Modeling the Birth Interval of Women of Reproductive Age in Ethiopia: Application of Cox-Proportional Hazard and Shared Gamma Frailty Models

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Abstract

Introduction: Birth interval is the time interval between two successive births. Short birth interval can have an impact on both maternal and child health. It can also speed up population growth and affect the effort of development by decreasing women's participation in productive activities. The objective of this study was to identify prognostic factors for the birth interval of women of reproductive age in Ethiopia using survival analysis.

Methods: The data for this study was extracted from the 2016 Ethiopia Demographic and Health Survey (EDHS). A total of 5,539 women who gave at least one birth from 2012 to 2016 were considered. The analysis employed Cox proportional hazard and shared gamma frailty models.

Results: The median time of birth interval was found to be 27 months. The predictor variables that were found to be significantly associated with birth interval include: age of women at the first birth, wealth index, current age of women, contraceptive use, mothers' occupation and breastfeeding status and religious affiliation. Moreover, the heterogeneity between the regions was significant at the 5% level.

Conclusion: The length of birth interval was found to be significantly longer for those women who were categorized under medium and rich wealth indices, who used contraceptive methods, who were followers of the Coptic Church, who were engaged in governmental and non-governmental jobs, who gave the first birth at the age of less than 15 years, and those women with multiple births. One of the unexpected results was that women who breastfed their children were more likely to have shorter birth interval compared to those who did not.

Keywords: *Birth interval, Cox proportional hazard model, Heterogeneity, Shared gamma frailty model*

1. Introduction

Birth interval is a period between two consecutive births. Short and long inter-pregnancy intervals have been linked to negative pregnancy outcomes. In particular, short birth intervals have been linked to the majority of detrimental effects and can have negative consequences for maternal and infant outcomes (Timæus and Moultrie, 2008).

Women's time of birth is argued to be a serious issue as a result of considerations that are related to the age of their youngest child. They may be worried about the impact of a short birth interval on the health and wellbeing of their existing children. They may also wish to delay conceiving to avoid the increased pressure that would result from having to care for two very young children simultaneously, particularly if childcare conflicts with other activities. Similarly, they may wish to postpone pregnancy while breastfeeding their youngest child. In some societies, engaging in sexual intercourse in the postpartum period is regarded as deviant, thus women may also wish to delay conception to avoid the social censure that can arise from short birth intervals (Timæus and Moultrie, 2008). There are health risks related both to pregnancies in a short time interval and those in long time intervals, but the majority of health risks are related to births that occur too close together (Shachar and Lyell, 2012).

Beyond health, narrowly spaced birth intervals speed up population growth and undermine development efforts. Women with narrow birth intervals have more children relative to women with wide birth intervals (Samuel et al., 2011). Shorter birth interval makes it difficult for women to become productive members of society, thereby limiting their contribution to economic development. Moreover, when a newborn baby comes, it is expected that the family will spend more of its limited resources in the form of care to the newborn, while the other children will receive an inadequate share of the resources (USAID, 2012).

A study conducted by Haile et al. (2016) in Aksum town, North Ethiopia, employed a multivariable logistic regression model to identify factors related to the need for birth spacing or limiting and not using long-acting and permanent contraceptive methods (LAPM). Education, occupation, husband's attitude towards LAPM, age, number of pregnancies, regular media exposure, and decider on the number of children to bear were found to be significant factors of the desire for birth spacing.

Infants born less than two years after a preceding birth have higher under-five mortality rates. According to a report by CSA and ICF (2016), under-five mortality was dramatically higher among children born less than two years after the earlier birth (114 deaths per 1000 live births) than among children born three years after the earlier birth (44 deaths per 1000 live births).

A study by Samuel et al. (2011) found that wealth status, place of residence, maternal occupation, duration of breast feeding and contraceptives usage status were significantly associated with the birth interval among women of child bearing age in Southern Ethiopia using multivariable logistic regression. According to a study by Zenebu et al. (2013), mothers' education, husband occupation, age of the mothers, contraceptive use, sex of the index child and breast feeding practices were associated with short birth interval. This study also utilized multiple logistic regression model.

A number of studies have been conducted in Ethiopia with a focus on the factors that affect the desire for birth spacing by using logistic regression models. The present study, however, attempted to employ survival analysis models to identify factors that are associated with the birth interval of women of reproductive age in Ethiopia.

