Impact of High-Intensity Polio Eradication Activities on Children's Routine Immunisation Status in Northern India: Generating New Evidence From Household Surveys by Measuring Programme Exposure on the Child Level

Abstract

The objective of this paper is to analyse and quantify the side effects of the Polio Eradication Initiative on routine immunisation performance in India. Past studies have faced methodological challenges in assessing these side effects. This paper offers a methodological alternative for health policy analysts. The research uses secondary household survey data from the Indian District-Level Household and Facility Survey (DLHS), focusing on children aged 10-30 months in the Northern Indian states of Uttar Pradesh (*n*=34 327) and Bihar (*n*=20 525). Covering the years 2002 to 2008, this is the latest large-scale data from India that enables the matching technique used in this paper. District-level programme intensity data of the Polio Eradication Initiative in India was reconstructed using publicly available resources. The methodological innovation compared to previous studies consists of matching each child in the DLHS data set with a child-specific value of programme exposure depending on its district of residence, its birth date, and the date of the survey interview. Average and age-specific associations between polio programme exposure and children's full immunisation status were assessed using logistic regression, controlling for other determinants of immunisation. The regression results show that the link is negative in Uttar Pradesh and positive in Bihar. Age-specific analysis shows that the positive association diminishes for older children in Bihar and that a negative association emerges and become increasingly pronounced for older children in Uttar Pradesh. This indicates that heterogeneous results emerge across two neighbouring states with similar programme intensity and suggests that the catch-up of unvaccinated older children may be a channel through which negative effects

accrue. The method described in this paper, based on an analytical focus on individual-level programme exposure, can therefore help health policy implementers and evaluators to illuminate positive or negative interactions between a health intervention and a health system.

1 Introduction

More than 100 global health initiatives (GHIs) provide donor-generated funding of billions of dollars each year and are directed at health problems as diverse as blindness, malnutrition, or malaria [1]. A widely-held stance is that such interventions can strengthen but also disrupt country health systems. Concerns arise especially where mass campaigns are conducted at high intensity (e.g. measles campaigns or malaria mass drug administration) or if un-integrated initiatives duplicate functions of country health systems (e.g. in the case of some HIV/AIDS control and social marketing activities) [2; 3].

Although the existing literature on the GPEI is extensive, gaps remain in quantitative assessments of the interactions with country health systems [2]. In an effort to broaden the evaluation toolkit for GHIs, this paper uses micro-level campaign exposure data to analyse the relationship between the Indian Polio Eradication Initiative (PEI, initiated in 1994) and routine immunisation (RI) performance in the Northern Indian states of Uttar Pradesh and Bihar between 2002 and 2008 as a case study of the interactions between high-intensity GHI mass campaigns and country health systems.

The few quantitative evaluations of the PEI include descriptive statistical analyses by Aylward et al. [4], and multivariate before-and-after comparisons by Bonu et al. [5] and Bonu et al. [6]. A major challenge of these analyses is that they conflate the introduction of polio mass campaigns with broader health system and socio-economic developments, making it difficult to attribute effects to polio eradication. Studies that appreciate interactions between intervention and health system more explicitly include national-level time-series analyses by Gauri and Khaleghian [7], who assess polio coverage rates alongside political determinants of immunisation, and Closser et al. [8], whose use of programme intensity data links the PEI directly to health system performance. However, these aggregate analyses can mask locally

heterogeneous effects that might alleviate or exacerbate existing patterns of social marginalisation, and the absence of discernible effects in these studies contradicts qualitative assessments that consistently report both positive and negative interactions between polio eradication and national routine immunisation programmes [8-11]. In other words, we still lack a quantitative methodology that enables us to better understand the side-effects of mass-campaign-based public health efforts such as polio eradication on country health systems.

