Application of Survival Analysis Techniques to Study Infant Mortality in Nigeria

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Abstract: Infant mortality rates are one of the health indicators in a given community or country. The study is to find out factors that is strongly associated to these high rates of infant mortality rates in Nigeria. The data was collected from the Nigeria Demographic Health Survey (NDHS) of which 6212 women of reproductive ages were selected for the study. Survival analysis techniques; such as Life table, Kaplan-Meier, and cox proportional hazard model were statistical tools used in analyzing time to event data. Results from Hazard curve rate shows that infant are most liable to die at age 7months and 9months and are least risked to death at ages 1month and 10months. The Kaplan-Meier survival plots indicate that female sex, rich families and higher education has higher chances of infant survival than otherwise. The Cox-proportional hazard approach showed that Infants born to mother with secondary and higher education has a low Hazard ratio (exp β) 0.944 and 0.650 compared with those born to mother with low education having an hazard ratio of 1.164. The study also affirmed that socio-economic and biological factors are strongly associated with high infant mortality rates.
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1.0 Introduction

A country's infant mortality rate is only a reflection of the quality of health delivery available to the citizens, and to a large extent a reflection of the quality of life enjoyed by the citizens of a country. Infant and child mortality rates are important indicators of societal and national development. In general, the developing or under developing countries have a very high infant mortality rate as compared to advance and developed countries. This has attracted many researchers in order to identify the factors strongly associated with high infant mortality rate and to evaluate the various government interventions. The study is aimed at identify factors responsible for infant mortality in Nigeria and this includes: biological, environment and socio- economic.

The data set was collected from the 2013 Nigerian Demography Health Survey (NDHS). The project is funded by the United States Agency for International Development (USAID) with contributions from other donors such as UNICEF, UNFPA, WHO and UNAIDS. A representative sample of 38522 for the 2013 households was randomly selected to participate in the survey, and these households contained 38948 women aged between 15-49 years of age. Out of the 38948 women interviewed, it should be noted that only 6212 women were considered for this research because we excluded all woman whose child is more than 11months. These women were interviewed by distributing questioners and information on their birth history were recorded. The information on the birth history includes; Child survival status (alive or dead); Male or female and Age at the day of interview if the child is alive and if dead, the age at death. Information on other characteristics of the woman recorded in the survey were the education level, place of residence, partner's education, household's income and others.

There are various authors who have carried out studies on factors responsible for infant mortality. Among them are: a paper by Mosley et al. (1984), an analytical framework for the study of child survival in developing countries which is a framework for the study of determinants of child survival in developing countries. The study incorporates both Social and Biological variables and integrates research methods used by social and medical scientists to study child survival. The frame work is based on the premise that all social and economic determinants of child mortality necessarily operate through a common set of biological mechanism or proximate determinants that exert an impact on mortality. Bailey (1988) examined the factors determining infant mortality using data from fertility and family planning survey in Uganda sponsored by the international research centre in Canada. The results of the analysis indicated that Background factors (current place of residence of the mother, religion and mother's tribe). Demographic factors (mother's age, age at first marriage, number of children ever born and duration of breast feeding), Social-economic factors (maternal and paternal education and occupation, household income) are the key determinants of infant and child mortality. Many other studies on the same research topic, in different countries, using survey data are in agreement with these results (Limin, 2003, Mondai et al., 2008, Nuwaha et al., 2011b, Uddin et al,2009).

A study by Hobcraft et al. (1984) identified five main social-economic factors that influence infant and child survival and these include mother's education, mother's work status, husband's occupation, husband's education and type of place of residence. They used a simple tabular analysis followed by a multivariate approach in order to assess the relative importance of each of the five variables. The study used the World Fertility Survey data that was based on enquiries from 28 developing countries. In Asian countries, mother's level of education was seen to be strongly associated with mortality of the child during the first five years of their life. In America, results indicated that the husband's education was most important and in a few African countries, infant mortality was relatively strongly associated to husband's occupation and education.

Ssengonzi and Shannon (2002) examined the effect of female migration on the health and survival of the most vulnerable migrants (infants and children) in Uganda. He used the Log logistic regression techniques to analyze the probability of a child surviving up to the age of five. Results showed that 10% of the children die before age five and within group difference in mortality exists in urban and rural children depending on their mother's migration status. Other variables like parent's education, household size, household hardship and mother's age at first birth, duration of breast feeding and place of delivery were seen to be significant.

