PAPER TITLE

Gains in understanding the differentials of child survival using single- and multi-level models: a comparative study of Egypt, Sudan and Yemen

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Abstract:

Three similar settings of a varying pace in lowering childhood mortality are introduced. Survival to age five years is empirically related to bio-demographic and socio-economic differentials. An "event-history" of child losses to mothers was constructed from maternity histories data, to create time-varying co-variates. Regression analyses deployed a marginal logistic model (adjusting for survey design), Cox model, and, a multilevel logistic model, respectively. The multilevel analysis forwards an innovative attempt with a "regional-split" of the variance components of unmeasured effects.

Unequivocally, deaths of older siblings prior to the birth of every index child were the strongest predictors of poor survival settings. New events of older siblings death after the birth of the index child were rare, yet capture "immediate" risk spells. A conception / birth / death of a subsequent sibling entailed time-varying excess risk. Evidently, those measures spell-out "within-families" inter-dependencies of survival, slightly attenuating key effects as those of birth-spacing and maternal age at birth. Adjusting for measures of familial child losses considerably explains "between-families" variation in mortality compared to other level operands. The splitting of the variance components underpin "true" regional unmeasurable effects.

1 Introduction

During the second half of the past century, governments in many parts of the developing world, have worked to increase the quantity and the quality of modern health services available to their populations. Before independence, most colonial governments introduced health programmes and that with other associates of development, such as increasing levels of education, led to improved child care practices and better utilisation of health services. Early attempts to measure mortality levels in the developing world populations were based on efforts to register all birth and death through a vital registration system. Despite many attempts the coverage and quality of vital registration systems remain poor at the national level.

Most recent efforts to estimate mortality levels and trends at the national level are based on large-scale surveys and censuses. With the birth of special-purpose surveys, using representative sample of a population of interest, many researchers found it possible to investigate the demographic dynamics of many populations. Two prominent and influential surveys have been the World Fertility Survey (WFS) initiated in 1977 and conducted in almost 42 developed and developing countries and the Demographic and Health Surveys (DHS) which continue today in their second and third phases. DHS capitalised on the legacy of the WFS data collection techniques and analytical methodology- making DHS the leading source of population-based data on maternal and child health in the developing world.

The successful legacy of the DHS programme transcended to the maternal and health surveys sponsored by the League of Arab States' Pan Arab Project for Child Development (PAPCHILD) programme plus its Gulf Family Health Survey (GFHS) – which were carried-out together in over 15 countries since 1989.

The life-cycle of the PAPCHILD surveys is typical of that found elsewhere with the WFS and DHS. The PAPCHILD survey for Yemen, Yemen Demographic and Maternal and Child Health Survey (YDMCHS, 1991/92), is the first representative demographic sample survey post unification in 1990. Sudan, until this point in time, remains with the PAPCHILD, Sudan Maternal and Child Health Survey (SMCHS, 1992/93), as the latest representative demographic sample survey of the country (following SDHS-I (1989/90) and excluding the war affected regions of the Southern country). Egypt's PAPCHILD survey, Egypt Maternal and Child Health Survey (EMCHS, 1991) was preceded with Egypt's first demographic and health survey (EDHS-I, 1988/89) and followed by two more surveys; EDHS-II (1992) and EDHS-III (1995), respectively.

The onset of reductions in child mortality took place at similar times for all three countries, round about the mid 1970s. Yet the rate of change has varied in size and consistency – Egypt leads the group with a fairly significant reduction in under five mortality from 197 deaths per thousand in the mid 1970s to 81 deaths per thousand in the mid 1990s. Sudan's rate of change seems minimal - the two decades period witnessed a small drop from 123 deaths per thousand to 113 deaths per thousand. The rate of change in Yemen was the slowest at the start of that period, accelerating considerably in recent years- a drop from 237 deaths per thousand to 122 deaths per thousand.

A number of bio-demographic, socio-economic and contextual factors continue to affect the course of childhood mortality transition in the three countries. This study utilises maternity histories to obtain child- and family-specific variables to model child survival to age five years. A "cross-country" comparison of child survival correlates is presented using a fixed set of multivariate relations which further reflects subtle methodological gains. The paper concludes by agglomerating a multitude of comparisons within the context of demographic theory and literature. Taken overall, results are remarkably similar to earlier investigations using WFS- and DHS-based studies, suggesting unchanging relations overtime.

2 Data & Study Methodology

Our analytical framework draws heavily on pioneering work on infant and child mortality (Trussell and Hammerslough, (1983); Hobcraft, McDonald and Rutstein, (1983, 1984, 1985), Curtis *et al* (1993)). In the following section, we offer an overview of the models deployed by this study.

Logistic Models:

The logistic model falls into the broad realm of generalised linear models in which a linear predictor is connected with the expected value of the dependent variable via a so-called link function (McCullagh & Nelder, 1983). In the case of binary dependent variables, the logistic function is the most frequently used link due to its relative ease of interpretation.

If we consider π_i be the probability that child *i* will die before age 5 years – we are interested in assessing the dependence of π_i = prob (Y_i =1, child dies before age 5) on explanatory variables X1, X2,…,Xp, respectively. One restriction is $0 \leq \pi_i \leq 1$. Expressing Y_i in terms of π_i

$$Y_i = \pi_i + e_i \qquad (2.1)$$

$$logit(\pi_i) = log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 X1_i + ... + \beta_p Xp_i \text{.................}(2.2)$$

which can be re-written as

$$\pi_i = \left(\frac{exp(\beta_0 + \beta_1 X1_i + ... + \beta_p Xp_i)}{1 + exp(\beta_0 + \beta_1 X1_i + ... + \beta_p Xp_i)}\right) \text{.............................}(2.3)$$

This is a simple model that describes the ratio between the observed proportion of births dying before age five and the proportion of those who do not as an exponential function of a linear combination of covariates. The logit is the logarithm of the odds, and logit differences are logarithms of odds ratios, that is the ratio of the odds of death to survival - when this ratio departs from unity it implies excess risk for the relevant groups or class of the covariate. Given the ease is statistical interpretation, logistic models are quite commonly used in demographic research with the adaptation of special adjustment of exclusions of recent births to alleviate some of the bias caused by censoring of survival experience.

Cox Proportional-Hazards Model:

Originated by Cox (1972), this model is widely deployed in demographic studies of child mortality since they obviate the need to exclude recent births given censorship of experience by the survey time. Studies by Millman *et al* (1986) and Palloni *et al* (1992) have shown that Cox model give consistent estimates to those produced by logistic models and the more restricted hazard models. Collett (1994) provides a clear description the Cox model, customised below to fit our child mortality framework.

In the case of child mortality, survival data is modelled with Cox's semi-parametric model so termed since no particular form of probability distribution is assumed for the survival times (ages of death in the case of dead children) is made. The hazard of death at a particular time for this model depends on the values x1, x2, .., xp of p explanatory variables X1, X2, .., Xp. The values of these variables will be assumed to have been recorded at the time origin of the study. Thus, if a model starts by allocating certain categories of these explanatory variables as reference groups, then the hazard associated with those is $h_0(t)$, or the *baseline* hazard. Usually, it remains more convenient to allocate these explanatory variables baseline values to the more advantaged groups, so that the corresponding hazard ratio estimates describe the relative excess hazard associated with disadvantaged groups relevant to such a set of explanatory variables. Whenever the hazard ratio ψ departs from unity, it will either imply excess risk and vice versa. Hence, the hazard function for the i[th] child can be written as

$h_i(t) = \psi(x_i)\ h_0(t)$ ………(2.4)

where $\psi(x_i)$ is a function of values of the vector of explanatory variables for the i[th] child. The function $\psi()$ can be interpreted as the hazard at time t for a child whose vector of explanatory variables is x_i, relative to the hazard for a child for whom x=0 (Collett, 1994). Since the relative hazard $\psi(x_i)$ can not be negative, it is convenient to write this as $exp(\eta_i)$, where η_i is a linear combination of the p explanatory variables in x_i.

$$\eta_i = \beta_0 + \beta_1 X1_i + \beta_2 X2_i + ... + \beta_p Xp_i \text{.................}(2.5)$$

The proportional hazard model then becomes

$$h_i(t) = exp(\beta_0 + \beta_1 X1_i + \beta_2 X2_i + ... + \beta_p Xp_i) h_0(t) \text{.................}(2.6)$$

which can be re-expressed as

$$log\left(\frac{h_i(t)}{h_0(t)}\right) = \beta_0 + \beta_1 X1_i + \beta_2 X2_i + ... + \beta_p Xp_i \text{.......................}(2.7)$$

Often when an appropriate parametric form $h_0(t)$ is unknown, or is not of primary importance, it would be more convenient if it was unnecessary to substitute any particular form for $h_0(t)$ – an approach introduced by Cox (1972). The model is then non-parametric with respect to time but parametric in terms of the covariates. This does not supply absolute measures of risk but does supply the relative risks for each birth, since although $h_i(t)$ is unknown but the same for each birth (Armitage and Berry (1994, p.485). The model is fitted by the maximum likelihood technically termed partial likelihood (Armitage and Berry 1994). The full power of the proportional-hazards model comes into play when there are several covariates (Kalbfleisch and Prentice, 1980) and (2.6) represents a multiple regression model. A tempting feature of this model is how it facilitates the introduction of time-varying covariates which can not readily be incorporated in the logistic model mentioned earlier. Cox models will be used in our present study to serve that purpose.

