Use of the shared frailty model to identify the determinants of child mortality in Rwanda

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Abstract

According to United Nations Development Programme report, achieving the 4^{th} Millennium Development Goal(MDG) means that Rwanda will have to reduce under-five mortality from 196 to 47 deaths per 1000 live births between 2000 and 2015, UNDP(2003). Even though Rwanda had made very considerable progress in improving child survival during 5 years preceding the 2005 RDHS, all the achievements only brought the country indicators around to those of 1990's, that is before the ravaging 1994 Genocide against Tutsi. Controlling for the effects of unobserved risk factors that would interfere with child mortality, this study aims to identify and rank order the most important factors that contributed to child survival in Rwanda between 2000 and 2005 based on the 2005 RDHS data. The key determinants would be prioritized in order to avoid an eventual misallocation of scarce resources. The analysis of relevant data showed that frailty effects were significant in childhood with child deaths mostly determined by socioeconomic and demographic factors such as household socioeconomic status being the most important.

***Key words**: child mortality, Cox regression, unobserved heterogeneity, shared frailty.*

Introduction

Following the 1994 Genocide against Tutsi all the MDG indicators for Rwanda fell behind the starting line. The country also faces the structural constraints of being a landlocked country, high transport costs, low natural resource base, limited land availability, high population growth rate (>2.5%) and high population density (>365 persons per km^2), PRB(2009), UNDP(2007).

In 2005 the national average of HIV prevalence was 3.0% being higher in urban (7.3%) than in rural (2.2%) areas while it was very high within the richest households (6.5% for women, 4.1% for men) compared to the poorest (2.6% for women, 1.3% for men). The prevalence was the highest among women who attained secondary school or higher education (6.4%) compared to those with primary education (2.8%) and to those with no formal education (3.3%), ORC Macro and NISR (2006).

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Nevertheless, Rwanda has made impressive progress in trying to achieve MDGs particularly in reducing infant and child mortality rates in the period after war and Genocide against Tutsi of 1994. Rwanda has posted real GDP growth of 6% to 10% over 10 years (1995-2005), and it was 11.2% in 2008 and tax revenue collection has improved considerably (this was 12.2% of GDP in 2002), NDP (2003). With the MDGs' target of 50% by 2015, the seats held by females in parliament were 48.8% in 2005, INSR (2007), and 56% in 2008 which is the highest women's participation in parliament in the world, UNDP (2008). The country has achieved remarkable progress in accelerating child survival and primary school enrollment. The latter was 95% in 2005, and 97% in 2008, UNDP(2008), Unicef (2008), INSR(2007). The trend in under five mortality was 151 in 1992, 196 in 2000, 152 in 2005, INSR(2006) and 103, Mini DHS (2008), UNDP(2008). However, this mortality rate is still high compared to the goals to achieve and the current global standards. Furthermore, the most important factors explaining the observed differential performance in child survival are still not well known to allow more fructuous priorities and hence optimal allocation of limited resources. This is the most important problem that this study attempts to address.

Many studies have shown significant association between child mortality and socioeconomic factors (Hobcraft(1993), Hobcraft et al.(1984), Omariba et al. (2007)), demographic factors, Omariba et al. (2007), Hobcraft et al.(1985), biological factors, Omariba et al. (2007) or environmental factors, Mutunga (2007) through making use of surveys data. Investigating the association between socioeconomic status and infant and child mortality, Hong, R. et al. (2007) reported a negative relationship between household income level and children mortality risks in Cambodia. Diverse studies also reported the effect of mother's education on reducing the child mortality but less than infant mortality, for example Omariba et al. (2007). Similar studies emphasized the theory that mother's education works through changing feeding and care practices, leading to better health seeking behavior and by changing the traditional familial relationships. Hobcraft(1993) argued that education can contribute to child survival by making women more likely to marry and enter motherhood later and have fewer children, utilize prenatal care and immunize their children. A combined analysis of demographic and Health Surveys' data from 25 countries: Bolivia, Brazil, Colombia, Dominican Republic, Ecuador, Guatemala, Mexico, Peru, Trinidad and Tobago (in Americas) ; Egypt, Morocco, Tunisia(in North Africa) ; Botswana, Burundi, Ghana, Kenya, Liberia, Mali, Senegal, Togo, Uganda, Zimbabwe (in Sub-Saharan Africa) ; and Indonesia, Sri Lanka, Thailand (in Asia) showed a clear evidence of association between the mother's education and child survival, Hobcraft(1993).