From a statistical and data analysis point of view, different models have been used by different authors to study child survival. Ssengonzi and Shannon (2002) used Logistic regression techniques on the 1995 Ugandan Demographic Health Survey (UDHS) data set to determine the relationship between child survival and migration status. Some authors choose to use Log linear models to do the analysis for instance Curtis and McDonald (1991) used it to determine the effect of birth spacing on infant mortality in Brazil.

The Logistic model is the most popularly used model because it assumes that child survival is a binary response (child is dead or alive, Kazembe et al. (2012). All the above mentioned models ignore time to event and therefore fail to include the exposure to the risk of the event overtime. Other models like the Cox proportional hazard model by Cox (1972), are widely used to deal with time to event data and their relevancy on research in survival analysis in demography and related fields has increased over the years.

A study by Samson B. Adebayo and Ludwig Fahrmeir (2002) analyze child mortality in Nigeria with flexible geo-additive survival models. This class of models allows to measure small area district-specific spatial effects simultaneously with possibly nonlinear or time varying effects of other factors. Inference is fully Bayesian and uses recent Markov chain Monte Carlo (MCMC) simulation. The application is based on the 1999 Nigeria Demographic and Health Survey.

Definition of Terms

Mortality: Age at death and cause provide an instant depiction of health status.

Rate: The measure of the frequency with which an event occurs in a defined population during a given length of time. Rates are special cases of ratio and tend to be associated with population change. Rate is number of relevant event over population at risk multiply by k, where k is usually 1000.

Mortality rate: is a measure of the number of deaths (in general, or due to a specific cause) in particular population, scaled to the size of that population per unit of time, Mortality rate is typically expressed in units of deaths per 1,000 individuals per year.

Infant mortality rate (IMR): This is the number of infant deaths (children younger than one year of age) per 1000 live births. The rate is the total number of newborns dying under one year of age divided by the total number of live births during the year multiplied by 1000.

Crude death rate: This is the number of deaths in a given year per 1000 mid-year population.

Standardized death rate: These are rates used only for comparative purposes in order to eliminate the influence of population structure on Crude Death Rate. The rate may be standardized for age composition, sex composition and occupation composition.

Age specific death rate: This indicates the number of deaths per year in a specific age (group) per 1000 persons in the age (group).

Age and sex specific death rate: These are rate calculated for particular age and sex group of the population.

Fetal Mortality Rate (Stillbirth): This refers to dead born. Complications arising during birth are the main causes of death among almost all infants who were alive when labour started but were born dead.

Perinatal Mortality Rate: This is used to refer to deaths that might somehow be attributed to obstetric events such as stillbirths and neonatal deaths in the first week of live.

Neonatal Mortality Rate (NMR): This measure the risks to which births are exposed to in the first month. It often results from the condition of the woman and the environment.

Post-neonatal Mortality Rate (PNMR): This is measure as deaths to children between one and eleven months after birth.

Maternal mortality rate: Is the number of death as a result of complications of pregnancy and childbirth. This rate is conventionally defined as the number of deaths due to puerperal causes per 10,000 or 100,000 births.

Live birth: Complete expulsion or extraction from its mother of a product of conception, irrespective of the duration of pregnancy, which after such separation, breathes or shows any other evidence of life such as beating of the heart, pulsation of the umbilical cord, or definite movement of voluntary muscles, whether or not the umbilical cord has been cut or the placenta is attached; each product of such a birth is considered live-born.

2.0 Methodology

Survival analysis is a branch of statistics for analyzing the expected duration of time until one or more events happen, such as death in biological organisms and failure in mechanical systems. **I**t is a statistical method or tool used to analyze time to events data. (Cleves et al.,2008, Klein and Goel, 1992).

The survival function

Given a random variable T that denotes the survival time, the survival function denoted by $S(t)$ is defined as

$S(t) = P(T > t) = 1 - F(t) = 1 - $ Z0$t f(u)\, du,$

Where:

$f(t)$ and $F(t)$ are the probability density and the cumulative density functions respectively of a given distribution. The expression above is the probability of surviving beyond time t.