The methodology introduced in this paper yields two principal insights. First, exposure to an additional polio mass immunisation campaign in Uttar Pradesh between 2002 and 2008 was on average linked to lower odds for a child to attain full routine immunisation status, whereas the relationship was positive in Bihar. Second, the negative association is more pronounced for older children in Uttar Pradesh. In Bihar, the size of the positive link is smaller for older children. These findings are consistent with the notion that PEI and country health systems interact and suggest that this interaction can be heterogeneous even within one high-intensity context.

2 Methods

The logistic regression model in Equation (1) was estimated to examine the relationship between the PEI and RI in India. The model assesses the association between the immunisation status of a child and the number of polio immunisation rounds to which it has been exposed (*pol*), controlling for other determinants of full immunisation. Common determinants of immunisation in the literature [7; 12-20] are child characteristics like age and sex (*CHI*), characteristics of the mother like education (*MOT*), household characteristics like wealth (*HH*), and health system characteristics (*INF*, controlled for by location and time dummy variables). I also include an interaction term between campaign exposure and child age because older children's catch-up of routine immunisation may be affected differently

than young children's scheduled routine immunisation sessions (*INT*). The variables and vectors in the regression model are displayed in Table 1 (variables in brackets entered the full model but have been excluded from the restricted model that is reported in Section 3). Goodness-of-fit of the restricted model was based on the Pseudo-R^2 and the Akaike Information Criterion (AIC) [21-23]. Logistic regression was chosen because of the binary nature of the immunisation index [24; 25]. Robustness checks are described in the Discussion Section 4 and a selection is presented in the supplementary Appendix Tables A1 (Uttar Pradesh) and A2 (Bihar). The model was estimated using the statistical software Stata 12 [26].

$$\text{logit}[P(y = 1)] = \alpha + \beta_p pol + \beta_c CHI + \beta_m MOT + \beta_h HH + \beta_i INF + \beta_x INT \quad (1)$$

I draw on data from the District-Level Household and Facility Survey (DLHS), which includes district identifiers for Uttar Pradesh and Bihar [27-29]. The DLHSs use systematic stratified sampling to survey women, their husbands, village leaders, and health facilities across India. This analysis uses repeated cross-sections of the last two survey rounds, conducted in 2002-2004 (DLHS II) and 2007-2008 (DLHS III). The inclusion of two survey rounds helps to increase the variance of campaign exposure as the PEI became more intense over time. The sample of children was limited to the ages of 10 to 30 months in order to match the available campaign data (see below).

The immunisation status as dependent variable consists of a binary index that takes the value of 1 if full immunisation is attained. A child achieves this status if it has received all three doses of the diphtheria, pertussis, and tetanus vaccine (DPT) and the oral polio vaccine (OPV); and one dose of each BCG, measles, and hepatitis B vaccine. In contrast to the

official Indian immunisation schedule [30; 31], I excluded OPV and hepatitis B from the immunisation index owing to potential endogeneity and recall biases (OPV) and low coverage (hepatitis B).[1] The data used for constructing this immunisation index is based on parent recall and vaccination card information [19].

[1]The results are robust to alternative immunisation indices that include the OPV and hepatitis B vaccine.

Table 1. Variables Included in Logistic Regression Model

<<INSERT TABLE 1 HERE>>

Source: Own elaboration.

Notes. Vectors indicated by *CAPITALISED ITALICS*. Dummy variables of "health system-level characteristics" capture effects beyond healthcare, e.g. political and other infrastructural differences. Variables [in brackets] have been estimated in full model but are not reported in this paper.

The independent variable of principal interest is the child's exposure to polio mass immunisation campaigns (*pol*). This is a child-specific variable, indicating the number of polio immunisation campaigns that took place during the child's lifetime in the respective district. These 6-11-day-long mass immunisation campaigns take place on pre-specified dates and typically include one day during which children are vaccinated at "immunisation booths" (Uttar Pradesh) and 1-2-week-long house-to-house vaccination activities (Uttar Pradesh and Bihar) in order to vaccinate *all* children below the age of five years (either nationally or in selected regions) [11]. So-called "mop-up" campaigns complement these activities, taking a similar shape but being performed *in reaction* to polio outbreaks to contain further transmission of the disease.

