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WEALTH-BASED INEQUALITY IN CHILD IMMUNIZATION IN INDIA: A DECOMPOSITION APPROACH

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Summary. Despite years of health and medical advancement, children still suffer from infectious diseases that are vaccine preventable. India reacted in 1978 by launching the Expanded Programme on Immunization in an attempt to reduce the incidence of vaccine-preventable diseases (VPDs). Although the nation has made remarkable progress over the years, there is significant variation in immunization coverage across different socioeconomic strata. This study attempted to identify the determinants of wealth-based inequality in child immunization using a new, modified method. The present study was based on 11,001 eligible ever-married women aged 15–49 and their children aged 12–23 months. Data were from the third District Level Household and Facility Survey (DLHS-3) of India, 2007–08. Using an approximation of Erreyger's decomposition technique, the study identified unequal access to antenatal care as the main factor associated with inequality in immunization coverage in India.

Introduction

Despite years of health and medical advancement, children still suffer from various vaccine-preventable infectious diseases. It is estimated that worldwide approximately 6.3 million children under the age of five years died in 2013, 22% of which occurred in India (WHO, 2014). However, most of these under-five child deaths can be attributed to diseases that were preventable and treatable through simple and affordable interventions (WHO & UNICEF, 2005). Pneumonia, diarrhoea, malaria, measles, tetanus, HIV/AIDS and malnutrition are the primary causes of death in the developing world (World Bank, 1993). Immunization is regarded as the most effective public health intervention to fight such diseases (World Bank, 1993; WHO & UNICEF, 2005).

India was one of the first nations to react to vaccine-preventable diseases (VPDs) by launching the Expanded Programme on Immunization (EPI) back in 1978. Over the years, India has made remarkable progress in child immunization. As reported by the NFHS reports I, II and III, during the 1980s full child immunization coverage was below

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20%, increasing to 36% in the early 1990s and further to 44% in 2005–06 (IIPS & Macro International, 2014). Recently, the Indian Government's Ministry of Health and Family Welfare declared that the country had reached 61% full immunization coverage in 2012. These figures, though they look impressive, do not say anything about disparities in the prevalence of immunization. The available evidence suggests that there are disparities in child immunization by economic status in India (Sahoo, 2012). But what is the explanation for this wealth-based inequality in immunization? Surprisingly, despite the importance of the question, very few studies have been conducted in India to understand and identify the factors associated with inequality in child immunization (see Lauridsen & Pradhan, 2011; Mathew, 2012). These limited studies have made a major contribution to the literature, but they suffer from several drawbacks. For instance, Mathew (2012) conducted a systematic review of the literature to identify and explore factors associated with inequalities in child immunization, but the study did not employ any empirical data analysis to arrive at its conclusion. Similarly, the study of Lauridsen and Pradhan (2011) had a number of flaws. Firstly, they considered only 9582 children, which is far lower than the number reported in the NFHS-3, and they did not justify the reason behind choosing that sub-sample. Secondly, the study used data from different sources pertaining to different time points (NFHS-3, Census 2001, Central Statistical Organization and National Sample Survey, 2004–05), which were highly questionable (Bailey, 2008; McLeod, 2010). Thirdly, they considered *per capita* income, poverty ratio and economic status as three independent variables in the same regression model. But the inclusion of these three variables, which roughly act as proxies for standard of living, simultaneously in the model is not scientific and invites an additional problem of multicollinearity. Fourth, the study excluded some key variables from the analysis, such as region, availability of an immunization card and mother's awareness. Given this background, the present study attempted to identify the determinants of wealth-based inequality in child immunization using a modified and new method in India.

Methods

Data source

Data were taken from the third District Level Household and Facility Survey (DLHS-3) on Reproductive and Child Health (RCH) conducted in 2007–08, which provides national-level estimates of maternal and child health, family planning and other reproductive health indicators. The DLHS-3 gathered information from around seven lakhs (720,320 households) from 601 districts all over India. Respondents comprised both ever-married women aged 15–49 and unmarried women aged 15–24. However, the present study was based on 11,001 eligible ever-married women aged 15–49 and their children aged 12–23 months. Details of the survey design are available in the DLHS-3 national report (IIPS, 2015). A list of variables used in the study, along with their definitions, is given in Table 2.

