The Springer Series on Demographic Methods and Population Analysis

Volume 46

Series Editor
Kenneth C. Land, Duke University

In recent decades, there has been a rapid development of demographic models and methods and an explosive growth in the range of applications of population analysis. This series seeks to provide a publication outlet both for high-quality textual and expository books on modern techniques of demographic analysis and for works that present exemplary applications of such techniques to various aspects of population analysis.

Topics appropriate for the series include:

- General demographic methods
- Techniques of standardization
- Life table models and methods
- Multistate and multiregional life tables, analyses and projections
- Demographic aspects of biostatistics and epidemiology
- Stable population theory and its extensions
- Methods of indirect estimation
- Stochastic population models
- Event history analysis, duration analysis, and hazard regression models
- Demographic projection methods and population forecasts
- Techniques of applied demographic analysis, regional and local population estimates and projections
- Methods of estimation and projection for business and health care applications
- Methods and estimates for unique populations such as schools and students

Volumes in the series are of interest to researchers, professionals, and students in demography, sociology, economics, statistics, geography and regional science, public health and health care management, epidemiology, biostatistics, actuarial science, business, and related fields.

More information about this series at http://www.springer.com/series/6449

Christos H. Skiadas • Charilaos Skiadas
Editors

Demography and Health Issues

Population Aging, Mortality and Data Analysis

Springer

Editors
Christos H. Skiadas
ManLab, Technical University of Crete
Chania, Crete, Greece

Charilaos Skiadas
Department of Mathematics/Computer Science
Hanover College
Hanover, IN, USA

ISSN 1389-6784 ISSN 2215-1990 (electronic)
The Springer Series on Demographic Methods and Population Analysis
ISBN 978-3-319-76001-8 ISBN 978-3-319-76002-5 (eBook)
https://doi.org/10.1007/978-3-319-76002-5

Library of Congress Control Number: 2018940767

Printed on acid-free paper

This Springer imprint is published by the registered company Springer International Publishing AG part of Springer Nature.
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

This book deals with demography and health issues with special attention on population aging, mortality, and data analysis. Emphasis is done on the introduction and use of quantitative methods and advanced data analysis methods in various aspects of demography and health.

The quantitative methods, with the aid of informatics and computing, received special attention in the last decades of the twentieth century and have further developed and applied in the first part of the twenty-first century. These methods already have done considerable changes in various scientific fields and of course in estimating vital aspects of demography and health.

Mortality, population aging, and data analysis are further developed while the tools used are friendly to end user. Accordingly, a large number of people are "ready" to understand and apply the new tools, thanks to the fastgrowing literature both theoretical and applied along with many "computer packages" and visual support.

The interdisciplinary works are considered as an important task of the new era along with the development of fields like Data Science and Big Data Analysis important to handle large data sets familiar in international studies in demography and health sciences. In a view the twenty-first century is already characterized by an optimistic way of data analysis approaches. We have a large number of people educated and trained to collect and store data sets and vast and expanded networks to disseminate information. Demography and health have most benefited and more developments are in progress.

Accordingly we have edited this book by selecting and providing the material in order to support the quantitative data handling along with qualitative study and analysis. This book covers very important topics on demography and health issues organized in six chapters.

Chapter one focusses on Demography and Related Applications in Health Status and the Lifespan Limit, including three papers on modeling and estimation of the health state and the healthy life expectancy of a population and a paper on exploring the limits to human life span, a challenging subject renewed last years after several publications in Nature.

Chapter two on Mortality Modeling and Applications includes four contributions including the establishment and development of a mortality database for developing countries, an application in Brazil, and two methodological papers for forecasting mortality and evaluation of the health trends with application in Greece.

Chapter three on Statistical Models and Methods in Biostatistics and Epidemiology includes a contribution on the cumulative rate of kidney cancer statistics in Australia, a paper on the reliability of mortality shifts in the working population in Russia, and a three-way data analysis applied to specific mortality trends. All papers focus on important statistical methodologies and related applications.

As far as new methods and tools are introduced in demography and health issues, the four papers included in Chapter four on Stochastic and Neuro-Fuzzy Methods provide interesting information on handling and applying advanced methodologies. Space-time variables, stochastic distance estimation, Monte Carlo methods in health research, and attitude measurement by a neuro-fuzzy approach are analyzed and applied.

Chapter five on Data Analysis in Demography includes six papers covering important topics on data handling and related statistics. Data decomposition, statistical analysis of health risks, an inference system for mortality data, a study on the Jackson exponentiality test, intervention analysis, and special statistics are the main topics studied.

Health Sciences, Demography, Risk, and Insurance is the topic presented in Chapter six in the seven papers included. Risk factors and risk estimates, job insecurity measurement, health estimates of some countries of the rapid developing world, social capital, income inequality and the health of the elderly, retirement scheme from the Italian mortality experience, and application of a Probit model for analyzing the death clustering of the Tribes of Central and Eastern India are presented and further analyzed.

We thank all the contributors and especially the authors of this book and of course the Springer team for help and support.

Chania, Crete, Greece — Christos H. Skiadas
Hanover, IN, USA — Charilaos Skiadas
December 2017

Contents

Chapter 28
Sibling Death Clustering Among the Tribes of Central and Eastern India: An Application of Random Effects Dynamic Probit Model

Laxmi Kant Dwivedi and Mukesh Ranjan

28.1 Introduction

The Infant mortality rate (IMR) has been considered as a highly sensitive measure of population health. This reflects the apparent association between the causes of infant mortality and other factors that are likely to influence the health status of populations such as their economic development, general living conditions, social wellbeing, rates of illness, and the quality of the environment (Whitehouse 1982). There were around 4.6 million deaths (74% of all under-five deaths) occurred within the first year of life (WHO 2011). Globally, IMR has decreased from an estimated rate of 63 deaths per 1000 live births in 1990 to 34 deaths per 1000 live births in 2013 (UNICEF 2014).