Note that $S(0) = 1$, $S(t) \to 0$ as $t \to \infty$. It is a downward sloping curve and can be estimated by using the Kaplan-Meier method.

The Hazard function

Given a set containing individuals who are at a risk of experiencing a certain event denoted by $R(t)$ (risk set) or individuals who have not yet experienced the event by time t, the probability of an individual in the risk set experiencing the event in the small time interval $[t, t + \Delta t)$ is defined as $h(t)\, \Delta t$. Therefore the hazard rate is defined as:

$h(t)=\lim 1/\Delta t P(t \le T < t+\Delta t | T \ge t)$.

$\Delta t \to 0$

Life Table

The life table is a mathematical model that portrays mortality condition at a particular time among a population and provides a basis for measuring longevity. A life table is constructed mainly to summarize the mortality experience of a group or cohort of people. It shows, on the basis of current mortality rates, the number, out of 1000 births or some convenient starting number that survives in a certain specific age and dying between this successive points of age. Assumptions in the construction of life table

a. The group or cohort is closed to migration so that changes in membership of the group are only through losses due to death.

b. People die at each age according to a fixed schedule (the ASDR).

c. The cohort originates from some standard numbers 1,000, 10,000 or 100,000 of births. The starting number is called the 'radix' of the life table.

d. The cohort normally contains members of only one sex. It is possible to construct a life table for both sexes but sex differential in mortality are pronounced enough to warrant separate treatment.

Notations of Life Table and their Algebraic Relationship.

l_x = number surviving to exact age x

L_x = number of year lived by the life table cohort between age x and $x+1$

p_x = probability of surviving at least one year after age x

q_x = probability of dying

T_x = total number of years lived after age x

e_x = complete expectation of life i.e. average period in years lived beyond age x by those who attain age x.

d_x = number of death in age x

$$d_x = l_x - l_{x+1}$$

$$d_0 = l_0 - l_1$$

$$p_x = \frac{l_{x+1}}{l_x}$$

$$q_x = 1 - \frac{l_{x+1}}{l_x} = \frac{l_x - l_{x+1}}{l_x} = \frac{d_x}{l_x}$$

$$L_x = \frac{1}{2}\left(l_x + l_{x+1}\right)$$

$$T_x = \sum_x^{\infty} L_x$$

$$T_{x+1} = T_x - L_x$$

$$e_x = p_x\left(1 + e_{x+1}\right)$$

For the abridge life table, a slight change in notation accompanies the change in interval. Another subscript placed before a term indicates the number of years in the interval. This applies to ${}_nq_x$, ${}_np_x$, ${}_nL_x$. It does not apply to l_x, T_x, and e_x which refer to an exact age. For example, ${}_nq_x$ is the probability of dying between age x and $x+n$, for an abridge table. Some of the life table notations can be stated more explicitly:

$${}_n p_x = \frac{l_{x+n}}{l_x}$$

$${}_n q_x = 1 - {}_n p_x$$

$${}_n d_x = l_x \times {}_n q_x = l_x - l_{x+n}$$

$${}_n L_x = \frac{n}{2}\left(l_x + l_{x+n}\right)$$

$${}_n M_x = \frac{{}_n d_x}{{}_n L_x}$$

$${}_n q_x + {}_n p_x = 1$$

The Kaplan-Meier

The Kaplan-Meier estimator also refers to as the product limit estimator presented by Kaplan and Meier (1958). It is a non-parametric statistic used to estimate the survival function from lifetime data. It gives a simple and quick estimate of the survival function in the presence of censoring.

Let $S(t)$ be the probability that a member from a given population will have a lifetime exceeding time, t. For a sample of size N from this population, let the observed times until death (or loss to follow-up) of the N sample members be

$t_1 \leq t_2 \leq t_3 \leq \ldots \leq t_N$

Corresponding to each t_i is n_i, the number "at risk" just prior to time t_i, and d_i, the number of deaths at time t_i. The Kaplan–Meier estimator is the non-parametric maximum likelihood estimate of $S(t)$, where the maximum is taken over the set of all piecewise constant survival curves with breakpoints at the event times t_i. It is a product of the form.