Random-effects / Multilevel Models:

For some time now, and since the analysis of the WFS data , some concern was felt about ignoring the correlation between sibling's survival outcomes. In essence, children within any one household, because they are cared for by the same mother and share the same housing environment, tend to be similar in their experience. As a result, they provide less information than would have been the case if the same number of children were from unique households. Similarly, households are random members within geographical clusters, sharing common cluster facilities and characteristics. Given the statement of interest, this hierarchical structure is often ignored. By contrast, the multilevel modelling approach views the population structure , as of potential interest in itself, so that a sample designed to reflect that structure is not merely a matter of saving costs as in traditional survey design, but can be used to collect and analyse data about the higher level units in the population (Goldstein, 1995).

During the past decade, considerable progress has been made towards the estimation of multilevel models. Several researchers, including Mason et al (1983), Goldstein (1986), Raudenbush & Bryk (1986) and Longford (1987), have developed techniques and computer programs for fitting hierarchical linear models that incorporate normally distributed random errors at various levels.

Random-effects logistic models assume that the child's probability of death equals the fixed effects, (2.2 above), plus a random perturbation on the logit scale. To introduce adjustment for "intra-level" correlations, a random effect is assigned for each level of clustering. These effects are captured by random variables and assumptions are made about those, for example, they are independent and follow a normal distribution. The random variables have a mean of zero and variance given by the variance component estimate of the model. By estimating a variance component for those random variables, one can test whether they are sizeable and significantly different from zero. When the variance-components are tested against their standard errors and found to be significant then the "true" random effect is sizeable and its 95% C.I. shifts away from zero and vice versa. If the variance component of the frailty distribution is zero (or insignificant), then observations from that level are independent. A larger variance implies greater heterogeneity in frailty across the members of that level and greater correlation among observations belonging to that member.

The multilevel structure presents the child at the first level (i^{th} level), the mother or household at the second level (j^{th} level) and the cluster at the third level (k^{th} level), respectively. The transition of model 2.2 to incorporate the variance structure of the multilevel structure is in using a single variance term at each of the three levels. These terms are assumed not to depend on any of the explanatory variables.

$$Y_{ijk} = \pi_{ijk} + e_{ijk} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(2.8)$$

$$\text{Logit}(\pi_{ijk}) = \ln(\frac{\pi_{ijk}}{1-\pi_{ijk}}) = \beta_{jk} + \beta_1 X1_{ijk} + \beta_2 X2_{ijk} + .. + \beta_p Xp_{ijk} \ldots\ldots(2.9)$$

With the probability of death before age five re-written as:

$$\pi_{ijk} = \frac{\exp(\beta_{jk} + \beta_1 X1_{ijk} + \beta_2 X2_{ijk} + .. + \beta_p Xp_{ijk})}{1+\exp(\beta_{jk} + \beta_1 X1_{ijk} + \beta_2 X2_{ijk} + .. + \beta_p Xp_{ijk})} \ldots\ldots\ldots.(2.10)$$

The expression $\boldsymbol{\beta_{jk} + \beta_1 X1_{ijk} + \beta_2 X2_{ijk} + .. + \beta_p Xp_{ijk}}$ is known as the **fixed part of the model.** In the equation (2.8) $\mathbf{e_{ijk}}$ is the error term on the probability scale of the departure of the i^{th} child actual value of his/her logit$(\boldsymbol{\pi_{ijk}})$ from that predicted by the fixed part of the model. Basically, in the multilevel case of several clusters which are regarded as a random sample of clusters from a population of clusters (the same for households within these clusters), we assume a regression relation for <u>each household</u> within <u>each cluster</u> with parallel slopes. So $\boldsymbol{\beta_{jk}}$ can be re-expressed as

$$\beta_{jk} = \beta_0 + V_k + U_{jk} \ldots\ldots..(2.11)$$

hence replacing the value of $\boldsymbol{\beta_{jk}}$ in the model above,

$$\text{Logit}(\pi_{ijk}) = \ln(\frac{\pi_{ijk}}{1-\pi_{ijk}}) = \beta_0 + \beta_1 X1_{ijk} + \beta_2 X2_{ijk} + .. + \beta_p Xp_{ijk} + V_k + U_{jk} \ldots\ldots..(2.12)$$

Where $\boldsymbol{\beta_0}$, with no subscripts is a constant, and, $\mathbf{V_k}$ is the departure of the $\mathbf{k^{th}}$ cluster's intercept from the overall value, a level-3 residual, which is the same for all households in the $\mathbf{k^{th}}$ cluster. $\mathbf{U_{jk}}$ is the departure of jk^{th} household's intercept from the overall value, a level-2 residual which is the same for all children in the jk^{th} household. In general , wherever an item has three subscripts **ijk**, it *varies* from child to child within a household, and from household to household within clusters. Where an item has a **jk** subscript only it varies across households but has the same value for all the children within a household, and, in the same order an item with only a **k** subscript will vary between clusters but remain constant for all households (and hence all children within those households). In equation (2.12), both V_k , U_{jk} are random quantities, whose means are equal to zero; they form the random part of the model. The standard assumption is that at different levels random variables are un-correlated and that they follow a normal distribution so that it is sufficient to estimate their variances σ^2_v and σ^2_u , respectively. The estimation technique involves the restricted iterative generalised least squares estimation (RIGLS; Goldstein, 1989) and the second order penalised quasi-likelihood estimation (PQL; Goldstein, 1995; Goldstein and Rasbash, 1996).

The Study's Innovation:

Our first innovation is in the set of "familial-mortality" indicator variables which refine measures of previous mortality of older siblings as and when they occur given the first five-years exposure for every index child. For subsequent births an indicator time-varying variable is used to express the status of subsequent pregnancy (a conception, a birth and in some cases, a death). The first five-years exposure for each child was broken into a sequence of discrete time units or records to depict the changing status of the time-varying variable. Each discrete time unit for each child is treated as a separate observation or 'episode'. For each of these observations, the dependent variable is coded 0 whilst the index child is alive and changing to value 1 if the index child dies before age five. Figure 2.1 below shows an example of a hypothetical example of the time-varying states of the explanatory variables for two index births, A and B. For child A, at age fifteen months, his mother would have conceived his subsequent sibling, so the a new "episode" is created between the discrete value months fifteen and sixteen to capture the change of "Status of subsequent birth" from value 0 to value 1 to indicate change of status from no conception to conception, respectively. The index child will hence keep the new value of his / her time varying covariates until death aged twenty months.

For index child B, one older sibling (older than the immediately previous sibling) died when index child B reached age ten months. Then when index child B reached age fifteen months his/ her mother fell pregnant with a subsequent pregnancy which was delivered when the he / she reached age twenty four months. The latter subsequent birth survived for four months only and died when the index child B reached age twenty eight months. Index child B then survives post age five years, during which time he experienced one extra older sibling death and one subsequent pregnancy's conception, birth and death, consecutively.