Adjusting for a number of socioeconomic factors child survival was found better for those who were of birth order 2-3, birth interval more than 2 years, but maternal age, maternal education and gender of the child had no significant association with child mortality in Kenya, Mutunga (2007). Ssengonzi et al.(2002) used the 1995 Uganda Demographic and Health Survey data to examine whether migration of women improves the survival chances of their children to age five. Results showed that up to 10% of children die before age five and within-group differences in mortality exist among urban and rural Ugandan children depending on their mother's migration status and several other factors including parents' education, household headship, mother's age at birth, duration of breastfeeding, and place of delivery.

Omariba et al. (2007) examined the determinants of infant and child mortality in Kenya, by controlling for frailty effects. They compared the results of Weibull shared gamma frailty survival models to those of standard Weibull survival models in order to examine the extent to which child survival risks continue to vary net of observed factors and the extent to which non frailty models are biased due to the violation of the statistical assumption of independence. It was found that there was great variation between families in the risk of child mortality that was not accounted for by the measured factors. The effect of household socioeconomic status was stronger for child mortality than for infant mortality.

It is assumed that during DHSs there is an increased probability of reporting erroneous information especially dates of the events happened far in the past. In addition, some relevant variables for specific studies are not measured or measurable during the survey. The capabilities of frailty models in accounting for unobserved or unobservable risk factor effects in survival data analysis have been widely documented by Vaupel et al.(1979), Clayton and Cuzick(1985), Klein(1992), Grambsch and Therneau(1998), Zorn and Box-Steffensmeier(1999), Therneau et al.(2000), Therneau and Grambsch (2000), Rondeau et al.(2003), Keele(2007), etc.

In this study the gamma-distributed shared frailties at woman level were adjusted for in order to find out relevant, less biased and ranked determinants of child mortality in Rwanda. In this paper no assumption is made about the underlying probability distribution of the child time to death which leads to a semi parametric shared frailty model.

Material and Methods

Data

This study analyzed data from the most recent Rwanda Demographic and Health Survey conducted in 2005 (2005 RDHS) by the Institut National de la Statistique du Rwanda (INSR) with the technical assistance of Macro

International Inc., USA. The 2005 RDHS became available in July 2006 and the datasets were provided on request by Macro International Inc..

The 2005 RDHS was conducted on a two-stage nationally representative sample of 4820 men aged 15 to 59, and 11321 women aged 15 to 49 distributed in 10272 households. More details about the sample design and selection of sample units can be found in INSR and ORC Macro (2006). Of 11321 women who participated in the survey only 5393 gave birth to 8649 children between 2000 and 2005 but among them 106 live births were born in the months of interview making their survival time unavailable. Of 8543 live births, 6277 aged 12 to 59 months and born to 4703 mothers constituted our sample whose 6047 live births were still alive by the date of interview.

The time to event data required for the analysis of child survival were mainly compiled from the birth history section of the 2005 RDHS Woman's Questionnaire data. Data on individual live birth characteristics, those of the parents and the household that are likely to determine the under-five children's mortality were identified and considered in the survival data analysis.

The data management and initial exploratory analysis were done using SPSS and R packages while the main data analysis was conducted using R software, R Development Core Team(2009).

Analytical method

This study is based on Mosley and Chen (1984) analytical framework for the study of child survival in developing countries according to which child mortality may change because of changes in background variables operating through proximate determinants or because of changes in proximate determinants themselves. All tests (Log-rank, hazard proportionality, frailty significance, etc.) were conducted at 5% level of significance and based on parameter and statistic P-values.