In order to construct this exposure variable, the DLHS data had to be complemented by the district-level intensity of polio immunisation in Uttar Pradesh and Bihar. Because administrative programme data was inaccessible, I reconstructed this data using publicly available data and documents from the Indian National Polio Surveillance Project and the GPEI. I subsequently matched the district-level campaign data with the child-level DLHS data, creating a unique value of campaign exposure for each child based on its birth month and the month of the survey interview (see Fig. 1; child age was capped at 30 months because polio campaign activity only dates back as far as 1999 while the first DLHS II interview was conducted in January 2002). This means that children of the same age in the same district can be exposed differently to the PEI, which helps us isolate potential synergetic or disruptive effects between the programmes on the service delivery level.[2] In other words, this methodology exploits exogenous variation in the survey data collection to establish a unique child-level value of exposure to the polio campaigns. Whereas the data used to construct the

[2]The dates within each of the districts in Uttar Pradesh and Bihar were surveyed span up to 21 months per survey round. In only 27 out of 214 cases (12.6%), all survey data had been collected within the same month.

campaign intensity is uniform on the district level, more fine-grained administrative data from other programmes might offer opportunities to exploit further within-district variation for analysis in future research.

Fig. 1. Schematic Depiction of Constructing the Polio Campaign Exposure Variable (*pol*)
<<INSERT FIGURE 1 HERE>>
Source: Own illustration.
Notes. For illustrative purposes only. Not based on actual data.

The sign and significance of the polio campaign exposure variable indicate whether a higher exposure to the polio programme is associated positively or negatively with the log odds of a child to receive full immunisation. This relationship can be interpreted with the help of theoretical arguments, for instance the balance between counteracting forces like health workforce absorption and increased awareness about public health programmes [e.g. 8]. Given that Uttar Pradesh and Bihar are two contexts in which polio eradication has taken place at very high intensities (children being exposed to up to 24 immunisation rounds by the age of 30 months in 2008), it is reasonable to hypothesise that a discernible statistical relationship exist, even if its direction is ambiguous from a theoretical perspective.

Because disruptive effects of the PEI may be mitigated if missed vaccinations can be easily followed up during subsequent routine immunisation sessions, I will also examine age-specific effects through the interaction between the age of the child and the exposure to polio immunisation campaigns (*POLxAGE*). By interacting polio campaigns with child age, we can identify different levels of the campaign impact depending on a child's age. For instance, if the campaign exposure variable is negative and the interaction term is positive, this would be consistent with the argument that negative effects of the PEI diminish the older the child is.

3 Results

I first investigate the overall link between polio eradication and routine immunisation uptake. Table 2 presents the results for the restricted regression model. The control variables show the expected signs in accordance with the immunisation literature. Not shown are the district dummy variables to control for district-specific effects on children's immunisation status.

The main insight from this table relates to the association between the exposure to polio campaigns and a child's odds to be fully immunised. The variable of interest (*pol*) is significant at the 0.1 per cent level in both Uttar Pradesh and Bihar. In Uttar Pradesh, the

coefficient of -0.056 corresponds to a *decrease* of 5.45% in the odds of a child to be fully immunised *when exposed to an additional polio campaign*, in the presence of the given control variables.[3] In Bihar, exposure to an additional campaign corresponds to 4.3% *higher* odds of full immunisation. This means that, for example, increasing the exposure from 14 to 15 polio campaigns would coincide with a lower probability of full immunisation from 12.2% to 11.6%, given a hypothetical male child at the age of 20 months in the district of Bareilly in Uttar Pradesh who represents median sample characteristics of the DLHS III. On average across the sample, this translates into a 0.83 percentage point *lower* (Uttar Pradesh) and a 0.63 percentage point *higher* (Bihar) expected probability of receiving full immunisation with every additional polio mass immunisation campaign.[4]

In short, children in Bihar exhibit a *higher* probability of vaccination uptake when exposed to higher polio campaign intensity. Conversely, high exposure is linked to *lower* attainment of full immunisation in Uttar Pradesh (I discuss in Section 4 whether we could consider these relationships to be causal).

