An Investigation of Spatial Variation of Childhood Disease in India: A Bayesian Semi Parametric Approach

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Abstract

Although diarrhoea and malaria are the leading causes of child mortality and morbidity in developing countries, few studies have examined the pattern and determinant of these ailments. The purpose of this paper is to examine the relative contribution of a wide range of factors more specifically spatial effects to the prevalence of child morbidity (diarrhoea, fever & ARI) using individual data for five year children from the third round of National Family Health Survey (NFHS-3). We highlighted the inequalities in child health by mapping the residual state spatial effect using geo-additive logit model that simultaneously controlled for spatial dependence in the data, potential nonlinear effects and other categorical factors. A high prevalence of diarrhoea, fever and acute respiratory is observed in the Eastern, Central and Northern states, while lower disease prevalence is observed in Southern states followed by Western states. In addition, children who are underweight and those from poorest quintile have significantly higher association with diarrhoea, fever and ARI. The results show that disease like, diarrhoea, fever, and ARI appears to be higher in children who are smaller in size at the time of birth compare to those children who are normal size at birth. Diarrhoea, fever, and ARI were observed to show an interesting association with child's age, the risk of three ailments increased in the first 8-10 months after birth, with a gradual improvement thereafter. The effects of socioeconomic factors vary according to the disease. The residual spatial map could help governments to improve health care interventions and achieve Millennium Development Goals (MDG4).

Keywords: Diarrhoea, fever, acute respiratory infection, geoaddative regression, Bayesian semi parametric, India.

Introduction

Social and economic development in India has led to substantial improvement in living conditions and child survival during the past two decades. However, these gains have been unevenly distributed across the states of India. Although child mortality has declined in India, several states in the region continue to experience relatively high child mortality rates. The primary causes of persistence high mortality are infectious diseases. Particularly important are diseases for which effective immunization is not widely available, such as diarrhoea, fever and acute respiratory infections (ARI). Diarrhoea and respiratory infection are common childhood disease worldwide (Goldman *et al*., 2002). The world summit for children in 1990 called for a worldwide reduction in child mortality to below 70 deaths per 1000 live births by the year 2000 (UNICEF, 2001). Unfortunately investment in health systems and interventions necessary to achieve such reduction in the 1990s were not adequate with needs. The mortality reduction in target was reached for only five of 55 countries with an under five mortality rate of 100 or more in 1990 (UNICEF, 2001; Black *et al*., 2003). The fourth Millennium Development Goals aims to reduce mortality among children under five by two-third by 2015, from the base year 1990 (UN, 2001). India's under five mortality decline from (U5MR) decline from 125 per 1000 live births in 1990 to 74.6 per 1000 live births in 2005-06. U5MR is expected to further decline to 70 per 1000 live births by 2015. This means India would still fall short of the target of 42 per 1000 live births by 2015. To bridge this gap, one first needs to understand what ails the young? Worldwide, large percentage of children under age of five has died of acute respiratory infection (nineteen percent) and diarrhoea (thirteen percent) in the year 2002. This is also true for India where these two diseases along with measles and tetanus have been identified as the major causes behind infant mortality both in 1997 as well as 1998. An in-depth analysis of these two diseases namely diarrhoea and acute respiratory infection becomes mandatory not only because of their degree of fatality but also because they are not preventable by vaccination (Chakrabarti, 2012).

Childhood chronic undernutrition and related morbidities like diarrhoea, fever, and acute respiratory infection are major health problem in developing countries, especially in South Asia. Undernutrition and associated morbidities among children under the age of five are responsible for 35 percent deaths and 11 percent of global disease of burden (Black et al., 2008). These diseases disproportionally affect poor children in low and middle income countries. Socioeconomic inequality in the distribution of child mortality and morbidity are well document, both among countries and regions of the world and within individual societies (Victora *et al*., 2003). The National Health Policy of India emphasizes the Government's commitment to improve the health status of one of the most vulnerable groups of the society i.e. the infant and young children. More than three-fifth of all 2.3 million child deaths in India in 2005 were from five causes: pneumonia, prematurity, low birth weight, diarrhoeal diseases, neonatal infections and birth asphyxia and birth trauma (Bassani *et al.*, 2010). Each of the major cause of neonatal deaths can be prevented and treated with known highly effective and widely practical interventions such as improvements in prenatal care, intrapartum care (skilled attendance, emergency obstetric care, and simple immediate care for new born babies), postnatal family-community care (preventive post natal care, oral antibiotics, and management of pneumonia) (Darmstadt *et al.*, 2005).

A plethora of studies have focused on mortality figures or on indices measuring the nutritional status of the child to analyse the channels through which the socio-economic conditions and family composition influence the health of the child. However, to best of our knowledge very few studies have focused into the child morbidity pattern and its determinant across the different households particularly based on India and more specifically regions in India. Fewer still has attempted to analyse the factors that govern whether a household will seek formal care in the event that a child has contracted illness. In view of the threat caused by diarrhoea and respiratory illness not only in India but also worldwide and in depth analysis of these tow disease becomes very important (Chakrabarti, 2012). Studies (Goldman *et al.*, 2002; Duraisamy, 2001; Krupnick *et al.*, 1996) drawing data from developing economics have looked into the incidence of these two diseases and examined their determinants. Their findings show that occurrence and transmission of such diseases are largely affected by behavioural pattern and the environmental conditions surrounding the household. However, the determinants differed according to the types of disease. Study based on Jakarta (Krupnick *et al.*, 1996) showed that defence mechanism of mother (washing hands after using toilet) significantly reduces the chance of her child or herself getting diarrhoea.

Acute respiratory infection (ARI) represent one of the main health problems in children less than five years of age and are the leading cause of death in developing countries. Infant have the highest risk of pneumonia in their first three months of life. Nearly 70-75% of all deaths in infants are due to pneumonia. In both developed and developing countries, children of smokers exposed to passive smoking are most susceptible to pneumonia than those not exposed to cigarette smoke. Indoor air population is also strongly suspected of being an important contributor to ARI child health (World Bank, 1993). Victora (1999) added a few socio-economic (particularly low income, parental low education levels, place of residence), demographic (age, birth spacing and gender of child), nutritional and behavioural (including low birth weight, malnutrition, and lack of breast feeding), and environmental (overcrowding, biomass-burning stoves) factors as the risk factors. Boys are more likely to suffer than girls, and infants are more vulnerable to suffer from ARI compared to toddler and child who may have the chance to build up some natural immunity (Victora, 1989).