Construction of the Concentration Index

The Concentration Index (CI) quantifies the degree of income-related inequality in a specific health variable and can be used to measure the degree to which health subsidies

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can better target the poor. There are various ways by which the CI can be calculated (Kakwani, 1980), but there is an intense debate regarding the appropriateness of any given method. Most studies analysing health sector inequalities have adopted the method proposed by Wagstaff *et al.* (1991); this was originally recommended for binary variables and takes the form:

$$C = 2\mathrm{cov}(x, h)/\mu$$

where cov(x,h) is the covariance between the relative rank of the variable (x) and the health variable itself (h) and μ is the average level of health.

However, this index (C) has some limitations (Wagstaff, 2005) and does not satisfy all the conditions of rank-dependent indices (see Kjellsson & Gerdtham, 2012). Wagstaff himself maintained that since the bounds of the CI are probably dependent on the mean of the health variable, the Concentration Index should be normalized by dividing it either by the reciprocal of the mean of the variable or the bound of the Concentration Index. Another problem is that rankings of indices are sensitive to the type of health variable. Thus, different rankings are observed for inequalities in ill health and inequalities in health variables (Clarke *et al.*, 2002). Furthermore, the value of the index is arbitrary to a great extent when the health variable is of a qualitative nature (Erreygers, 2006; Zheng, 2006). Fortunately, these loopholes have largely been resolved by the work of Erreygers (2009). The index proposed by Erreygers (generally denoted by E), which satisfies all the four properties desirable for a good rank-dependent index, has two versions: one for a binary variable and the other for continuous variable. Erreygers defined the corrected concentration index for a binary variable as:

$$E(h) = \frac{8}{n^2}\sum_{i=1}^{n} Z_i h_i \tag{1}$$

where h_i is a binary variable that is equal to 1 if the i^{th} child is fully immunized and 0 otherwise, and $Z_i = \frac{n+1}{2} - \gamma_i$, where n is the number of individuals in a given population and γ_i denotes the socioeconomic rank of the individual ranging from the richest ($\gamma_i = 1$) to the poorest ($\gamma_i = n$). The expression of the Concentration Index for a continuous variable (Erreygers, 2009) is defined as:

$$E(h) = \frac{8}{n^2(b_h - a_h)}\sum_{i=1}^{n} Z_i h_i \tag{2}$$

where b_h is the maximum value of h and a_h is the minimum value. In case of a binary variable (1, 0), the difference ($b_h - a_h$) eliminates.

Decomposition analysis

Wagstaff *et al.* (2003) proposed a procedure for decomposing the causes of health sector inequalities into the contributions of explanatory factors in the context of a linearly additive explanatory model. However, for a binary dependent variable the linear decomposition does not directly apply (Chen *et al.*, 2007). As a solution to this problem, Doorslaer *et al.* (2004) suggested the 'marginal effects' representation for the decomposition technique in the case of non-linear models with binary dependent variables. However, the problem with Doorslaer's formulation is that it is based on an

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original formula of the Concentration Index, which itself is not free from flaws (see Wagstaff, 2005). To fix this technical fallacy, Erreygers (2009) provided a decomposition technique based on his corrected concentration index given by the following expression:

$$E(h) = 4\left[\sum_{j=1}^{q} \theta_j^* V(X_j) + V(\varepsilon^*)\right] \tag{3}$$

where θ_j^* represents the regression coefficient of the j^{th} variable, $V(X_j)$ is the Generalized Concentration Index of X_j and $V(\varepsilon^*)$ is the generalized concentration index of the errors (Kjellsson & Gerdtham, 2013), where:

$$V = \frac{2}{n^2}\sum_{i=1}^{n} Z_i h_i \tag{4}$$

However, the problem still persists when the health variable depends on both binary and continuous explanatory variables, as is the case in the present study. Therefore, the formula provided by Erreygers (2009) is not strictly applicable here and needs further modification. An attempt was therefore made to derive the decomposition formula for a combination of continuous and binary explanatory factors. To begin with, for dependent variables that are binary in nature, the corrected Concentration Index is given by:

$$E(h) = \frac{8}{n^2}\sum_{i=1}^{n} Z_i h_i$$

Now, assuming $h = f(x_1,x_2,x_3)$, the above expression is re-written as:

$$E(h) = \frac{8}{n^2}\sum_{i=1}^{n} Z_i f\left(x_{1,}x_{2,}x_3\right) \tag{5}$$

Where x_1 and x_2 are binary variables and x_3 is a continuous variable. For a linear model then the expression would be:

$$E(h) = \frac{8}{n^2}\sum_{i=1}^{n} Z_i(a_0 + a_1x_1 + a_2x_2 + a_3x_3 + e_i) \tag{6}$$