2. Materials and Methods

2.1 Source of data

The data for this study was extracted from the 2016 EDHS weighted data set. The Central Statistical Agency (CSA) conducted the 2016 Ethiopia Demographic and Health Survey (EDHS) from January 18 to June 27, 2016, to provide data for monitoring Ethiopia's population and health situation. The 2016 EDHS was Ethiopia's fourth Demographic and Health Survey since 2000 (CSA and ICF, 2016). The analysis in this study utilized data on all women who gave at least one birth from 2012 to 2016 GC.

2.2 Variables of the study

The response variable of this study was the time interval (in months) between the most recent successive births. Several predictors were considered in this study to investigate the important relative contribution of different potential risk factors to birth intervals. The predictor variables which are expected to influence the gap of time between successive births include religion, place of residence, mothers' education level, current age of mothers, wealth index, marital status, maternal age at first birth, contraceptive use, mothers' occupation, breastfeeding status, type of birth, child live status and sex of the child.

2.3 Survival analysis

Survival analysis is a collection of statistical procedures for data analysis in which the outcome (variable of interest) is the time until an event occurs. The time variable is usually expressed as survival time since it gives the time that an individual has "survived" over some follow-up period. The basic data structure is a tuple, i.e., (start, stop, event), where the first two elements signify the start and end time of the study, while the third element signifies whether the event has occurred or not.

The study of survival data focuses on predicting the probability of response, survival, or mean lifetime, comparing the survival distributions of experimental animals or human patients, and the identification of risk and or prognostic factors associated with response, survival, and the progress of disease (Lee and Wang, 2003).

2.3.1 Survival function

The survivor function is fundamental to survival analysis because obtaining survival probabilities for different values of "t" provides crucial summary information from survival data (Kleinbaum and Klein, 2005). Suppose a group of individuals have survival times $t_1, t_2, \ldots, t_N$, some of which may be censored. These values can be regarded as the values of a continuous random variable "T" with probability density function $f(t)$ and cumulative distribution function $F(t)$ (Wienke, 2010). $F(t)$ is defined as:

$$F(t) = P(T < t) = \int_0^t f(u)du \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

This represents the probability that the survival time is less than some value t (Collett, 2014). The survivor function $S(t)$, which represents the probability that an individual will survive beyond t, is given by:

$$S(t) = 1 - F(t) = P(T \geq t) = \int_t^\infty f(u)du \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

2.3.2 Hazard function

The hazard function, denoted by $h(t)$, is a function that measures the probability of failure in an infinitesimally small time period $(t, t+\Delta t)$, given that the individual has survived up to time t (Cox, 1972). Mathematically, this is defined as:

$$h(t) = \lim_{\Delta t \to 0} \left\{ \frac{P(t < T \leq t + \Delta t \mid T > t)}{\Delta t} \right\}, \ t \geq 0 \quad \ldots\ldots\ldots\ldots \text{(3)}$$

The hazard function can also be expressed as:

$$h(t) = \frac{f(t)}{S(t)} = -\frac{\partial}{\partial t}\log[S(t)] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

2.3.3 Cox proportional hazards model

The Cox proportional hazards regression model is a flexible tool for assessing the relationship between multiple predictors and time-to-event outcome*s* (Lee and Wang, 2003). This model provides an expression for the hazard at time t for an individual with a given set of explanatory variables (Kleinbaum and Klein, 2012):

$$h(t \mid X) = h_0(t)\exp\{\textstyle\sum_{i=1}^{k}\beta_i X_i\} = h_0(t)\exp\{X'\beta\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

where $h_0(t)$ is the baseline hazard, and the vectors $X = (X_1, X_2, \ldots, X_k)'$ and $\beta = (\beta_1, \beta_2, \ldots, \beta_k)'$ are covariates and unknown regression parameters, respectively. The Cox PH model is a semi-parametric model because the distribution of the baseline hazard function is left unspecified.