Previous studies on child disease have focussed on various socioeconomics, demographics or health related factors that are available in a specific data set. However, most of the studies have neglected aspects for the spatial effects. The purpose of this paper is to examine the relative contribution of a wide range of factors more specifically spatial effects to the prevalence of child morbidities (diarrhoea, fever & ARI). Selection of the variables is inspired by the conceptual framework for proximate determinants of childhood morbidity and mortality in developed countries by Mosley and Chen (Mosley & Chen, 1984). In practice of course selection is limited by the set of covariates available in data set in hand. To fulfil our needs, we apply the generalized geoaddative model as an alternative to the common linear model for analysing childhood disease in India (Fahrmeir & Lang, 2001). This methodology will enable us to account for nonlinear, location effects on childhood morbidities as the state level and to assess temporal and geographical variation in diseases while simultaneously controlling for important risk factors.

Data and Methods:

The present study utilizes data from the third round of National Family Health Survey (NFHS), which was conducted in 2005-06. The survey was designed to provide estimates on various aspects of demographic behaviour, including fertility, mortality, family planning, HIV related knowledge and on important aspects of nutrition, health and health care. It was done in collaboration with the International Institute for Population Sciences (IIPS), Mumbai, India, ORC Macro, Calverton, Maryland, USA, and the East-west Center, Honolulu, Hawaii, USA. IIPS coordinated these surveys and collaborated with number of Field Organizations for survey implementation. The survey covers a representative sample of about 124, 385 ever-married women in the age group 15-49, who were captured in the two phase from the 29 states of India. The survey adopted two-stage sampling design in rural areas and three-stage sampling design in urban areas. In rural areas, the villages were selected at the first stage using probability proportion to size (PPS) sampling scheme. The required numbers of households were selected at the second stage using systematic sampling. In urban areas, block were selected at first stage, census enumeration blocks (CEB) containing approximately 150-200 households were selected at the second stage, and the required number of household were selected at the third stage using systematic sampling technique.

Statistical methods

In the descriptive table, frequency table were generated to show the disease prevalence by state and by factors. Chi-square tests and Mann-Whitney tests were used to investigate the association between factors and diseases. In the present study, however, the NFHS data contains geographical or spatial information, such as the state of individual in the study and the presence of non-linear effects for some covariates means that strictly linear predictors cannot be assumed. Analysing and modelling geographical patterns for health and survival, in addition to the impact of other covariates, is of obvious interest in many studies. In a novel approach, the geographical patterns of childhood morbidity and the possibly non-linear effects of other factors were therefore explored within a simultaneously, coherent regression framework, using a geoaddative, semi-parametric, mixed model (Fahrmeir & Lang, 2001; Brezger *et al*., 2005; Kandala *et al*., 2007; Kandala *et al*., 2008; Khatab & Fahrmeir, 2009). We replace the strictly linear regression

$$\eta_j = x'\beta + w_j'\gamma$$

With a geoaddative predictor, leading to the geoaddative regression model:

$$\eta_j^{geo} = \beta_{oj} + x_j'\beta_j + f_1^j(z_1) + \dots\dots\dots + f_k^j(z_k) + f_{geo}^j(s_i)$$

were x_j and β_j are vectors of categorical covariates in effect coding and the corresponding parameters, functions $f_1^j \dots\dots f_k^j$ represents nonlinear effects of continuous covariates $z_1 \dots . z_k$, and the function f_{geo}^j represents the geographic effects of spatial variable s = {1…29}, indicating states in a country. The spatial effects may be further split into spatially correlated (structured) and uncorrelated (unstructured) effects as: $f_{geo}^j(s_i) = f_{str}(s_i) + f_{unstr}(s_i)$

The rationale behind this is that a spatial effect is a surrogate of many unobserved influential factors, some of which may have strong spatial structures and others only present locally.

Within a Bayesian context, all parameters and function (say *f* for non-linear effects) are considered as random variables upon which appropriate priors are assumed. Independent diffuse priors are assumed on the parameters of fixed effects. For the non-linear effects, a Bayesian P-Spline prior based on Lang & Brezger (2004) and Brezger and Land (2006) were assumed. The P-spline allows for non-parametric estimates of *f* as a linear combination of the basis function (B-spline):

$$p(z) = \sum_{j=1}^{j} \beta_j B_j(z)$$

where $B_j(z)$ are B-splines basis functions and the coefficient β_j correspond to the vector of unknown regression coefficients. Smoothness of function *f* is achieved by penalizing difference of coefficient of adjacent B-splines (Eilers & Marx, 1996) or in Bayesian approach, as in this case, where β_j values are further define to follow first-or second order Gaussian random walk smoothness priors:

$$\beta_1 = \beta_{j-1} + u_1 \qquad \beta_1 = 2\beta_{j-1} - \beta_{j-2} + u_1,$$

With *i.i.d.* (independent and identically distributed) errors $u_1 \sim N(0,\tau^2)$. The variance τ^2 controls the smoothness of *f*. Assigning a weekly informative inverse gamma prior ($\tau^2 \sim IG(\varepsilon,\varepsilon)$) with ε very small, it is estimated jointly with the basis function coefficients. For further clarification and explanation of the concept, see Eilers & Marx (1996), Lang & Brezger (2004) and Brezger & Lang (2006).

For the geographical effects $f_{geo}^{j}(s_i)$, s= 1…29, a Gaussian Markov random field prior is assumed. Basically, this is an extension of first-order random walk priors to two-dimensional spatial array (Rue & Held, 2005). For the structural spatial effects $f_{str}(s)$ a Gaussian markov random field prior was chosen, which is common in spatial statistics (Besag *et al.*, 1991). Unstructured spatial effects are i.i.d. random effects:

$$(\mathrm{f_{str}(s)} \mid \mathrm{f_{str}(t)}; \mathrm{t} \neq \mathrm{s}, \tau^2) \sim \mathrm{N}(\sum_{\mathrm{t}\varepsilon\partial_{\mathrm{s}}} \mathrm{f_{str}(t)} / \mathrm{N_s}, \tau^2 / \mathrm{N_s})$$

Where N_s is the number of adjacent sites and $t\varepsilon\partial_s$ denotes that site t is a neighbour of sites s. Again, τ^2 controls the amount of spatial smoothness. In order to be able to estimate the smoothing parameters for non-linear and spatial effects simultaneously, highly dispersed but prior hyper-priors are assigned to them. Hence for all the variance components, an inverse gamma distribution with hyper parameters a=1 and b=0.005 or a=b=0.001 is a common choice. In the present application, sensitivity of the results with the choice of prior was investigated by changing the parameters *a* and *b*. The results turn out to be less sensitive to the various choices. The results reported here are those of a=b=0.001. Also, mixing and convergence of the samples were monitored through plotting of sampling path and estimation of autocorrelations.