$$\hat{\hat{S}}(t) = \prod_{ti<t} \frac{ni - di}{ni} \quad (1)$$

The Cox-proportional hazard model

The most commonly used regression model is the Cox-proportional hazard model. With this model the distribution for the baseline hazard function is not specified and that is why it is called a semi-parametric model. The Cox-proportional hazard model is a more general model in modelling the hazard and survival function because it does not place distributional assumptions on the baseline hazard. The Cox model was introduced by Cox (1972). It has the form:

$h(t|X) = h_0(t) \exp(\beta_1 Xi_{1+} \beta_2 Xi_2 + \ldots + \beta_p Xi_p)$ (2)

$= h_0(t) \exp(X_i . \beta)$

This expression gives the hazard rate at time t for subject i with covariate vector (explanatory variables) X. The main objective in fitting the Cox proportional hazard model is to come up with estimates of the regression parameters (β's). Assuming that there are no tied event times, Cox (1972) described how to estimate the regression parameters (β's) by maximizing the partial likelihood given by:

$$L(\beta) = \prod_{i=1}^{n} \left[\frac{e^{xi\beta}}{\sum_{j\in R(ti)} e^{xj\beta}}\right] \delta i \quad (3)$$

$i = 1, 2\ldots, n; j = 1, 2,.., m,$

where $R(ti) = \{ j: t_j \geq t_i \}$, denotes the risk set at time t_i, n represents the number of individuals in the data set and m the observed survival times. Only event times contribute their factor to the numerator but both the censored and uncensored observations are included in the denominator where the sum over the risk set includes all individuals who are still at risk just before time t_i. It is easy to work with the partial log-likelihood which is given by;

$$l(\beta) = \ln(\mathrm{L}(\beta)) = \sum_{i=1}^{n} \delta i(\dot{x}i\beta) - \sum_{i=1}^{n} \delta i \ln\left[\sum_{j\in R(ti)} e^{xj\beta}\right]$$

(4)

Let β, denote the maximum partial likelihood estimate for β obtained by maximizing the partial log-likelihood function, the first derivative of $l(\beta)$ with respect to β is called a vector of efficient scores and is given by

$$U(\boldsymbol{\beta}) = \frac{dl}{d\beta} = \boldsymbol{X}^T\boldsymbol{\delta} - \sum_{i=1}^{n} \boldsymbol{\delta}_i \frac{\sum_{j\in R(t_i)} \exp\left(\boldsymbol{X}_j^T\boldsymbol{\beta}\right)\boldsymbol{X}_j}{\sum_{j\in R(t_i)} \exp\left(\boldsymbol{X}_j^T\boldsymbol{\beta}\right)},$$

where $\delta = [\delta 1,\ldots,\delta n]T$ denotes the vector of censoring indicators and X is the $n \times p$ matrix of covariate values with the jth row containing covariates of the jth individual ($X(j)$). To calculate the maximum likelihood estimates β ˆ, we solve a nonlinear system $U(\beta) = 0$ and we use the Newton Raphson algorithm. The information matrix $I(\beta)$ is given by the negative of the second derivative of $l(\beta)$;

$$I(\boldsymbol{\beta}) = -\frac{d^2 l}{d\beta^2}.$$

3.0 Data Analysis and Results

Analysis was carried out using SPSS Software.

Table 1: Classification by Region in Nigeria

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	North Central	898	14.5	14.5	14.5
	North East	1258	20.3	20.3	34.7
	North West	1922	30.9	30.9	65.6
	South East	574	9.2	9.2	74.9
	South South	755	12.2	12.2	87.0
	South West	805	13.0	13.0	100.0
	Total	6212	100.0	100.0	

Table 2: Categories of Religion respondents in Nigeria

		Frequ Ency	Percent	Valid Percent	Cumulative Percent
Valid	Catholic	510	8.2	8.3	8.3
	Other Christian	2031	32.7	32.9	41.1
	Islam	3588	57.8	58.1	99.2
	Traditionalist	45	.7	.7	99.9
	Other	4	.1	.1	100.0
	Total	6178	99.5	100.0	
Missing	99	34	.5		
Total		6212	100.0		

Table 3: Sex of Child

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	3079	49.6	49.6	49.6
	Female	3133	50.4	50.4	100.0
	Total	6212	100.0	100.0	