Here, a_i values are the coefficients of the model, which are equivalent to a marginal effect. Since $\sum Z_i a_0 = 0$:

$$E(h) = \frac{8}{n^2}\sum_{i=1}^{n} Z_i(a_1x_1 + a_2x_2 + a_3x_3 + e_i) \tag{7}$$

or:

$$E(h) = \frac{8}{n^2}a_1\sum Z_i x_1 + \frac{8}{n^2}a_2\sum Z_i x_2 + \frac{8}{n^2}a_3 L\sum Z_i x_3 + \frac{8}{n^2}\sum Z_i e_1 \tag{8}$$

where $L = \frac{1}{(b_h - a_h)}$ (since x_3 is continuous in nature).

This equation gives the distribution of inequality in health variables across different explanatory variables when the model is linear. However, it requires some modifications to make it usable for non-linear models. This is because in a non-linear model

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coefficients are not equivalent to the marginal effect (Brooks, 2014). Thus, the marginal effect for each variable was derived using the following formula:

$$a_i^* = \alpha_i p_i \tag{9}$$

Here a_i, p_i and a_i^* stand for the coefficients, probabilities and marginal effects of the k^{th} variable. Thus, the relationship for a non-linear model for n cases is defined as:

$$E(h) = \frac{8}{n^2} a_1 p_1 \sum Z_i x_1 + \frac{8}{n^2} a_2 p_2 \sum Z_i x_2 + \frac{8}{n^2} a_3 p_3 L \sum Z_i x_3 + \frac{8}{n^2} \sum Z_i e_1 \tag{10}$$

Substituting a_i^* for $a_i p_i$ yields:

$$E(h) = \frac{8}{n^2} a_1^* \sum Z_i x_1 + \frac{8}{n^2} a_2^* \sum Z_i x_2 + \frac{8}{n^2} a_3^* L \sum Z_i x_3 + \frac{8}{n^2} \sum Z_i e_1 \tag{11}$$

The following expressions were deduced using Eqns (1) and (2):

$$\frac{8}{n^2} \sum Z_i x_1 = E(x_1)$$

$$\frac{8}{n^2} \sum Z_i x_2 = E(x_2)$$

$$\frac{8}{n^2} \sum L Z_i x_3 = E(x_3)$$

Thus, Eqn (11) can be re-written as:

$$E(h) = \left[a_1^* E(x_1) + a_2^* E(x_2) + a_3^* E'(x_3) + E(e) \right] \tag{12}$$

Here, $a_1^* E(x_1)$ and $a_2^* E(x_2)$ are contributions of binary variables, while $a_3^* E'(x_3)$ reflects the contribution of continuous variables.

Results and Discussion

Spatial variation in full immunization of children

Considerable variation in full immunization coverage was found across the regions and states of India using the 2007–08 DLHS-3 data. Figure 1 shows that southern India had the highest coverage (74%), while the central region (40.8%) had the worst performance in terms of full immunization coverage. Table 1 shows that Tripura has been facing the worst situation with only 21.9% of children covered by full immunization, while Tamil Nadu was found to have the highest coverage at 79.6%. It was also found that more than 70% of children were vaccinated in Himachal Pradesh, Delhi, Punjab, Karnataka, Goa, Kerala and Tamil Nadu; however, Uttar Pradesh, Bihar, Orissa, Madhya Pradesh, and the states in the north-east, with the exception of Sikkim and Mizoram, had a coverage of less than 50%. Furthermore, immunization coverage was not uniform across union territories, and was found to be lowest (51.9%) in Dadra and Nagar Haveli, and highest in Pondicherry (80.6%).