Fully Bayesian inference is based on the analysis of posterior distribution of the model parameters. In general, the posterior is analytically intractable, which makes it almost impossible for direct inference. Markov Chain Monte Carlo (MCMC) are therefore used to generate samples from the prior distribution which allow estimation and inference for all parameters to be made. Detail information about this modelling approach for models with geoaddative predictors has been implemented in BayesX, software for Bayesian analysis using MCMC and Restricted Maximum Likelihood technique. For more information on the software see Belitz *et al.*, (2009). All analyses were performed with BayesX software.

Table 1 shows the general profile of children during the last five years preceding the survey in the selected sample. The results reveal that most children are rural resident, they account for approximately 75 percent of the sample while 25 percent of children belongs to urban resident. Among the children, 52 percent are male and majority of the children are breastfeeding and only 42 percent of children are received vitamin A. The proportions of children who were underweight are found to be approximately 43 percent. About 54 percent of the children had their mother's normal body mass index, 39 percent underweight and only approximately 6 percent are overweight. Majority of the children belongs to Hindu religion (78 percent) and approximately 67 percent were other caste including general and other backward class. The distribution of the sample by household wealth index indicates that 25 percent of children live in the poorest households, while 20 percent of children live in households that fall in the middle quintile. Additionally, 14 percent of children were from richest wealth quintiles. The majority of the children were from the states of Uttar Pradesh (21 percent) followed by Maharashtra (approximately 8 percent) and West Bengal (7percent) whereas the minority of the children were from the states like Sikkim (0.04 percent) followed by Mizoram (0.09 percent).

Table 1: Percentage distribution of background characteristics included in the study. Data refer last five years preceding the NFHS-3 (2005-06) survey in India

Background Characteristics	Percentage	N	**Background Characteristics**	Percentage	N
Place of residence			**State**		
Urban	25.34	19483	Jammu And Kashmir	0.82	1226
Rural	74.66	32072	Himachal Pradesh	0.44	995
Sex of the child			Punjab	1.98	1307
Male	52.12	26799	Uttaranchal	0.74	1228
Female	47.88	24756	Haryana	1.83	1256
Vitamin A			Delhi	0.92	1251
No	58.47	27623	Rajasthan	6.23	2023
Yes	41.53	21023	Uttar Pradesh	20.76	7051
Breastfeeding			Madhya Pradesh	6.81	3016
No	32.49	18128	Chhattisgarh	2.12	1592
Yes	67.51	33427	Bihar	11.1	2320
BMI of women			Jharkhand	3.33	1657
Underweight	38.82	16039	Orissa	3.46	1781
Normal Weight	54.16	28585	West Bengal	7.35	2368
Overweight	5.81	3933	Arunachal Pradesh	0.12	870
Obesity	1.21	860	Assam	2.55	1532
Religion			Manipur	0.21	1912
Hindu	78.01	35409	Meghalaya	0.32	1093
Muslim	17.31	8682	Mizoram	0.09	848
Other	4.68	7464	Nagaland	0.17	2108

Caste			Sikkim	0.04	653
SC	23.75	11349	Tripura	0.29	639
ST	9.64	8386	Goa	0.1	988
Other	66.6	31820	Gujarat	4.62	1571
Wealth Index			Maharashtra	7.8	3038
Poorest	25.47	9200	Andhra Pradesh	5.57	2292
Poorer	22.42	9571	Karnataka	4.77	2188
Middle	19.81	10659	Kerala	1.81	1017
Richer	17.99	11300	Tamil Nadu	3.66	1735
Richest	14.3	10825			
Underweight					
No	57.5	25960			
Yes	42.5	15346			

Table 2 displays the odds ratio and 95% credible intervals of categorical variables on diarrhoea, fever and ARI. The findings show that compared with children from urban areas, those from rural areas were less likely to suffer from diseases like diarrhoea, fever and ARI but this was only significant for diarrhoea. Female children were significantly less likely to get ill from all three diseases compared to male children (OR=0.860, CI: 0.805, 0.919; OR=0.932, CI: 0.883, 0.985 & OR=0.844, 1.006 respectively). Those given vitamin A were less likely to suffer from diarrhoea, fever and ARI than their counterpart but the results were insignificant. Children who were being breastfed were significantly less likely to suffer from diseases compared to those not being breastfed (OR=0.888, CI=0.814, 0.973; OR=0.889, CI=0.831, 0.949; OR=0.906, CI=0.812, 1.020). Compared with children from underweight mothers those children whose mothers were normal weight, overweight weight and obesity were less likely to be infected with diarrhoea, fever and ARI, however, the results were not significant. Muslim children were significantly more likely to suffer from three ailments [OR=1.211, CI=1.097, 1.339; OR=1.418, CI=1.313, 1.534; OR=1.339, CI=1.195, 1.502 respectively) whereas children belongs to other religion were more likely to get diarrhoea and less likely to infected with fever and ARI and results are not significant. Similarly, compared with children from schedule caste those in schedule tribes and other caste were less likely to diarrhoea, fever and ARI, however the results were only significant for fever and diarrhoea for schedules tribe’s children. Compared with children from the poorest household, findings show that those from households in the other wealth quintile were more likely to suffer from fever and these were all significant. Richest household were less associated with diarrhoea and ARI and it was only significant for ARI. Underweight children were more likely to suffer from diarrhoea, fever and ARI and the results were significant for diarrhoea and fever (OR=1.172, CI=1.090, 1.261; OR=1.178, CI=1.109, 1.253; OR=1.082, CI=0.985, 1.187 respectively).