One of the targets under United Nations Millennium Development Goals (UNMDGs) is to reduce IMR by two-thirds between 1990 and 2015. For India, it translates into a goal of reducing IMR from 88 infant deaths per thousand live births in 1990 to the level of 29 infant deaths per thousand live births by 2015. The recent figure of IMR for India, is 37 infant deaths per 1000 live births (Sample Registration System (SRS) 2015). Hence, it clearly reflects that India lagged far behind in achieving mortality related UNMDGs goal. In India, the issue of high IMR exists with a lot of regional variations across the states. For example, among the bigger states and UTs, IMR varies from 12 in Kerala to 50 in Madhya Pradesh (SRS 2015). In view of these statistics, child survival in India needs sharper focus. This includes better managing neonatal and childhood illnesses, improving child survival, particularly among vulnerable communities and we need a different approach to tackle the IMR & under 5 mortality rate (U5MR). Survival risk remains a key challenge for the disadvantaged who have little access to reproductive and child health services.

L. K. Dwivedi · M. Ranjan (✉)
International Institute for Population Sciences (IIPS), Mumbai, Maharashtra, India

C. H. Skiadas, C. Skiadas (eds.), *Demography and Health Issues*,
The Springer Series on Demographic Methods and Population Analysis 46,
https://doi.org/10.1007/978-3-319-76002-5_28

Major states in the heartland of India fell significantly short of UNMDGs targets related to infant mortality, by more than 20 points.

In the backdrop of high mortality situation prevailing in the developing nations across the world including India, the situation of high mortality is not only an issue of concern itself but it also have a strong linkages with the intra-family clustering of deaths in a particular region. In other words, there may be a situation when there is a high mortality in the region but deaths are not randomly distributed in the entire exposed families of the area rather there are certain high- risk families which only experiences deaths frequently and other families in the nearby in spite of sharing the similar socio-cultural environment do not experience frequent child loss. This situation is known widely among researcher as death clustering. This phenomena was first highlighted by Das Gupta (1990) in her paper while studying child mortality in rural Punjab. Since then it is on the research agenda while studying infant mortality and also a new dimension of familial component got added and entire research community has seen this phenomena as another important approach for studying infant and child mortality.

Among various social groups, it has been found that on average, an Indian child has 25 percent lower likelihood of dying under age five as compared to an Adivasi or Tribal child (Das et al. 2010). According to the third round of the National Family Health Survey (IIPS 2007), in rural areas where a majority of *adivasi* children live, contributed about 11 percent of all births and almost one-fourth of all deaths under the age of 5 years. Children born to women from scheduled castes (SCs) and scheduled tribes (STs) have higher mortality rates than children born to women from other backward classes and other than these classes (i.e., general/advanced classes). A nationally representative study of India based on the 1981 census also indicated that under-five mortality among STs and SCs was significantly higher than non-tribal population (Das et al. 2014). The gap in infant mortality between tribal and non-tribal populations was substantial in the early months after birth, narrowed between the fourth and eighth months, and enlarged mildly afterwards (Ranjan et al. 2016). In a study on clustering of infant deaths in families in central and eastern region of India, it was found that among SCs & STs, infant death clustering is mainly affected by the scarring factor that is effect of previous infant deaths in families on the survival status of index child in Jharkhand and Madhya Pradesh,while mother-level unobserved factors were important in Odisha and both scarring and mother-level unobserved factors were key factors in Chhattisgarh (Ranjan et al. 2018).

Tribes are varied in terms of their socio-economic and political development. The term “Scheduled Tribes” refers to specific indigenous peoples whose status is acknowledged by the Constitution of India. The tribal population in India, according to the 2011 census, was 87 million and it constitutes around 8.2 percent of the total Indian population. Around 80 percent of them found in central India and a large part of the rest in the north-eastern states. The maximum share of tribal population is contributed by Madhya Pradesh (14.7%), followed by Odisha (9.2%), Jharkhand (8.3%) and Chhattisgarh (7.5%) to the India’s population. A majority of tribal population living in these states are the Particularly Vulnerable Tribal Groups (PVTGs) (Ministry of Tribal Affairs 2015). They are socially as well as economically backward in the sense that they have little access to the resources for their development, low rate of literacy, relatively small population size, dwindling in numbers and some of the groups are at the verge of extinction. They are distributed in various ecological zones beyond the state boundaries with immense variation in subsistence pattern, technological development, ways of living and contact with outside world as well as with different worldviews in respect with neighborhoods called mainstream population. Accordingly, the present research was undertaken to investigate the extent of clustering of infant deaths among tribal families by rural-urban in the central and eastern states of India. This paper also explores whether infant deaths are uniformly distributed among tribal mothers across different states of this region after adjusting the confounding variables using random effects dynamic probit model. Lastly, the reduction in infant deaths will be worked out by changing the level of scarring factor and literacy status of women.

28.2 Materials and Methods

In order to examine the family level infant death clustering bivariate analysis was carried out and for capturing the linkages between survival prospects of siblings and mother specific unobserved heterogeneity, the random effects dynamic probit model was applied. The random effects dynamic probit panel data model has the advantage of simultaneously capturing unobserved heterogeneity and the causal positive or negative scarring mechanisms at the same time in the model. The model also accounted for the endogeneity factor which arose due to the inclusion of previous sibling-survival status in the model, thus avoiding the potential bias in previous studies.

