 0.811)
Contraceptive use (No)					
Yes	-0.064	0.029	0.044	0.938	(0.881, 0.998)
theta (θ)	0.0191178	0.008752			

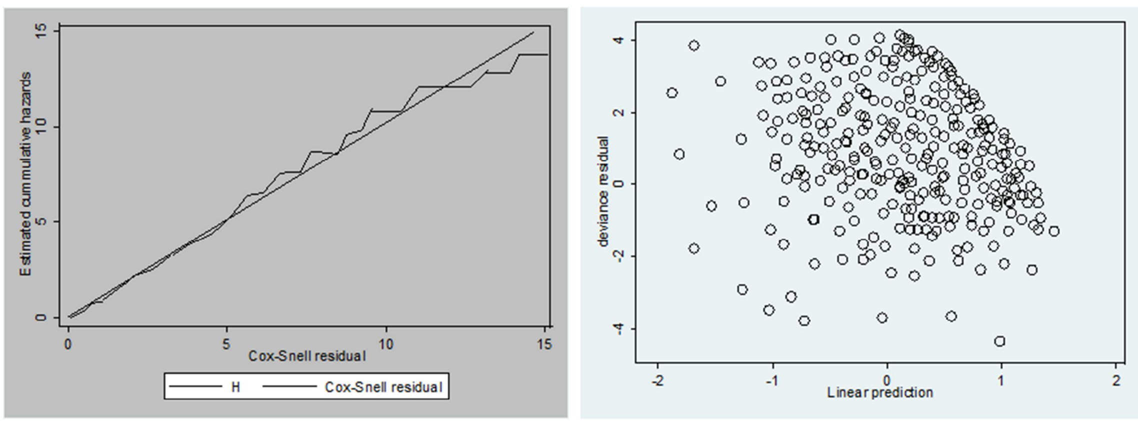
Note: Likelihood-ratio test of theta=0: chibar2 (01)=134.77 Prob>=chibar2=0.000 standard errors of hazard ratios are conditional on theta.

3.4. Model Diagnosis for Cox PH & Shared Gamma Frailty Model

Comparing the jagged line with the reference 45° line, we observe the hazard function follows the 45 degree line very closely except for very large values of time. The deviance residuals seem to be approximately symmetrically distributed about zero and there exists not as such clearly outlying observation. Overall, the cox proportion hazard and shared gamma frailty models fit the data very well.



(a)Cox-Snell residuals plot Cox PH model (b): Deviance residual plot Cox PH model



(c) Cox-Snell residuals plot Cox with frailty model (d) Deviance residual plot Cox with frailty model

Figure 1. *Model Diagnosis for Cox PH & Shared Gamma Frailty Model.*

3.5. Comparison of Cox PH versus Shared Gamma Frailty Model

In order to compare the efficiency of the models the Akaike's Information Criterion and Bayesian Information Criterion was used. The lower value of AIC or BIC suggests a better model. Table 5 gives the log-likelihood, AIC and BIC values of the two models. From the table we can see that the shared gamma frailty model has both a minimum AIC and BIC value, indicating that this model fit the data better than the Cox PH model which did not take in to account the clustering.

Table 5. *Comparison of Cox PH and Frailty Model for Birth Interval in Ethiopia.*

Model	Log-like (null)	Log-like (model)	AIC	BIC
Cox PH	-73268.41	-72192.03	144416.1	144532.7
Shared gamma frailty	-	-72131.74	144293.5	144402.9

3.6. Effects of Covariates on the Variance of Frailty

Significance of the effects of heterogeneity due to geographical location or region on birth intervals of Ethiopian women has been mentioned in the previous section. Examining the effects of different covariates on the heterogeneity could also be of interest. However, the frailty models, considered in this study for modeling birth intervals, cannot be extended to define the frailty parameter as a function of covariates, hence the effect of subject specific covariates on the random effect corresponding to region cannot be examined. A different approach is introduced to examine the effects of covariates on the variances of frailty distributions (i.e. random effects) using a sensitivity analysis, where the change of the size of the estimated variance is assessed by excluding each of the covariates sequentially one at a time from the best fitted model cox with frailty, where the heterogeneity due to region is considered. The estimated random effects corresponding to region are presented here.

