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Vaccination coverage in India in 2011: A small area estimation approach

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ABSTRACT

Information on population health indicators in India come from a number of surveys that vary in periodicity, scope and detail. In the case of immunization, the most recent coverage indicators are derived from the first round of Annual Health Survey (AHS-1, 2010-11), but these were conducted only in 9 of 35 states and union territories. The most recent national surveys of immunization coverage were conducted in 2009 (Coverage Evaluation Survey) by UNICEF. Therefore, reliable immunization coverage data for the entire country since 2009 is lacking. We used an established approach of small area estimation to predict coverage rates of several vaccinations for the remaining 26 states (not covered by AHS-1) in 2011. In our method, we considered a linear mixed model that combines data from five cross sectional surveys representing five different time points. Our model encompasses sampling error of the survey estimates, area specific random effects, autocorrelated area by time random effects and hence, borrows strength across areas and time points both. Model-based estimates for 2011 are almost identical to the AHS-1 estimates for the nine states, suggesting that our model provides reliable prediction of vaccination coverage as AHS-1 estimates are highly precise because of their large sample size. Results indicate that coverage inequality between rural and urban areas has been reduced significantly for most states in India. The National Rural Health Mission has had both supply side and demand side effects on the immunization programme in rural India. In combination, these effects may have contributed to the reduction of vaccination coverage gaps between urban and rural areas.

1. Introduction

Q3 Despite a long standing national programme for universal immunization in India (UIP, since 1985), only 61% of India's birth cohort (consists of approximately 27 million infants, the largest in the world) is fully immunized [1]. In the context of UIP, full immunization implies conforming to the EPI vaccination schedule Bacillus Calmette-Guérin (BCG), diphtheria-pertussis-tetanus (DPT), oral polio, and measles. It is estimated that one in three incompletely vaccinated children in the world is in India. Vaccination coverage rates are much lower than that of its South Asian neighbouring countries. For example, based on the latest demographic and health surveys, the coverage rate of three doses of DPT vaccine in India (72%) lags rates in Sri Lanka (99%) and Bangladesh (93%).

According to the Coverage Evaluation Survey (CES 2009) [1], the reasons for low immunization coverage pertain to issues on the demand and supply side. Lack of parental knowledge about the whole vaccine schedule is responsible for high proportion of incomplete immunization while fear of side effects is one of the major reasons for no immunization [1,2]. Poor populations and those with lower levels of education are most vulnerable to impacts of low levels of advocacy and communication. Limited cold chain infrastructure and capacity in many states [3], vaccine stock outs [4], significant delay in placement of procurement orders and irregular supply of vaccines [5] – all these supply side factors also have a direct impact on vaccine availability affecting immunization coverage.

Reliable and current vaccination coverage rates are useful in monitoring progress, measuring programme performance, estimating the risk that children face for vaccine preventable diseases

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(VPD) and the risk of VPD outbreaks that can jeopardize the disease prevention goals, understanding infectious disease dynamics, among others.

In India, population level immunization coverage information is derived from the many national level health surveys, although these vary in frequency, scope and detail. The most recent estimates are available from the first round of Annual Health Survey (AHS 2010-11), which are confined only to nine high focus states (Bihar, Jharkhand, Uttar Pradesh, Uttarakhand, Madhya Pradesh, Chhattisgarh, Orissa, Rajasthan and Assam). Although these high focus states are important in that their health indicators lag national averages, it is also important to have reliable immunization coverage estimates for the remaining 26 states and union territories (UTs). The latest nation-wide data that covers all 35 states and UTs are from CES 2009. Since 2005, significant investments have been made in improving the immunization programme under the National Rural Health Mission (NRHM) [6]. However, in the absence of precise and up-to-date data on immunization coverage, it is unclear if these investments have improved immunization coverage.

We used a small area estimation [7] approach to predict vaccination coverage rates for states and UTs that are not covered by AHS-1 for 2011. To obtain small area estimates, we used a linear mixed model that combines data from five cross sectional health surveys representing five separate time periods. This type of model leads to considerable gain in efficiency in estimating small area parameters [7–9], as compared to the estimates based on a single cross sectional survey.

2. Methods

2.1. Estimation parameter and geographical scale

We estimated coverage rates of the following vaccines: BCG (to prevent tuberculosis), DPT (to prevent diphtheria, pertussis, tetanus-DPT3), OPV (to prevent poliomyelitis - Polio3), and measles. The vaccination coverage rate is defined as percentage of children age 12–23 months who received the full complement of vaccines, irrespective of their age at vaccination (at any time before the survey) and source of information (vaccination card or mother's self-report). For most routine immunization coverage surveys WHO recommends using children aged 12–23 months if final primary immunization (measles, in the context of EPI) is at 9 months of age [10]. In addition to these individual vaccines, we estimated the proportion of fully immunized children who received all EPI vaccines.