The potential problem which has been found in the empirical specification of the earlier models include the problem of left truncation & endogeneity, measurement error and time inconsistency (Bolstad and Manda 2001; Curtis et al. 1993; Guo 1993; Sastry 1997). It would be very important to understand these unaddressed problems of the earlier models. First, left truncation is the problem associated with retrospective data. It means an age cut-off is used to select the respondents. The interviewees may be a representative sample at survey date, but they will not be so for earlier years (Rindfuss et al. 1982).This non-representativeness of the sample over the years along with the recall bias, a common practice in previous research has been to discard information on children who were born before an arbitrarily selected date, such as 10 or 15 years before the date of the survey (Bhargava 2003; Bolstad and Manda 2001; Curtis et al. 1993; Guo 1993; Madise and Diamond 1995; Sastry 1997). This left truncation of the data by calendar time occurs at the different points in the birth history, creating additional complications. Many studies have even discarded the first-born child in every family. This will result in a severe loss of information. Moreover, left truncation of the data, whether by calendar time or by birth order of child, will lead to the problem that the start of the sample does not coincide with the start of the stochastic process under study. The next issue is of measurement error as it can be seen that the risk of mortality among index child is a function of the preceding child's survival status. Positively correlated measurement in these variables will tend to create an upward bias in the scarring coefficient that is coefficient of previous child survival. This potential problem is addressed in the present model. The other problem related with variables inconsistent with time has been sorted out in the present model. It is usually seen that data in retrospective surveys with regard to child, year of birth and death is available for the larger number of years. In our case, information was available for more than 35 years before the survey date. These surveys typically gather information on variables such as household assets, toilet facilities, electricity or access to piped water at the date of the survey. The time inconsistency problem is that, in such cases, data that pertain to the survey date are less informative. It means the information of certain predictors which are though important one are not available for all the children under study. In the present analysis, where the entire birth history of each tribal mother was used, the problem was even more severe. We, therefore, did not include any currently dated variables as explanatory variables in the model.

By ignoring these potential problems, bias will be created because previous child's survival status and its correlation with survival status of index child will confound the causal interpretation of previous death in the family. In order to avoid these biases, modelling of the initial condition (mortality risk for first-born children) jointly with the dynamic mortality process for the second and higher-order births need to be applied (Arulampalam and Bhalotra 2006, 2008; Heckman 1987; Manski and McFadden 1981; Oettinger 2000; Wooldridge 2010). The present study used the dynamic panel data model along with the initial condition to assess the death clustering among tribes of central and eastern India. Model with such initial condition will estimate the scarring effect that is effect of previous death in families on the survival status of the index child without bias and establish the true impact in studying the death-survival relationship among siblings. The relative contribution of social factors, that is, literacy status vis-à-vis biological factors, that is, survival status of sibling is examined in explaining the infant deaths.

28.2.1 Data Source

The data used in the study is taken from National Family health Survey-3 which was conducted in 2005–06. It interviewed 124,385 ever married women aged 15–49 at the time of the survey. It has a complete retrospective history of births together with a record of child deaths for each mother, for a period spanning more than 35 years (1970–2006). Thus, it would give sufficient number of cases for analysis as well as we would be able to construct (unbalanced) panel data for mothers. Further full retrospective birth history has been used for all the statistical analysis in the study.

28.2.2 The Empirical Model

The dependent variable that is infant death of index child and the main covariates survival status of the preceding child (i.e. lagged variable) were both coded as binary variables -one if a child died before the age of 12 months and zero otherwise. By taking child specific and mother specific covariates along with preceding child (lagged variable), the random effect dynamic probit model was applied. Children who were younger than 12 months at the time of the survey were dropped from the sample because they had not 12 months of exposure to mortality risk. When the index child was not singleton but instead twins they were also dropped from the model so that siblings should be identified properly.

28.2.3 Choice of Independent Variables

The predictors like, sex and birth order of the child, mother's education, religion, caste and place of residence, exposure to mass media, availability of toilet facility, type of fuel used for cooking and standard of living, mother receiving tetanus immunization during pregnancy and preceding birth interval were considered as the main determinants of infant and child mortality for most of the Indian states (Pandey and Tiwary 1993). Apart from the above factors, the tribal children, in fact, face certain adverse realities like insufficient food intake, frequent infections, and lack of access to health services. They also have the lack of awareness about environmental sanitation and personal hygienic practices, proper child rearing, breastfeeding and weaning practices (Pandey and Tiwary 1993; Reddy 2008). Women's autonomy, social class, mother's education and quality care received by the children has been cited as some of the reasons for clustering (Madise and Diamond 1995). Causal factors that determine equality levels in the distribution of mortality risks for children between families or between mothers may conveniently be divided into two factors: Bio-demographic differentials and differentials in other socioeconomic characteristics of the families (and/or the mother) (Zaba and David 1996). Bio-demographic factors include mother's age, fertility levels, and birth-spacing patterns, as well as inherited genetic disorders and the mother's medical condition and disease profile. Socioeconomic differentials includes characteristics of the families like income, occupation, and social class, and level of education, as well as factors relating to the wider environment of the child, such as the community, the neighbourhood, and the family's ecological and disease environment. The socio-economic category also contains the much-discussed "maternal competence" factor (breastfeeding behaviour and behaviours or attitudes that affect the child health). Other authors have likewise stressed the connections among clustered mortality, family size, and fertility patterns (Ronsmans 1995). Taking the idea that the death of one child 'scars' the family, making the next child in that family more vulnerable

(Arulampalam and Bhalotra 2006). Studies often attribute death clustering to socio-demographic covariates: either a causal scarring effect (the previous sibling's survival status being included as a covariate) or unobserved heterogeneity (with family or community-specific effects) (Reddy 2008). Some studies included both, but without accounting for the bias induced by potential correlation between the unobserved heterogeneity and previous child's survival-status (Bolstad and Manda 2001; Curtis et al. 1993; Ronsmans 1995; Sastry 1997). The present study is using econometric dynamic panel data model which at the same time capture both the unobserved heterogeneity and the causal positive or negative scarring mechanisms. This model has also been used in few of the earlier studies referred to as 'state dependence' if panel data are used (Arulampalam and Bhalotra 2006, 2008; Heckman 1987; Manski and McFadden 1981; Wooldridge 2010). This model accounts for the endogeneity of previous sibling-survival status, thus avoiding the potential bias in previous studies.

The child-specific covariates considered in the model are Sex of the index child, Survival status of the previous sibling;

mother specific covariates in the model include Educational attainment, religion of the mother, mother's age at the birth of index child and wealth status of the household; *and community level variables* are state of residence and place of residence.