[3]The change in the odds is calculated from the coefficient as follows: $1 - e^{1*(-0.056)} = 1 - 0.9455 = 0.0545$ [21]. The odds of an event with a probability of success p are $(p / [1 - p])$.

[4]Owing to constant change in the odds of full immunisation, the response in terms of expected probability is non-linear across the sample; thus the deviation from the preceding example.

Table 2. Overall Regression Results in Uttar Pradesh and Bihar (Restricted Model)

<<INSERT TABLE 2 HERE>>

Source: Own estimation.

Notes. Coefficients reported. Standard errors in parentheses. District dummy variables not displayed. Coefficient values of different models cannot be immediately compared due to varying samples.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

The second area of investigation concerns age-specific relationships between immunisation status and PEI exposure. The regression results are summarised in Table 3 and show that, for both Uttar Pradesh and Bihar, the signs of the campaign exposure variable (*pol*) and the child's age (*ch_age*) are positive and significant, whereas the coefficient of the interaction term is negative and significant at the 0.1 per cent level. Because older children are more likely to be exposed to a higher number of campaigns, Table 4 further analyses the exposure for sub-samples stratified by age. The broad trend of these results is consistent with the pooled samples: Whereas point estimates are predominantly negative in Uttar Pradesh, they tend to be positive in Bihar. All statistically significant results are negative in Uttar Pradesh and positive in Bihar.

Fig. 2 summarises Tables 3 and 4 and depicts the change in the log-odds of the polio campaign coefficient depending on the child's age for Uttar Pradesh and Bihar in the pooled sample (lines) and across sub-samples stratified by age (bars). The graphical analysis reinforces the varying conclusions for the two Indian states. Panel a displays the results for Uttar Pradesh and suggests that the polio campaign exposure coefficient turns negative at an age of 12 to 13 months in the pooled sample, and that statistically significant results for individual age sub-samples are all negative and clustered at higher ages (24 to 27 months). Starting from a higher level, the association of an additional polio campaign with the odds of attaining full immunisation status in Bihar (Panel b) remains positive for all age groups, but it appears to weaken among older children.

Table 3. Comparison of Age-Specific Model Results Uttar Pradesh and Bihar

<<INSERT TABLE 3 HERE>>

Source: Own estimation.

Notes. Coefficients reported. Standard errors in parentheses. Only main results displayed. Coefficient values of different models cannot be immediately compared due to varying samples.

[a]Suggested interpretation of interaction term.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 4. Main Age-Stratified Regression Results in Uttar Pradesh and Bihar (Restricted Model)

<<INSERT TABLE 4 HERE>>

Source: Own estimation.

Notes. Coefficients reported. Standard errors in parentheses. Control variables (restricted model) not displayed. Coefficient values of different models cannot be immediately compared due to varying samples.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Fig. 2. Relationship Between Polio Campaign Exposure and Child Age

<<INSERT FIGURE 2 HERE>>

Source: Own illustration.

If these statistical associations point at a causal relationship (which needs to be established in further research using e.g. household panel data), this would suggest that young children in Uttar Pradesh are less affected by disruptions of routine immunisation than older children, who are less likely to catch up when exposed to an additional polio immunisation campaign. In Bihar, it would suggest that a positive stimulus accrues largely at the scheduled routine immunisation session rather than at follow-up sessions for unvaccinated children.

4 Discussion

The statistical associations presented in this paper are consistent with the claim that counteracting forces have resolved, on average, into negative effects for routine immunisation in Uttar Pradesh and positive effects for Bihar. The age-specific analysis further suggests that the main channel through which negative effects accrue is not the scheduled routine immunisation session itself but rather the catch-up of unvaccinated older children. In contrast, where synergies are realised, positive outcomes appear to be concentrated around the scheduled routine session. I discuss in this section the extent to which a causal interpretation of these results is justified, and the implications for our understanding of the impact of PEI using this evaluation approach.