2.3.4 Hazard ratio

Hazard ratio is a ratio of two hazard functions. Suppose X^* denotes one individual's set of predictors and X denotes another individual's set of predictors. The hazard ratio of these two individuals can be written as a ratio of an estimate of $h(t \mid X^*)$ to an estimate of $h(t \mid X)$:

$$\hat{HR} = \frac{\hat{h}(t \mid X^*)}{\hat{h}(t \mid X)} = \frac{h_0(t)\exp\{X^{*\prime}\hat{\beta}\}}{h_0(t)\exp\{X'\hat{\beta}\}} = \exp\{\textstyle\sum_{i=1}^{k}\hat{\beta}_i(X_i^* - X_i)\} \quad \ldots\ldots\ldots\ldots\ldots (6)$$

This ratio is constant or proportional and does not depend on t. The covariates act multiplicatively on a baseline hazard which may vary freely over time (Collett, 2014). This assumption greatly facilitates the interpretation of covariate effects since the effect of a given covariate compared to the absence of that covariate is expressed as a single constant.

2.3.5 Frailty model

The classical and most frequently applied model assumes a proportional hazards structure which is conditional on the random effect. Frailty models are extensions of the Cox proportional hazards model that are used when the study population is heterogeneous. The frailty approach is a statistical modeling method that aims to account for the heterogeneity caused by unmeasured or unobserved covariates (Duchateau and Janssen, 2008; Wienke, 2010; Hanagal, 2011). To accomplish this, the hazard function in Equation (5) can be extended to incorporate a term (Z) that specifically measures heterogeneity, popularly referred to as a frailty term (Collett, 2014):

$$h(t \mid X, z) = z h_0(t)\exp\{X'\beta\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

2.3.6 Shared gamma frailty model

The standard assumption about frailty in shared gamma frailty models is that it follows a gamma distribution. The frailties Z_i ($i = 1, 2, \ldots, n$) are assumed to be identically and independently distributed random variables. In this study, Z_i are assumed to follow a gamma distribution given by:

$$f_Z(z,\theta) = \frac{z^{\frac{1}{\theta}-1}\exp(-z/\theta)}{\Gamma\left(\frac{1}{\theta}\right)\theta^{\frac{1}{\theta}}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

where θ is the frailty parameter.

3. Results and Discussion

Data for the analyses in this study were extracted from the 2016 Ethiopian Demographic and Health Survey (EDHS). Information on a total of 5539 women who gave at least one birth between 2012 and 2016 was utilized. The response variable of this study was the time interval (the time gap) between the most recent successive births (measured in months). The time interval between the most recent successive births can be considered as time-to-event. Based on this, the interval of time was closed if it was the time between two successive births and open-ended if only one birth occurred during the study period. The research considered a closed time interval as occurrence of the event and open-ended time as censored. By taking this definition into account, about 2505 (45.2%) of women have a closed-ended birth interval and the remaining 3034 (54.8%) have an open-ended birth interval during the study period. The overall median birth interval was 27 months.

3.1 Descriptive analysis

Table 1 pertains to the summary of birth intervals disaggregated by socio-economic, demographic and biological factors. Nearly half of all respondents were Muslim (48.7%), followed by followers of Coptic (Orthodox) Church (30.3%). Overwhelming majority of respondents resided in rural areas (82.8%) and were married (94.7%). When we come mothers' education, 3803 (68.7%) were not educated, while 1279 (23.1%), 301 (5.4%), and 156 (2.8%) had primary, secondary and higher educational levels, respectively. Moreover, about three-fifth and thee-tenth of mothers had their first birth at 15-19 and 20-24 years of age, respectively. The descriptive statistics also revealed that 2981 (53.8%), 813 (14.7%) and 1745 (31.5) of the respondents were categorized under poor, middle and rich wealth indices, respectively.

Table 1: Descriptive summary of birth intervals by socio-economic, demographic and biological factors