The educational attainment of respondent's partner has been categorized into two categories viz. literate and illiterate. Wealth status of the household has been divided into three categories poor, middle &rich. Mother's age at child birth was taken as continuous variable as it will take into account both mother's age and child's birth interval. Religion was taken in two categories hindus and others.

28.2.4 Statistical Model

The dynamic panel data model was:

$$Y_{ij}^{*} = X_{ij}^{*}\beta + \gamma Y_{ij-1} + \alpha_i + u_{ij} \tag{28.1}$$

Let there be n_i children of mother i. For child j $(j = 1,2\ldots,n_i)$ of mother i $(i = 1,2,\ldots,N)$, the unobservable propensity to experience an infant death, Y_{ij} * is specified in Eq. (28.1). Where X is a vector of strictly exogenous observable child-specific and mother-specific characteristics and β is the vector of coefficients associated with X. The dynamic panel data model of Eq. (28.1) has the panel consisting of a naturally time ordered sequence of siblings within mothers. A child is observed to die when his or her propensity for death crosses a threshold; in this case $Y_{ij}^{*} > 0$. The model has a random intercept α_i, to account for time-invariant mother specific unobserved characteristics. This picks up any correlation of death risks among siblings arising, for example, from shared genetic characteristics or from innate ability of their mother.

The model also includes the observed survival status of the previous siblings, Y_{ij-1}, the coefficient which picks up scarring. The estimated parameter γ should be interpreted as the 'average' effect of scarring over the time period considered. In models of this sort, the previous sibling's survival status, Y_{ij-1} is necessarily correlated with unobserved heterogeneity, α_i. In order to identify a causal effect, we need to take account of this correlation in the estimation. This is referred to as the 'initial conditions' problem (Heckman 1987; Wooldridge 2010). We are thus able to model the initial condition of the process as a natural extension of the model given in Eq. (28.1). We specify the equation for the first-born child of each mother as

$$\mathrm{Y}*_{\mathrm{i1}} = \mathrm{Z_i}' \lambda + \theta\, \alpha_{\mathrm{i}} + \mathrm{u_{i1}} \tag{28.2}$$

i = 1... N and j = 1.

Where, Z_i is a vector of strictly exogenous covariates. In general, Eq. (28.2) allows the vector of covariates Z to differ from X in Eq. (28.1). However, we set the two vectors of covariates to be the same given that we observe the process from the start. Eqs. (28.1) and (28.2) together specify a complete model for the infant survival process. In this way, the endogeneity of the 'lagged dependent variable', that is, the previous child's survival status is taken into account. The effect of unobservable mother's characteristics in Eqs. (28.1) and (28.2) to be correlated by specifying this unobservable as $\theta\alpha_i$. We assume that u_{ij} is independently distributed as a logistic distribution, and that the mother specific unobservable, α_i, are independent and identically distributed as normal. Marginalizing the likelihood function with respect to α_i, gives for mother i. Previous analyses of dynamic models with unobserved heterogeneity have shown the potential sensitivity of the estimates to the assumption made about the distributional form for unobserved heterogeneity, α_i (Heckman and Singer 1984). A weakness of the normality assumption is that it may not be flexible enough to account for the fact that some families never experience any child deaths and that, in some families, all children die (the mover-stayer problem). Our sample does not contain any families in which all children die in infancy. However, there are many families that experience no infant deaths, and this is accommodated by allowing for a single (empirically determined) mass at minus infinity: a very large negative value for α_i gives a very small value for Y_{ij}^*, and hence a very small probability of observing death of the index child (Narendranathan and Elias 1993). A test of H_0: $\sigma_\alpha^2 = 0$ is a test that there is no unobservable characteristics of the mother in the model.

This can be tested by using a likelihood ratio test (or a standard normal test) but the test statistic will not have a standard chi-square (or a standard normal) distribution since the parameter under the null hypothesis is on the boundary of the parameter space. The standard likelihood ratio (normal) test statistic is 0.5 χ^2 (1) (0.5 N(0, 1)) for positive values.

In addition to mother-specific unobserved heterogeneity, community level random effects were included in the model to account for the sampling design, which involved clustering at the community level. Failure to allow for community level unobserved heterogeneity in the likelihood maximization would provide consistent parameter estimators but inconsistent standard errors (Deaton 1997). Although the model is multilevel, we have chosen to treat the community level effect as a nuisance parameter. This is because we cannot interpret a time invariant community level effect in any meaningful manner. To the extent that families migrate or the infrastructure of different communities develops at different rates, the assumption of a time invariant community effect is restrictive: we expect that children of the same mother, who are born at different dates, may experience different community level effects. In any case, in this paper, the focus is not on estimation of the variance that is associated with mothers versus communities but, rather, on robust estimation of the scarring effect, which is captured in the parameter γ.

28.3 Results

28.3.1 Sample Characteristics of Tribal Mothers and their Children

Table 28.1 shows the characteristics of 2494 sampled tribal mothers (or families) and their 9069 children in the central and eastern region of India. From the table it is observed that 70 percent families never experienced any infant deaths while rest 30 percent families experienced all infant deaths. Among 30 percent families, nearly 10 percent families experienced clustered of infant deaths (families with at least two deaths) and rest 20 percent had only one infant death. Nearly 90 percent families belong to Hindus. Of total families, most of them were illiterate (89%). Almost substantial proportion (94%) of tribe mothers resides in rural areas. Nearly, 89 percent families were poor while less than 5 percent families falls in rich wealth group. A majority of tribe mothers (96%) did not have improved sanitation facilities and defecated in open or have unhealthy disposal of stool. Nearly 60 percent families receive safe drinking water. The child characteristics shows that there were 9069 total children born during 1970–2006, nearly 12 percent died as infant. There were 10 percent such children whose sibling also died as infant. Of total births of central and eastern regions, nearly 43 percent and 20 percent births took place in Madhya Pradesh & Odisha, respectively. More than half of the children were male. Births with first order contributed 27 percent of the total sampled children. Nearly 17 percent births born as second or higher order and the gap between two successive births were less than 24 months while 56 percent births were of second or higher order and had birth interval more than 24 months.