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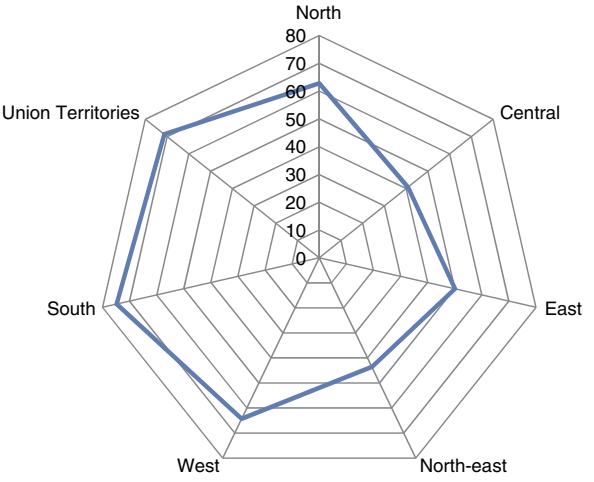


Fig. 1. Regional variation in full immunization of children aged 12–23 months. See Table 1 for regional classification of Indian states. Data source: DLHS-3, 2007–08. $F = 5.9$ ($p < 0.01$).

Inequality in coverage of specific components of full immunization

No uniformity was observed in the coverage of specific doses of vaccines required for full immunization among those who had had at least one vaccine (see Fig. 2). The percentage of children receiving a vaccine against measles was 65%, while the BCG, which is primarily used against tuberculosis, had a coverage of 85%. It is important to note here that the percentages of children receiving at least one dose of DPT and one dose of Polio were as high as 99.9% and 88.6%, respectively, but those figures for 'three doses of DPT' and 'three doses of Polio' fell drastically to 64 % and 60 % respectively. This indicates that some children who initiated the immunization schedule did not complete it successfully.

Wealth-based inequality in immunization

Figure 3 shows a concentration curve demonstrating the wealth-based inequality in immunization in the study sample. To draw this curve, the cumulative proportion of children aged 12–23 months with full immunization (ranked by wealth quintile, beginning with the lowest quintile) was plotted against the cumulative percentage of population (ranked by wealth quintile). The concentration curve lies below the line of equality. This implies that full immunization coverage is concentrated towards the richer section of the population.

To see if there was any relationship between immunization coverage and the degree of its inequality across the states of India, the Concentration Indices for the different states were used as an indicator of inequality and the percentage of children covered by full immunization was plotted against this (Fig. 4). States were classified into four categories (I–IV) depending on their location. Most states were placed in the first quadrant (I), where inequality favouring the rich was accompanied by a high coverage of

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Table 1. Full immunization coverage for states and union territories of India of children aged 12–23 months DLHS-3, 2007–08

Region	State	Full immunization coverage (%)
North	Delhi	67.3
	Haryana	59.6
	Himachal Pradesh	82.2
	Jammu & Kashmir	62.2
	Punjab	79.8
	Rajasthan	48.7
	Uttarakhand	62.9
Central	Chhattisgarh	59.3
	Madhya Pradesh	36.0
	Uttar Pradesh	30.2
East	Bihar	41.4
	Jharkhand	54.0
	Orissa	62.3
	West Bengal	75.7
North-east	Arunachal Pradesh	13.3
	Assam	50.7
	Manipur	47.4
	Meghalaya	33.1
	Mizoram	54.2
	Tripura	38.2
	Sikkim	76.8
West	Goa	89.8
	Gujarat	54.8
	Maharashtra	69.0
South	Andhra Pradesh	66.7
	Karnataka	76.7
	Kerala	79.6
	Tamil Nadu	81.6
Union territory	Andaman & Nicobar Islands	83.6
	Chandigarh	73.0
	Dadra & Nagar Haveli	57.9
	Daman & Diu	85.7
	Lakshadweep	86.2
	Pondicherry	80.2

full immunization of children. This implies that, in most states, fully immunized children tended to belong to the higher income group. The states in the second quadrant (II) exhibited inequality favouring the richer segment but relatively lower immunization coverage. Thus, full immunization was less in such states and most of the children who were fully immunized were from a good economic background. These states included Arunachal Pradesh, Assam, Tripura, Meghalaya, Manipur, Uttar Pradesh and Madhya Pradesh. In these locations, lower coverage of full immunization was probably due to factors such as structural and institutional set up rather than economic status. Moving towards the third quadrant (III), it is observed that in Bihar and Orissa

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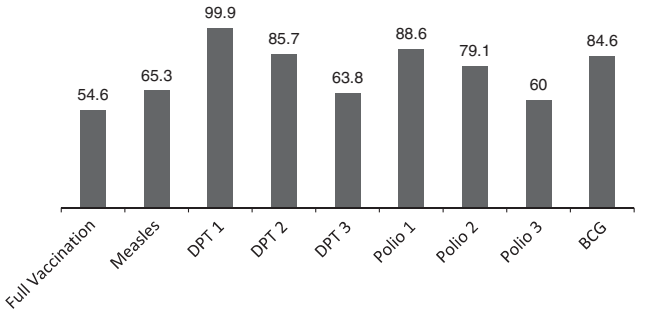


Fig. 2. Percentage of children aged 12–23 months who received specific vaccine. Source: DLHS-3, 2007–08.