Variable	Categories	Censored	Event	Total (100%)
Religion	Orthodox	1147	529	1676 (30.3)
	Catholic	21	16	37 (0.7)
	Protestant	642	389	1031 (18.6)
	Muslim	1187	1512	2699 (48.7)
	Others	37	59	96 (1.7)
Residence	Urban	619	332	951 (17.2)
	Rural	2415	2173	4588 (82.8)
Mothers' education level	No education	2016	1787	3803 (68.7)
	Primary	740	539	1279 (23.1)
	Secondary	182	119	301 (5.4)
	Higher	96	60	156 (2.8)
Wealth index	Poor	1399	1582	2981 (53.8)
	Middle	508	305	813 (14.7)
	Rich	1127	618	1745 (31.5)
Marital status	Single	10	1	11 (0.2)
	Married	2808	2436	5244 (94.7)
	Widowed	103	33	136 (2.5)
	Divorced	113	35	148 (2.7)
Mothers' age at first birth	<15	247	143	390 (7.0)
	15-19	1796	1426	3222 (58.1)
	20-24	865	805	1670 (30.1)
	25+	126	131	257 (4.6)
Mothers' age	15-19	7	43	50 (0.9)
	20-24	268	502	770 (13.9)
	25-29	818	823	1641 (29.6)
	30-34	813	602	1415 (25.5)
	35-39	663	393	1056 (19.1)
	40-44	336	117	453 (8.2)
	45-49	129	25	154 (2.8)
Contraceptive use	No	1955	2073	4128 (72.7)
	Yes	1079	432	1511(27.3)
Mothers' occupation	Not working	1521	1619	3140 (56.7)
	Government	859	528	1387 (25.3)
	Non-Government	654	358	1012 (25.0)
Breastfeeding status	No	128	92	220 (4.0)
	Yes	2906	2413	5319 (96.0)
Type of birth	Singleton	3000	2382	5382 (97.2)
	Multiple	34	123	157 (2.3)
Child live status	Died	197	233	420 (7.8)
	Alive	2837	2272	5109 (92.2)
Sex of child	Male	1556	1287	2843 (51.3)
	Female	1478	1218	2696 (48.7)

Among the latest births, 2843 (51.3%) and 2696 (48.7%) were male and female children, respectively. About 97.2% of these latest births were singletons, and 5109 (92.2%) of the children were alive at the time of the survey. Regarding breastfeeding status, nearly all mothers under study (96.0%) did breastfed their latest child. Moreover, 4128 (72.7%) of the mothers did not use contraceptive methods, while the remaining 1511 (27.3%) used the same.

3.2 Multivariable survival analysis

The multivariable survival analysis of this study was done by assuming Cox proportional hazard and shared gamma frailty models whereby the covariates were selected based on the results of univariable analysis and then using the backward selection method. The model parameters were estimated using the method of penalized likelihood.

3.2.1 Test of variance of cluster effects

One of the assumptions of the Cox PH model is that all members of the population are homogeneous. Thus, we need to test whether this assumption is plausible or not. To do so, the population was classified based on geographical location which was considered as a cluster. This classification was the division of the population into nine regions and two administrative cities, and the classification was considered as a frailty term. To identify whether there is a regional effect on the time length of the birth interval, the regional effect was considered as the cluster effect.

We can see from the results of the estimated variability of regional effect in Table 2, the frailty parameter has a significant effect on the time length of the birth interval. This indicates that there is heterogeneity among the population based on geographical location (region) and this heterogeneity of an individual needs to be included in the model.

Table 2: The estimated variance of the cluster effect

Frailty parameter	Standard deviation SE (H)	LCV	Penalized marginal log-likelihood	P-value
0.124736	0.0541509	2.14038	-11842.68	0.010625

3.2.2 Results of multivariable shared gamma frailty model

The test of cluster effect shown above revealed that geographical location (region) did affect the time length of the birth interval and couldn't be ignored in the analysis. Thus, we need to go for shared gamma frailty model. As an initial step, univariable shared gamma frailty models were fitted for each of the candidate predictor variables. And then the statistically significant covariates in the univariable analysis, namely, place of residence, religion, wealth index, age of mothers at first birth, current age of mothers, contraceptive use status, mothers' occupation, breastfeeding status, type of birth and child live status, were included in multivariable analysis of shared gamma frailty model. Parameter estimates of the shared gamma frailty model by using penalized likelihood estimation are presented in Table 3.