Table 28.1 Sample characteristics of Tribal mothers & their children, central & eastern India, 2005–06

Mother/Family Characteristics #	Percent	Number
State		
Jharkhand	19.2	**464**
Odisha	23.7	**617**
Chhattisgarh	18.8	**696**
Madhya Pradesh	38.3	**717**
Families with		
No infant death	70.3	**1782**
One infant death	20.5	**494**
At least two infant death	9.2	**218**
Religion		
Hindu	89.5	**2226**
Others	10.5	**268**
Mother's education		
Illiterate	80.8	**1970**
Literate	19.2	**524**
Place of residence		
Urban	6.2	**278**
Rural	93.8	**2216**
Wealth index		
Poor	88.6	**2129**
Middle	6.8	**189**
Rich	4.7	**176**
Sanitation Facility		
Improved	3.6	**151**
Not improved	96.4	**2343**
Drinking water		
Safe	59.9	**1514**
Unsafe	40.1	**980**
Total	**100.0**	**2494**
Child characteristics $	**Percent**	**N**
Infant death		
No	88.5	8045
Yes	11.5	1024
Previous infant death		
No	10.0	896
Yes	90.0	8173
State		
Jharkhand	18.5	1655
Odisha	21.1	2028
Chhattisgarh	17.9	2456

(continued)

Table 28.1 (continued)

Mother/Family Characteristics #	Percent	Number
Madhya Pradesh	42.5	2930
Sex of the child		
Male	50.6	4616
Female	49.4	4453
Birth interval		
Birth order 1	26.9	2494
BO> = 2 & BI<24 months	17.0	1497
BO> = 2 & BI> = 24 months	56.1	5078
Total	**100.0**	**9069**

Note: # is based on sample of mother and $ is based on sample of children who born between 1970 and 2006

28.3.2 Distribution of Infant Deaths among Tribes by Background Characteristics in Central and Eastern India

Table 28.2 shows the distribution of 1024 infant deaths and 8045 births who survived at least age 12 months among tribal families by selected background characteristics in the central and eastern India. Of total infant deaths, Madhya Pradesh experienced 45%, Odisha observed 20%, Chhattisgarh and Jharkhand each contributed nearly 17% infant deaths. A majority of infant deaths took place among Hindus. 87% tribal children who died during infancy had mothers as illiterate. Most of the deaths took place in rural areas. Nearly 91% infant death occurred in poor families. Among total infant deaths, 20% infant deaths also had a prior sibling who died as infant.

28.3.3 Clustering of Infant Deaths among Families in the Central and Eastern India

Tables 28.3a and 28.3b shows the clustering of infant deaths among tribal families by region of residence in the central and eastern India. In urban areas it is noticed that among 278 families who had one or more live births, nearly 78% families never experienced any infant deaths while remaining 22% families experienced all infant deaths. Of 22% families who have experienced any infant deaths, nearly 7% families have contributed 52% clustered infant deaths (2 or more infant deaths). In the Rural areas, of total 2216 families, nearly 85% families have given two or more births which accounted for 96% of total 8179 children. Further, of total 938 infant deaths in rural areas, there were 71% families who never experienced any infant deaths, 20% families experienced exactly one infant deaths and had 48% of total infant deaths

Table 28.2 Distribution of births that not died as infant & Infant deaths among tribal families by background characteristics, Central & eastern India, 2005–06

Variables	Percent	Number	Percent	Number
State				
Jharkhand	17.0	173	18.7	1482
Odisha	20.4	221	21.2	1807
Chhattisgarh	17.7	277	17.9	2179
Madhya Pradesh	44.9	353	42.2	2577
Religion				
Hindu	90.1	923	89.7	7188
Others	9.9	101	10.3	857
Mothers education				
Illiterate	87.1	891	85.5	6773
Literate	12.9	133	14.5	1272
Place of residence				
Urban	5.3	86	5.7	804
Rural	94.7	938	94.3	7241
Wealth index				
Poor	91.2	908	89.3	6957
Middle	6.8	77	6.7	599
Rich	2.1	39	4.0	489
Previous infant death				
Yes	80.0	817	91.3	7356
No	20.0	207	8.8	689
Sex of the child				
Male	54.3	570	50.1	4046
Female	45.8	454	49.9	3999
Birth interval				
Birth order 1	34.2	359	25.9	2135
BO> = 2 & BI<24 months	29.4	294	15.4	1203
BO> = 2 & BI> = 24 months	36.5	371	58.7	4707
Total	**100**	**1024**	**100.0**	**8045**

while remaining 9% families experienced two or more infant deaths and the extent of clustered infant deaths in such families was 52%.

28.3.4 Result of Random Effects Dynamic Probit Model & Unobserved Heterogeneity

Table 28.4 shows the results of random effects dynamic probit model of infant deaths among tribes in the central and eastern India. After adjusting for mother, child and community level characteristics in the model, it is observed that infant deaths is more

Table 28.3a Clustering of infant deaths among tribal families in urban areas of central& eastern India, 2005–06

Total Children ever born	Infant deaths per family 0	1	2	3	5	Total Families	Children	% Children
1	45	2	0	0	0	47	47	5.3
2	58	7	0	0	0	65	130	14.6
3	55	5	2	0	0	62	186	20.9
4	34	12	4	1	0	51	204	22.9
5	13	7	4	1	0	25	125	14.0
6	7	3	2	0	0	12	72	8.1
7	3	1	1	0	1	6	42	4.7
8	1	4	2	0	0	7	56	6.3
9	0	1	0	1	0	2	18	2.0
10	1	0	0	0	0	1	10	1.1
Families	217	42	15	3	1	**278**	**890**	
% families	78.1	15.1	5.4	1.1	0.4	**6.8**		
Infant deaths	0	42	30	9	5	**86**		
% infant deaths	0.0	48.8	34.9	10.5	5.8	**51.2**		