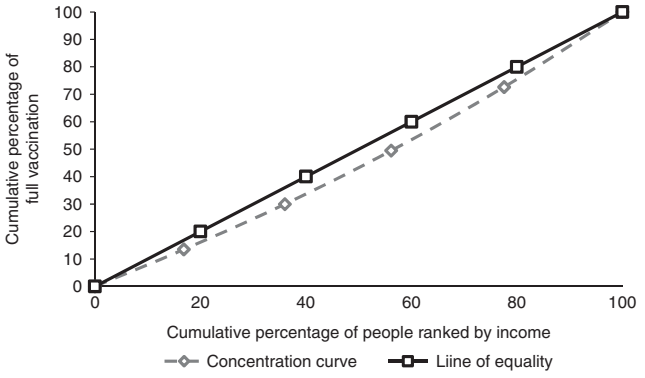


Fig. 3. Concentration curve. Source: DLHS-3, 2007–08.

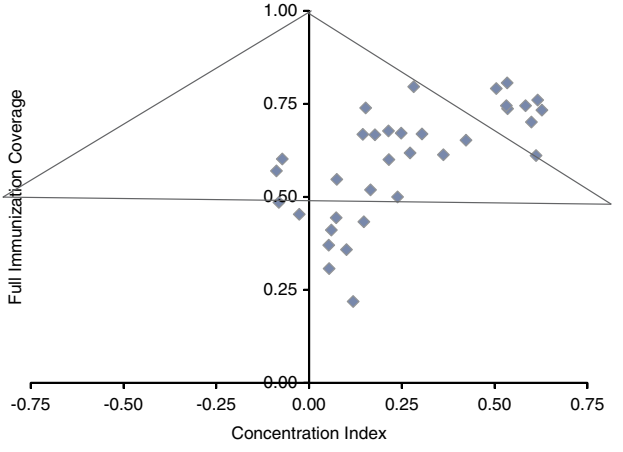


Fig. 4. Inequalities in full immunization of children aged 12–23 months and its coverage by state. Source: DLHS-3, 2007–08.

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Table 2. Definition of selected variables

Variable	Definition
Full immunization	Living children aged 12–23 months who received one dose of BCG, three injections against DPT, three doses of polio (excluding polio 0) and one vaccine against measles
Immunization card	Immunization card seen with the ever-married women aged 15–49 who had a living child aged 12–23 months
Birth order	Birth order of child is 5 or more
Education	Ever-married women aged 15–49 with 10 or more years of schooling
Age of mother	Age of ever-married women at time of birth of youngest child
Religion	Household belonging to Islam
North-east	Household in north-east India
North	Household in northern region of India
East	Household in eastern part of India
West	Household in western region of India
South	Household in south India
Centre	Household in the central region of India
Union Territories	Household in any of the six union territories
Antenatal care	Ever-married women aged 15–49 who received any antenatal care during pregnancy
Check-up	Children aged 12–23 months who had a check-up within 24 h of birth
Postnatal care	Ever-married women aged 15–49 who received postnatal care within 2 weeks of delivery
Distressed child	Children aged 12–23 months who were deprived of the first polio vaccine in the first 2 weeks after birth, did not have an immunization card and lived in a rural area

immunization coverage was less than 50%, but the inequality favoured the poor, implying that although full immunization coverage was less, it was concentrated in the poorer children. Finally, in Chattisgarh and Jharkhand (in the fourth quadrant IV) around 60% of children were immunized and it was concentrated in the lower income group. Therefore, in most parts of India it was observed that immunization coverage became high when it remained skewed towards the richer section of the community.

