IOSR Journal of Research & Method in Education (IOSR-JRME)
e-ISSN: 2320–7388,p-ISSN: 2320–737X Volume 6, Issue 6 Ver. VII (Nov. - Dec. 2016), PP 33-38
www.iosrjournals.org

Effect of Preceding Birth Interval on Under-five Mortality: Evidence based on Bangladesh Demographic and Health Survey, 2011 data

Tazia Hossain
Department of Business Administration, Notre Dame University Bangladesh

Abstract: *For the few last decades, demographers have given notable attention towards the study of birth interval on child mortality. This study is concerned with the analysis of preceding birth interval on under-five mortality using the data of Bangladesh Demographic Health Survey (BDHS), 2011. The key independent variable is the length of the preceding birth interval measured as the number of months between two successive births of a mother. Several child and mother-specific variables were used. Hazard ratios are calculated to estimate relative risk. Kaplan Meier approach and log-rank test is used for bivariate analysis to examine the association of selected covariates with under-5 mortality. Semi Parametric Cox Proportional Hazard Model is introduced for survival analysis. Shorter preceding birth interval significantly affects under-five mortality. Under-five mortality risk is drastically high among the children with preceding birth interval 0 to 24 months. This study suggests to make women aware about under-five mortality and to use contraception to control the spacing of their pregnancies. In order to create the desired data set that is extracted from 2011 BDHS-Birth Recode data.*
Keywords: *Bivariate and survival analysis, preceding birth interval, under-five mortality.*

I. Introduction

The infant and child mortality in Bangladesh has been a topic of interest to population researchers and has become a burning issue and received increased attention in recent years. Under-five mortality rate is a reflection of the health and nutritional status of children below the age of five years and also indicates the social, cultural and economic progress in the country. According to key findings of BDHS, 2011, Infant and under-5 mortality rates for the past five years are 43 and 53 deaths per 1,000 live births, respectively. At these mortality levels, one in every 23 Bangladeshi children dies before reaching his or her first birthday, and one in every 19 children does not survive to his or her fifth birth day. Though Bangladesh has achieved the Millennium Development Goal (MDG) 4 target of 48 deaths per 1,000 live births by the year 2015, still the rate is too high. There are many socioeconomic, demographic determinant of child mortality such as: mother's education level, wealth index, mother's age at birth, size of child at birth, preceding birth interval etc. Preceding birth interval is defined as the length of time between two successive births. Birth spacing pattern provides insights on maternal and child health. There exist many studies which try to find the effect of preceding birth interval on under-five mortality. But it should be further studied to give more attention and to highlight the increased risk of under-five death due to short birth interval. Birth interval or spacing is the interval between two successive births. Several studies have been done that sibling death tend to be associated with shorter birth spacing. The Bangladesh Maternal Health Services and Maternal Mortality Survey (BMMS) carried out in 2001 is a nationally representative survey that shows that birth intervals are generally long in Bangladesh (BMMS report, 2001). Among non first birth nearly 1 in 6 children (16 percent) is born after a 'too short' interval (≤ 24 months). In the Matlab area of Bangladesh, DaVanzo et al. (2008) in an in-press article find that shorter intervals are associated with higher mortality after controlling for other correlates of under-five mortality. The major objective of this study is to determine the effect of preceding birth interval on under-five mortality in Bangladesh .This study has shown that children born less than 24 months after a previous sibling has a risk of death. Birth interval with 0 to 24 months has highly significant effect on under-five mortality and has 73% more rate of failure compared to the children whose preceding birth interval is 24 to 36 months.

II. Data Source

The data utilized for the analysis are extracted from the nationally representative 2011 Bangladesh Demographic Health Survey (BDHS). Bangladesh Demographic and Health Surveys (BDHS) is a part of the worldwide Demographic and Health Surveys program, which is designed to collect data on fertility, family planning, and maternal and child health. This survey conducted under the authority of the National Institute of Population Research and Training (NIPORT) of the Ministry of Health and Family Welfare and implemented through a collaborative effort of Mitra and Associates of Dhaka. In this survey, all ever-married men of age 15-

54 who were usual members of the selected households or who spent the night before the survey in the selected households were eligible for individual interview. This study utilized the 2011 birth dataset.