Life Table

In order to obtain the Hazard Rate Curve of sample under study, so as to ascertain the age at which infant are most liable to die. Survival rate was gotten from the life table and plotted against the age in month to give the curve below;

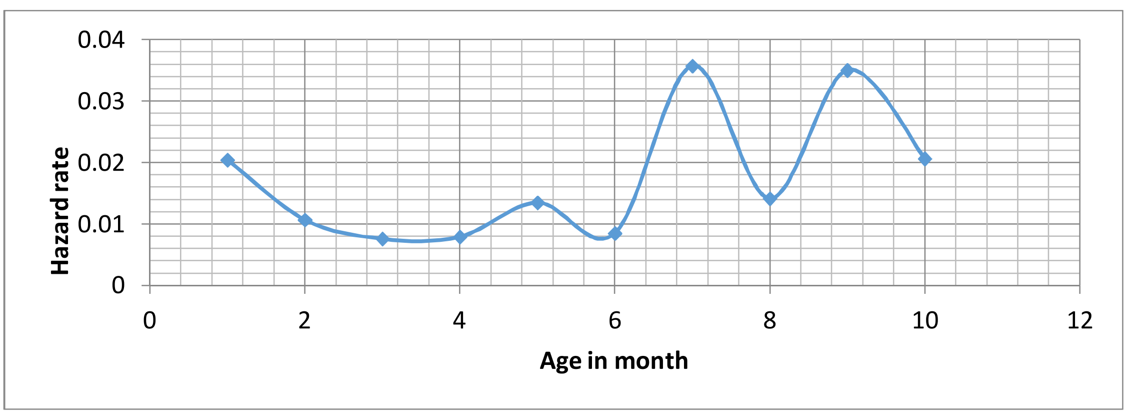

Fig1: Hazard Curve Rate

From figure1: the Hazard curve rate above, it can be deduced that infant are most liable to die at ages 7months and 9months, and are least risked to death at ages 1month and 10months.

Kaplan-Meier

In order to ascertain the effect of some selected variable on the effect of mortality, we make use of the Kaplan Meier. The following output was obtained;

Sex of Child

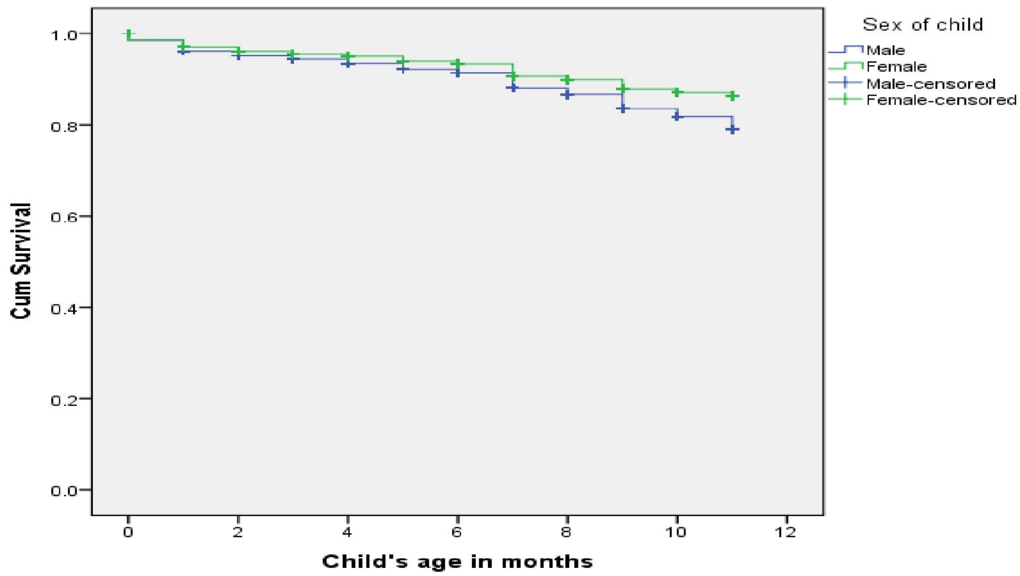

Fig2: survival curve for sex of child

From the above survival plot, it can be deduced that female infant have a higher chance of survival that the male infant.