Table 6. *Examination of the effect of different covariates on the variance parameter of the frailty distributions.*

Covariates	Frailty parameter
Mother age	0.0192312
Residence	0.0194613
Mother Education	0.0198609
Wealth index	0.0180213
Mother age at first birth	0.0215946
Child birth order	0.0181297
Survival Status of the index child	0.0185649
Breastfeeding status	0.01917182
Contraceptive use	0.0192060
Frailty parameter for shared gamma frailty=0.0191178	

The analysis shows that mother age at first birth is the most important covariate for adjusting heterogeneity due to region, because excluding mother age at first birth from the shared gamma frailty causes the highest change in the size of the random effect corresponding to region. The result show that excluding mother age at first birth from this model increases the region random effects from 0.0191178 to 0.0215946, i.e. mother's age at first birth is an important variable for region random effects. However, excluding child birth order from the shared gamma frailty model decreases the region random effects; this could be because child birth order may not be an important covariate for analyzing birth intervals. Since both the birth interval and child birth order can be considered as outcomes of fertility, it would be appropriate to model both the outcomes simultaneously.

4. Discussion

From this study, it is found that different factors have different effects on the length of birth interval. Place of residence is an important factor in explaining the variation of vital events in the country like Ethiopia. In this study the place of residence was found to be significant differential for timing of birth interval and the result suggest that urban women have longer birth interval than rural women. A study conducted by [6] has shown that urban rural variation in birth interval length. Urban women have slightly longer birth intervals between births compared with rural women. Higher exposure to modernization elements by women lived in urban areas could be one of the reasons for having longer birth intervals than women lived in rural areas. Traditional values and norms may be less adhered to in urban centers. Information such as use of contraceptives and ways of leading a better life are less diffused in rural areas. These differences and others may make urban women to have longer inter- birth intervals than rural women. This finding was similar with recent studies done by [11, 27, 28] women from the urban areas have significantly smaller likelihood of birth compared to the women from the rural parts. The findings of this study revealed that the educational level of women had a significant effect on the length of birth interval. An imaging result obtained from Table 2 show higher educated woman have 12 percent larger birth interval than that of illiterate women, while secondary educated mothers have 14.7 percent larger birth intervals than that of illiterate women.

A similar study in Ethiopia, Amhara region by [28] and [29] in Bangladeshi suggest that education were significantly associated with timing of birth interval. Women with no formal education are more likely to have subsequent birth after the index child as compared to women with some formal education. Such an association between educational status and fertility planning has been observed in previous studies in Ghana and Nigeria where it was found that educated women are less likely to report next birth than uneducated women [30]. This could be due to the fact that educated women have better access to family planning information and services than uneducated women. This finding also similar with studies done by [29]. This finding is also agreed with studies by [16]. Wealth index has been observed to have significant influence on the timing of birth intervals. Women of medium and higher wealth index have shorter birth interval than women belonging to lower wealth index. The risk of having next birth by women of medium and higher wealth index is 1.108 and 1.233 times higher compared to respondents of lower socio-economic stratum. A similar study in Pakistan by [31, 32] in Rural Manipur, India and [17] in Bangladeshi supports the present study. Age at first birth is important significant predictors of birth interval in the multivariate analysis. The shared gamma frailty result revealed that, mothers having first birth before reaching 20 years of age, have high number of parity in their reproductive life span; while mothers having first birth at higher age usually having higher birth interval. This fact should be taken on account for fertility program of government. Clearly, some socio-cultural activities, family traditions also need to be changed.

From our findings we can suggest women to marry at later age. Or government can take necessary steps to resist women to marry before a certain age, say 20 years. Additional attention should be given to newlywed couples and implementing reproduces health programs among the adolescents. Also mothers should be encouraged to breastfeed their child. Our study is comparable with the findings of [33] in Ethiopia and [17] in Bengladshi. The analysis shows that birth order of a child is another important covariate for birth interval, where the likelihood of birth increases as the order increases, i.e. likelihood of births is significantly lower in earlier births compared to the later births. This study is also similar with the study conducted in Bengladshi [16] and Ethiopia [13]. The survival status of the previous child has been found to be important in determining child-spacing patterns for both social and biological reasons [6, 32, 31] The social reason is that, couples who have experienced the loss of a child at infancy avoid contraception with the motivation to have another child as a replacement. Biologically, the death of an infant interrupts breastfeeding, leading to an early return of ovulation and, in the absence of contraception, increases likelihood of early subsequent conception. The reason behind this is that couples want make deliberate efforts to bear another child in the hope of replacing the lost one. Our findings also comparable with the findings of [29]. The survival of previous child has 0.815 times lower hazard of having subsequent birth than the dead of previous child (HR=0.815). The present study also provides strong evidence of the negative impact of child lost on child spacing.