The basic tools for analyzing time to event data are survival function $S(t)$ and hazard function $h(t)$, where T is a positive random variable taking on the exact event time and having the probability density function $f(t)$. Assuming a continuous time to event

$$S(t) = Pr[T > t] = \int_t^\infty f(u)du \Leftrightarrow f(t) = -\frac{d}{dt}S(t). \tag{1}$$

The hazard function also known as instantaneous failure rate is defined as

$$h(t) = \lim_{\Delta t \to 0} \frac{Pr[t \le T \le t + \Delta t | T > t]}{\Delta t}. \tag{2}$$

This is the conditional probability of experiencing the event of interest within a very small time interval of size Δt having survived up to time t.
A closely related function to the hazard function is the cumulative hazard function denoted by $H(t)$ and defined as

$$H(t) = \int_0^t h(u)du \tag{3}$$

which is the accumulation of the hazard over time. Thus the result (5) becomes obvious,

$$S(t) = \exp(-H(t)). \tag{4}$$

The most commonly used estimator of the survival function is the Kaplan-Meier estimator given by

$$S(t) = \prod_{t_{(j)} \leq t} \frac{n_j - d_j}{n_j} \tag{5}$$

where $t_{(1)} < t_{(2)} < \cdots < t_{(r)}$ are the r ordered distinct event times, d_j is the number of events and n_j is the number of individuals at risk at time $t_{(j)}$ respectively. Kaplan-Meier estimator, univariate model and non parametric tests such as log-rank and Wilcoxon tests are well documented in Collet(2003).

In the Cox proportional hazards (PH) model, Cox (1972) the basic analysis tool is the hazard function such that the Cox PH model for the i^{th} individual is given as

$$\begin{aligned} h_i(t|X) &= h_0(t)\exp(\beta' X_i) = h_0(t)\exp(\eta_i) \\ &= h_0(t)\exp\left(\sum_{j=1}^{p} \beta_j X_{ji}\right); \quad j = 1, \ldots, p; \quad i = 1 \ldots, n \end{aligned} \tag{6}$$

where

$$\beta = (\beta_1, \beta_2 \cdots \beta_p)' \; ; \quad X_i = (x_{1i}, x_{2i}, \ldots, x_{pi})'$$

The element η_i in (6) is the linear component or linear predictor, X_i is a vector containing the p characteristics of the i^{th} individual and $h_0(t)$ the baseline hazard function.
In practice it is convenient to write the above model as

$$\psi = \frac{h_i(t)}{h_0(t)} = \exp(\beta' X_i) = \exp\left(\sum_{j=1}^{p} \beta_j X_{ji}\right); \quad j = 1, \ldots, p; \quad i = 1 \ldots, n \tag{7}$$

which represents a constant function known as the hazards ratio. In the Cox PH model no assumptions are made about the shape of the underlying hazard function, $h_0(t)$, but the model assume that the ratio of the hazard functions for any two observations is independent of time. This implies that population group hazards are proportional over time. In addition, the Cox PH model presupposes that observations are independent and that the censoring mechanism is independent of the survival time distribution.

Each variate in the linear component η_i appears with a corresponding β term, and $\exp(\beta)$ is the change in risk for unit increase in a quantitative explanatory variable X_j or the proportionate increase in risk for individuals in a given level compared to the risk for individual in a fixed reference level of a factor variable X_j. The more the hazard ratio is above 1.0, then the greater the variable; the more the risk of death is increased.

For a sample of n individuals with m distinct observed and ordered survival times; $t_1, t_2, \ldots, t_m$ and δ_i an event indicator such that $\delta_i = 0$ if the j^{th} survival time $t_{(j)}$ is right-censored and $\delta_i = 1$ otherwise, Cox(1972) showed that the model β-parameter estimates can be obtained by maximizing the partial likelihood function

$$L(\beta) = \prod_{i=1}^{n} \left\{ \frac{\exp(\beta' X_i)}{\sum_{l \in \mathcal{R}(t_{(j)})} \exp(\beta' X_l)} \right\}^{\delta_i}; \quad i = 1 \ldots n, \; j = 1 \ldots m \tag{8}$$

Where $R(t_{(j)})$ is the risk set and X_i the vector of covariates for the individual who fails at time $t_{(j)}$. This is equivalent to maximizing the corresponding partial log-likelihood function

$$\log L(\beta) = \sum_{i=1}^{n} \delta_i \left[\beta' X_i - log \left(\sum_{l \in R(t_{(j)})} \exp(\beta' X_l) \right) \right]. \tag{9}$$

The maximization is achieved by using iterative methods such as the Newton-Raphson procedure, Dobson(2002).