Wealth Index

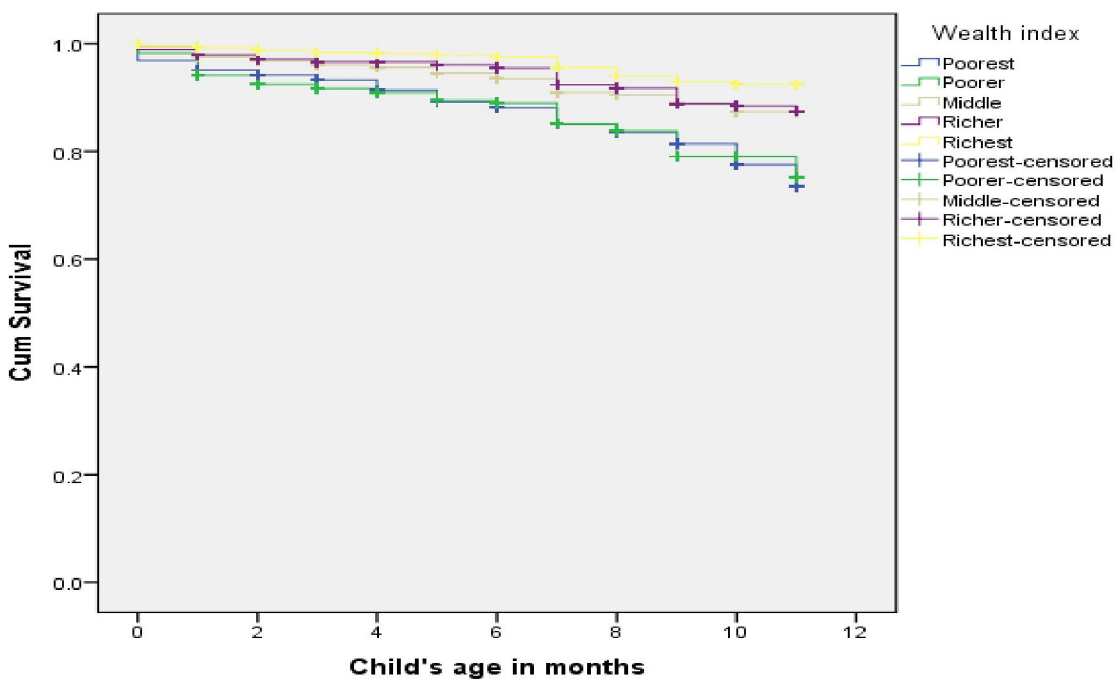

Fig3: Survival Plot for wealth index

The plot above shows that infants born to rich families have the higher chance of survival while those born to the poor family have the lowest chance of survival.

Mother's Education Attainment

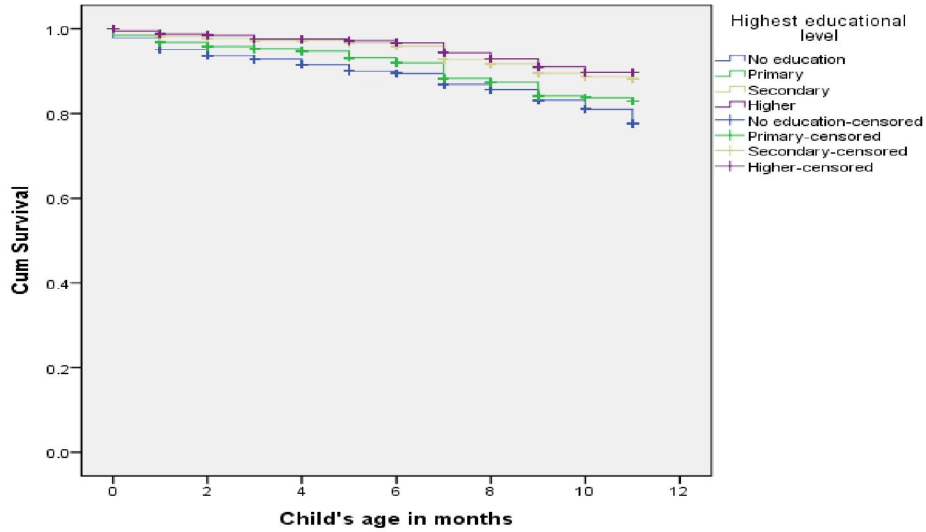

Fig 4: Survival curve for mother's education of mother

The survival curve for infants born of mothers with higher education is above the survival curve of the infants born of mothers with secondary and primary education.