Figure 2.1: A Hypothetical example of the change in status of the time-varying-covariates

	t_0	t_1	Count of older sibling deaths	Status of subsequent birth 0=no conception 1=conception 3=birth 4=death	Index Child survival status 0=alive 1=dead)
Child: A	0	15	0	0	0
	15	16	0	1	0
	16	20	0	1	1
Child: B	0	9	0	0	0
	9	10	1	0	0
	10	15	1	1	0
	15	24	1	3	0
	24	28	1	4	0
	24	60	1	4	0

The Cox model produces hazard ratios (relative risks) rather than odds ratios. The relationship between the odds ratio (OR) and relative risks (RR) is complex, and the assumed approximation of equality is generally considered unsatisfactory if the event frequency is above 10% (Gray, 1990). It is however possible to estimate odds ratios from relative risks. To improve on the comparison of the Cox model results to those of the logistic regression we employ the formulae below transferring the Cox model risk ratios (RR) to odds ratios (OR*) (Gray, 1990; Boerma and Bicego, 1992).

$$\frac{RR(1-\text{Pref})}{(1-RR\text{xPref})} = OR^* ......(2.13)$$

Where:

RR = Relative Risk ratios resulting from a Cox model.

Pref = the prevalence of under-5 mortality in the reference group(s) in the multivariate relation.

The second innovation is with the structure of the variance components of the multilevel-logistic regression model (2.12). The latter can be re-expressed as

$$\text{Logit}(\pi_{ijk}) = \ln(\frac{\pi_{ijk}}{1-\pi_{ijk}}) = \beta_0 + \beta_1 X1_{ijk} + \beta_2 X2_{ijk} + .. + \beta_p Xp_{ijk} + \sigma_v v_k + \sigma_u u_{jk} ...(2.14)$$

Where v_k and u_{jk} have a N~(0,1) standard normal distribution and σ_v is a scale parameter that indicates the variation across clusters on the logit scale and is the standard deviation of the normal distribution of V_k . σ_u is a scale parameter that indicates the variation across household or families on the logit scale and is the standard deviation of the normal distribution of U_{jk} .

One extension to this formula that our analysis experiments with is the estimation of one scale parameter σ_v, which indicates the variation across clusters. Motivated by Sastry (1997) findings, we could split the variance into components with respect to a collective feature for each country e.g. clusters within the same governate or region. This calls for more than one slope to describe the cluster-effect. Returning to original logistic equation formula (2.9), the breakdown of β_{jk} will be estimated by:

$$\beta_{jk} = \beta_0 + V1_k + V2_k + .. + Vn_k + U_{jk} ......(2.15)$$

Where ***n*** corresponds to the number of regional divisions, for example regions are five in the case of Egypt, six in the case of Sudan and two in the case of Yemen, respectively.

The revised model (2.12) becomes:

$$\text{Logit}(\pi_{ijk}) = \ln(\frac{\pi_{ijk}}{1-\pi_{ijk}}) = \beta_0 + \beta_1 X1_{ijk} + \beta_2 X2_{ijk} + .. + \beta_p Xp_{ijk} + \sigma_{v1} v_k + .. + \sigma_{vn} v_k + \sigma_u u_{jk} ...(2.16)$$

$\sigma_{v1},\dots, \sigma_{vn}$ are the scale parameters that indicate the variation across clusters, within regions 1,..,n, on the logit scale, respectively. Also, these are the standard deviation of the normal distribution of $V1_k,..,Vn_k$ respectively. When any of $\sigma_{v1},\dots, \sigma_{vn}$ estimate to zero, it will imply that clusters within their respective region have zero correlations.

Theoretically, it is equally viable to split the household-effects to match those of the segregated cluster-effects above, but in all our trials this proved to be computationally intensive and models require a large number of iterations (1000+) before convergence.

Lastly, from the variance-component we could calculate "intra-cluster" and "intra-household" correlation coefficients based on the formula given below. The formula treats the error term associated with the i^{th} child of the j^{th} mother / household in the k^{th} cluster as having a standard logistic distribution with mean 0 and variance $\pi^2/3$. (Kotz & Johnson (1970); Pebley *et al* 1996).

For "intra-cluster" correlation;

$$\rho_v = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_u^2 + \pi^2/3} ....(2.17)$$

For "intra-household" correlation;

$$\rho_u = \frac{\sigma_v^2 + \sigma_u^2}{\sigma_v^2 + \sigma_u^2 + \pi^2/3} ....(2.18)$$

Both values will lie between zero and 1 - if we encounter a high “intra-household” correlation it will indicate household-family environments are more heterogeneous than expected if clustering was ignored and hence a child’s survival chance **are** affected by household-specific unmeasured factors. Otherwise, if the variance-components estimates behind these correlation are small and insignificant then a child’s particular membership if any one household (in any one cluster) should have little if no effect on his/her survival chances.

One final modification comes with adjusting for survey design. Survey data generally has three important characteristics: sampling weights –also called probability weights, clustering and stratification. Including the sampling weights in the analysis gives estimators that are approximately unbiased; weights will also affect the estimation of standard errors for these estimates. In the case of Yemen, sampling weights have to be used given that the household sample was not self-weighting. In these surveys mothers are not sampled independently, that is to say a group of households, hence women, are sampled as a “cluster”; accounting for clustering is necessary for “honest” estimates of standard errors and hence, valid p-values, and confidence intervals whose true coverage is close to 95%. Furthermore, in these surveys, different groups of clusters are often sampled separately. These groups are called strata. For example, in the case of Sudan 230 clusters belonged to six governate strata and then sampling was done proportional to percentages of urban and rural clusters within governates. Thus, strata are statistically independent and can be analysed as such. Typically, this produces smaller estimates of standard errors. It is hence important to use sampling weights in order to get the point estimates right. Considering the clustering and stratification of the survey design gets the standard errors right. The *svy* commands in STATA© provide variance estimators suitable for use with multistage sample data described above. (For a detailed discussion of the advantages of using svy commands refer to Chapter 30, *Overview of survey estimation* (p.320-333) STATA© 6.0 User’s Guide, STATA Corp 1999).

To recap, our study’s units of measurements are child records obtained from the PAPCHILD surveys retrospective maternity histories. To maintain comparability across countries the set of predictor variables is kept the same, which include:

The bio-demographic covariates which are the maternal age at birth, sex, length of the preceding birth interval, survival status of the preceding birth and an interaction term of birth order with counts of older siblings mortality prior to the birth of the index child. The new additions are the time-varying covariates of extra older siblings death and the survival status of the subsequent pregnancy.

The socio-economic indicators which are the literacy of mothers, the literacy of husbands, the type of area of residence, and whether husbands' occupation was in agriculture.

The cluster "contextual" indicators describe the cluster's type of sanitation, the source of water supply and the cluster access to electricity, respectively. Many of the variables concerned with the timing and clustering of births, such as previous birth interval, survival of the previous child, deaths of any older siblings, deaths of siblings older than the prior birth will not apply to first births. Results shown hereforth will only concern higher-order births born in the period 5-15 years before the survey. But in a few occasions communalities are reported. Fitting of the survey logistic and Cox model was carried out using the statistical software package STATA© (STATA Corp, 1999) and the multilevel logistic model using the multi-level statistical software MLwiN© (MLwiN,1998), respectively.

3 Contrasting Three Countries

The results of fitting the models for higher order births to the data from the three PAPCHILD surveys will now be examined. For practical purposes, we chose with these tables to concentrate on the common fixed-effects of the survey logistic model, the added time-varying effects captured by the Cox model and further, the added multi-level fixed (cluster-characteristics) and random effects. Tables 3.1 and 3.2 show the cross-countries comparative results of under-five mortality of higher-order births, and the characteristics of random-effects of under-five mortality of higher-order births, respectively.

The tabular results are presented in a non-conventional form that signals the gains in incorporating time-varying covariates, versus using the multilevel logistic framework. To reduce repetition of three model results for each country, the table has been adapted to depict newer coefficients with the changing models. The multilevel logistic *without* the cluster-characteristics effects is robust in comparison to the marginal and survey logistic model. The variables that are included in the models will be discussed during the interoperation of the results. The percentages of births in each category for each covariate, the odds ratio estimates and the corresponding 95% confidence intervals are shown in Table 3.1.