Modeling the unobserved heterogeneity as random effect

Most surveys such as DHSs and other multipurpose surveys will not always be able to provide to a specific study all the information it requires to achieve satisfactorily accurate outcomes. However, these can be reached by collecting additional data or by using appropriate data analysis techniques that minimize biased results and conclusions. In the application of the Cox PH model, the independence and hazards proportionality assumptions of the model may be violated especially by the presence of clustered event times among groups such as families or geographical units. It is often impossible to include all important factors into the analysis. In addition there exist intrinsically unobservable variables such as ability, common environmental exposures and omitted variables in the available data. This type of missing information is referred to as unobserved heterogeneity which generates an unexplained heterogeneity in observed time to event data.

The Cox PH model can be extended to accommodate a random effect term through the linear component that accounts for the unobserved heterogeneity. Then the model can generally be classified as either marginal or random effects model, Wienke(2003), Rodriguez (2005), Therneau et al.(2000), Therneau and Grambsch(2000) Klein (1992), Clayton and Cuzick(1985). The extended Cox PH model with a frailty term can be written in the form

$$h_{ij}(t|X,Z) = h_0(t)Z_{ij}\exp(X'_{ij}\beta) \tag{10}$$

where z_{ij} is the frailty effect of the i^{th} individual in the j^{th} group or cluster, with Z being a positive random variable having a probability density function $g(z)$ with mean 1 and unit variance θ. When frailties z_{ij} are shared among members of a certain group or cluster j, the derived shared frailty model takes the form

$$h_{ij}(t|X,Z) = h_0(t)Z_j\exp(X'_{ij}\beta) \tag{11}$$

where Z_j is the j^{th} group frailty effect. Those individuals who possess $Z_j > 1$ are more frail for reasons left unexplained by the covariates and will have an increased risk of failure all else being equal, Gutierrez (2002).

When frailties are integrated out, the unconditional survival function is independant of frailties Z_j but of its variance θ (Rodriguez (2005), Gutierrez (2002)) such that, in case of gamma frilties, the marginal hazard function is given by

$$h(t|X) = \frac{h_0(t)\exp(X\beta)}{1+\theta H_0(t)\exp(X\beta)}. \tag{12}$$

One approach to estimate frailty model is via the use of penalized partial log-likelihood. In the case of the gamma frailty model Therneau et al. (2000) proved that the solution to the penalized partial likelihood model, with penalty function

$$g(\omega,\theta) = -\frac{1}{\theta}\sum[\omega_j - exp(\omega_j)] \tag{13}$$

coincides with the EM algorithm solution (Klein et al.(1997, Klein(1992)) for any fixed value of θ. In this study we applied the penalized partial log-likelihood approach by assuming that the data for the i^{th} child, member of the j^{th} woman's siblings follows a proportional hazards shared frailty model

$$h_i(t) = h_0(t)\exp(X_{ij}\beta + \omega_{ij}\psi) = h_0(t)z_{j(i)}\exp(X_i\beta), \tag{14}$$

$j(i)$ specifies that child i belongs to woman j, $z_{j(i)} = 1$ if i belongs to j and $z_{j(i)} = 0$ otherwise.

To test for frailty effect on individual hazards we utilized the likelihood ratio test (*LRT*) as advised Keele (2007), and Therneau et al. (2000).

