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Analyzing Child Survival in Ghana

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Abstract

Efforts aimed at reducing child mortality in developing countries, including Ghana, are not likely to meet the criteria set under the Millennium Development Goals Four. Part of the problem is the non-availability of adequate data and absence of rigorous statistical analysis. In this study, non parametric Survival analysis techniques, using a moving cohort, with some of the data right-censored, were used to estimate the survival and hazard functions and identify associated risk factors. The Weibull and Log-logistic distributions fitted child survival data appropriately. The study showed that 10% of children born would not survive by year five. Furthermore, the age of the mother, level of education and residence of mother, significantly influenced child survival. The factors suggested cultural practices or norms play substantial roles in child survival, and that female education must be given high priority.

Keywords: Censoring, Contraceptive use, Prognostic factors, Weibull distribution

1 Introduction

Child survival and its converse mortality are key indicators of child health and significant indicators of a country's priorities and values. Research on Child mortality and the phenomenon that influence it has been led by Social and Medical approaches. While Social approaches have emphasized the roles of socioeconomic and cultural factors, Medical approaches have emphasized biological processes of diseases [1]; these approaches however, have not focused on the techniques of measurements of mortality. However, the appropriate understanding and management of this phenomenon are dependent on accurate, precise and informative measurements.

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With the apparent failure to achieve Millennium Development Goal (MDG) 4, the need to explore the use of alternative statistical methods is imperative to the understanding of this crisis [2]. The increasing interest in better measures continues to lead to the development of more accurate and less expensive methods [3]. However, these methods must provide better and more informative statistics on Child Survival. The lack of this, over the years, has been partly due to the problem of non-availability of adequate and reliable data and the problem of robust statistical estimators.

Despite the extreme importance of appropriate and effective measures, child mortality has seen only the application of basic statistical methods that do not allow for detailed and rigorous analysis of this phenomenon. These techniques do not differentiate forecast from actual measurements and give no indication of confidence around point estimates [2]. Central rates, particularly child mortality rates as well as their specific rates, are the most widely used measures of estimating child mortality and hence survival. These static measures do not consider the obvious effect of time on mortality, and are influenced by overlaps (since the deaths during a period usually do not match the risk of that period), population composition (and therefore do not allow for fair direct comparison) and lack measures of precision: The consequence of this lack of precision is lack of predictive value and confidence in future results and limitation to statistical manipulations.

In this study, we apply survival analysis techniques, as an alternative to the central rates, and demonstrate its advantage as a more informative measure of Child survival.

2 Methodologies

2.1 Data Set

The data for this study was obtained from the Ghana Statistical Service and was collected in the Ghana Maternal Health Survey of 2007. The Survey which was the first of its kind in Ghana provided reliable and nationally representative data to study this phenomenon [4]. The current cohort is used in this study. By this method, a single cross section of time is used and manipulated to represent a cohort. Thus, different individuals may have different start points within the selected study time frame (2002 to 2007). Time to death from birth, for the dead, and the period of observation from birth, for those alive, is derived from the data as estimates of each child survival during the period. These are classified as censored (for those not dead) and uncensored (for those dead). Thus, the age of a child at death and the age of a child at the date the data was collected are used. Since the date of birth for children are known, all censored data are right censored. Some socio-economic and demographic covariates are also extracted for study of their impact on child survival.

2.2 Methods

In estimating the survival function$S(t)$, we assumed that the times at which the deaths of children occur are a realization of some random process; thus child survival are a probabilistic or stochastic process. The time to death for any Child, T, is therefore a random variable having a probability distribution $f(t)$ and consequently a cumulative distribution function $F(t)$ and from which the hazard function $h(t)$, can be found.

2.2.1 Basic concepts in survival

Let T, denote the survival time from birth. The distribution of T can be characterized by three equivalent functions [5].