Table 3.1: Cross-country Comparison of Under-5 mortality Analysis for HO-Births

Correlates (%)	N=13263	Egypt	N=8498	Sudan	N=12703	Yemen
		Survey Logistic (OR)		Survey Logistic (OR)		Survey Logistic (OR)
Sex						
Male	51.2	0.94 (0.84,1.06)	51.6	1.19*** (1.05,1.36)	52.0	1.12* (1,1.27)
Female (Ref)	48.8	1.00	48.5	1.00	48.0	1.00
Mother's age at birth						
< 18 years	2.7	1.44*** (1.09,1.9)	3.6	1.25 (0.88,1.77)	4.3	1.10 (0.85,1.41)
18-19 years	5.1	1.03 (0.81,1.32)	5.9	0.88 (0.65,1.19)	6.9	0.91 (0.72,1.16)
20-24 (Ref)	27.0	1.00	25.7	1.00	26.4	1.00
25-29	29.7	0.89 (0.77,1.03)	27.4	0.99 (0.81,1.2)	26.5	0.88* (0.77,1.01)
30-34	21.4	0.81** (0.68,0.98)	21.0	1.04 (0.84,1.29)	18.7	0.85* (0.72,1.01)
35 +	14.0	0.91 (0.75,1.11)	16.3	1.19 (0.91,1.56)	17.3	0.96 (0.77,1.18)
Previous Birth Interval						
< 18 month	24.0	2.80*** (2.44,3.22)	26.1	2.43*** (2.03,2.90)	44.8	2.80*** (2.35,3.34)
18-23 month	17.4	1.50*** (1.28,1.75)	18.5	1.19* (0.98,1.44)	17.5	1.59*** (1.29,1.96)
24-35 month (Ref)	28.7	1.00	32.2	1.00	20.8	1.00
36+ month	29.8	0.57*** (0.48,0.66)	23.2	0.69*** (0.55,0.87)	16.9	0.58*** (0.45,0.75)
Birth Order X Previous Deaths						
B2-3 X 0 deaths(Ref)	39.8	1.00	30.1	1.00	32.3	1.00
B4-6 X 0 deaths	20.9	1.07 (0.91,1.26)	23.8	0.87 (0.71,1.06)	22.8	0.76*** (0.64,0.9)
B7+ X 0 deaths	3.3	1.54*** (1.11,2.14)	9.1	0.81 (0.57,1.15)	5.7	0.69** (0.49,0.97)
B2-3 X 1+ deaths	3.4	1.81*** (1.4,2.35)	4.9	1.66** (1.1,2.5)	3.1	1.32* (0.98,1.77)
B4-6 X 1 deaths	12.0	1.79*** (1.5,2.15)	10.6	1.35** (1.04,1.76)	11.5	1.27** (1.05,1.52)
B7+ X 1 deaths	4.6	1.55*** (1.18,2.04)	6.7	1.08 (0.78,1.5)	6.3	1.21* (0.97,1.52)
B4-6 X 2+ deaths	5.4	2.11*** (1.67,2.65)	4.6	1.31 (0.89,1.93)	5.7	1.03 (0.79,1.33)
B7+ X 2+ deaths	10.6	1.96*** (1.6,2.39)	9.6	1.24 (0.9,1.72)	12.5	1.31** (1.04,1.64)
Previous Child Survived to Birth of Index Child						
Yes (Ref)	85.9	1.00	90.0	1.00	85.4	1.00
No	14.1	1.50*** (1.31,1.71)	10.0	1.68*** (1.42,1.99)	14.6	1.89*** (1.62,2.21)
Area						
Urban (Ref)	34.2	1.00	33.4	1.00	23.4	1.00
Rural	65.9	1.26*** (1.08,1.47)	66.6	0.96 (0.81,1.15)	76.6	1.06 (0.87,1.3)
Mother attended School						
No	69.5	1.26*** (1.09,1.47)	70.4	1.39*** (1.12,1.72)	94.1	1.27 (0.93,1.73)
Yes (Ref)	30.5	1.00	29.6	1.00	5.9	1.00
Husband attended School						
No	63.7	1.17*** (1.04,1.32)	40.4	1.37*** (1.12,1.67)	68.0	1.24*** (1.07,1.45)
Yes (Ref)	36.3	1.00	59.6	1.00	32.0	1.00
Husband in Agriculture						
No	50.0	0.96 (0.85,1.09)	42.6	1.00	75.7	1.00
Yes (Ref)	50.0	1.00	57.4	1.06 (0.91,1.24)	24.3	1.12 (0.98,1.28)

Gains from the Cox Proportional Hazard Model

		Cox (OR)*		Cox (OR)*		Cox (OR)*
Years Before Survey						
"0-4"	15.7	0.68*** (0.6,0.76)	14.8	0.97 (0.83,1.13)	19.2	0.68*** (0.59,0.76)
"5-9" (Ref)	22.5	1.00	26.8	1.00	32.8	1.00
"10-14"	21.9	1.07 (0.97,1.19)	22.6	0.95 (0.83,1.09)	24.3	1.23*** (1.09,1.38)
"15+"	39.8	1.41*** (1.29,1.56)	35.7	0.99 (0.86,1.12)	23.7	1.61*** (1.42,1.83)
Extra Sibling Deaths						
None (Ref)	97.9	1.00	97.3	1.00	97.5	1.00
1 Extra deaths	2.1	3.98*** (3.20,5.07)	2.72	4.19*** (3.3,5.39)	2.5	0.87 (0.73,1.03)
Status Subsequent Birth						
0 = None (Ref)	60.5	1.00	54.4	1.00	54.3	1.00
1 = Conception	19.8	2.60*** (2.28,2.96)	22.6	1.82*** (1.51,2.18)	22.8	0.17*** (0.15,0.18)
3 = Birth	18.0	3.12*** (2.53,3.89)	21.3	2.05*** (1.6,2.68)	21.0	0.07*** (0.06,0.08)
4 = Death	1.8	4.52*** (3.14,6.93)	1.8	4.26*** (2.73,7.36)	1.9	0.11*** (0.09,0.15)

Continued……

Gains from the Multilevel Logistic Regression						(Table 3.2.1Continued)
Correlates (%)	N=13263	Egypt	N=8498	Sudan	N=12703	Yemen
		Multi-level Logit (OR)		Multi-level Logit (OR)		Multi-level Logit (OR)
Cluster Electricity						
Elec-Yes (Ref)	96.6	1.00	30.1	1.00	52.4	1.00
None	3.4	0.97 (0.66,1.43)	69.9	0.91 (0.68,1.23)	47.6	1.33*** (1.11,1.58)
Cluster Sanitation						
Toilet/Shared (Ref)	71.6	1.00	4.7	1.00	16.9	1.00
Pit/Latrine	17.2	1.29*** (1.09,1.53)	63.2	1.74* (0.93,3.27)	41.6	1.21 (0.91,1.6)
Open-Air/Other	11.3	1.08 (0.88,1.33)	32.1	1.71* (0.97,3.03)	41.5	1.3 (0.95,1.78)
Cluster Water Supply						
Gover-Piped (Ref)	79.0	1.00	31.7	1.00	40.4	1.00
Well/Pumped	21.0	1.03 (0.87,1.21)	49.7	1.54** (1.09,2.19)	40.9	0.99 (0.81,1.21)
Other			18.6	1.19 (0.89,1.6)	18.7	0.97 (0.77,1.23)
	100.0		**100.0**		**100.0**	
Cluster-effect(s.e.)		0.12*** (0.03)		0.10** (0.05)		0.08*** (0.03)
"Intra-cluster" Correlation		0.035		0.024		0.023
Household-effect		0.01 (0.06)		0.81*** (0.12)		0.15*** (0.05)
"Intra-household" Correlation		0.038		0.217		0.065

The innate survival advantage for girls should fizzle-out, especially since mortality to age five is being considered. The net survival advantage for girls is weak which is perhaps more normative behaviour of the differential.

The models bear a strong suggestion that survival chances for children improve slowly with increasing age of mother beyond age 18 up to age 35. In the case of Egypt, and compared with children born to 20-24-year-old mothers, the overall average deviations in the odds ratios suggests a 44 per cent net increase for births to 18-19-year-olds, and a net decrease of 19 per cent for those born to 25-29 and 30-34-year-old mothers respectively. However, second and higher birth to very young mothers are rare (close to 10 per cent for < 20 years and about 5 per cent of < 18 years), few of the individual parameter estimates are statistically significantly different from the reference group of 20-24-years-old-mothers. In view of this high variability around the parameter estimates, it is unwise to try to make statements about broad regional patterns or individual country estimates.

The next correlate considered is the unmistakable excess mortality associated with shorter birth intervals. Evidently there will be a greater population impact for the spacing of births than for the age of the mother. The length of the preceding birth interval dominates as the most influential effect across countries and methods. The percentage of births with a preceding birth intervals of < 18 months in Egypt is 24 per cent, almost half Yemen's 45 per cent, yet the excess risk is the same with an odds ratio estimate of 2.80: 1.0 compared to the baseline birth interval of 24-35 month (p-value <0.001). Conversely, the percentage of births with a preceding birth interval of 36+ months in Yemen is 17 per cent, which is close to half that of Egypt's 30 per cent, yet the beneficial effects are of the same magnitude; roughly a reduction in risks of about 42 per cent. Considering the two countries levels of contraceptive use, this result could be worrying. Sudan is caught-up somewhere in between where the shift from shorter to longer birth intervals is taking place with lower risks, lower benefits in both directions.