Table 2: Results of fixed showing the odds ratio and 95% credible intervals for diarrhoea, fever, and ARI NFHS-3 (200-06), India

Background Characteristics	Diarrhoea		Fever		Acute respiratory infection (ARI)	
	Odds Ratio	95 % CI	Odds Ratio	95 % CI	Odds Ratio	95 % CI
Place of residence						
Urban(R)	1.000					
Rural	0.903*	[0.825, 0.985]	0.964	[0.899, 1.037]	0.925	[0.923, 1.028]
Sex of the child						
Male(R)	1.000		1.000		1.000	
Female	0.860*	[0.805, 0.919]	0.932*	[0.883,0.985]	0.924	[0.844, 1.006]
Vitamin A						
No(R)	1.000		1.000		1.000	
Yes	0.958	[0.885, 1.035]	0.960	[0.901, 1.023]	0.976	[0.877, 1.078]
Breastfeeding						
No(R)	1.000		1.000		1.000	
Yes	0.888*	[0.814, 0.973]	0.889*	[0.831, 0.949]	0.906*	[0.812, 1.020]
BMI of women						
Underweight(R)	1.000		1.000		1.000	
Normal Weight	0.980	[0.907, 1.059]	0.965	[0.908, 1.027]	0.984	[0.895, 1.083]
Overweight	0.978	[0.846, 1.140]	0.926	[0.823, 1.040]	0.877	[0.722, 1.062]
Obesity	0.731	[0.518, 1.002]	0.861	[0.686, 1.067]	0.881	[0.592, 1.263]
Religion						
Hindu(R)	1.000		1.000		1.000	
Muslim	1.211*	[1.097, 1.339]	1.418*	[1.313, 1.534]	1.339*	[1.195, 1.502]
Other	1.146	[0.993, 1.319]	0.959	[0.856, 1.072]	0.987	[0.819, 1.192]
Caste						
SC(R)	1.000		1.000		1.000	
ST	0.873	[0.765, 1.006]	0.896*	[0.804, 0.998]	0.828*	[0.691, 0.995]
Other	1.000	[0.917, 1.093]	0.964	[0.898, 1.039]	0.959	[0.860, 1.068]
Wealth Index						
Poorest(R)	1.000		1.000		1.000	
Poorer	1.013	[0.894, 1.138]	1.124*	[1.026, 1.234]	1.104	[0.956, 1.268]
Middle	1.075	[0.955, 1.216]	1.104*	[1.004, 1.222]	1.093	[0.943, 1.275]
Richer	1.008	[0.882, 1.153]	1.127*	[1.008, 1.197]	0.923	[0.778, 1.094]
Richest	0.900	[0.763, 1.061]	1.042*	[0.907, 1.197]	0.794*	[0.634, 0.989]
Underweight						
No(R)	1.000		1.000		1.000	
Yes	1.172*	[1.090, 1.261]	1.178*	[1.109, 1.253]	1.082	[0.985, 1.187]

*Note: ®: Reference category & *: Significant at 0.05%*

Figure 1, 2 and 3 show the nonlinear effects of child's age, education of mothers in single year and mother's age at first birth through Bayesian P-splines (Lang & Brezger, 2004) for diarrhoea, fever and ARI respectively. Also, shown are the posterior means and 95% credible. The results shows that nonlinear relationship exists between child's age and morbidity among children considered thereby justifying the inclusion as nonlinear effect. Findings shows that there was continues worsening of diarrhoea, fever and ARI among children upto about 12 months of age and decrease thereafter. After this age, a sinusoidal relationship was evident. The effect of years spent in school by mothers on diarrhoea shows that the risk of diarrhoea increased in children whose mothers had educated upto about 10 years of schooling thereafter a steady decline was observed. Similar patterns were observed for fever and diarrhoea. Findings on mothers age at birth show that those children of mother who gave birth at older ages have less chance of diarrhoea as compared to the children of mother who deliver their first child at younger age. The results were similar for fever and ARI.

Figure 1: Posterior means of nonlinear effects and its 95% credible interval of child’s age, mother’ single year education and mother’s age at the time of birth on diarrhoea

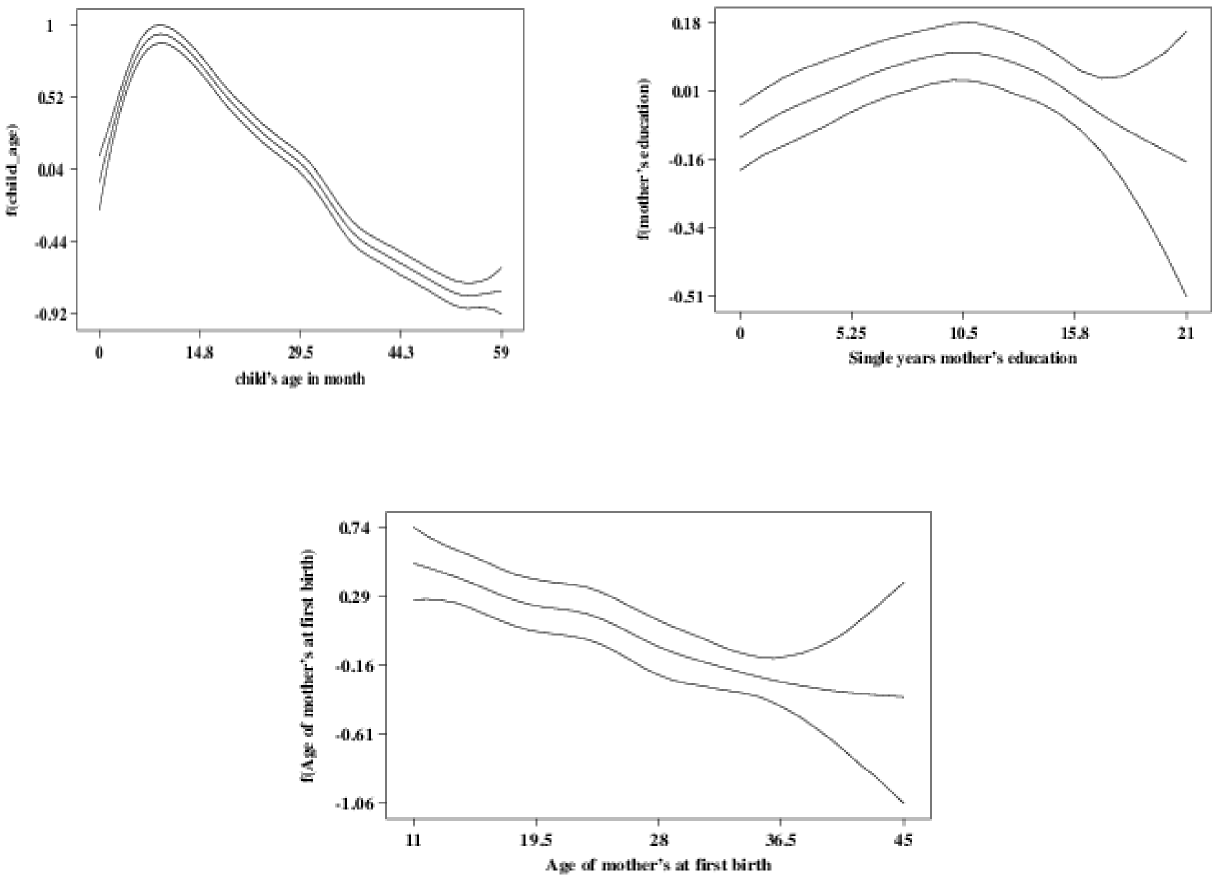


Figure 2: Posterior means of nonlinear effects and its 95% confidence interval of child's age, mother' single year education and mother's age at the time of birth on fever