Survival Function [S(t)]
$S(t) = P(a\ Child\ survives\ longer\ than\ t) = P(T > t)$

From the definition of the cumulative density function, $F(t)$, of T,

$$S(t) = 1 - P(a\ \ Child\ dies\ before\ t) = 1 - F(t) \qquad (1)$$

$S(t)$ is a non increasing function of time with properties

$$S(t) = \begin{cases} 1 & for\ t = 0 \\ 0 & for\ t = \infty \end{cases}$$

Probability Density function [f(t)]
The survival time has a probability density function defined as the limit of the probability that a Child dies in the short interval t to $\triangle t$ per unit width $\triangle t$, or simply the probability of dying in a small interval per unit time. It can be expressed as:

$$f(t) = \frac{\lim_{\triangle t \to 0} \mathrm{P[a\ Child\ \ dying\ \ in\ the\ \ interval}\ \ (\mathrm{t}, \mathrm{t}+\triangle \mathrm{t})]}{\triangle t} = \frac{\lim_{\Delta t \to 0} P[x \in (t, t+\Delta t)]}{\Delta t}$$

Where x is a Child dying
$f(t)$ is a non negative function such that;

$$f(t) = \begin{cases} \geq 0 & for\ all\ t \geq 0 \\ = 0 & for\ all\ t < 0 \end{cases}$$

Hazard function [h(t)]
The hazard function, $h(t)$, gives the conditional failure rate. It is the probability of a Child dying in a small interval of time assuming that the Child has survived to the beginning of that time interval.

$$h(t) = \frac{lim_{\triangle t \to 0} P\begin{bmatrix} a\ Child\ \ dying\ \ in\ the\ interval\ \ (t, t+\triangle t) \\ given\ \ the\ Child\ has\ survived\ \ to\ t \end{bmatrix}}{\triangle t} = \frac{\lim_{\Delta t \to 0} P[x_t \in (t, t+\Delta t)]}{\Delta t}$$

Where x_t is a Child dying after he/she has survived to time t
The hazard is also known as the instantaneous failure rate, the force of mortality, the conditional mortality rate or the age specific death rate. All these three functions can be depicted graphically and are related by

$$h(t) = \frac{f(t)}{S(t)} \qquad (2)$$

2.2.2 Estimating the survival functions

In this study we used a non parametric method, the Life Table method (LT), to estimate the survival functions. LT estimates the survival functions for each interval, and utilizes

their mid points to estimate the hazard and density functions and the upper limit to estimate survival functions as follows [6];
For the i^{th} interval, let t_i be the start time and q_i be the conditional probability of dying. Then:

$$\hat{S}(t_i) = \prod_{j=1}^{i-1}(1-\hat{q}_j)$$

$$\hat{f}(t_{mi}) = \frac{\hat{S}(t_i)-\hat{S}(t_{i-1})}{b_i} = \frac{\hat{S}(t_i)\hat{q}_i}{b_i}$$

$$\hat{h}(t_{mi}) = \frac{d_i}{b_i(n_i - \frac{1}{2}d_i)} = \frac{2\hat{q}_i}{b_i(1-\hat{p}_i)}$$

Where
t_{mi} is the mid-point of the i^{th} interval,
d_i is the number of children dying in the i^{th} interval,
n_i is the number of children exposed in the i^{th} interval,
$q_i = \frac{d_i}{n_i}$ is the conditional probability of dying in the i^{th} interval,
$p_i = (1 - q_i)$ is the conditional probability of dying in the i^{th} interval,
b_i is the width of the i^{th} interval.

The standard errors are estimated [6] [7] by:

$$s.e.\left(\hat{S}(t_i)\right) \simeq \hat{S}(t_i)\sqrt{\sum_{j=1}^{i-1}\frac{\hat{q}_j}{n_j(1-\hat{q}_j)}}$$

$$s.e.\left(\hat{h}(t_{mi})\right) \simeq \hat{h}(t_{mi})\sqrt{\frac{\left\{1-\left[\frac{1}{2}\hat{h}(t_{mi})b_i\right]^2\right\}}{n_i\hat{q}_i}}$$

$$s.e.\left(\hat{f}(t_{mi})\right) \simeq \hat{S}(t_i)\hat{q}_i\sqrt{\frac{\left(\sum_{j=1}^{i-1}\frac{\hat{q}_j}{n_j(1-\hat{q}_i)}+\frac{(1-\hat{q}_i)}{n_j\hat{q}_j}\right)}{b_i}}$$

2.2.3 Log rank test

The Log-rank test [8], a non parametric test, was used in this study to test for any difference in the survival functions of the groups. This test is the most widely used technique when data are censored and measures the difference in survival for the different groups at each of the given time. For a k factor group, this test the hypothesis that;

$$H_o: S_1(t) = S_2(t) = \cdots = S_k(t) \qquad \text{for all } t$$

Against the alternative:

H_1: $\quad not\ all\ S_j(t)\ are\ equal. \qquad j = 1, 2, ..k.$

where $S_j(t)$ is the survival function for the j^{th} group

The log-rank test is tested as a chi-square test which compares the observed numbers of failures to the expected number of failure under the hypothesis.
Thus, given that O_j and E_j is the observed and expected number of deaths respectively for the j^{th} group, the test statistic is given by;

$$\chi^2 = \sum_{j=1}^{k} \frac{(O_j - E_j)^2}{E_j}$$

where

$$E_j = \sum_{all\ t} e_{jt}$$

$$e_{jt} = \frac{n_{jt}}{\sum_{all\ j} n_{jt}} \times d_t$$

and

n_{jt} is the number of children still exposed to the risk of dying at time up to t for the j^{th} group
d_t is the total number of deaths for all groups at time t. Thus:

$$d_t = \sum_{all\ j} d_{jt}$$

has approximately the chi-square distribution with $k-1$ degrees of freedom. A large chi-square value will lead to a rejection of the null hypothesis in favor of the alternative that the k groups do not have the same survival distribution.

2.2.4 Proportional hazard regression

The Cox proportional regression as proposed by Cox [9], was used to determine the effect of some socio economic and demographic factors on Child survival. In this model, the hazard for an individual is assumed to be related to the covariates through the equation;

$$h_i(t) = \lambda_0(t)\exp\{\beta_1 x_{i1} + \cdots + \beta_k x_{ik}\}$$

Taking the logarithm of both sides, the model can also be written as

$$\log h_i(t) = \alpha(t) + \beta_1 x_{i1} + \cdots + \beta_k x_{ik}$$

where $\alpha(t) = \log \lambda_0(t)$.

While $\alpha(t)$, can be specified for particular distributions, its specification is however unnecessary in a Cox model and it can take any form. The ratio of the hazard for two individuals i and j is given by;

$$\frac{h_i(t)}{h_j(t)} = \frac{\lambda_0(t)\exp\{\beta_1 x_{i1} + \cdots + \beta_k x_{ik}\}}{\lambda_0(t)\exp\{\beta_1 x_{j1} + \cdots + \beta_k x_{jk}\}}$$

$$= \exp\{\beta_1\left(x_{i1} - x_{j1}\right) + \cdots + \beta_k(x_{ik} - x_{jk})$$

$\beta_1, \dots, \beta_k$ are therefore a measure of the relative risk for the i^{th} child, over the j^{th} with respect to the change in the x_l^{th} covariate, $l = 1, \dots, k$ respectively.

2.2.5 Determining the Survival Models

Survival models are useful in summarizing the survival pattern, suggesting further studies, and generating hypothesis. In this study the graphical approach was used to fit the survival distribution, with the hazard plot guiding the choice of the probable distributions. From the shape of hazard plot (Figure 1) the Weibull and Log-logistic distributions were assumed appropriate.

The hazard plotting technique [10] involves the plotting of the survival function (or a function of it) against the cumulative hazard function (or a function or it): They are designed to handle censored data. The cumulative hazard function, $H(t)$, is defined as;

$$H(t) = \int_0^t h(t)dt$$

Where from equation (1) and (2)

$$h(t) = \frac{-S^{|}(t)}{S(t)}$$

and thus

$$H(t) = -\ln[S(t)]$$

For our assumption of a Weibull distribution,

$$f(t) = \lambda\gamma(\lambda t)^{\gamma-1}\exp[-(\lambda t)^\gamma]$$

$$S(t) = \exp[-(\lambda t)^\gamma]$$

And hence the cumulative hazard is given by

$$H(t) = (\lambda t)^\gamma \qquad where\; t > 0$$

Thus

$$t = \frac{1}{\lambda}[H(t)]^{\frac{1}{\gamma}}$$

$$\ln t = \frac{1}{\gamma}\ln H(t) + \ln\frac{1}{\lambda}$$

Thus a graph of $\ln t$ against $\ln H(t)$ yielded a straight line graph with intercept $\ln\frac{1}{\lambda}$ and gradient $\frac{1}{\gamma}$ which lead to the estimation of shape (γ) and scale (λ) parameter of the Weibull distribution.

For a Log-logistic model,

$$f(t) = \frac{\alpha\gamma t^{\gamma-1}}{(1+\alpha t^{\gamma})^2}$$

$$S(t) = \frac{1}{1+\alpha t^{\gamma}}$$

And hence, the cumulative hazard is given by

$$H(t) = \ln(1+\alpha t^{\gamma})$$

$$t^{\gamma} = \frac{\exp[H(t)] - 1}{\alpha}$$

And hence

$$\ln t = \frac{1}{\gamma}\ln\{exp[H(t)] - 1\} - \frac{1}{\gamma}\ln\alpha$$

Thus a graph of $\ln t$ against $\ln\{exp[H(t)] - 1\}$ yielded a straight line graph with intercept $-\frac{1}{\gamma}\ln\alpha$ and gradient $\frac{1}{\gamma}$ which lead to the estimation of shape (γ) and scale (α) parameter of the log logistic model.