A consistent survival advantage is associated with birth intervals in excess of three years. Long intervals are the exception in these settings (23 per cent for Sudan and 17 per cent for Yemen, but 30 per cent in the case of Egypt) especially in a setting where contraception is so low. Hence, longer birth intervals are probably the result of low fecundability or of contraception failure where it exists, or what could be differential omission of mis-carriages or dead children. Yet such events need not be very high in order to wipe-out the apparent survival advantage associated with this group (Hobcraft, 1994).

Turning to previous mortality among the older siblings of the index child. These measures draw heavily on the precision of the date of occurrence of a child death for the preceding births. These are death events of older siblings in the family previous to the birth of the index birth expressed as interaction terms with the birth order group of the index birth. Higher-order births especially in a family setting characterised by short birth intervals will further underpin such effects.

Creating an interaction term of older siblings, previous to the preceding birth, counts of death with birth order groups involved a one-off recursive programmed-counter.

This birth order based measure is divided into three groups, a low-risk group (birth order 2-3), medium-risk group (birth order 4-6) and high-risk group (birth order 7+). For the low-risk group either 0 or 1 counts of deaths can be the case; for the medium and high-risk groups, 0, 1 or 2(+) counts are plausible. Cross countries and measures of mortality, the most prevalent interaction term is the birth order 2-3 with no count of older siblings deaths, hence used as a baseline category.

To clarify our discussion, Figure 3.1 presented below relates the birth order groups with the counts of deaths of older siblings (prior to the immediately previous birth), reporting on estimates odds ratios from the survey logistic regression of Table 3.1.

Figure 3.1 Counts of Older Siblings (previous to the preceding birth) Deaths

Birth Order Groups	Egypt			Sudan			Yemen		
	0	1	2 (+)	0	1	2 (+)	0	1	2 (+)
2-3	**1.00**	**1.81*** **	**--**	**1.00**	**1.66** **	**--**	**1.00**	**1.32***	**--**
4-6	**1.07**	**1.79*** **	**2.11*** **	**0.87**	**1.35** **	**1.31**	**0.76*** **	**1.27** **	**1.03**
7+	**1.54*** **	**1.55*** **	**1.96*** **	**0.81**	**1.08**	**1.24**	**0.69** **	**1.21***	**1.31** **

*** Sig. at 1%, ** Sig. at 5%,* Sig. at 10%,

A state of no previous deaths with birth order groups 4-6 and 7+ compared to the reference parity group 2-3, could perhaps imply an ideal familial-setting of high fertility, low mortality in Sudan and Yemen, but not Egypt. For forth to sixth births, where all "earlier" birth are alive, there are significant lower mortality differences compared with the reference group [re-defines them again]. Similarly, for seventh and higher order births where no earlier child putative of an advantaged family survival background, there are clear indications of lower mortality risks in Sudan and Yemen, but not Egypt.

Of the total sample, less than five per cent of later births are in the birth order 2-3 experiencing 1 older sibling death, hence parameter estimates have large standard errors. For index children who are second or third births, the odds of death are increased by about 81 per cent in Egypt and 66 per cent in Sudan, respectively, if the first born child died, compared with the reference group in this context, which contains all second and third births with a surviving first birth.

For fourth to sixth births where one earlier birth had died prior to the birth of the index child, and compared to the same reference group, the average odds of death are increased by about 79 per cent in Egypt which is higher than the estimates of 35 per cent in Sudan and 27 per cent in Yemen, respectively. Where the index child is a seventh or higher order birth, one death among the five or more earlier births is only unsurprisingly associated with a small average excess mortality for the index child and significant only in Egypt.

In the case of Egypt, compared to the baseline category, births orders two or three with surviving older siblings, excess mortality is almost doubled when two or more of these children had died prior to fourth and higher index births, respectively. In Yemen, the highest and most significant excess risk is apparent with birth order group 7+ and 2+ counts of older siblings deaths.

It can be further noted that the odds ratio associated with all the categories identifying non-surviving earlier births are generally greater than one, with no fewer than nine out of a possible twelve coefficients (shaded cells in Figure 5.1) being significantly different from one (p-value < 0.05). By and large, events of deaths of older siblings are systematic and clear indicators of familial settings of higher exposure to child loss; more so in Egypt in comparison to the Sudan and Yemen.

Not surprisingly, there is a clear and strong association between the death of an immediately preceding child before the birth of the index child and that index child's own survival chances. With this variable care was taken to avoid uncertainty surrounding the category of preceding children who "may be" dead due to imprecise dating, and were hence allocated a missing value for the covariate. In the case of Sudan, there is an average two third increased risk associated with a preceding sibling's death for the index child. Yemeni higher order births could suffer a close to doubling of risks of death before age five compared to Egypt's 50 per cent increased risks. It is also worth mentioning that effects of other bio-demographic factors such as sex and maternal age at birth attenuate slightly once the familial history of mortality is controlled for.

By and large, in the cases of Sudan and Yemen the death of the immediately previous sibling is a stronger *timely* correlate for the survival chances of the index child perhaps slightly weaker for Egypt. While in Egypt, with the lower prevailing mortality levels, the older sibling mortality, spell-out more of this inter-dependency e.g. health-condition or parenting practices within the household.

Given the socio-economic differential of area of residence, rural Egypt has the only significant disadvantage with an average estimate of 26 per cent increased risks of death before age five for higher order birth born in rural Egypt. The lack of maternal schooling seem to show the most sizeable effect in Sudan with increased risk estimates of 39 per cent compared to Egypt's 26 per cent, both countries with two-third of higher order births born to mothers with no schooling. Probably in Egypt the burden is circumvented by wider-spread and better implemented maternal and child health / family planning activities in operation.

Interesting enough, two-fifth of later births belong to mothers' whose husbands have no schooling compared to two-thirds in Egypt and Yemen yet the order of higher risk is found in Sudan. The estimates for Sudan shows increased risks of 37 per cent, followed by Yemen's 24 per cent and Egypt's 17 per cent, respectively. This could be due to a complex economic differential arising from the association of education with levels of income and living standards.

Turning to the first gain from the Cox model, period-effects are considered, the trend shows improvements by lower risks in Egypt and Yemen, with no change for the Sudan, a trend confirmed also with first births analysis. Compared to the baseline period ("5-9" years before the survey), the recent period 0-4 years before the survey, Yemen and Egypt repeat estimates of a one-third drop in mortality risks, while for the Sudan the trend is showing little change if any at all.

The "extra sibling death" is the first of the two time-varying variable applicable only to higher-order births to capture the extra risk triggered by the "newer event" of death of an older sibling, who was alive at the time of birth of the index birth. A rare event occurring to less than three per cent of higher order births for these countries, yet triggers as much as a four-fold excess mortality risks for index births in Egypt and Sudan, respectively. In Yemen, the extra risk is almost absent, which is rather perplexing, given that the percentage of " an extra sibling death" is comparable to the previous two. This result for Yemen, perhaps, could be flagging an issue with data quality.

The second time-varying covariate is the indicator of the status of the survival status of the subsequent pregnancy. The baseline state considered is that of no subsequent conception; slightly more than half of the higher order birth remain with no subsequent pregnancy taking place before their fifth birthday. About one-fifth of higher order births exit the exposure time with a subsequent concept taking place; the average significant excess risk parameter estimate corresponds to an odds ratio of 2.6 : 1 in Egypt and 1.82 : 1 in Sudan but is completely reversed for Yemen. Another one-fifth of higher order births exit their exposure time with a subsequent birth taking place; similarly, the excess risks are trebled in the case of Egypt and doubled in the case of Sudan, respectively, but the dramatic and unexplainable reversed influence maintains for Yemen. The remaining tiny percentage of higher order births (less than two per cent) exit the exposure period with a subsequent child's death; these bear the highest estimates of all previous states, with more than a four-fold increased risks estimated for Egypt and Sudan, respectively. The estimation for Yemen persists with reduced rather than increased risks in the range of 89 per cent lesser risk of death before age five.