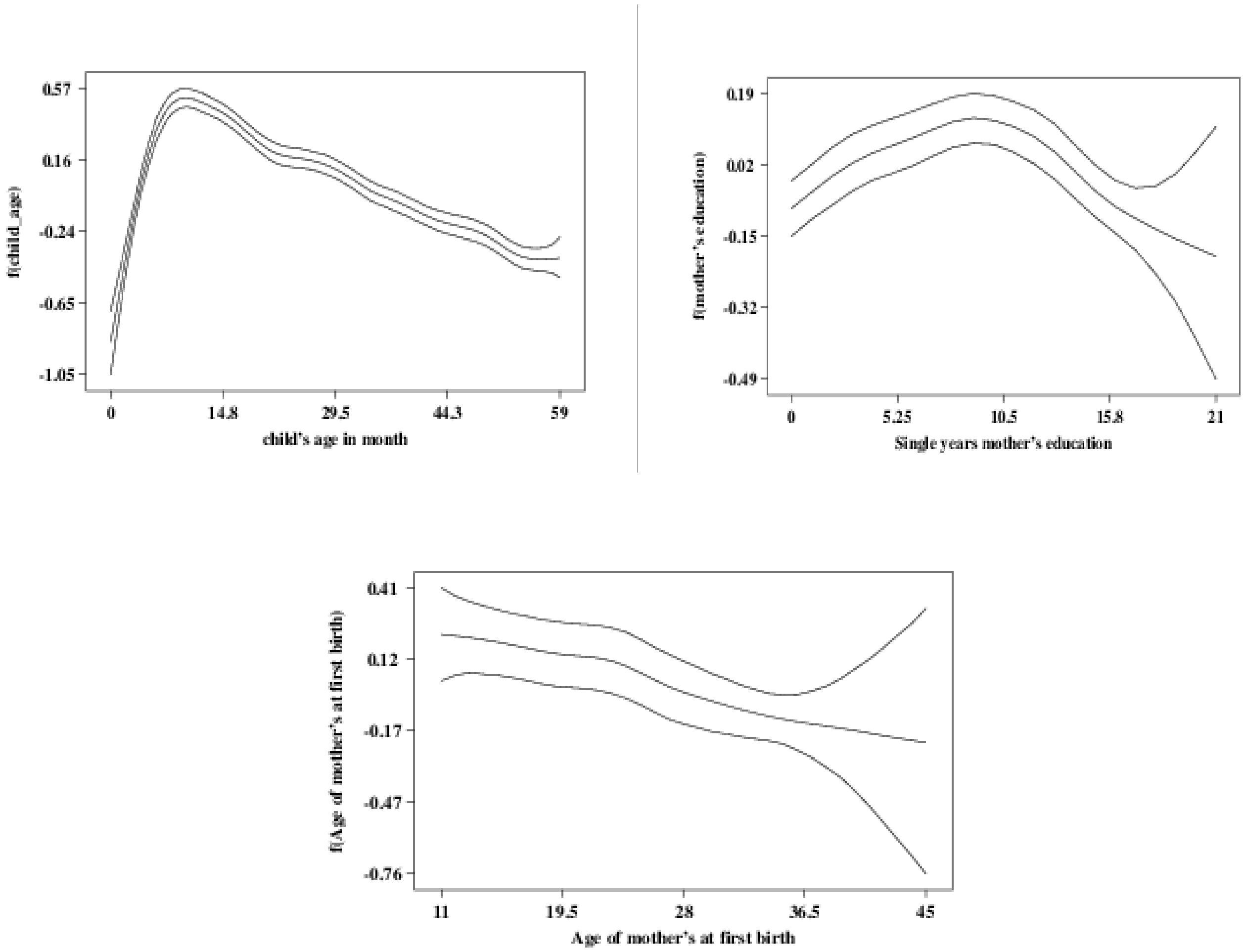
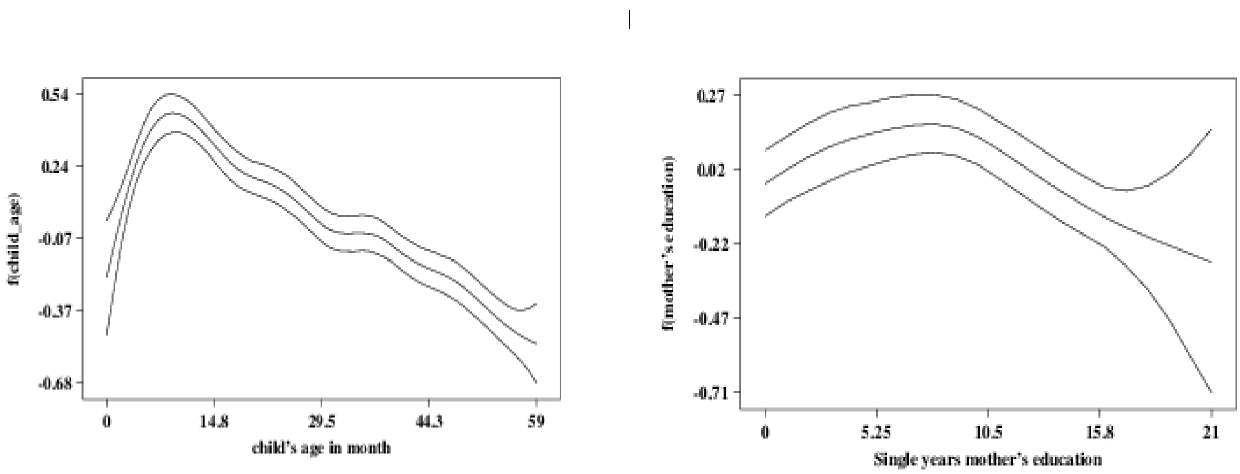
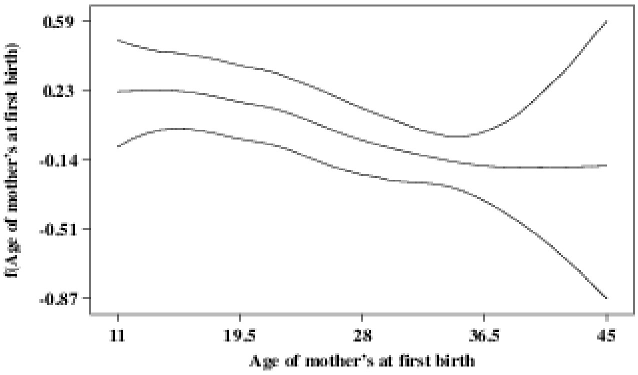