III. Variables

3.1 Dependent Variable

Dependent variable is under-five mortality status. The variable B5(Child is alive) in BDHS 2011 data, gives value "1" if child is alive and "0" for death. The dependent variable "Mortality" gives value "1" if child is death and "0" for alive which is obtained from re-coded variable B5. Dependent variable or event is under-five mortality (death at 0 to 59 months after birth).

The event of interest is death under age of five years and the variable censoring indicator generated from the variable age at death (BDHS-2011) is defined as

$$\text{Censoring indicator} = \begin{cases} 1; \ if\ a\ child\ dies\ before\ age\ 5, \\ 0; \ otherwise \end{cases} \quad \ldots \quad (1)$$

3.2 Independent Variable

3.2.1 Preceding birth interval:

In the dataset, the variable preceding birth interval means the time between two successive births, is given as continuous variable. However, for simplicity of our study, we divide the variable into 3 categories, such as: preceding birth interval 0-24, interval 25-36 and interval above 36.

3.2.2 Size of child at birth

There are five categories for this variable. These are: very large, larger than average, average, smaller than average and very small. The first category is made by merging very large, larger than average and average categories. Moreover, by merging smaller than average and very small categories, we define the second category, small.

3.2.3 Gender of child

Gender is also a factor of low birth size. So, this gender variable has 2 categories. These are: male and female.

3.2.4 Wealth index

In the dataset, there are 5 categories for this variable. These are: poorest, poorer, middle, richer and richest. From the above categories, we make 3 categories for our study. By merging poorest and poorer categories, the first category is created, which is Poor. Second category is middle and third category is created by merging richer and richest.

3.2.5 Dummy variables for level of education

The study also controls for the effect of education on birth weight. For the logistic regression run, the educational attainment variable has been categorized into four: (1) no education or incomplete primary, (2) completed primary education, (3) completed at most secondary education, (4) completed at least higher education.

3.2.6 Mother age at Birth

A U-shaped relationship has been suggested in some studies to explain the effect of maternal age on birth weight with teenage mothers and those of higher age being at greater risk of having low birth size baby. Therefore, we recoded the variable into age groups: 15-19 years; 20-29 years; 30-34 years and > =35 years.

3.2.7 Place of delivery

There are 11 categories for this variable, which are: respondent's home, government hospital, special medical college, district hospital, maternal and child welfare centre, upazilla health complex, health and family welfare centre, private hospital, private medical college hospital, NGO static clinic and others. Place of delivery related with health care services are categorized as hospital and home and others are categorized as others.

IV. Methodology

To incorporate survival time along with censored and uncensored observations and to provide valid estimates commonly bivariate technique used in survival analysis which is known as Product-Limit (PL) estimator. Log-Rank test is also used to compare survival probabilities between two or more groups of individuals.

4.1 Product-Limit (PL) Estimator

Bivariate analysis will be conducted by using Product Limit (P-L) estimator for survival function. This is also known as Kaplan and Meier estimate, from the authors who first discussed its properties (Kaplan and Meier,1958). The advantage of using P-L method is that censoring is taken into account in estimating the survival functions. Let (t_i, δ_i); i = 1,…,n represent a censored random sample of lifetimes. Suppose, there are k(k ≤ n) distinct time points $t_1, t_2, \ldots, t_k$ at which events occur. Also, let d_j denote the number of events at time t_j and n_j is the number of observation available at t_j.

Then the P-L estimator of survival function S (t_j) is defined as,

$$S(\hat{t_j}) = \prod_{i=1}^{j}\left(1 - \frac{d_j}{n_j}\right) \qquad \ldots (2)$$

4.2 Logs-Rank Test

Log-rank test is employed to compare the survival probabilities between two or more groups of individuals. Let us consider m groups. Our main interest is to test the null hypothesis

H_O : Survival functions for all groups are equal.

H_A : At least one survival function is different to others.