Table 3: Results of the fitted shared gamma frailty model

Covariate	$\hat{\beta}$	HR	se($\hat{\beta}$)	Z	p-value	95% CI
Residence (Ref. = Urban)						
Rural	0.0634	1.07	0.0785	0.8068	0.420	0.91-1.24
Religion (Ref. = Orthodox).						
Catholic	0.2762	1.32	0.2594	1.0648	0.287	0.79-2.19
Protestant	0.0139	1.01	0.0860	0.1614	0.872	0.86-1.20
Muslim	0.1935	1.21	0.0744	2.6006	0.009	1.05-1.40
Others	0.3737	1.45	0.1473	2.5374	0.011	1.09-1.94
Wealth index (Ref. = Poor)						
Middle	-0.1587	0.85	0.0658	-2.4116	0.016	0.75-0.97
Rich	-0.1859	0.83	0.0611	-3.0420	0.002	0.74-0.94
Age at 1st birth (Ref. = <15)						
15-19	0.3695	1.45	0.0890	4.1500	0.000	1.22-1.72
20-24	0.6589	1.93	0.0936	7.0391	0.000	1.61-2.32
25+	1.1063	3.02	0.1280	8.6399	0.000	2.35-3.89
Age (Ref. = 15-19)						
20-24	-0.5457	0.58	0.1613	-3.3821	0.001	0.42-0.79
25-29	-0.9851	0.37	0.1600	-6.1566	0.000	0.27-0.51
30-34	-1.2328	0.29	0.1621	-7.6060	0.000	0.21-0.40
35-39	-1.5835	0.21	0.1658	-9.5539	0.000	0.15-0.28
40-44	-2.1289	0.12	0.1836	-11.5929	0.000	0.08-0.17
45-49	-2.8611	0.06	0.2571	-11.1281	0.000	0.03-0.09
Contraceptive (Ref. = No)						
Yes	-0.4179	0.66	0.0587	-7.1144	0.000	0.59-0.74
Mother occupation (Ref. = No work)						
Government	-0.1680	0.85	0.0554	-3.0350	0.002	0.76-0.94
Non-Government	-0.2532	0.78	0.0609	-4.1599	0.000	0.69-0.87
Breastfeeding status (Ref. = No)						
Yes	0.2342	1.26	0.1074	2.1797	0.029	1.02-1.56
Type of birth (Ref. = Multiple)						
Single	1.5487	4.71	0.0951	16.2862	0.000	3.91-5.67
Child live status (Ref. = Died)						
Alive	-0.1308	0.88	0.0707	-1.8485	0.065	0.76-1.01

Frailty parameter, Theta: 0.0349787 (SE (H): 0.0177761) p = 0.024549
penalized marginal log-likelihood = -11410.02
Convergence criteria: parameters = 6.12e-06 likelihood = 8.38e-05 gradient = 8.47e-09
LCV = the approximate likelihood cross-validation criterion in the semi parametrical case = 2.06619
Best smoothing parameter estimated by an approximated Cross-validation: 48545.5, DoF: 8.91

3.2.3 Model adequacy checking

A plot of the Cox-Snell residuals against the cumulative hazard is presented in Figure 1. As Hosmer et al. (2008) stated, if the model fits the data well, the plot of the cumulative hazard function against the Cox-

Snell residuals should be approximately a straight line with slope one. We can clearly see from the figure that the points approximately follow a 45-degree line from the origin. Thus, the Cox-Snell residuals supported that the shared gamma frailty model fits the data set.

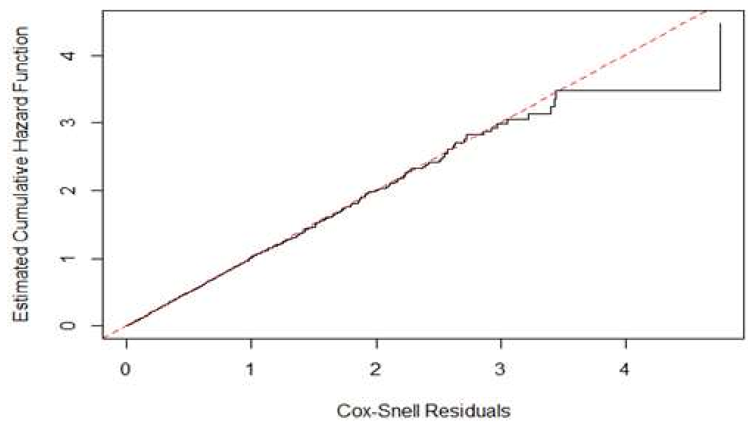

Figure 1: A plot of the Cox-Snell residuals against the cumulative hazard

3.2.4 Interpretation of results

After controlling for other prognostic factors and assuming the frailty model, the hazard ratio is used to interpret mothers' time interval till the next birth, which is expressed as $\hat{HR} = \exp(\hat{\beta})$. The hazard rates of a Muslim woman and 'other' religion follower woman were found to be 1.21 and 1.45, respectively. This implies that the time to have the next birth for a woman whose religion was Islam or 'other' was faster than that of an Orthodox woman.