Figure 3: Posterior means of nonlinear effects and its 95% confidence interval of child's age, mother' single year education and mother's age at the time of birth on ARI





Figures 4, 5 and 6 give the state specific net spatial effects of diarrhoea, fever and ARI. The left panels of the figures show the residual spatial effects while the right panel indicates the map of credible intervals used in assessing the significance of the residual spatial effect. The left panel of the figure reveals the lower risk of diarrhoea, fever and ARI were observed in the states namely Kerala, Tamil Nadu, Karnataka and Andhra Pradesh whereas the higher risk of morbidity were found in states like Mizoram , Arunachal Pradesh, Nagaland, Rajasthan, Madhya Pradesh, Uttar Pradesh etc. From the maps of credible intervals, the risk of diarrhoea, fever and ARI among children from states with black (white) colour were significantly lower (higher) while it was not significant those shaded in gray.

Figure 4: Map of India for diarrhoea (a) Total residual spatial effect and (b) its corresponding 95 % posterior probabilities

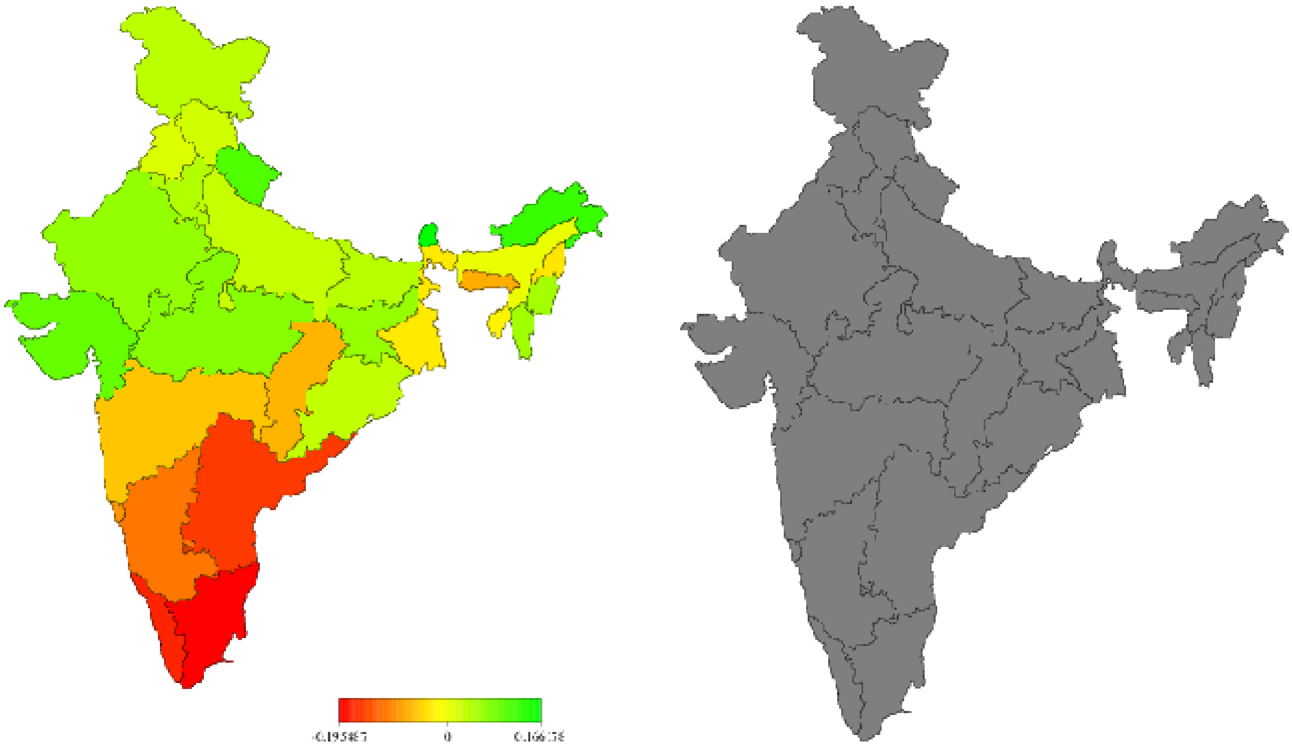


Figure 5: Map of India for fever (a) Total residual spatial effect and (b) its corresponding 95 % posterior probabilities