Determinants of child mortality

In this study all the variables were defined as categorical. Variables that are likely to influence the under five children mortality were identified and categorized based on Mosley and Chen (1984) analytical framework for the study of child survival in developing countries and the existing literature; for example Masset and White (2003), Hong et al.(2007), Omariba et al. (2007), Mutunga (2007), INSR and ORC Macro (2006), Ssengonzi et al.(2002). The particularity in mortality pattern of Multiple births has been documented by a number of authors such as Kunst and Justesen(2000). Other variables and their categorization are self explanatory and some additional details can be found in Mosley and Chen (1984). Table 1 presents the sample distribution of child births and deaths by selected determinants of child mortality

Table 2 : Sample births and deaths distribution by survival determinants

Determinant	Births	%*	Deaths	%**	Determinant	Births	%	Deaths	%**
Demographic factors					Surface,Rain,Tanker truck	3163	50.4	130	4.1
Mother's migration status					Other	88	1.4	3	3.4
Urban non migrant	355	5.7	7	2.0					
Rural non migrant	4909	78.2	197	4.0	*Toilet facility*				
Rural -Urban migrant	916	14.6	21	2.3	Flush toilet	62	1.0	1	1.6
Urban-Rural migrant	97	1.5	5	5.2	Pit latrine	5952	94.8	216	3.6
Sex of household head					No facility	263	4.2	13	4.9
Male	5158	82.2	185	3.6					
Female	1119	17.8	45	4.0	*Cooking fuel*				
Mother age at 1st birth					Low pollution fuel	516	8.2	7	1.4
Under 20	2158	34.4	92	4.3	High pollution fuel	5761	91.8	223	3.9
20 - 24	3263	52.0	117	3.6	*Mother smokes*				
25 and above	856	13.6	21	2.5	Yes	343	5.5	15	4.4
Sociocultural factors					No	5934	94.5	215	3.6
Religion									
Catholic	2748	43.8	98	3.6	**Proximate/ Biological factors**				
Other Christian	3229	51.4	121	3.7	*Sex of the child*				
Muslim	138	2.2	5	3.6	Male	3166	50.4	114	3.6
Other	162	2.6	6	3.7	Female	3111	49.6	116	3.7
Province									
City of Kigali	568	9.0	16	2.8					
South	1477	23.5	46	3.1	*Birth order*				
West	1716	27.3	47	2.7	First order	1161	18.5	47	4.0
North	1123	7.9	32	2.8	2 - 4	2968	47.3	108	3.6

East	1393	22.2	89	6.4	5+	2148	34.2	75	3.5
Socioeconomic factors									
Mother's education					*Preceding birth interval*				
No education	1719	27.4	64	3.7	No previous birth	1172	18.7	47	4.0
Primary	3932	62.6	159	4.0	<18 months	391	6.2	19	4.9
Secondary and Higher	626	10.0	7	1.1	18 -30 months	2058	32.8	70	3.4
Mother's occupation					>30moths	2656	42.3	94	3.5
Not working	1199	19.1	36	3.0					
Agriculture	4442	70.8	182	4.1	*Birth status*				
Sales	290	4.6	7	2.4	Singleton	6131	97.7	219	3.6
Other	346	5.5	5	1.4	Multiple births	146	2.3	11	7.5
Socioeconomic status									
Medium	3690	58.8	152	4.1					
Low	1274	20.3	57	4.5	*Mother's age at birth*				
High	1313	20.9	21	1.6	Under 20	389	6.2	19	4.9
Partner's education					20 - 34	4575	72.9	171	3.7
No education	1918	30.6	87	4.5	35 and above	1313	20.9	40	3.0
Primary	3528	56.2	129	3.7					
Secondary and Higher	831	13.2	14	1.7	*Place of delivery*				
Environmental factors					Homes	4365	69.5	180	4.1
Source of drinking water					Public sector	1755	28.0	46	2.6
Piped water	1808	28.8	53	2.9	Private sector	90	1.4	1	1.1
Well water	1218	19.4	44	3.6	Other	67	1.1	3	4.5

The child semi-parametric gamma shared frailty model

The first stage comprises the selection of factors to be included in the final models.