Decomposition of inequality in full immunization

As a first step towards decomposition, it is necessary to identify the factors affecting child immunization in India. For this purpose, the following non-linear model was estimated:

$$FI_i = \frac{1}{1 + e^{-\left(\alpha_0 + \beta' Z' + \gamma' V' + \varepsilon_i\right)}}$$

Here, Z' represents the vector of the key determinants of full immunization that were identified in a survey of the literature. It is important to note here that in addition to the key variables, a set of regional dummies were also included, which were captured by V'. This model was estimated using the Generalized Linear Model approach. The results of the estimated model, along with decomposition measures, are given in Table 3.

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Table 3. Decomposition of inequality in full immunizationof children aged aged 12–23 months, DLHS-3, 2007–08

Variable	Coefficient	Marginal effect	CI	Contribution to CI of full immunization	Relative contribution (%)
Immunization card	0.174***	0.107	0.108	0.012	4.764
Birth order	−0.295**	−0.182	−0.041	0.008	3.089
Education	0.141***	0.087	0.007	0.001	0.236
Religion	−0.368***	−0.227	0.390	−0.088	−36.287
Age of mother	0.020***	0.012	0.040	0.000	0.204
Antenatal care	0.651***	0.401	0.365	0.146	60.109
Check-up	0.173**	0.107	0.347	0.037	15.229
Postnatal care	0.154**	0.095	−0.073	−0.007	−2.845
Distressed child	−0.487***	−0.300	0.042	−0.013	−5.144
North-east	−0.950***	−0.586	−0.047	0.027	11.215
South	0.267***	0.164	0.154	0.025	10.425
Centre	−0.761***	−0.469	−0.112	0.052	21.512
West	−0.314***	−0.194	0.023	−0.005	−1.851
East	−0.283***	−0.175	−0.173	0.030	12.423
Total				0.244	100.000
Residual				0.017	6.921
Scaled deviance	3171.782 (value/df = 1.25)				
Scaled Pearson's χ^2	2533.000 (value/df = 1)				
Adjusted log-likelihood	−2568.123				
LR χ^2	981.054***				

Since the value of the intercept term is not required to estimate the contribution, it is not reported here.

The study could not include place of residence, working status of mother and population covered by health centre as these are highly correlated with other explanatory variables and hence invite a multicollinerity problem.

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

It is important to note that various diagnostic tests, as reported in the final row of Table 3, justify the appropriateness of the model. Regression coefficients and their marginal effects are reported in the second and third columns, respectively, while the fourth and fifth columns report the CI and the contribution of the CI. Finally, the relative contribution of each explanatory variable in explaining inequality in complete immunization is presented in the sixth column. It may be noted that benchmark regions in this case include the northern region and union territories. The equation was estimated several times, including and excluding regional dummies, to find the appropriate benchmark regions. Though there is no hard and fast rule regarding the decision about benchmark regions, those regions were used as benchmark regions to reduce the degree of multicollinearity in the best possible manner.

Table 3, column 3, shows that the coefficient for possession of an immunization card was positive and statistically significant, indicating that the probability of full

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immunization was higher for children with an immunization card. This result is obvious because parents with a child immunization card will find this useful to follow the immunization schedule, and hence get their children vaccinated on time. Secondly, consistent with other studies (Pande, 2003), it was observed that immunization status had a strong association with birth order. The negative sign of the coefficient indicates that higher birth order had a discouraging effect on child immunization. Similarly, mothers with at least 10 years of formal education are associated with a higher likelihood of child immunization. This can be attributed to changes that accompany maternal education, such as better communication and understanding, and changes in mind-set and superstitious beliefs, which enhance health-care-seeking activities.

These findings are consistent with those of other studies, which have emphasized the importance of maternal education for child immunization (Thang *et al.*, 2007). Consistent with Kumar and Ram (2013) this study also found that the chance of childhood immunization increased with maternal age. This may be due to the effects of factors like knowledge and experience, which are accumulated over time, on the perceived importance of immunization and also on child fatalities that occurred due to poor immunization. The positive coefficients for antenatal and postnatal care suggest that for mothers, the seeking of pregnancy-related health care was associated with a higher likelihood of their children being fully immunized, compared with their counterparts who did not seek such health care. In the same way, newborn check-up, another health-care-related variable, was also found to be positively related to full immunization. This can be attributed to learning sessions that mothers are exposed to during healthcare, where the importance of the timely immunization babies is emphasized.