likely to occur in families who experienced prior infant deaths in comparison to those families who never experienced any prior infant loss and result was statistically significant ($p < 0.01$). Infant deaths was more likely to occur in the states of Madhya Pradesh in comparison to Jharkhand ($p < 0.05$). Mothers age at birth of index child was found to be negatively associated with infant deaths and as mother's age at child's birth increases, infant deaths is less likely and it is statistically significant ($p < 0.01$). Further, infant deaths among female child was less likely to be seen in comparison with male child. Religion, mother's education, place of residence and household wealth was found to be statistically not significant factors affecting infant deaths in this region. The value of intra class correlation which represent intra mother correlation coefficient by value of theta was found to be statistically not significant which represent that mother level unobservable characteristics do not affect the child mortality outcome and the initial condition problem was empirically unimportant in the region. This was further supported by the fact that intra class correlation was not significant which also make the estimated mother specific unobservable to be not significant as was depicted in the model. Further, mother level unobserved factors was also found to be not significant in all four states of the central and eastern India. The insignificant value of theta and mother specific unobserved heterogeneity and similar significant value of coefficient of previous death in both random effect dynamic probit model and the probit model suggest that probit model was equally better model to capture infant deaths. So, we have used the probit model based simulation to examine the effect of scarring and literacy on infant deaths in the region and in its four states.

Table 28.3b Clustering of infant deaths among tribal families in rural areas of central& eastern India, 2005–06

	Infant deaths per family									
Total children ever born	0	1	2	3	4	5	6	Family	Children	% Children
1	290	28	0	0	0	0	0	318	318	3.9
2	345	51	7	0	0	0	0	403	806	9.9
3	362	67	10	2	0	0	0	441	1323	16.2
4	251	83	20	4	0	0	0	358	1432	17.5
5	163	87	27	6	3	0	0	286	1430	17.5
6	90	65	31	8	0	0	0	194	1164	14.2
7	44	35	15	6	6	1	0	107	749	9.2
8	10	16	12	6	4	0	0	48	384	4.7
9	7	15	9	6	4	0	0	41	369	4.5
10	3	4	4	3	0	2	1	17	170	2.1
11	0	1	1	0	0	0	0	2	22	0.3
12	0	0	1	0	0	0	0	1	12	0.1
Family	1565	452	137	41	17	3	1	**2216**	**8179**	
% family	70.6	20.4	6.2	1.9	0.8	0.1	0.0	**9.0**		
Infant deaths	0	452	274	123	68	15	6	**938**		
% infant deaths	0.0	48.2	29.2	13.1	7.2	1.6	0.6	**51.8**		

Table 28.4 Result of random effects dynamic probit model of infant death by selected background characteristics among tribes, central & eastern India, 2005–06

Covariates	Coefficient	95% Confidence interval	
Previous death			
No ®			
Yes	0.516***	0.376	0.656
States			
Jharkhand®			
Odisha	0.112	−0.057	0.280
Chhattisgarh	0.113	−0.055	0.280
Madhya Pradesh	0.212**	0.048	0.375
Mothers age at child birth	−0.020***	−0.029	−0.010
Sex			
Male ®			
Female	−0.097**	−0.183	−0.010
Religion			
Hindu®			
Others	0.156	−0.030	0.342
Education			
Literate®			
Illiterate	0.092	−0.049	0.234
Place of residence			
Urban®			
Rural	0.054	−0.128	0.235
Wealth			
Poor®			
Middle	0.070	−0.105	0.244
Rich	−0.124	−0.373	0.126
Constant	**−1.165*** **	**−1.504**	**−0.827**
Rho	**0.0447**	**0.0105**	**0.1716**
Theta	**2.384**	**0.5199**	**10.9325**
Estimated variance of mother specific unobservable			
	0.154		
N	**9069**		

Note*p < 0.01; **p < 0.05;*p < 0.1;** ® refers to reference category; The model also included interactions of all regressors with a dummy for first-born child (not shown)

28.3.5 Probit Model based Simulation Results of Effects of Scarring and Literacy on Infant Deaths in Central & Eastern India

Table 28.5 shows the probit based simulation results of predicted probability of infant deaths among tribes in the central and eastern India and its four selected states.

Table 28.5 Simulation results based on probit model of reduction in infant deaths among tribes of infant deaths, Central and eastern India, 2005–06

States	Overall Predicted Probability (a)	Predicted Probability when no scarring (b)	Percent reduction (b-a/a) *100	Predicted Probability when all mothers were literate (c)	Percent Reduction (c-a/a) *100
Central & eastern India	0.113***	0.100***	11.5	0.098*	0.13
Jharkhand	0.105***	0.097***	6.9	0.117	12.24
Odisha	0.109***	0.101***	7.5	0.071**	34.68
Chhattisgarh	0.113***	0.094***	16.3	0.085*	24.84
Madhya Pradesh	0.120***	0.106***	11.7	0.115	4.95

Note***$p < 0.01$; **$p < 0.05$;*$p < 0.1$

It can be concluded that overall predicted probability of infant death was 0.113 for central and eastern region but when we removed the clustering of deaths in families the predicted probability reduced to 0.100 leading to a decline of 11%. It shows that scarring contributed 11% decline in the family level clustering of infant deaths in the central & eastern India. Similarly for states within this region scarring factor was statistically significant for all states and the family level clustering of deaths attributed due to scarring factor was maximum in Chhattisgarh (16%) and Madhya Pradesh (12%) respectively. In Jharkhand and Odisha, 7% and 8% clustering could be reduced by eliminating the effect of scarring factor at family levels respectively. As literacy was found to be a significant factor affecting infant deaths so we have also predicted the situations where it is assumed illiterate women as literate and examined the reduction in predicted probability of infant deaths. For central & eastern Indian region, literacy led to a reduction of 13 infant death though it was moderately significant ($p < 0.1$).On the other hand the states like Odisha and Chhattisgarh experienced a 34% and 25% reduction in infant deaths only if we would provide education to illiterate women.