Wealth index was one of the prognostic factors that influence the time of women's birth interval in this study. The hazard rates of the next birth of a woman who was categorized under the middle and rich categories of wealth index were 0.85 and 0.83, respectively. This implies that women who were categorized as being middle and rich had more time to have the next birth than that of a woman in the poor category. The hazard ratios of age at first birth for mothers in the age groups 15-19, 20-24 and ≥ 25 were 1.45, 1.93 and 3.02, respectively. This indicates that the rates of having the next birth for a woman who gave the first birth at age groups 15-19, 20-24 and ≥ 25 were 1.45, 1.93 and 3.02 times that of a woman who gave the first birth at the age of less than 15 years.

The current age of mothers during the study period was also another factor that influenced the length of birth interval. Based on the results presented in Table 3, a woman in the age group <20 years had significantly smaller time to have the next birth than women from all higher age groups. The hazard ratio for mothers with singleton birth was found to be 4.71. The implication is that the time to next birth for women who gave birth to a singleton was significantly shorter than those women with multiple births.

As expected, women who used contraceptives had significantly longer birth interval compared to those who didn't (HR=0.66, p-value < 0.001). Moreover, women who breastfed their children and those who were not engaged in any kind of work were more likely to have shorter birth intervals.

3.3 Discussion

The main goal of this study was to model the birth interval of women in Ethiopia by using shared gamma frailty model. The covariates considered in this study included: place of residence, religion, education status of mothers, wealth index, marital status, mothers' age at first birth, current age of mothers, contraceptive use, mothers' occupation status, breastfeeding status, type of birth, child live status and sex of child.

Multivariable analysis was performed by selecting the covariates based on the backward selection method, and the parameters were estimated using penalized likelihood method. The test of cluster effect revealed that geographical location (region) did affect the time length of the birth interval. For this reason, the shared gamma frailty model was employed to account for the heterogeneity due to regional variation.

Wealth index has been observed to have a significant influence on the length of birth interval. Women who were categorized into medium and rich categories of wealth index had longer birth intervals than women belonging to poor wealth index status. This finding is in agreement with the study by Hailu and Gulte (2016). The religious affiliation of respondents was also found to have significant effect on the birth interval of the women in the study. This finding is supported by studies of Rabbi et al. (2013), Kamal and Pervaiz (2012) and Singh et al. (2010).

The age of women at the first birth was an important predictor variable that has a significant effect on the length of birth interval. The findings of this study revealed that mothers having first birth at an early age have a high number of children in their reproductive life span. The outcome of this study was supported by the study conducted by Rabbi et al. (2013) in Bangladesh. Similarly, the current age of respondents during the study period was also one of the covariates which affect the time of the birth interval and this finding was comparable with a similar study conducted in Bangladesh by Ahammed et al. (2019).

Contraceptive use status was one of the important proximate determinants of fertility, which had a direct effect on birth interval dynamics. Couples use contraceptive methods either for birth spacing or for stopping fertility. The result of this study showed that women who used contraceptive methods had wider subsequent birth interval than those who never used contraceptives. This result is comparable with the findings of Chowdhury and Karim (2013), Gyimah et al. (2012), and Singh et al. (2010). In addition to this, mothers' occupation was also the other prognostic factor that influences the time interval of birth. Women who were not engaged in any kind of work were more likely to have shorter birth intervals compared to those who were working in government and non-government organizations. The study conducted by Rabbi et al. (2013) supported this finding.

In this study, women who breastfed their children were more likely to have shorter birth interval compared to those who did not. This result is unexpected since naturally breastfeeding delays the return of fertility in the mother, thus contributing to longer birth intervals (lactational amenorrhea arising from breastfeeding lengthens birth intervals). This finding contradicts with the results reported by Hemochandra et al. (2010) in rural Manipur, India. According to this study, breastfeeding emerged as an important protective covariate that extended the birth interval irrespective of parity.

4. Conclusion

The aim of this study was to investigate the prognostic factors of the birth interval of women in Ethiopia by using shared gamma frailty model. The population was heterogeneous with respect to geographical location (region), and hence, the shared gamma frailty model was employed to account for this heterogeneity. The results revealed that breastfeeding, contraceptive usage status, maternal occupation, marital status of women, age at first birth, current age of women, wealth index, type of birth (singleton versus multiple) and child live status were significantly associated with the length of successive birth intervals.

Limitations of the study

Although it was anticipated that there can be heterogeneity in the time interval between successive births within regions, the study did not consider this intra-region heterogeneity.

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