Further additions made to the multi-level models include the cluster "contextual" variables describing sanitation, type of water supply and access to electricity supply**.** In Yemen, child residence in clusters with no electricity evidently indicate excess mortality risks of one-third. Residence in clusters lacking toilet-sanitation bears moderate extra risks in Sudan (71 per cent) and Egypt (29 per cent) for children under five. The safer the cluster's water supply the higher the returns for the health status of its residents – in Sudan, clusters with well/pumped water supply bear 54 per cent extra risks of child mortality before age five compared to clusters with piped water supplies.

The bottom-half of Table 3.1 (p.13) presents the estimates of random-effects influencing survival chances of higher-order births. It is worth noting at this stage that both the unmeasured cluster-effect and household-effect were considerably reduced in size and significance with the multivariate relations shown in Table 3.1.

The variance component σ^2_v of the cluster effect remains significantly different from zero for the three countries. The variability in magnitude varies from highest in Egypt (0.12***), lower in Sudan (0.10**) and lowest in Yemen (0.08***). Yet if we were to judge those effects by the "intra-cluster" correlation coefficients, the often *ignored* correlation would seem rather small (Egypt, ρ_v =0.035, Sudan, ρ_v =0.024 and Yemen, ρ_v =0.023).

If we are to consider the variance component σ^2_u of the household effect, it is close to zero in Egypt (0.01), yet significantly different from zero in both Sudan (0.81***) and Yemen (0.15***). The "intra-household" correlation coefficient is Egypt (0.038) is almost a by-product of the higher-hierarchical "intra-cluster" correlation. But for Sudan (ρ_u = 0.217) the "intra-household" correlation coefficient is more than four times that of Egypt and more than three times that of Yemen (ρ_u = 0.065). Perhaps for the Sudan a mutli-level model is required to accommodate this sizeable "intra-household" correlation feature of the data. Not readily shown in Table 3.1, we also acknowledge how the indicator variable of the survival status of the previous sibling loses magnitude and significance in the multilevel logistic model. Pebley ***et al*** (1996) suggest that this is not due to correlation between the random characteristics and previous child survival but more to the non-linear nature of the model used.

Turning our focus to the cluster random-effect split by country regions, shown in Table 3.2 below, we observe five cluster-effect estimates for Egypt, six for Sudan and two for Yemen, respectively.

Table 3.2: Characteristics of Random-Effects of Under-5 mortality Analysis for Higher-Order Births

		Variance Component Cluster (s.e.)			
Egypt (Regions)		**Sudan (Regions)**		**Yemen (Regions)**	
Urban Gover	**0.29** (0.13)**	**Khartoum**	**0.0 (0.0)**	**North & West**	**0.05** (0.02)**
Urban Lower	**0.1 (0.11)**	**Eastern**	**0.26 (0.18)**		
Rural Lower	**0.04 (0.04)**	**Central**	**0.02 (0.07)**	**South & East**	**0.27** (0.11)**
Urban Upper	**0.07 (0.1)**	**Darfur**	**0.22* (0.13)**		
Rural Upper	**0.16*** (0.05)**	**Kordofan**	**0.0 (0.0)**		
		Northern	**0.7 (0.49)**		
		Variance Component Household (s.e.)			
	0.0 (0.0)		**0.75*** (0.11)**		**0.14*** (0.05)**
		"Intra-Cluster" Correlation			
		"Intra-Household" Correlation			
Urban Gover	**0.081**	**Khartoum**	**0.000**	**North & West**	**0.014**
Household	**0.081**	**Household**	**0.186**	**Household**	**0.055**
Urban Lower	**0.029**	**Eastern**	**0.060**	**South & East**	**0.073**
Household	**0.029**	**Household**	**0.235**	**Household**	**0.111**
Rural Lower	**0.012**	**Central**	**0.005**		
Household	**0.012**	**Household**	**0.190**		
Urban Upper	**0.021**	**Darfur**	**0.052**		
Household	**0.021**	**Household**	**0.228**		
Rural Upper	**0.046**	**Kordofan**	**0.000**		
Household	**0.046**	**Household**	**0.186**		
		Northern	**0.148**		
		Household	**0.306**		

*** Sig. at 1%, ** Sig. at 5%,* Sig. at 10%,

Firstly, considering results for Egypt, splitting the cluster-variance component into 5-regional estimates, the Urban Governates (Cairo & Alexandria) and Rural Upper Governate emerge with the two sizeable and significant unexplained components, having "intra-cluster" correlations ρ_v= 0.081 and ρ_v= 0.041, respectively. This is an interesting feature of the analysis since the heterogeneity expected with-in the Urban Governates may not be readily similar to that of Rural Upper Governates. Feasibly, "true" heterogeneity in socio-economic and environmental conditions exist "within" both regions; both densely populated, with varying levels of access to population services.

For Sudan, Khartoum and Kordofan variance-components at the cluster-level reduce to zero, but since the household-effect is substantial, the “intra-household” correlation holds at $\hat{\rho}_u$ =0.186 ; a situation similarly found in the Central governate ($\hat{\rho}_u$ = 0.190). But for the Northern, Eastern and Darfur governates the cluster-effects are sizeable yet insignificant leaving a high “intra-household” correlation $\hat{\rho}_u$ of 0.306, 0.235 and 0.228, respectively. Perhaps the more worrying is the intra-cluster correlation of Darfur (0.228), since the variance-component estimate at the cluster level is marginally significant. These correlations might suggest that births within households are likely to be moderately correlated, more than could be accounted for by one marginal model.

A striking finding with the variance-component split in the case of Yemen, in that the larger of the two is the one belonging to the “South & East” (contrary to what we have encountered with first births analysis). The estimate of the “North & West” “intra-cluster” correlation is ($\hat{\rho}_v$ =0.014) and the “intra-household” correlation is ($\hat{\rho}_u$ =0.055), respectively. For the “South and East” region, the “intra-cluster” correlation is ($\hat{\rho}_v$ =0.073) and the “intra-household” within is ($\hat{\rho}_u$ =0.111). All being equal, and with the same level of unmeasured heterogeneity at the household level, this could indicate the unexplained cluster-correlation in the “South & East” region is five times that in the “North & West” region. Probably that effect extends to the underlying house-hold effect but splitting the variance component for the household level proved to be computationally intensive and would require further research.

Key findings and country summary

With this sub-section we aim to agglomerate key findings for *all*-births in each country for the sake of potential policy implications. The survival chances for higher-order births in Egypt, stand to benefit from lengthier birth intervals and keeping to lower parity births, both conditions enhanced by better rates of contraception. The striking finding we ended-up with is how the controls for the familial history of mortality almost fully explained any household-effects (unmeasureable by the observed covariates) in the case of Egypt. This implies the characteristic of child losses in a family or household unit is a clear marker of “higher-risk” families or households prompting more health-worker surveillance. Especially to Egypt, and with improving mortality levels, “over-crowding” under-pin the correlation in survival chances (for a detailed discussion, see Aaby, 1988,1992).

As with first births, higher-order births appear to benefit moderately when born to mothers with some schooling, with their survival chances almost unimproved when their fathers had some schooling or worked in a none agriculture-related occupation.

Rural areas in Egypt still pose higher risks compared to urban areas for higher-order births, and moderate risks where localities still lack in planned toilet-sanitation and piped-water supplies**.** Recent improvements captured by the "period-effects" are perhaps capturing benefits of extended programmes of Primary Health Care (PHC/MCH/FP) maternal and child health care thus enhancing children's survival to age five years.

For both first births and higher order births in Sudan, some evidence of a sex differential in mortality was observed to the disadvantage of male births – this could be due, in part, to the under–reporting of female deaths. Lack of maternal and paternal education bears a considerable risk to all births.

For first births the cluster random-effects are not apparent and hence that alleviates the need for a adjusting unmeasured heterogeneity. But in the case of higher-order births there is a considerable element of unmeasured heterogeneity between households but not clusters, particularly when mortality before age five is the case. The observed correlates add little to explain those effects which implies that the dynamics of heterogeneity in Sudan estimated at the household level could be borne of a multitude of socio-economic and behavioural factors unmeasureable by cross-sectional sample surveys.