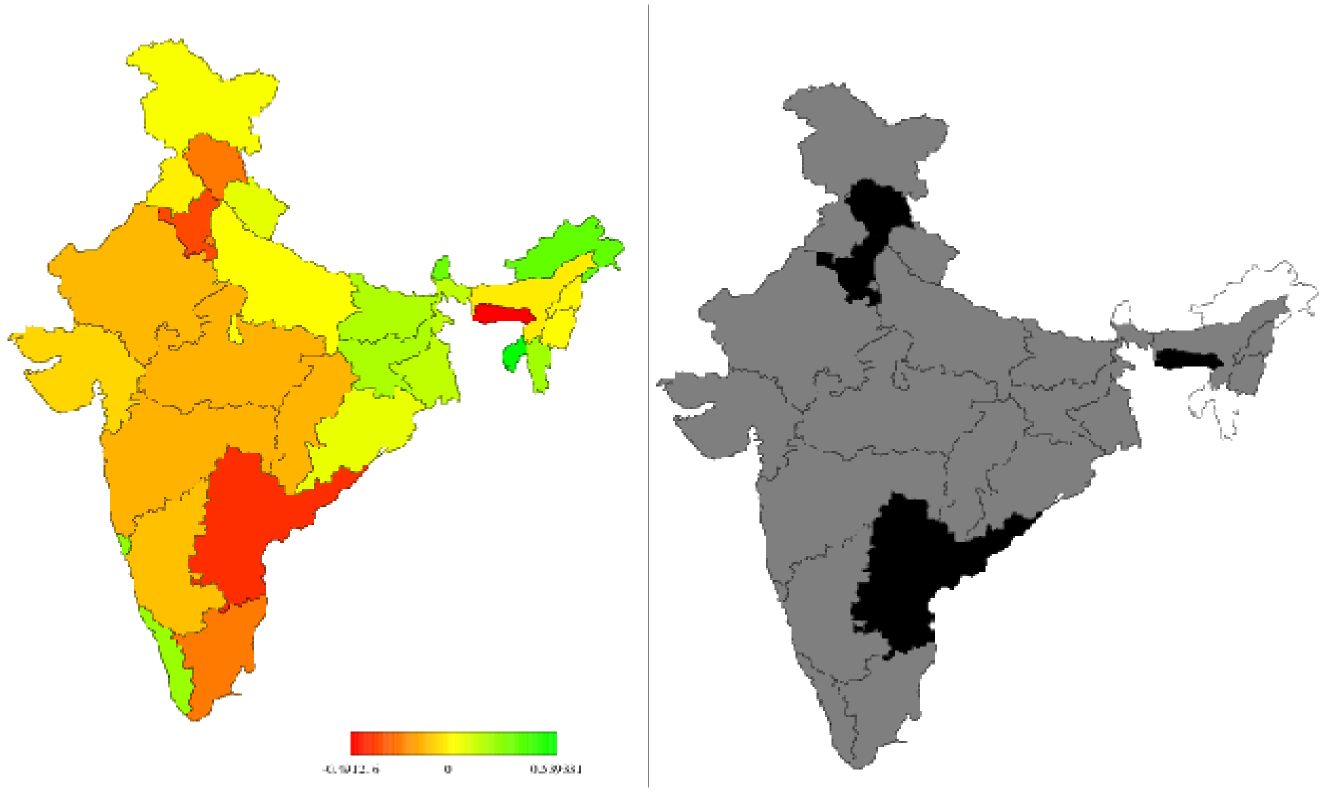
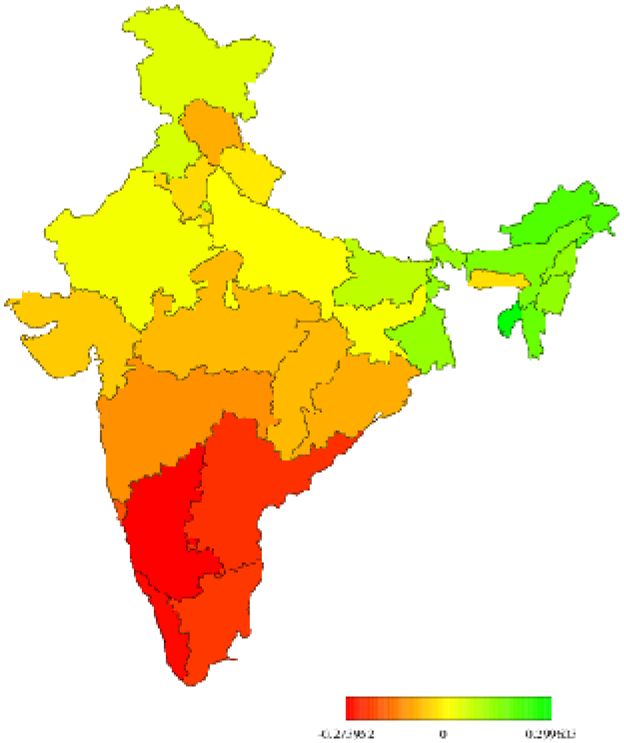


Figure 6: Map of India for ARI (a) Total residual spatial effect and (b) its corresponding 95 % posterior probabilities



Discussion and Conclusion: This study set out to estimate the relationship that exist between socioeconomics, public health and spatial determinants of morbidity among children measured through prevalence of diarrhoea, fever and ARI in India. The vital question in this study was to identify areas of high and low risk of diarrhoea, fever and ARI after adjusting for risk factors. The data used in the analysis was based on self-reported accounts by mother to measure residual spatial pattern at states level. Our analyses reveal that geoaddative models are needed to adequately assess nonlinear covariate effects and geographical effects. After controlling for covariates, the residual spatial effect identifies a clear and strong spatial structure at the state level in India. This shows that high prevalence of child morbidity appears mainly in the states like Sikkim, Arunachal Pradesh, Jharkhand, Gujarat, Uttaranchal, Madhya Pradesh, Orissa and Mizoram. From the analyses we were able to establish that the Southern states (Andhra Pradesh, Karnataka, and Tamil Nadu) were relatively at lower risk for all three response outcomes. However, the residual spatial variations were significantly weak as demonstrated by the corresponding probability map. Lack of excess risk in spatial effects can be explained by the fact that much of the total variability in the response variables has already been explained by fixed covariates (Kazembe & Namangale, 2007).

After we controlled for the spatial dependence in the data, the fixed effects show the importance of child age, mother's age at first birth, mother's education, and sex of the child. The paper also provides evidence that individual risk factors influence the pattern of disease. For instance, the result shows that age and sex of the child are important predictor for all three ailments. The effect of age is particularly interesting. Generally children at younger ages (0-12 months) are at greater risk of disease than children at later age, probably because of acquired immunity. This might be because of malnutrition in early feeding practice while a child's immune system is not sufficiently developed to protect him or her from contamination by bacteria. The results emphasis the need for intervention targeted at this group and may include micronutrient supplements, e.g. Vitamin A (Sachs & McArthur, 2005). The findings are generally as expected and consistent with the existing literature. Children of highly educated mother's are at lower risk of ailments than other children (Cleland & Sathar, 1984; Hobcraft *et al*., 1985; Madise et al., 2003). This finding suggests that these mothers were likely to have more health care knowledge to protect their children and to deal with these conditions more effectively. The World Bank had found that mother's education can significantly reduce childhood morbidity by improving the mother's health seeking ability. Children who are breastfed have lower chance of diarrhoea, fever and ARI respectively as compared with children who are not breastfed. These findings are consistent with those of earlier studies that also documented a negative association between breastfed and risk of diseases (Victora *et al*., 1989; Arifeen *et al*., 2001). An important finding that emerges from the study is the negative association between mother's body mass index (BMI) and childhood disease indicating that high BMI values are less prone to infected with three types of ailment. Mother's with low BMI values indicate poor quality of food and hence, may also imply weakness of the children, making children more susceptible to infected with diseases. Furthermore, children born to underweight mothers may be more susceptible to infection than children whose mothers are well nourished (Borooah, 2004).