Mathematically,

H_O: S_1(t) = S_2(t) = … = S_m(t),

H_A: At least one is different

Where$S_i(t)$ is the survival function for the ith group, i = 1,…,m. Let $t_1 < t_2 < \ldots < t_j < \ldots < t_N$ denotes the distinct times of failures observed in the total sample obtained by combining all groups of interest.

Let d_{ij} be the number of events occurred at t_j in group i, d_{ij} be the number of individual at risk at time t_j in group i. Then $d_j = \sum_{i=1}^{m} d_{ij}$ be the number of events at t_j and $n_j = \sum_{i=1}^{m} n_{ij}$ be the total number of individuals at risk at time t_j . Also let,$O_i = \sum_{j=1}^{N} d_{ij}$ be the total number of failures for group i.

4.3 Cox's Proportional Hazard Regression Model

The Cox's proportional hazard model is most widely used multiple regression method for modeling survival data.

Proportional hazard (PH) models can be of two types. They are briefly discussed below:

a) Parametric Proportional Hazard (PH) Model: If $h_0(t)$ is specified with a parametric functional form, the model is known as parametric proportional hazard (PH) model.
b) Semi parametric Proportional Hazard (PH) Model: If $h_0(t)$ is defined arbitrarily the model is called semi parametric proportional hazard (PH) model.

4.4 Semi-parametric Cox's PH Model

In semi-parametric Cox's PH model, the form of baseline hazard function $h_0(t)$ is unknown or unspecified. It implies that the distribution of lifetime random variable T is unknown. The major limitation of using parametric PH model is that one has to assume a distribution for T. In practice, it is not always feasible to assume a specific distribution for T. For this reason, one may measure the effects of covariates on lifetime T by fitting a statistical semi-parametric PH model given as follows:

$$h(t|x) = h_0(t)C(x) \qquad \ldots (3)$$

Where C(x) has a known parametric form such as $C(x) = e^{\beta' x}$ and $h_0(t)$ is left as an arbitrary function. This model is also known as the Cox PH model.

4.4.1 Bivariate Analysis

Survival Curves for Different covariates

Graphical presentation of survival plot for the variables: age of mothers, region, mother's education level, wealth index, birth order number, sex of child, place of residence, place of delivery, size of child at birth, preceding birth interval obtained from P-L method for the current study are given below along with Log-rank test where the variable time is measured in days.

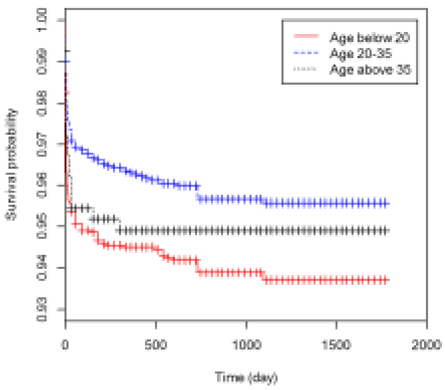

Figure 1: Survival curves for age of mothers (p-value =0.00)

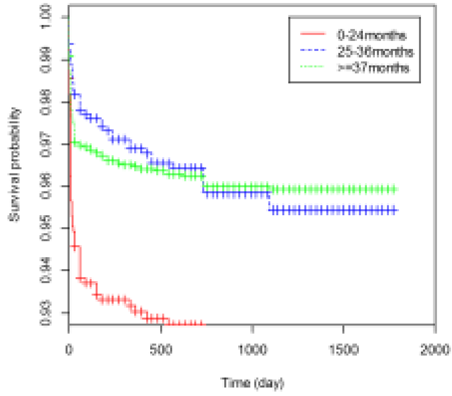

Figure 2: Survival curves for preceding birth interval (p-value =0.00)

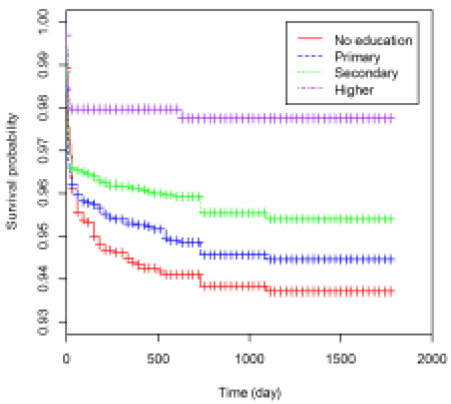

Figure 3: Survival curves for mother's education level (p-value =0.00)