2.2.6 Evaluation of the goodness of fit

The appropriateness of our models was assessed by the Kolmogorov Smirnov Test. This non parametric test, tests the hypothesis that, two samples of data are from the same distribution, against the alternative that the underlying distributions are different. The test statistic is the maximum absolute difference between their cumulative distribution functions. The observed cumulative density functions were therefore tested against the expected cumulative density functions generated from the assumed models for any significant difference.

3 Main Results

Tables 1 and 2 show the Hazard, Density, Cumulative hazard and Survival estimates with their standard errors. The results show the error of estimating these functions are less than half a percent (0.005) for the hazard and density estimates and up to about half a percent, for the Cumulative hazard and Survival estimates. The child's highest risk of dying is in the first year of life and generally decreases over time. About 6 percent (probability of 0.0618903) of children born die in the first year and this represents about 60 percent of the total child deaths. About 10 percent of children born die by age 5 years (Survival probability of 0.8972530): This translates to about a 1 in 10 chance of a child dying by age 5 years.

Table 1: Hazard, and Density estimates for child survival

Time	Hazard, h(t)	Standard Error of h(t)	Density, f(t)	Standard Error of f(t)
0.5	0.0618903	0.0031248	0.0618903	0.0031248
1.5	0.0146614	0.0018336	0.0137540	0.0017207
2.5	0.0151715	0.0022199	0.0140239	0.0020527
3.5	0.0111297	0.0024748	0.0101317	0.0022533
4.5	0.0032733	0.0023108	0.0029466	0.0020802

Table 2: Survival and Cumulative hazard estimates for child survival

Time	Survival Probability, S(t)	Cumulative Hazard, H(t)	Standard error of S(t) and H(t)
1	0.9381100	0.0638881	0.0031248
2	0.9243560	0.0786580	0.0035269
3	0.9103320	0.0939459	0.0040342
4	0.9002000	0.1051383	0.0045815
5	0.8972530	0.1084174	0.0050180

Six of the Socio-Economic and Demographic factors are shown in Table 3 to be individually significant prognostic factors for Child survival at 5% significance. From the regression analysis (Table 4), Singletons, Children born in urban communities and those born in areas that had benefited from the R3M interventions and those with Christian mothers have better survival chances. The intervention in the R3M regions (Ashanti, Eastern and Greater Accra) was designed to reduce maternal morbidity and mortality by increasing contraceptive prevalence through availability and utilization of contraceptives and comprehensive abortion care. The results suggest a success story for the intervention.

Table 3: Log rank test of Prognostic factors for Child Survival

Variable	D.F	Chi-Square	P-Value
Socio Economic:			
R3M Region	1	8.36333	0.004*
Rural or Urban	1	7.69284	0.006*
Mother Ever Schooled	1	7.54756	0.006*
Mother's HLEA**	3	1.41820	0.701
Mother's Religion	3	9.55382	0.023*
Demographic:			
Mother's Firstborn	1	0.41857	0.518
Singleton or Not	1	39.55300	0.000*
Child's Gender	1	3.02506	0.082

Mother's Age (Categorized)	2	8.11144	0.017*

*: Means significant at the 5% level of significance
**: Mother's HLEA represents Mother’s Highest Level of education Achieved

Table 4: Cox's regression Analysis of Child Survival

Variable	level	D.F	B	S.E (B)	t	Sig**	Exp(B)
Socio Economic:							
Rural or Urban	Urban	1	-0.1700	0.1050	-1.610	0.105	0.8440
Ever Schooled	Yes	1	-0.1120	0.1080	-1.040	0.008*	0.8937
R3M Region	R3M	1	-0.1470	0.1030	-0.144	0.036*	0.8629
Religion	Moslem	3	0.1970	0.1230	1.590	0.406	1.2170
	Others		0.1260	0.1840	0.690		1.1350
	Trad/Spiri***		0.2090	0.1950	1.070		1.2330
Demographic:							
Mothers Age		1	-0.0144	0.0076	-1.890	0.044*	0.9857
First born	Yes	1	0.0520	0.1300	0.400	0.320	1.0540
Child's Gender	Male	1	0.1430	0.0898	1.590	0.100	1.1540
Singleton or Not	Single	1	-0.9100	0.1520	-5.990	0.000*	0.4023