28.4 Discussion & Policy Implications

In the present paper, an attempt has been made to examine the clustering of infant deaths at family level for aboriginal's (tribal population) living in the forested hill tracts of peninsular India in four states of the central and eastern India. Most of these tribes are the Particularly Vulnerable Tribal Groups. The challenge of inaccessibility to health services and their health care seeking behaviour seem to dominate the discourse in tribal health (Balgir 2006).

In the present research article, the discussion is primarily based on the findings related to clustering of infant deaths from the study. We started examining the level of infant death clustering where we have estimated the extent of death clustering among scheduled tribes by region of residence. It has been found that among various caste groups, the scheduled tribes have the highest number of families with at least two infant deaths (9%) where nearly more than half of the total infant deaths are concentrated. State wise clustering of infant deaths in families suggest that Madhya Pradesh has the highest level of clustered deaths as nearly 11% families experienced 57% of two or more infant deaths (table not shown) suggesting clearly the existence of clustering in the central and eastern Indian region. Since most of the tribal families are located in rural areas, so we have also examined the extent of clustering by region of residence which suggest that for rural areas the clustering is more pronounced than urban areas as the number of vulnerable families (those experienced two or more infant deaths) were higher in rural areas.

The scarring effect (both positive as well as negative) has played an important role in intra-family death clustering in all states. In the first model, random effects dynamic probit model, obtained from the estimate for scarring by taking endogeneity and mother specific unobserved heterogeneity into account which indicated the positive influence of previous infant death in families on infant death of the index child. In this model, mother specific unobserved heterogeneity did not influence the child survival and the coefficient for previous death was almost same in both random effect dynamic probit model and probit model. Insignificant mother level unobserved factor suggests that the biological and other implicit characteristics of women in the central and eastern India are homogeneous leading to no variation between mother in terms of these characteristics. It clearly indicate that tribal women constitute a homogenous group across different regions of India and follow the similar socio-cultural practices. The simulation analysis suggests that for central and eastern region, scarring factor alone can reduce the infant mortality by 12%. However, for the state like Odisha illiteracy plays a greater role than scarring. The infant deaths in the state like Chhattisgarh is much influenced by scarring mechanism as it has contributed maximum in reducing the infant deaths once the effect of scarring has been eliminated. Eliminating illiteracy among tribal women in Chhattisgarh also resulted into reduction in infant death but the effect is lesser than scarring.

The findings suggest that, in the states like Odisha and Chhattisgarh the infant deaths among tribal families could be reduced to a significant level if we address both education and previous deaths in families.

It's a consequential findings from the study because, if we control the risk of death for the children of first and second order, the experience gained by mother in rearing of these two children would automatically help in reducing the risk of infant death of the next child and this would reduce infant deaths significantly. The findings of scarring effects suggest a higher pay-off to interventions designed to reduce mortality than previously recognized. It is known as the activation of a social multiplier (Manski 1999). So it indicates that reducing the risk of death of a child automatically implies in reducing the risk of death of his or her succeeding siblings. It is seen that once scarring effect is eliminated from the model, it would also underestimate the mortality levels up to certain extent.

A study conducted by Monica Das Gupta on twentieth-century in rural Punjab, demonstrated that families who had already experienced the loss of other children stood an increased chance of losing further children (Das Gupta 1990). This relationship applied to a child's survival chances at all stages of childhood following the neonatal period. It is understandable that, siblings share a large number of highly relevant demographic characteristics of the mother, such as the mother's age; her breastfeeding patterns; and her level of fecundity, which strongly correlates with length of birth interval. These factors are already well documented in previous studies on infant and child mortality (Hobcraft et al. 1983). Arulampalam and Bhalotra (2006) have argued that deaths may cluster in families not only because of unobserved heterogeneity—because of siblings share certain traits—but also as a result of a causal process driven by the scarring effects on mothers and families from an earlier child death, making the next child in the family more vulnerable. One of the ways in which interfamilial scarring occurs is when a mother quickly conceives again after the death of an infant through either resumed fecundity or the wish to replace the child that was lost. In addition, scarring may occur when an infant death causes the mother to become depressed, which may also have serious deleterious health effects on the next infant, either after its birth or in the womb. The mother level, insignificant unexplained variation in all four states in the region can be attributed due to homogeneity in culture, poverty and hazardous environmental factors in all states. Income, occupation, "Maternal competence" factor which concerns the mother's breastfeeding behaviour or other attitudes and behaviours that affect her children's health, inherited genetic disorders and the mother's medical condition and disease profile may be other factors which explain the significant but no inter-family unobserved heterogeneity. Some of the previous studies too shown that the unexplained variation between families or mothers cannot always be found, or, in some cases, it appears to be very modest (Das Gupta 1990; Guo 1993). Guo (1993) also came out with the similar findings by conducting the study in a Latin American developing country, Guatemala. that the variation between mothers was only slight once family income level and mother's educational attainment were controlled for. Sastry (1997) too found that inter-family heterogeneity to be small and unimportant in his study on Brazilian population, but only after controlling for heterogeneity at the community level. Sastry, therefore, argued, much in line with Guo that shared environmental conditions were more important determinants of shared frailty than either parental competence or genetic and biological factors.

Scarring involves responsive behaviour which may be amenable as it is shown that there is some causal process whereby frequent infant death in the family is affected by the previous sibling's death. If the causal process works through the fecundity mechanism, policies that improve the uptake of contraception are likely to reduce death clustering among the tribes. More specific policy insight depends on identifying the mechanism underlying scarring. While unobserved heterogeneity involves largely untreatable factors like genes or fixed behaviour and unalterable family specific traits is central to the nature-nurture debate (Pinker 2003). There is a need for systematic and comparative research in the different tribal communities at different time periods to understand the role of scarring mechanisms and to examine the conditions of appearance or disappearance of this hazards. In India, as in many other developing countries, health services are made available largely in response to demand. If child deaths are heavily concentrated in some families, this would suggest that substantial improvements in child mortality could be achieved by adopting the more cost-effective techniques of focusing healthcare resources specifically on the sub-group of families with a high risk of child death.