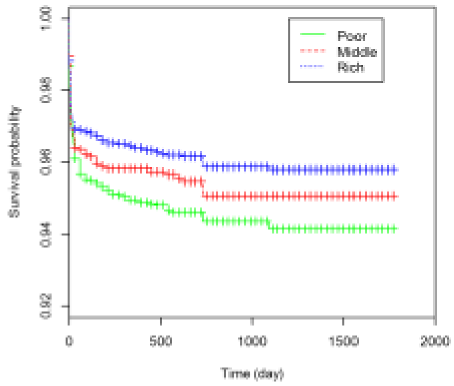

Figure 4: Survival curves for wealth index (p-value =0.01)

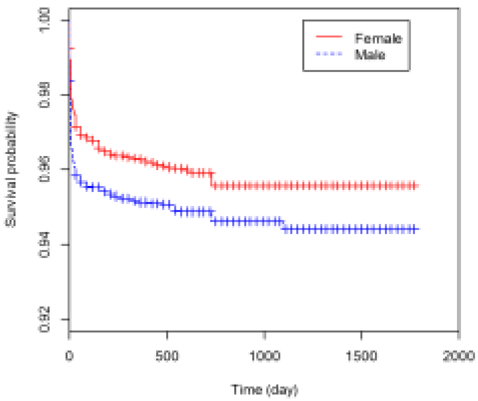

Figure 3.5: Survival curves for gender of child (p-value =0.01)

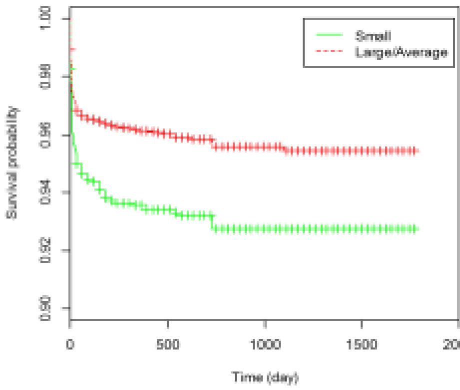

Figure 3.6: Survival curves for size of child at birth (p-value =0.00)

K-M approach and log-rank test for bivariate analysis are conducted here. It can be seen that children with preceding birth interval 0-24 months seem to live lowest life compared to the interval 25-36 and above 36. Since p-value is 0.00, the survival experience among different groups of preceding birth interval differs significantly. So, preceding birth interval is a potential determinant for under-5 mortality. From the p-value, we identify nine variables that have significant effects on under-5 mortality. Children of mothers aged 20- 35 are more likely to survive compare to the other groups. . It is observed that the children of mothers with higher education tend to live a longer life than the children of mothers with other education levels, because mother with higher education have better knowledge about child health and maternal health. Also the children from rich family seem to live longer life compared to the children from middle and poor families. Female children tend to live longer life than male children. Normal (large/average) size of child tend to live longer life compared to a small child. So the variables are : age of mothers, mother's education level, wealth index,, gender of child, size of child at birth and preceding birth interval found to have statistically significant effect on under-5 mortality in the bivariate analysis that will be included in the regression analysis.

4.4.2 Survival Analysis

Three Cox proportional hazard model is discussed to see the effect of preceding birth interval on under-five mortality:

1. Modeling the hazard only for preceding birth interval as a covariate.
2. Modeling the hazard for preceding birth interval, demographic and socio-economic factors.