Based on the findings, it can be concluded that reduction of infant and child mortality could increase the subsequent birth intervals. The duration of breastfeeding shows a consistent direct relationship with birth spacing. This may be due to the fact that lactational amenorrhea arising from breastfeeding lengthens birth intervals. For example in this study women who breast feed their index child were more likely to have longer birth interval practice as compared to those who do not breast feed their child. Contraceptive use is one of the important proximate determinants of fertility, which has direct effect on birth interval dynamics. Couples use contraceptive methods either to space birth intervals or for stopping fertility. The result of Table 3 show that women who use contraceptive devices are found to be subject to a hazard of having subsequent birth 0.938 lower than those who never use any kind of contraceptive devices (HR=0.938). In most developing countries aside from Sub-Saharan Africa, contraception is used much more for limiting than for spacing. In Sub Saharan Africa, however, majority of contraceptive use is for spacing; because many people want large families and birth spacing is common in many African traditions [16]. Similar effect of contraceptive use has been observed in a study conducted in Southern and Northern Ethiopia where contraceptive users space birth longer than the non-users in each observed births.

The result of Cox PH with frailty show that the heterogeneity parameter θ is estimated to be 0.0191 (se: 0.0087) and the likelihood-ratio test of, H0: $\theta=0$ is rejected with p- value (<0.000), meaning that the correlation within geographical location or within region cannot be ignored. Or since its p-value=0.000, there is a significant frailty effect, implies correlation within region cannot be ignored. In other word, the gamma frailty models indicating that frailty variable (region) is very highly significantly related to the timing of birth interval. Thus, there is much evidence pointing towards a population that is indicating heterogeneity. The results reveal that after accounting for heterogeneity and other confounders in the data, women who reside in rural places were 1.256 times more likely to have subsequent birth compared with women who resides in urban places. The time ratio of primary or secondary education level women to have subsequent birth after the index child was reduced by 9.4% and 14.7% respectively as compared to those with no formal education after accounting for heterogeneity and other confounders in the data. The hazard of women whose previous children alive to have subsequent birth is reduced by 18.5% as compared to the time ratio for those children dead after accounting and controlling for other factors. The time ratio of women who breastfeed their child to have subsequent birth after the index child was reduced by 22.7% as compared to those do not breastfeed after accounting for heterogeneity and other confounders in the data. After accounting for heterogeneity and other factors, regarding to contraceptive use, women who use any of the contraceptive methods to have subsequent birth after the index child was reduced by 6.2% as compared to those did not use any of the contraceptive methods.

5. Conclusion

Birth interval is considered as one of the important indicators for describing the overall socioeconomic wellbeing of a country because of its direct relation to fertility rate. This study revealed that socio-economic, demographic and proximate variables have important effect on length of birth interval in Ethiopia. Mother age, place of residence, mother education level, wealth index, mother age at first birth, child birth order, survival status of the previous child, breast feeding status and contraceptive use were found to have significant effect on the length of birth interval for Ethiopian women. The results confirm that the shared gamma frailty model have less AIC or BIC values suggesting that shared gamma frailty model is the most powerful one in predicting the birth intervals of women among regional states of Ethiopia when compared to cox proportional hazard model. This tells us in the setting of correlated observations, the Cox frailty models are recommended for providing statistically valid estimates of the effects of proximate determinants after adjusting for the background variables and unobserved random effects.

The finding of this study may be interesting and revealing to the health planner and executors to design proper future policies and plans for improving maternal and child health, and thereby for controlling the birth spacing through natural ways. It may also provide a baseline as well as scientific endeavor to the future researchers working on this crucial area of human research. Interventions made to improve maternal and child health programs should consider the above modifiable factors. For example women education should be encouraged to decrease the likelihood of short birth interval. In addition, promotion of contraceptive use and breast feeding is crucial to promote birth spacing. Government should educate women for exclusive breastfeeding period of six month and at least two years with weaning. It widens not only birth interval but also breast milk increases the chance of child survival by increasing the immunity of child. Government should motivate couples to increase the birth interval length in case of death of preceding child and also strengthen health programs. It is necessary for the maternal and child health. If long birth interval is promoted in case of death of preceding child, it will cause decline in fertility. Urban rural differentials have been observed in birth intervals. Urban women have longer birth interval than their rural counter parts. This is because of the fact that urban women have better access to social institutions. Therefore expansions of infrastructures and accessible service providing facilities such as clinics, hospitals and schools have to be expanded in the rural areas. In this study we only considered modelling of birth interval in Ethiopia using shared gamma frailty term at regional level. That is, Mothers in a same cluster (region) usually shares the same frailty term. The authors recommend that better result could have been obtained in the modelling of birth interval of women in Ethiopia, if we include a frailty term at least in a pair wise manner such as frailty terms at community and mother level in the future.

Competing Interests

The authors declare that they have no competing interests.

Authors' Contribution

Both authors Yenefenta Wube and Zeytu Gashaw generated the idea, the corresponding author Yenefenta Wube contributed in the data analysis and interpretation, Zeytu Gashaw contributed as an advisory.

Ethics Approval and Consent to Participant

Not Applicable.

Consent for Publication

Not Applicable.

Availability of Data and Material

The analysis in this study is based on data available from the Ethiopian Demographic and Health Survey.

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