These results are in agreement with the previous literature concerning the importance of prenatal care utilization (Sahoo, 2012). However, distressed children were found to be more likely to drop out of immunization schedules. Thus, children residing in rural areas, without an immunization card and not having received the first dose of polio were at highest risk of not completing the full course of immunization. There is also evidence of differences due to religious affiliation. The present study found that children from Muslim families had a lower probability of receiving full immunization compared with their counterparts in non-Muslim families. Finally, a significant regional difference was found in the immunization coverage of children in India. Compared with the benchmark regions (Union Territories), the chance of immunization drop-out was observed to be relatively higher among the children residing in the North-East, East, West and Central regions, and relatively lower for the children residing in the South region of India.

From the decomposition analysis, the CI value of having an immunization card was positive, indicating that availability of an immunization card is concentrated in the richer section of the community. Given this value of CI, using Eqn (3) it was found that the contribution of this variable was around 5%. That is, the existing inequality in availability of an immunization card contributed 5% inequality in full immunization across economic class. Similarly, differences in mother's age and education also contributed positively to the biased distribution of child immunization. This result is quite expected because mothers belonging to higher income groups tend to have higher education and are slightly older at first delivery, and have better knowledge of health care and its benefits. Thus, they are more conscious of the need for immunization, and

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hence avail the immunization doses appropriately. Also, high birth order is concentrated towards the poorer sections of society, which is found to bring about an increase in inequality in the coverage by around 3%.

Antenatal care turned out to be the most vital factor, contributing 60% of the variation in full immunization. The probable justification for this finding may be that those women who receive antenatal care remain in touch with the institutional health care arrangements during pregnancy, and thus can easily be convinced about the need for immunization. This finding is further supported by the work of Srivastava and Saksena (1998), who found that antenatal care promotes the acceptance of immunization. In addition, the composite effect of not having an immunization card, living in a rural area and deprivation of the first dose of polio (interaction term) was identified as another culprit, whose relative contribution was estimated to be approximately 5%. Thus, those children getting their first dose may be more likely to be fully immunized because their parents, through this course, are expected to believe that immunization is a basic need for their child, provided they are not deprived of the immunization card and urban facilities.

Moreover, the study also revealed that child immunization was less concentrated in Muslims and this inequality negatively contributed around 36% inequality in immunization. Furthermore, concentration of postnatal care and check-ups of newborns towards the richer section positively contributes to unequal access to immunization. Lastly, inequality in accessing immunization as a consequence of dwelling in the Eastern and Southern regions increased inequality in full immunization, whereas, residing in North-east, West and Central regions of India negatively contributed to this inequality. In short, it was observed that inequalities in antenatal care were the key factors behind the inequality in child immunization in India that existed in the country in 2007–08.

Policy recommendations

The results of this study clearly indicate that immunization coverage in India in 2007–08 was biased in favour of children who belonged to the economically better-off part of the population. The decomposition analysis revealed that antenatal care, medical check-up of children immediately after birth, availability of an immunization card and birth order contributed more than 80% of the total socioeconomic inequalities in full immunization coverage. Of these determinants, antenatal care alone stands out, with a contribution of about 60%. Thus, the obvious policy suggestion is to develop strategies to reduce the rich–poor inequality in uptake of antenatal care. Since it is not sensible to cut down the antenatal care of economically better-off women, this inequality should be minimized by increasing the participation of the poorer section of the community. Thus, the early registration of potential mothers for antenatal care may play an important role. In addition, personal interaction with pregnant women on the part of Accredited Social Health Activists (ASHAs) could bring about successful changes in behaviour.

Secondly, rich–poor inequality in the medical care of newborn babies was found to explain 15% of the inequality in immunization. The problem of inequality in medical care mainly arises because of a low institutional birth rate, especially in rural areas, which is mainly caused by high travel and subsistence costs for pregnant women and

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their accompanying family members. Therefore, the existing government policy to promote institutional delivery by providing cash transfers should be continued and the amount of transfer should be increased periodically.

Thirdly, inequality in possession of an immunization card mainly arises from a careless approach by poorer families to keeping the card well maintained. Therefore, there is a need to educate targeted parents about the importance of the immunization card for timely completion of immunization. In addition, parents who are below the poverty line (in the BPL category) could be given small financial incentives to keep the immunization card well maintained until their child is fully immunized.

Finally, relatively higher birth order of children among mothers belonging to poor families was found to be yet another reason for immunization inequality. Thus, there is a need to encourage these mothers to extend the gap between pregnancies. In this context, easy access to modern contraceptives and making them affordable for poorer families play a crucial role.

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