India's national level immunization coverage indicators mask considerable state level variations, as well as persistent rural-urban differences. Hence, we define the unit of analysis (the geographical level of estimation) as state (and UTs)[1] by rural-urban, which results in $35 \times 2 = 70$ small areas or domains. We use the terms domain and small area interchangeably.

2.2. Data sources

We fitted our model using data from five cross sectional health surveys: DLHS-2, NFHS-3, DLHS-3, CES-09, and AHS-1. In Table 1 we present specific details about the surveys. Direct survey estimates of vaccination coverage rates were obtained from the published reports of the surveys [1,11–13]. Sampling errors, as measured by standard errors (SEs), associated with the survey estimates and the corresponding design effects were available at the small area level for all vaccines from NFHS-3 report [12]. However, for the other four surveys, SEs were not readily available. We calculated SEs by multiplying the simple random sampling (SRS) SE by the NFHS-3 design effects to account for the inflation in SE due to cluster sampling. This is justified by the similarity in sampling design across the five surveys. Note that reported NFHS-3 design effects were different across small areas and vaccination coverage rates, hence, we account for the differential clustering effect across small areas and vaccination type. SRS sampling variances (SE = square root of sampling variance) were obtained using the formula $\hat{p}\left(1-\hat{p}\right)/n$; where $\hat{p}$ is the coverage rate and n is the number of 12–23 months children surveyed. Both $\hat{p}$ and n were available for all vaccines and small areas across surveys.

NFHS-3 covered all 29 states but not the union territories. To obtain the SEs for 6 UTs, we used DLHS-3 survey that reports SEs for BCG and measles vaccination coverage [14]. For UTs, design effects were calculated from BCG coverage rate sampling errors (except for Lakshadweep, for which measles was considered) and used for all other vaccinations across surveys (DLHS-2, 3 and CES-2009). For a particular UT, same design effect is used for rural and urban areas.

Survey estimates were available for all five time points for some, but not all, domains. For example, DLHS-3 does not cover the state Nagaland. Hence, for Nagaland-urban and Nagaland-rural domain we have data from 3 time points (DLHS-2, NFHS-3, and CES-2009). See Table 1 for further details on the survey coverage. For model fitting, it is not essential to have equal number of data points corresponding to all domains (see Section 2.5).

2.3. Small area model

We used the following area level model:

$$y_{it} = \mu + \alpha_t + \beta_s + \gamma_a + h_{it}'\lambda + v_i + u_{it} + e_{it} \quad (1)$$

where

- y_{it} is the vaccination coverage estimate (or some transformed version of it to ensure normality) corresponding to the ith small area (defined as state by rural-urban) and tth time point; $t = 1, \ldots, T_i$ (total number of time points corresponding to area i) and $i = 1, \ldots, m$ (total number of areas: $35 \times 2 = 70$).
  μ is the common mean effect.
- α_t is the fixed effect due to the tth time point.
- β_s is the fixed effect due to the sth geographical location, $s = 1, \ldots, S$ (total number of unique locations). Location can be state or a broader region where the state belongs.
- γ_a is the fixed effect due to the type of residence, a = rural or urban.
- h_{it}' is the vector of area specific fixed covariates which may change with time.
- v_i is the area specific random effect which captures the variability not explained by the fixed effects; $v_i \sim \text{iid}N\left(0, \sigma_v^2\right)$.
- u_{it} is the area by time random effect to capture the spatio-temporal interactions. We assume that u_{it}s are correlated across time for each i. First order autoregressive process is commonly used to incorporate such correlations:
  $u_{it} = \rho u_{it-1} + \varepsilon_{it}$, $|\rho| < 1$; $\varepsilon_{it} \sim \text{iid}N\left(0, \sigma_\varepsilon^2\right)$ and independent of v_i. Note that when ρ takes on the value 1, u_{it} follows a random walk model. If true value of ρ is close to 1, estimation of ρ could be problematic. It might fall outside the parameter space [8,9]. Random walk model for the area by time interaction term is a safer choice from model fitting perspective.
- e_{it} is the sampling error of vaccination coverage estimate y_{it}; where $e_{it} \sim \text{ind}N(0, \psi_{it})$, ψ_{it} is the (known) sampling variance of y_{it}. The sampling errors are independent of v_i and ε_{it}.

[1] A Union territory (UT) is a type of administrative division in India, similar to that of states. UTs include both urban and rural areas in them. Unlike states, which have their own elected governments, union territories are ruled directly by the Union Government (Central Government), hence the name union territory. UTs are much smaller in size compared to most states of India.

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