*: Means significant at the 5% level of significance
**Significance as calculated here is for the corresponding variable and not the level
***Trad/Spiri represents Mothers who are African Traditionalist or Spiritualist

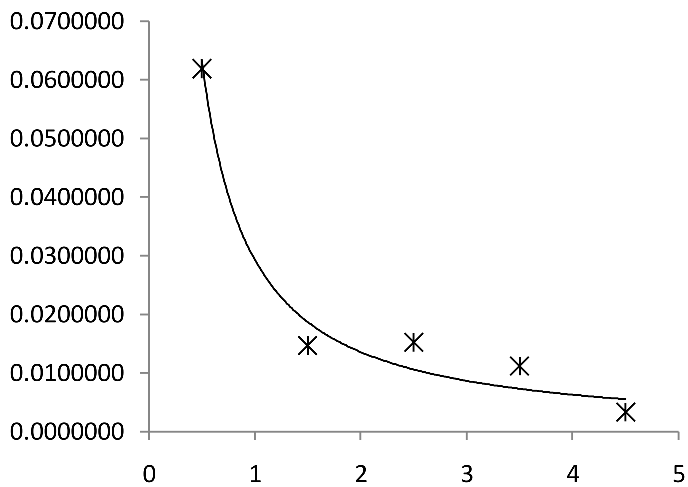

Figure 1: Hazard Plot for Child Survival

The hazard trend, as shown in Figure 1, shows a hazard that is decreasing at a decreasing rate and therefore suggests the Weibull ($\gamma < 1$) and log-logistic distributions, whose hazards behave in such a fashion. Consequently, the corresponding hazard plotting for these distributions are shown in Figure 2 and 3, with the estimated shape and scale parameters of the assumed distributions shown in Table 5. Table 6 shows the closeness of the expected values of child survival for our assumed distributions to the observed values. The appropriateness of our assumed distributions is confirmed by the Kolmogorov Smirnoff test as shown in Table 7.

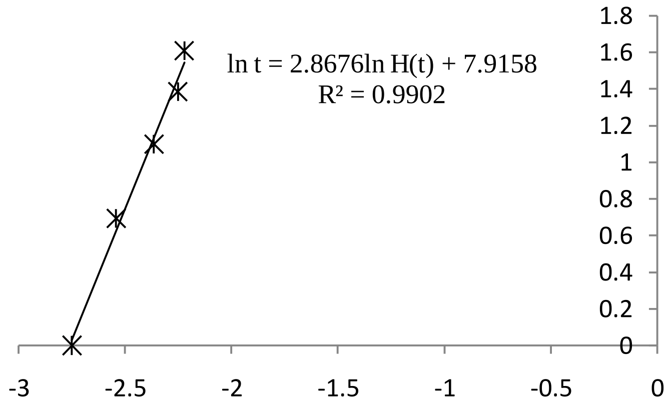

Figure 2: Graph of ln(t) against ln[H(t)] for Assumed Weibull Distribution

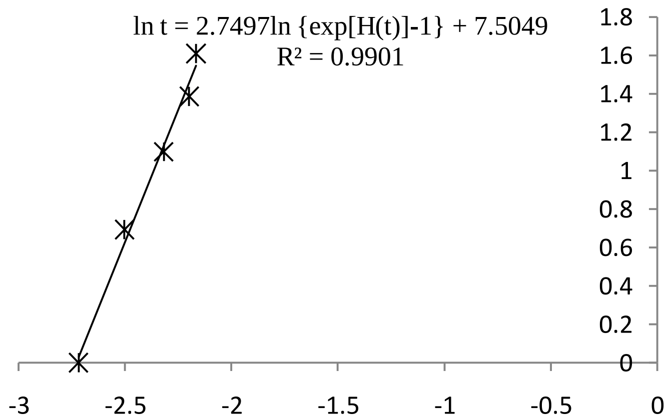

Figure 3: Graph of ln(t) against ln{exp[H(t)-1]} for Assumed Log-Logistic Model

Table 5: Parameter Estimates for Assumed Distribution

		Parameter Estimates		
	Assumed Distribution	**Shape**	**Scale**	**R-Square**
1	Weibull	0.348724	0.0003649	0.9902
2	Log-logistic	0.363676	0.0652615	0.9901

Table 6: Expected Child Survival Probabilities for assumed Distributions

		Expected Survival probabilities	
Time	Observed Survival	Weibull Assumed	Log-logistic Assumed
1	0.9381100	0.9386969	0.9387366
2	0.9243560	0.9225988	0.9225331
3	0.9103320	0.9113790	0.9113163
4	0.9002000	0.9024979	0.9024890
5	0.8972530	0.8950366	0.8951104

Both the Weibull and Log-logistic model are shown to fit child survival well and there is little to choose between them. Expected percentage of child survival by age 10 and 12 years are approximately 87% and 86% respectively, by both distributions as shown in Table 8.