Cox-proportional model

Suppose that t = (t,t$_2$,...,t_n) are n independent identically distributed survival time.

$$h\left(t|\boldsymbol{X}\right) = h_0\left(t\right) \exp\left(\boldsymbol{X}^T \boldsymbol{\beta}\right).$$

A total of 6212 survival times for the children under the age of five were considered in this study (n = 6212) together with the survival indicator which helps us to identify whether the survival time was censored or observed.

Table 4: Showing results from cox- proportional hazard model

	B	SE	Wald	Df	Sig.	Exp (B)
Female	-.796	.203	.125	1	.724	.451
Mother's Age Group						
Age_20_to_24	-1.04412	.344	4.809	1	.028	.352
Age_25_to_29	-.856	.347	6.102	1	.014	.425
Age_30_to_34	-.651	.363	3.211	1	.073	.522
Age_35_to_39	-.194	.365	.282	1	.035	.824
Age_40_to_44	-.781	.580	1.814	1	.034	.458
Age_45_to_49	-.757	1.045	1.806	1	.029	.469
Region						
North central						
North_east	.357	.343	1.081	1	.299	1.429
North_west	-.033	.385	.007	1	.931	.967
South_east	-.138	.421	.107	1	.744	.871
South_south	-1.936	.639	9.175	1	.0	.144
South_west	-.925	.434	4.549	1	.033	.396
Mother's Education Primary	.152	.311	.034	1	.853	1.164
Secondary	.058	.346	.193	1	.661	.944
Higher	-.430	.714	.363	1	.042	.650
Toilet facility						
Flushed_Toilet	-5.475	45.520	.014	1	.904	.004
Latrine	-5.387	45.519	.014	1	.906	.005
No_Facility	-5.756	45.519	.016	1	.899	.003

	B	SE	Wald	Df	Sig.	Exp (B)
Religion						
Christain	.160	1.048	.023	1	.879	1.173
Islam	-.187	1.044	.032	1	.858	.830
less_than_a_week	-.880	.305	8.353	1	.004	.415
at_least_once_a_week	-.292	.258	1.282	1	.258	.747
Wealth Index			.		.	
Poorer	.278	.313	.792	1	.373	1.321
Middle	-.154	.379	.165	1	.684	.857
Richer	.-.612	.407	.196	1	.041	.542
Richest	-.371	.634	.342	1	.038	.690
Place of Delivery			.		.	
Home	.487	25.279	.037	1	.847	1.628
Government_Health_Center	-.172	25.280	.029	1	.864	.842
Private_health_Centre	.444	25.281	.031	1	.860	1.560
TV_Less_than_once_a_week	.497	.271	3.372	1	.066	1.644
TV_at_least_once_a_week	.145	.258	.318	1	.573	1.156
			.		.	
Medical_personnel	.034	.332	.011	1	.342	1.035
Had_Checkup_after_delivery	-.313	.235	1.772	1	.027	.732

Test of Hypothesis

H_0= There is no covariate effect

H_1= There is covariate effect

Critical region

α = 0.05

Conclusions

Infants born to mother with secondary and higher education attainment has a low Hazard ratio.

(exp β) 0.944 and 0.650 compared with those born to mother with low education having an hazard ratio of 1.164. Those infants born to mothers with higher education have a significant-value of 0.042<0.05 and as such we reject the H_0 and conclude that there is a covariate effect. Considering the age group of mothers, it is deduced that irrespective of the age of the mother the hazard ratio remains low. Infant born at home have a higher risk to die, as the hazard ratio is greater than 1.

It can also be deduced that the frequency of watching television does not determine or causative to infant mortality and that wealth index is a strong covariate affecting infant mortality. Infant born in government owned health centers are at a lower risk to die compared with those born in private hospitals. This may be due to the fact that most government owned hospitals are well equipped and qualified medical staff on attendance at every particular time than the private medical centers. Going for checkup after delivery is a very important determinate of infant mortality as it has significant value 0.027 < 0.05.

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