To summarise our findings for Yemen, we find the lack in association of maternal age at birth and higher-order births mortality a shortcoming and could raise issues of data quality of mothers' age reporting. The sex differential in mortality is slightly higher for first births compared to higher-order birth, which could be in part due to under-reporting of female deaths. The evidence of the detrimental effects of short preceding birth intervals is unequivocal – Yemen is need of serious efforts of family planning with the clear message for spacing if not limiting fertility. Older siblings mortality indicates trailing correlations, and rather, that the survival status of the immediately previous child is a better proxy for the "familial mortality" risks to the index births.

The lack of explanatory power of the socio-economic differentials is perhaps indicative of a low-ceiling of the economic advantages commonly associated with factors such as parental literacy and urban residence. The "South & East" region emerges with evidence of more heterogeneity compared to the "North & West" region at the collective cluster level – pre-unification the "South & East" region is believed to have benefited more from better public health services and conditions as compared to the "North & West". Our result implies that for the advantaged "South & West", heterogeneity in survival chances prevails perhaps as a result of the uneven distribution in services availability and accessibility.

4 Discussion & Conclusion

This paper has covered a wide range of quite complex results. A series of three sets of regression models have been considered. The first model was a simplified approximation to those used in three of the major comparative analyses carried using data from WFS (Hobcraft, McDonald and Rutstein, 1983, 1984 and 1985). The second model allowed for the incorporation of time-varying effects of extra mortality effects in the family relative to the index child. The third model allowed adjusting for hierarchical clustering of birth within mothers and mothers dwellings within geographical clusters (Curtis *et al*, 1993; Sastry, 1997). With this section we aim to summarise broadly the common patterns which emerge from these models. Results are also supported by two comparative studies of survival chances of children born in the five-years period before DHS (Bicego and Boerma, 1991; Boerma and Bicego, 1992).

Regardless of model-deployment, a number of issues emerge from our comparisons. The three countries could further benefit from the spacing of births, the avoidance of higher-order births, and the concentration of childbearing in the central reproductive ages. The familial history of mortality, measured by both fixed and time-varying effects proved instrumental in capturing high mortality risks for children in the three settings. Whether the immediately previous child survives to the birth of the index child, is a clear and powerful indicator of the immediate risk for the index child in Sudan and Yemen, less so in Egypt. On the other hand, the complex effects of the interaction of birth order and older sibling mortality prior to the time of current births showed greater effects for Egypt. The time-varying risk effects due to the rare event of a new older sibling death occurring signals immediate risk periods for the current births in both Sudan and Egypt but not Yemen. The evidence from the status of a subsequent birth 's conception / birth / death are rather bewildering given "reverse – causality" effects. Yet the time-varying factor captures plausible interpretable immediate risks for births in the cases of Egypt and Sudan, respectively. For Yemen, the result obtained is by no means readily interpretable.

Some of our findings run contrary to common wisdom. Firstly, relationships between the education of the parents and the probability of survival of their children are moderate in Egypt and Yemen, but more substantial in Sudan, although there is some evidence that parental education may affect survival post infancy. With the exception of Rural Egypt, the urban-rural differential is rather weak. Husbands' occupation in agriculture deems higher risk for higher order births only in Yemen and are not clear-cut for the rest of the group. This weakening relationship of child survival and the typical socio-economic differentials could be a reflection of overriding economic hardship effects. Hobcraft (1993) speculates a similar interpretation as observed elsewhere for Uganda and Ghana,

The contextual “cluster-characteristics” variables described above were added to reduce unmeasured effects pertinent to the cluster-level (in the multilevel model). Overall, these variables add little explanatory power to reduce the latter effects, but some fixed-effect emerge on their own right. For Sudan and Egypt, clusters lacking planned sanitation and piped water supply are extra risk settings, while in Yemen, the disadvantage is to clusters lacking linkage to electricity supplies.

Turning to random effects, two effects are introduced, one at the cluster-level and one at the household-level. Taken over the three countries, the unmeasured effects at the cluster-level, though small in magnitude, are significant. Yet judging by the “intra-cluster” correlation coefficient, the implications compared with a marginal model that ignores the structural membership of observations within clusters would be minimal. The inclusion of random household effects via the multilevel logistic models was pertinent only to higher-order births analysis. For Sudan, we show a sizeable and significant household-effect unexplained by observed effects. No one interpretation readily lends itself for this effect, but this in part could be a result of the lack of “period” change seen earlier with Egypt and Yemen and the deteriorating socio-economic conditions in the country since the mid 1980s. One striking result was found in the case of Egypt, where controlling for familial history of mortality fixed-effects virtually eliminated the unmeasured effects at the household-level. Perhaps Egypt has the lowest level and hence variability in mortality, yet, knowledge about previous mortality in the household serves as a substantiate indicator of the household unmeasured *health-related* effects.   The same scenario could apply for Yemen if we rely on using only a bio-demographic model to explain child survival to age five. The unmeasured household effect reduces to zero, but increases to a significant magnitude once adjustment for socio-economic and contextual factors are added to the model. Perhaps, the unmeasured operand at the household level is the bigger family size in Yemen compared to Egypt, hence implying more sibling competition effects.

The conclusion to draw about the “observed” determinants of child survival is that they robust enough correlations being based on models that violate independence of measurement units. Overall many key effects were re-confirmed with this analysis. The parameter estimates might have attenuated when controlling for cluster and households effects. Previous research (Curtis et al (1993), Curtis and Steele (1996) and Guo (1993); Sastry (1997)) also observed the same effect. Yet the change is generally small and is not sufficient to alter the significance of any of the key effects.

But can we identify or disentangle any further implications to the fixed-effects when the random cluster and household effects remain detected and unexplained.

How can explain residual random effects? One possible set of factors not readily measurable by the survey relates to households' health beliefs regarding so be it beliefs about certain diseases and appropriate forms of treatment.

Another plausible explanation derives from the work of Das Gupta (1990) which suggested that some household, in similar circumstance of resource constraints, are more effective than others at taking care of their children-probably due to differences in ability to utilise such resources. Muhuri and Preston (1991) attributed differential care to the number of surviving sons relative to daughters. Typically adjustors are included to proxies of parental literacy and other socio-economic indices but those can not capture parental efficacy or priorities in child care.

Retrospective birth histories miss-out in including information on birth-specific utilisation of health, hence immunisation, services-perhaps with second and third round DHS surveys that information will become available.

If we speak in terms of a frailer sub-group, with an increased force of mortality (e.g. epidemic outbreaks, lack of immunisation, poor nutrition,..etc) frailer groups experience a quicker rate of decline of mortality even in favoured situations. In the case of Yemen-reduction in mortality rates at earlier ages (before age twelve months, say) permit more children from the frailer sub-groups to survive to an older age (age 1-4). But this influx of frailer children serves as a brake or "counter-current" on reductions in mortality rates at older ages. The size of the influx will depend on the absolute magnitude of the reduction in mortality rates at younger ages (i.e. on the number of lives being saved in the frailer subgroup) and on the chances a frailer child has of reaching an older age. If the influx is small enough, we may still observe declining mortality rates, but if the influx is large enough, observed mortality rates may actually go up (Manton *et al* ,1992).

There could be the issue of mis-specifying the distribution of the unmeasured effects. Heckman and Singer (1982) selected a simple parametric family of distributions to describe the distribution of unmeasured (unmeasurable) effects to investigate the sensitivity of parameter estimates (fixed effects) to ad hoc choices for the distribution of unmeasured heterogeneity (Normal, logNormal, Gamma, non-parametric mixed distribution) using hazard models on duration data. They used a non-parametric maximum likelihood estimator (NPMLE), implemented using the EM algorithm. NPMLE was a very robust estimator of structural parameters in duration models with general distributions of unmeasurable heterogeneity. They concluded that some qualitative properties of the distribution of an unmeasured variable can be inferred from the oscillation properties of the density of the observed duration. Moreover, an infusion is needed of theoretical and/or empirical information from sources external to a given data set for effective estimation of mixing distribution.

Another thought concerns the inter-dependencies of operands at levels of clustering. Casterline (1983) asserts that the interaction between characteristics measured at differing levels of aggregation in particular community and individual characteristics would provide a stimulus for further investigation, which he suspects will typically mean a search for omitted variables.

Where unexplained, the cluster-effects may not exactly “fit” the best classification of higher effects since a better definition could have been a “community-level” effect. Probably, adjustment for a higher-level in the hierarchy could have absorbed not just the cluster but also, the unexplainable household effects especially in the case of Sudan.