Table 2: Testing H_0: Hazard functions for individual variables are proportional

Determinant	χ^2	P-value	Determinant	χ^2	P-value
Mother's migration status			*Source of drinking water*		
Urban non migrant	Ref.	-	Piped water	Ref.	-
Rural non migrant	5.150	0.023	Well water	0.344	0.558
Rural - Urban migrant	4.475	0.034	Surface,Rain,Tanker truck	0.058	0.810
Urban-Rural migrant	0.393	0.531	Other	0.078	0.780
Sex of household head			*Toilet facility*		
Male	Ref.	-	Flush toilet	Ref.	-
Female	2.050	0.152	Pit latrine	3.022	0.082
			No facility	3.845	0.050

Mother's age at 1st birth			*Cooking fuel*		
Under 20	Ref.	-	Low pollution fuel	Ref.	-
20 - 24	0.210	0.647	High pollution fuel	0.317	0.573
25 and above	1.566	0.211	*Mother smokes*		
Religion			Yes	Ref.	-
Catholic	Ref.	-	No	0.006	0.939
Other Christian	0.007	0.932	*Place of delivery*		
Muslim	1.397	0.237	Homes	Ref.	-
Other	0.441	0.506	Public sector	5.058	0.025
Province			Private sector	0.360	0.549
City of Kigali	Ref.	-	Other	0.127	0.721
South	0.783	0.376	*Sex of the child*		
West	1.494	0.222	Male	Ref.	-
North	1.588	0.208	Female	0.254	0.615
East	0.178	0.673			
Mather's education			*Mother's age at birth*		
No education	Ref.	-	Under 20	Ref.	-
Primary	0.457	0.499	20 - 34	0.000	0.983
Secondary and Higher	0.018	0.892	35 and above	0.019	0.890
Mother's occupation			*Birth order*		
Not working	Ref.	-	First order	Ref.	-
Agriculture	1.566	0.211	2 - 4	0.000	0.998
Sales	0.093	0.761	5+	0.000	0.999
Other	0.452	0.501			
Socioeconomic status			*Preceding birth interval*		
Medium	Ref.	-	No previous birth	Ref.	-
Low	1.238	0.266	<18 months	0.000	0.999
High	0.089	0.766	18 - 30 months	0.000	0.999
Partner's education			>30moths	0.000	0.999
No education	Ref.	-	*Birth status*		
Primary	1.361	0.243	Singleton	Ref.	-
Secondary and Higher	3.460	0.063	Multiple births	2.295	0.130

The variables in Cox or extended Cox PH models are subject to verifying the hazards proportionality assumption at least after adjusting for other covariates and frailty. The proportionality assumption test statistic for overall model is 9.958 with a P-value of 0.517 which support the result of individual factor tests in Table 2.

Reading the results in Table 3, the candidate factors (P-value = 0.0500) for the stepwise variable selection for the multivariable PH model are: Mother's migration status, Province of residence, Mather's education, Mother's occupation, Socioeconomic status, Partner's education, Cooking fuel, Place of delivery and Birth status. Other variables are therefore discarded at this step of the model selection.

Table 3: Log-rank tests for determinants association with child survival

Variable	P - value	Variable	P - value
Demographic		*Environmental*	
Mother's migration status	0.0128	Source of water	0.1696
Sex of household head	0.6044	Toilet facility	0.3283
Mother's age at 1^{st} birth	0.0600	Cooking fuel	0.0026
Sociocultural		Mother smokes	0.5707
Religion	0.9693	*Proximate*	
Province	0.0000	Place of delivery	0.0275
Socioeconomic		Sex of the child	0.8041
Mather's education	0.0011	Birth order	0.6633
Mother's occupation	0.0184	Preceding birth interval	0.5048
Socioeconomic status	0.0000	Mother's age at birth	0.2586
Partner's education	0.0008	Birth status	0.0096

Stepwise model selection procedures enabled us to find a subset of variables that explain the maximum percentage of variability in the time to death such that adding or removing any variable lead to a lesser significant model. The common procedures used in selecting variables in linear models such as forward selection, backward elimination and stepwise selection have been extended to the Cox model, Collet(2003). All alternative stepwise procedures led to the best fitting model including only 6 factors namely Province, Socioeconomic status, Mother's education, Birth status, Partner's education and Frailty.