Poor nutritional and morbidity status of children is very common in less developed countries and more specifically in less developed states in India. Underweight children are more prone to recurrent illness episodes. It is evident from our study that childhood ailment is higher among underweight children. However, it is also found that in previous works that undernutrition acts as a catalyst for childhood morbidity (Scrimshaw *et al*., 1968; Dasgupta, 1997; Rao *et al.*, 2004).Children in richest quintile are at lower risk of diarrhoea and ARI, even when controlling for demographic and spatial factors. In richer households, children are often well fed, cared for and provided with safe and stimulating environment, through which they are more likely to survive, to have fewer disease and illness and to fully develop thinking, language, emotional and social skills (UNICEF, 2007). Hence the gradient of household socioeconomics characteristics remains crucial determinant of level of nutritional achievements among children. Betterment of such condition thus is expected to improve growth of children likely through better nutritional intake and reduce childhood morbidity. As compared to children living in Hindu household, those living in Muslim household were higher risk of three ailments.

This study examined the relative strength of the different factors contributing to childhood morbidity (diarrhoea, fever, & ARI) among under five children in India. The results of this study have implication for the strategy to implement primary health care programme more effectively. There is a need to implement an integrated package of immunization and Vitamin A supply and other child health care programmes to reduce the prevalence of child morbidity. Child's age effect suggests the need to pay attention to child feeding practices, particularly during the six months of age. More emphasis should also be given to the WHO guidelines on exclusive breastfeeding for six months after birth, as we found that children that are exclusively breastfed are at a lower risk of infection. Clearly, diarrhoea, fever and ARI will continue to be important causes of child deaths until mortality falls to very low rates. Furthermore, nearly two-third of the deaths in the 42 countries analysed (and 57% deaths worldwide) occurs in the predominant causes are pneumonia, diarrhoea and neonatal disorders – with very little contribution from malaria and AIDS (Black *et al*., 2003). The identification of the risk factors and recognition of morbidity can lead to selection of effective and affordable interventions that are appropriate for national delivery system. Efforts to reduce undernutrition, morbidity and mortality depend on the reducing poverty and raising people's living standards by improving the quality of homes and by increasing access to clean drinking water and adequate sanitation. Such interventions have positive impact on child health and to achieve the Millennium development Goals in India.

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Appendix A1:

Background Characteristics	Diarrhoea		Fever		Acute respiratory infection	
	Percent	P values	Percent	P values	Percent	P values
Place of residence						
Urban	8.9		14.1		4.9	
Rural	9.1	0.790	15.2	0.336	5.7	0.039
Sex of the child						
Male	9.6		15.5		5.6	
Female	8.5	0.000	14.3	0.009	5.3	0.082
Vitamin A						
No	9.6		15.0		6.3	
Yes	8.2	0.000	14.8	0.822	5.2	0.000
Breastfeeding						
No	6.7		14.2		4.6	
Yes	10.1	0.000	15.3	0.000	5.9	0.000
BMI of women						
Underweight	9.7		15.5		5.9	
Normal Weight	9.1		14.7		5.4	
Overweight	7.0		14.1		4.1	
Obesity	5.1	0.000	15.4	0.003	4.8	0.000
Religion						
Hindu	8.8		13.9		5.0	
Muslim	10.0		19.9		8.1	
Other	9.1	0.023	13.3	0.000	4.0	0.000
Caste						
SC	8.7		15.3		5.6	
ST	8.8		12.3		4.3	
Other	9.2	0.286	15.2	0.000	5.6	0.000
Wealth Index						
Poorest	8.9		14.5		5.5	
Poorer	9.0		16.0		6.4	
Middle	9.4		15.0		5.9	
Richer	9.5		15.0		4.9	
Richest	8.3		13.8		4.0	
Underweight						
No	8.9		14.6		5.9	
Yes	9.9	0.003	16.5	0.000	6.3	0.036
child's age in months	22.2	0.000	27.0	0.000	26.3	0.000
Education of mother's	5.1	0.962	5.2	0.279	4.6	0.000
Mother's age at birth	19.8	0.000	19.9	0.000	19.5	0.000

Note: χ^2 test was used for categorical data and Mann-Whitney test for continues data for bivariate analysis. For continues variables, results are shown as mean value.

A2:

Region	State	Diarrhoea	Fever	Acute respiratory infection
North	Jammu And Kashmir	10.1	18.7	7.3
	Himachal Pradesh	7.7	10.2	1.3
	Punjab	7.8	14.9	6.6
	Uttaranchal	12.9	16.9	4.1
	Haryana	10.3	9.0	2.6
	Delhi	8.4	12.2	6.1
	Rajasthan	10.4	12.0	6.4
Central	Uttar Pradesh	8.1	15.7	6.5
	Madhya Pradesh	12.2	13.2	3.5
	Chhattisgarh	5.2	11.4	4.1
East	Bihar	10.7	19.3	6.4
	Jharkhand	13.3	20.2	4.8
	Orissa	11.8	15.9	2.6
	West Bengal	6.5	20.0	12.4
Northeast	Arunachal Pradesh	14.9	20.3	6.3
	Assam	8.2	13.7	6.8
	Manipur	10.0	13.3	4.5
	Meghalaya	5.7	7.0	1.8
	Mizoram	11.1	17.1	4.0
	Nagaland	6.4	12.3	4.0
	Sikkim	16.7	20.4	5.0
	Tripura	8.4	29.4	13.4
West	Goa	6.8	21.0	3.6
	Gujarat	13.2	15.0	4.5
	Magarashtra	8.1	11.1	4.4
South	Andhra Pradesh	5.7	9.2	1.9
	Karnataka	8.7	13.5	1.7
	Kerala	6.8	23.4	2.7
	Tamil Nadu	5.5	9.2	3.6