Lastly, the strong household effects are a clear sign of a familial association in mortality. Probably information on behavioural factors e.g. infant feeding practices are more relevant. Cultural difference, income distribution, which could be skewed, extremes of poverty versus affluence make a good list of omitted variables. Probably the tool to understanding those familial association is a longitudinal study rather than cross-sectional data. Yet the fact remains that these associations remain best captured by familial “mortality-background” measures until further detailed good-quality data is collected.

References

Aaby, Peter (1988). *Malnutrition and overcrowding-exposure in severe Measles infection*. A review of Community studies. Reviews of Infectious Diseases (Chicago, Illinois), Vol. 10)

Aaby, Peter (1992). *Overcrowding and intensive exposure: major determinants of variations in measles mortality in Africa.* In: Mortality and society in Sub Saharan Africa, edited by Etienne van de Walle, Gilles Pison, and Mpembele Sala Diakanda. Oxford, England, Clarendon Press : 319-48.

Amin, Sajeda; Diamond, Ian; Steele, Fiona (1997). *Contraception and religiosity in Bangladesh.* In: The continuing demographic transition, edited by G. W. Jones et al. 1997. 268-89 pp.

Armitage, Peter and Berry, Geoffrey (1994). Statistical methods in medical research. 3rd Edition, Oxford Boston Blackwell Scientific Publications, 620p

Boerma, J. T. and G. T. Bicego (1992). *Preceding birth intervals and child survival: searching for pathways of influence*. Studies in Family Planning.. 23, no. 4: 243-56.

Breslow, N.E; Clayton, D.C (1993). *Approximate inference in generalized linear mixed models*. JASA 88:9-25, 1993.

Casterline, J. B (1983). *Community effects on fertility.* In: The collection and analysis of community data: WFS Seminar on Collection and Analysis of Data on Community and Institutional Factors : 65-75.

Casterline, J. B. (1987). *The collection and analysis of community data*. In: The World Fertility Survey: an assessment, edited by John Cleland and Chris Scott in collaboration with David Whitelegge. [London, England], International Statistical Institute by Oxford University Press : 882-905.

Cesar, Cibele C.; Palloni, Alberto; Rafalimanana, Hantamalala (1997). *Analysis of child mortality with clustered data: a review of alternative models and procedures.* CDE Working Paper, No. 97-04, [1997]. 36, [13] pp. University of Wisconsin, Center for Demography and Ecology: Madison, Wisconsin.

Collett, D (1994). *Modelling Survival Data in Medical Research.* Texts in Statistical Sciences, London , Chapman & Hall

Cox, D.R (1972). *Regression Models and Life-tables* (with Discussion). Journal of the Royal Statistical Society (Series B) 34: 187-220

Curtis, Sian L.; Diamond, Ian; McDonald, John W. (1993). Birth interval and family effects on postneonatal mortality in Brazil. Demography, Vol. 30, No. 1, Feb 1993. 33-43 pp

Curtis, Siân L.; Steele, Fiona (1996). Variations in familial neonatal mortality risks in four countries. Journal of Biosocial Science, Vol. 28, No. 2, Apr 1996. 141-59 pp.

Das Gupta, M. (1990). *Death clustering, mothers' education and the determinants of child mortality in rural Punjab, India*. Population Studies. 44, no. 3: 489-505.

Goldstein, H. (1986). Multilevel mixed linear model analysis using iterative generalised least squares. Biometrika, 73, 43-56.

Goldstein, H. (1989). *Restricted Unbiased Iterative Generalised Least Squares Estimation*. Biometrika, 76, 622-623.

Goldstein, H. (1995). *Multilevel Statistical Models*. London: Edward Arnold: New York, Wiley.

Goldstein, H. and Rasbash, J. (1996). *Improved approximations for multilevel models with binary responses.* Journal of the Royal Statistical Society, A. 159, 505-514.

Gray, R. H (1990). *Epidemiologic methods and case-control studies of mortality and morbidity.* In: Measurement and analysis of mortality: new approaches, edited by Jacques Vallin, Stan D'Souza, and Alberto Palloni. New York, New York / Oxford, England, Oxford University Press : 64-83.

Guo, Guang (1993). *Use of sibling data to estimate family mortality effects in Guatemala*. Demography, Vol. 30, No. 1, Feb 1993. 15-32 pp.

Heckman, JJ; Singer B, (1982). *Population heterogeneity in demographic models. In: Multidimensional mathematical demography.* Edited by Kenneth C. Land and Andrei Rogers. New York, N.Y., Academic Press, 1982. :567-599.

Hobcraft, J. N (1987). *Does Family Planning Save Lives?* Technical background paper prepared for the International Conference on Better health for Women and Children through Family Planning, Nairobi, Kenya.

Hobcraft, J (1993). *Women's education, child welfare and child survival: a review of the evidence.* Health Transition Review, Oct;3(2):159-75

Hobcraft, J (1994). *The Health Rationale for Family Planning : timing of births and child survival.* New York: United Nations. Department for Economic and Social Information and Policy Analysis. Population Division,112 p. ST/ESA/SER.A/141.

Hobcraft, J.; McDonald, J, and Rutstein, S.O. (1983). Child-spacing effects on infant and early child mortality. Population Index (Princeton, New Jersey) vol. 49, no. 4: 585-618.

Hobcraft, J.; McDonald, J, and Rutstein, S.O. (1984). Socio-economic factors in infant and child mortality: a cross national comparison. Population Studies. 38, no. 2: 193-223.

Hobcraft, J.; McDonald, J, and Rutstein, S.O. (1985). Demographic determinants of infant and early child mortality: a comparative analysis. Population Studies. 39, no. 3: 363-85.

Johnson, Norman L.; Samuel Kotz (1970). *Continuous univariate distributions*, Vol. 1.

Kalbfleisch,J.D. and Prentice, R.L. (1980). *The Statistical Analysis of Failure Time Data.* New York: Wiley.

Longford, N.T (1987). *A fast scoring algorithm for maximum likelihood estimation in unbalanced mixed models with nested random effects*. Biometrika 74, 817-27.

Manson, et al (1983). Missing.

Manton, Kenneth G.; Singer, Burton; Woodbury, Max A. (1992) *Some issues in the quantitative characterization of heterogeneous populations.* In: Demographic applications of event history analysis, edited by James Trussell, Richard Hankinson, and Judith Tilton. 1992. 9-37 pp.

McCullagh, Peter and Nelder, John, (1983). Generlized linear models (1st edition) London: Chapman and Hall, London.

MLwiN (1998). Multilevel Models Project, Institute of Education, University of London.

Muhuri, P. K. and S. H. Preston (1991). *Effects of family composition on mortality differentials by sex among children in Matlab, Bangladesh.* Population and Development Review. 17, no. 3: 415-34.

Neuhaus, J.M & N. P. Jewell (1990). *Some Comments on Rosner's multiple logistic for clustered data.* Biometrics 46: 523-534

Pebley, A. R. and S. Millman (1986). *Birthspacing and child survival.* International Family Planning Perspectives. 12, no. 3: 71-9.

Pebley, Anne R.; Goldman, Noreen; Rodríguez, Germán (1996) . *Prenatal and delivery care and childhood immunization in Guatemala: do family and community matter?* Demography, Vol. 33, No. 2, May 1996. 231-47 pp.

Palloni, A. and S. Millman (1986). *Effects of inter-birth intervals and breastfeeding on infant and early childhood mortality.* Population Studies. 40, no. 2: 215-36.

Palloni, A. et al (1992*). Missing*

Raudenbush, S.W. and Bryk, A.S. (1986). *A hierarchical model for studying school effects*. Sociology of Education, 59:1-17.

Rodríguez, Germán; Goldman, Noreen (1995). *An assessment of estimation procedures for multilevel models with binary response*: Journal of The Royal Statistical Society, Series A, 158: 73-89 pp.

Sastry, Narayan (1996*). Community characteristics, individual and household attributes, and child survival in Brazil.* Demography,Vol.33,No.2,May 1996.211-29 pp.

Sastry, Narayan (1997). *Family-level clustering of childhood mortality risk in Northeast Brazil.* Population Studies, Vol. 51, No. 3,Nov 1997. 245-61 pp.

Stata 6.0 (1999). Stata Reference Manual Release 6 Volume 2 (H-O):251-261. Stata Corp 1999. Stata Statistical Software: Release 6.0. College Station, TX: Stata Corporation.

Trussell, J. and C. Hammerslough (1983). *A hazards-model analysis of the covariates of infant and child mortality in Sri Lanka.* Demography 20, no. 1: 1-26.