Table 7a: Kolmogorov Smirnoff Test

Assumed Distribution	Maximum Difference	χ^2 Value	Sample size	P-Value
Log logistic	0.2000	0.40	5	0.819
Weibull	0.2000	0.40	5	0.819

Table 7b: Paired T-Test for Observed and Expected Survivals

	Mean Difference	T-Value	Sample Size	P-Value
Observed verses Weibull Survivals	0.000008	0.01	5	0.993
Observed verses Log-Logistic Survivals	0.000013	0.02	5	0.988

Table 8: Forecasted Probability of Child Survival

	Predicted Probability of Survival	
Time	Weibull Assumed	Log-logistic Assumed
10	0.8683052	0.8689786
12	0.8602934	0.8612430

4 Discussion and Conclusions

The importance of reducing child mortality, as captured in the MDGs, requires a proper understanding of the phenomenon of child mortality that can attract the requisite response to curb the menace. A rigorous analysis of child survival is therefore of great importance in the understanding and management of child mortality.

This study investigated the application of survival analysis techniques to the measurement of child survival. Estimates of survival, hazard, probability and their corresponding errors were calculated, tests and regression of some covariates on survival conducted, probability models developed and tested, and forecasts made for child survival. These were obtained from data on the 2007 Ghana maternal health survey. The results obtained by our estimates and our model were adequately displayed and discussed.

Several methods exist for the assessment of child mortality but most of the methods usually used are central rates. These static measures do not adequately capture, what they are intended to represent. In this study we have demonstrated that survival techniques, which are dynamic measures, can be applied to the study of child survival. Survival techniques do not only provide more information than the central rates, like child mortality rates which are widely used, but also give precision for their estimates and enable the modeling of this phenomenon. These models and estimates provide better information and predictive potential, and allow for more effective and direct comparisons for different countries. Furthermore, this method allows for the use of both parametric and non parametric techniques in the analysis of child survival and therefore has the potential to lead a more rigorous and deeper analysis of child survival that will enable a better understanding of the phenomenon and hopefully, attract the appropriate response to address it.

The results show that Child mortality is approximately 10 percent and that for a child, life after birth is well described by the logistic and Weibull models. Child survival shows a decreasing hazard rate, decreasing at an increasing rate with age: Survival therefore decreases at a decreasing rate. These models showed that the risk of losing a child, faded with time and agrees with the first third of the well known bathtub shape of mortality and with Hirve & Ganatra's description of their Kaplan-Meier survival curve [11]. The first year after delivery however remains the most crucial period for children survival: It is by far the riskiest period of a child's life and a focus at this period could reduce child mortality by up to 60%. The shape and scale parameters for the log logistic models was estimated to be 0.348724 and 0.0003649 respectively while those for the Weibull distribution that describe them are 0.363676 and 0.0652615 respectively. The shape and scale parameters of these distributions, give indication of "aging" and "living longer" respectively [12].

The risk of dying for any individual is determined by the covariates associated with the person. The low risk of dying and hence better survival of singletons, urban children, children from regions which benefitted from the R3M interventions, children of Older mothers and mothers who had ever been to school, as well as the high risk (worse survival) of Male and the first born, are all supported by other studies [13], [14], [15]. Of the four factors that significantly affect child survival, three of them are indicative of the state of the mother and well within the control of society i.e. whether a Mother had been to school, her age, whether a child was from one of the Regions that benefitted from the R3M interventions. Thus, discouraging early births, providing basic education for mothers, providing for good maternal health issues and perhaps a general focus on the state of mothers, could significantly improve child survival. As a child grows, the factors that influence his or her survival become increasingly diverse and that becomes a challenge for the young and unschooled mother who may not be prepared for the continuum of responsibilities associated with child rearing. Cultural practices and norms that tend to affect maternal health and female education need to be given serious consideration

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