It can also be useful in targeting interventions at the most vulnerable households. The government should not only try to reduce scarring mechanism among tribes, but it should also promote education, awareness among tribes about modern health facilities and infrastructure development in the tribal areas. The policy initiatives should be pro tribe culture and it should be encouraging. Mass media based information about government policies should be promoted.

References

Arulampalam, W., & Bhalotra, S. (2006). Sibling death clustering in India: State dependence versus unobserved heterogeneity. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 169*(4), 829–848.

Arulampalam, W., & Bhalotra, S. (2008). The linked survival prospects of siblings: Evidence for the Indian states. *Population Studies, 62*(2), 171–190.

Balgir, R. (2006). *Tribal health problems, disease burden and ameliorative challenges in tribal communities with special emphasis on tribes of Orissa*. Paper presented at the Proceedings of National Symposium on "Tribal Health" 19th–20th October.

Bhargava, A. (2003). Family planning, gender differences and infant mortality: Evidence from Uttar Pradesh, India. *Journal of Econometrics, 112*(1), 225–240.

Bolstad, W. M., & Manda, S. O. (2001). Investigating child mortality in Malawi using family and community random effects: A Bayesian analysis. *Journal of the American Statistical Association, 96*(453), 12–19.

Curtis, S. L., Diamond, I., & McDonald, J. W. (1993). Birth interval and family effects on postneonatal mortality in Brazil. *Demography, 30*(1), 33–43.

Das Gupta, M. (1990). Death clustering, mothers' education and the determinants of child mortality in rural Punjab, India. *Population Studies, 44*(3), 489–505.

Das, M. B., Kapoor, S., & Nikitin, D. (2010). *A closer look at child mortality among Adivasis in India.* World Bank Policy research working paper series.

Das, M. B., Hall, G. H., Kapoor, S., et al. (2014). Chapter 6—India: The scheduled tribes. In G. H. Hall & H. A. Patrinos (Eds.), *Indigenous peoples, poverty and development* (pp. 205–248). New York: Cambridge University Press.

Deaton, A. (1997). *The analysis of household surveys*. Washington, DC: Johns Hopkins University Press.

Guo, G. (1993). Use of sibling data to estimate family mortality effects in Guatemala. *Demography, 30*, 15–32.

Heckman, J. J. (1987). *The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process and some Monte Carlo evidence*. University of Chicago Center for Mathematical studies in Business and Economics.

Heckman, J., & Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica: Journal of the Econometric Society, 52*, 271–320.

Hobcraft, J., McDonald, J. W., & Rutstein, S. (1983). Child-spacing effects on infant and early child mortality. *Population Index*, 585–618.

International Institute for Population Sciences (IIPS) and Macro International. (2007). *National Family Health Survey (NFHS), 2005–06: India: Volume 1*. Mumbai: International Institute for Population Sciences and Macro International.

Madise, N. J., & Diamond, I. (1995). Determinants of infant mortality in Malawi: An analysis to control for death clustering within families. *Journal of Biosocial Science, 27*(1), 95–106.

Manski, C. F. (1999). *Identification problems in the social sciences*. Cambridge, MA: Harvard University Press.

Manski, C. F., & McFadden, D. (1981). *Structural analysis of discrete data with econometric applications*. Cambridge, MA: MIT Press.

Ministry of Tribal affairs. (2015). Retrieved from http://tribal.nic.in/

Narendranathan, W., & Elias, P. (1993). Influences of past history on the incidence of youth unemployment: Empirical findings for the UK†. *Oxford Bulletin of Economics and Statistics, 55*(2), 161–185.

Oettinger, G. S. (2000). Sibling similarity in high school graduation outcomes: Causal interdependency or unobserved heterogeneity? *Southern Economic Journal*, 631–648.

Pandey, G., & Tiwary, R. (1993). Demographic characteristics in a tribal block of Madhya Pradesh. *Social Change, 23*(2/3), 124–131.

Pinker, S. (2003). *The blank slate: The modern denial of human nature*. New York: Penguin.

Ranjan, M., Dwivedi, L. K., Mishra, R., et al. (2016). Infant mortality differentials among the tribal and non-tribal populations of central and eastern India. *International Journal of Population Studies, 2*(2), 26–43. https://doi.org/10.18063/IJPS.2016.02.004.

Ranjan, M., Dwivedi, L. K., & Mishra, R. (2018). Caste differentials in death clustering in central and eastern indian states. *Journal of Biosocial Science, 50*(2), 254–274. https://doi.org/10.1017/S0021932017000219.

Reddy, S. (2008). Health of tribal women and children: An interdisciplinary approach. Indian. *Anthropologist, 38*, 61–74.

Registrar General of India. (2015). *Sample Registration System (SRS) Statistical Report 2015*. New Delhi: Registrar General of India. Retrieved from http://www.censusindia.gov.in/vital_statistics/SRS_Reports_2015.html

Rindfuss, R. R., Palmore, J. A., & Bumpass, L. L. (1982). *Selectivity and the analysis of birth intervals from survey data*. Paper presented at the Asian and Pacific Census Forum.

Ronsmans, C. (1995). Patterns of clustering of child mortality in a rural area of Senegal. *Population Studies, 49*(3), 443–461.

Sastry, N. (1997). Family-level clustering of childhood mortality risk in Northeast Brazil. *Population Studies, 51*(3), 245–261.

UNICEF. (2014). *Levels & trends in child mortality.* Report. Retrieved from http://www.unicef.org/media/files/Levels_and_Trends_in_Child_Mortality_2014.pdf

Whitehouse, C. (1982). The health of children. A review of research on the place of health in cycles of disadvantage. *British Journal of General Practice*.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

World Health Organization. (2011). *Global health observatory data repository*. See http://apps.who.int/ghodata

Zaba, B., & David, P. H. (1996). Fertility and the distribution of child mortality risk among women: An illustrative analysis. *Population Studies, 50*(2), 263–278.