Results and discussion

This study has investigated the association between socioeconomic, socio-cultural, bio-demographic, environmental factors and the risk of child death in Rwanda accounting for gamma distributed shared frailties among siblings. Both the Standard Cox PH model that assumes independence in time to event data and the semi parametric gamma shared frailty model that controls for potential risk factors and gamma distributed frailties among siblings were estimated. The model β-parameters and their P-values, the hazards ratios (ψ) (7) and corresponding 95% confidence interval limits, the frailty variance (θ) (12) and, values of maximized log-likelihood of standard model and Integrated out-likelihood (I-likelihood) for frailty model are presented in Table 4.

The log-likelihood ratio test (LRT) for frailty effect is given by

$$LRT = 2 \times (-1901.60 + 1904.97) = 6.74$$

which is a chi-square statistic on 1 degree of freedom with the P-value

0.0094. This indicates that the frailty term significantly improves the child proportional hazard model. For the gamma shared frailty model, the estimate of $\theta = 1.50$ is statistically significant with a P-value of 0.0094, indicating that survival risks in childhood vary due to unobserved determinants shared by woman's siblings. This means that child survival times are clustered by woman and selected factors were not able to account for that heterogeneity or dependence in siblings' survivorship. It follows that no proportionality assumption can be formulated about their hazard rates without controlling for frailty effect. Therefore our interpretation was based on child shared frailty model.

Similar studies reported an eventual amplification of the frailty due to exclusion of or impossibility to utilize some variables such as breastfeeding, health care and HIV/AIDS factors in child mortality data analysis, Omariba et al. (2007). This is an important limitation of utilizing DHS data in such studies because, for example, the HIV/AIDS test status at time of death for children who died before interview date and their mothers cannot be collected by DHSs. Explanation on exclusion of breastfeeding and health care data from the analysis is detailed in Omariba et al. (2007). The strong direct and indirect links between HIV/AIDS and child mortality have been confirmed by many studies, Villamor et al. (2005), Lallemant et al. (2010), Jahn et al. (2010). In this study no data on HIV/AIDS test status were included in the child mortality analysis and the discussion drew from the literature to estimate its likely impact.

The 6 factors identified with standard model selection procedures were included in the final models in order to investigate any frailty effect, measure the effect of each factor in presence of the others and rank in order of importance the determinants of child mortality basing on P-values of model parameter estimates. The results in Table 4 revealed that, adjusting for gamma shared frailty effect at woman level, the child risk of death was mostly determined by household's socioeconomic status.

Table 4: Frailty and Standard Cox proportional hazard models for the child

	Frailty model		**Standard model**	
Determinant	β **(P-value)**	**Hazards ratio**	β **(P-value)**	**Hazards ratio**
Province				
City of Kigali	Reference	1.000	Reference	1.000
South	-0.442(0.170)	0.643(0.342, 1.206)	-0.426(0.160)	0.653(0.358,1.192)
West	-0.565(0.078)	0.568(0.303, 1.066)	-0.547(0.074)	0.579(0.317,1.055)
North	-0.495(0.140)	0.610(0.314, 1.184)	-0.485(0.130)	0.616(0.327,1.161)
East	0.296(0.330)	1.345(0.738, 2.451)	0.291(0.320)	1.338(0.757,2.364)
Socioeconomic status				

Medium	Reference	1.000	Reference	1.000
Low	0.097(0.560)	1.102(0.796, 1.527)	0.090(0.570)	1.094(0.804,1.487)
High	-0.790(0.003)	0.454(0.270, 0.762)	-0.778(0.002)	0.459(0.278,0.758)
Partner's education				
No education	Reference	1.000	Reference	1.000
Primary	-0.248(0.096)	0.780(0.582,1.045)	-0.255(0.070)	0.775(0.588,1.021)
Secondary and Higher	-0.603(0.056)	0.547(0.295, 1.014)	-0.607(0.045)	0.545(0.301,0.985)
Birth status				
Singleton	Reference	1.000	Reference	1.000
Multiple births	0.698(0.050)	2.010(0.999, 4.048)	0.710(0.022)	2.034(1.108,3.732)
Mather's education				
No education	Reference	1.000	Reference	1.000
Primary	0.212(0.180)	1.236(0.906, 1.687)	0.212(0.160)	1.236(0.921,1.660)
Secondary and Higher	-0.595(0.170)	0.551(0.237, 1.282)	-0.575(0.170)	0.562(0.248,1.277)
Frailty(P-value)	0.56			
θ *(frailty variance)*	1.50			
Likelihood ratio test	493, *df*=328.07, $P=1.01\times10^{-08}$		74.5, *df* = 11, $P=1.69\times10^{-11}$	
(I-)Log-likelihood	-1901.60, *n*= 6277,		-1904.97, n= 6277	
Wald test	62, *df*= 328.07, $P=1$		67.4, *df*=11, $P=3.84\times10^{-10}$	