TABLE: Estimates of covariates for under-5 mortality using Cox PH Model to see the effect of preceding birth interval

		Model:1			Model:2		
Variables	**Category**	**β**	**HR**	**P-value**	**β**	**HR**	**P-value**
Preceding Birth interval	0-24 months	0.594	1.812	0.00	0.55	1.733	0.00
	25-36 months	-	-	-	-	-	-
	>36 months	-0.015	0.985	0.93	0.030	1.031	0.87
Mother's age at birth	<20 years				0.393	1.481	0.03
	20-35 years				-	-	-
	>35 years				0.242	1.27	0.31
Gender of child	Male				0.049	1.050	0.70
	Female				-	-	-
Size of child at birth	Small				-	-	-
	Large/Average				-0.595	0.55	0.00
Mother's education level	No education				-	-	-
	Primary				0.103	1.109	0.53
	Secondary				-0.283	0.752	0.148
	Higher				-1.313	0.269	0.01
Wealth index	Poor				0.087	1.091	0.69
	Middle				-	-	-
	Rich				0.049	1.050	0.81
Place of delivery	Home				-	-	-
	Hospital/Clinic				0.435	1.554	0.01

It is observed that the covariates preceding birth interval between 0 to 24 months, mother's age at birth for less than 20 years, and size of child at birth which have significant effects on under-five mortality. For 1st model, only preceding birth interval is used as a covariate and it has significant effect with level of significance 0.001%. Birth interval with 0 to 24 months has highly significant effect on under-five mortality and has 81% more rate of failure compared to the children whose preceding birth interval is 24 to 36 months. From the 2nd semi parametric Cox PH model, it can be concluded that birth interval with 0 to 24 months has highly significant effect on under-five mortality and has 73.3% more rate of failure compared to the children whose preceding birth interval is 24 to 36 months. Children whose mothers are aged below 20 have 48.1% more rate of failure compared to the children whose mothers are aged between 20-30. This age group has significant and positive effect on under-5 mortality with level significance 0.05%. Mother's education level plays an important role on under-5 mortality. Children whose mothers have higher education has 26.9% less rate of failure compared to a child whose mothers have no education and has significant effect on under-five mortality with level of significance 0.01%. Children from poor family have 9.1% more rate of failure compared to a child from a middle class family and shows insignificant but positive effect on under-5 mortality. Normal(average/large) child has 55% less rate of failure compared to small child.

V. Conclusion

From the semi parametric Cox PH model, it is observed that the covariates which have significant effects on under-five mortality are: mother's education at secondary and higher level, preceding birth interval between 0 to 24 months, mother's age at birth for less than 20 years and large/average size of child. For under-five mortality preceding birth interval plays a vital role. If the birth interval between two Childs is less than two years, then the mortality rate becomes extremely high compared to the birth interval more than two years and it shows significant and positive effect. We can shape the effect for some covariates by promoting preceding birth interval with greater than 24 months, to encourage mother's education at secondary and higher level and to aware women to take children after 20 years for reducing under-five mortality. Based on the discussion of this study some Government should initiate awareness developing programs to motivate and inform spouses about optimal birth interval so that women may have higher birth interval, through campaign or mass media.

References

Journal Papers:

[1]. Mohammad, K. A., & Tabassum, T. (2016). The Impact of Socio-Economic and Demographic Factors on Under-Five Child Mortality in Bangladesh.*Imperial Journal of Interdisciplinary Research*, *2*(8)

[2]. Demographic, B. (2011). Health Survey BDHS (2011), Preliminary Report.*Addis Ababa: Federal Ministry of Health.*

[3]. Macro, O. R. C., & ICDDR, B. (2003). Bangladesh maternal health services and maternal mortality survey 2001.

[4]. Rutstein, S. O. (2008). DHS WORKING PAPERS.

[5]. Hill, K., El Arifeen, S., Koenig, M., Al-Sabir, A., Jamil, K., & Raggers, H. (2006). How should we measure maternal mortality in the developing world? A comparison of household deaths and sibling history approaches. *Bulletin of the World Health Organization*, *84*(3), 173-180.

[6]. Kaplan, E. L., & Meier, P. (1958). Nonparametric estimation from incomplete observations. *Journal of the American statistical association*, *53*(282), 457-481.

[7]. Feigelson, E. D., & Nelson, P. I. (1985). Statistical methods for astronomical data with upper limits. I-Univariate distributions. *The Astrophysical Journal*,*293*, 192-206.

[8]. Nagelkerke, N. J. (1991). A note on a general definition of the coefficient of determination. *Biometrika*, *78*(3), 691-692.