Basing on individual P-values of model parameter estimates, the other three background factors including partner's education, province of residence and mother's education showed weak effects in presence of household's socioeconomic status and birth status being the only biological determinant of child death. In their decreasing order of importance birth status was followed by partner's education and mother's education was the weakest determinant.

The children living in household with low socioeconomic status were 10% more exposed to death than those in households with medium economic status while the chance of survival was 55% higher for those living in households with high socioeconomic status. The effect of socioeconomic status on child mortality has been confirmed time and again, Omariba(2007), Hong(2007), Hobcraft et al.(1984). Limited access to clean drinking water and low polluting cooking fuels are among factors of child mortality in households with low socioeconomic status, Mutunga (2007), Mosley and Chen (1984).

Once live births survived the first 12 months, the multiple births' risk of death was slightly more than 2 folds that of singleton births. This suggests a more enhanced health care for multiple births which should extend beyond their infancy.

The City of Kigali had the highest mortality and differences in child mortality rates between Provinces increased. Children in the more rural Provinces other than East had an increased chance of survival of more than 35% in South, 43% in West and 39% in North than those in City of Kigali. One explanation may be the high HIV prevalence in the city of Kigali (6.7%) which was (2005 RDHS) more than twice the national average of 3.0% while it was the lowest in the North (2%), INSR & ORC Macro (2006).

Being born to mother with no formal education increased the risk of dying in childhood by 45% compared to those whose mothers attained secondary and higher educational levels. Having a mother whose partner attained secondary and higher educational levels increased the chance of survival by more than 45% while this was 22% for those whose mother's partners only completed primary education compared to those whose mother's partners had no formal education. Furthermore, a child whose mother and her partner have attained secondary and higher educational levels had chance of surviving increased by 70% compared to those whose mother and her partner attained no formal educational level. These survival differences emphasize the role of education for better health of household members especially the under five children. The more educated parents tend to take their children to hospital promptly than less educated parents, Hobcraft (1993), and hence their children tend to survive the first 5 years of their life.

Conclusion and recommendations

This study was able to delineate the most important determinants of child mortality in Rwanda that would be prioritized in order to save most of children's lives with limited resources. This would help all actors pro under-five survival in Rwanda to accelerate and realize high performance in achieving the 4th millennium development goal. Subsequently, the results of this study can be very useful for planning, forecasting and evaluating eventual intervention outcomes.

The study found that child mortality in Rwanda varies due to unobserved risk factors that were not captured by the 2005 RDHS at the household level. Adjusting for birth status and frailty the child shared frailty model was dominated by socioeconomic determinants. The household's socioeconomic status was the most important determinant of child mortality, followed by the mother partner's education and mother's education and Province of residence with a significantly weak effect.

The observed weak association between mother's education and child mortality can be explained by the HIV prevalence (Jahn et al. (2010) which was the highest among women who had attained secondary or higher education (6.4%) compounded with an improved access to medical care through the national policy for medical insurance schemes that cover 85% of health service costs.

The observed strong effect of household's socioeconomic status suggests that the policies of equitable distribution of economic resources and increasing household's income be enhanced to achieve higher performance. Increasing the number of educated mothers and fathers can play an important role in improving child survival in Rwanda.

This study utilized information about births and deaths occurred between years 2000 and 2005. It is possible that considering a longer woman reproductive life span can improve results by increasing the number events occurred at a woman level. However, event dates reporting errors are much increased and explanatory variables might significantly change over a long time period which arises the problem of time varying frailties.

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