Robustness tests have demonstrated little or no sensitivity of the statistical results towards alternative immunisation indices, parent recall, sub-sample analyses of districts with poor immunisation coverage, models including a squared child age and exposure variables, and alternative functional forms (probit models and linear models with robust standard errors; results presented in supplementary tables). Given my analysis of repeated cross-sectional data sets (rather than e.g. panel data), it is difficult to establish firmly a causal relationship with these results. However, I have reason to believe that causality – if present – is more likely to run from campaign exposure to immunisation status than the other way round: I analysed

non-OPV full routine immunisation status that is less influenced by OPV mass campaigns (e.g. less likely to influence recall), children at the same age with different levels of exposure show systematically different immunisation results, and the results are reproduced in districts with very low immunisation coverage where we would otherwise expect the confounding effect to disappear. Given that the same estimation methodology yielded heterogeneous outcomes in Uttar Pradesh and Bihar, it is also unlikely that the underlying polio campaign data biases the results systematically in either direction.

Limitations apply despite the robustness of the results. Firstly, as the statistical model is focused on programme intensity, potential systemic effects of the PEI on routine immunisation cannot be fully explored in this study. Nation-wide longitudinal and higher-frequency data might help to shed light on systemic changes following the introduction of the programme. Secondly, due to data availability, the statistical analysis covered the period from 2002 to 2008. Recent programme developments such as India's "107 Block Plan" are therefore not reflected in the research findings [8]. Thirdly, although this study has revealed considerable inter-state variations in Northern India, it does not shed light on how these patterns materialise. Identifying and modelling political determinants in a cross-state or cross-country study could contribute to understanding factors of success or failure of global health interventions. For instance, Atun et al. [3] emphasise political desirability and government commitment as factors for the integration of GHIs into national health system, which might be modelled through the presence of democratic institutions to understand the demands of the local population (e.g. public engagement, consultations, and other feedback mechanisms) [2]. Lastly, the analysis focused only on the link between the PEI and routine immunisation. The PEI may also interact with other elements of the Indian health system, such as antenatal care [8]. The data set developed for this analysis provides scope for studying such interactions in the field of reproductive and child health in future research.

The possibility that older children benefit less or are further excluded from the routine immunisation activities in Bihar and Uttar Pradesh offers further space for reflection. In light of the observed patterns, we could hypothesise that programme governance of the PEI is geared towards readily measured elements as basis for operational and strategic decision-making, discriminating against areas on which "evidence" sheds no light. In the current context, where routine immunisation strengthening is promoted as a strategic objective and programme surveillance emphasises young children in particular [e.g., 32], such a bias could discriminate against older children who have already missed the opportunity to receive their routine immunisation in a timely manner. This would accentuate the exclusion of groups who already lag behind scheduled shots (and who are thus less readily "measured"). However, neither programmatic biases nor operational differences in the polio eradication activities explain the fundamentally different trends across the two states. Uttar Pradesh and Bihar follow the same programme policies after all. It is, however, possible that the overarching policies are interpreted and operationalised differently in Bihar and Uttar Pradesh. More general factors of "political will," differences in healthcare governance, and other state-specific factors may be at work as well, yet this remains subject to further research.

5 Conclusion

This paper has contributed to the evaluation of the Polio Eradication Initiative's using a novel methodology that goes beyond previous approaches of descriptive statistical analysis, before-and-after comparisons, and the study of national-level trends. I provided quantitative evidence that is consistent with the often-alleged interactions between the Polio Eradication Initiative and the Indian health system through the national routine immunisation programme. Although causality of the statistical associations needs to be established in future research, the findings indicate that positive effects may accrue for children in Bihar close to their

scheduled routine shots, whereas negative effects might be particularly pronounced for unvaccinated children in Uttar Pradesh who had missed their routine immunisation sessions several months earlier. The different trends also point at the importance of state-level factors in determining the response of local health systems to global health interventions.

Despite the limitations of this study, the research findings underline the need to address potential interferences and synergies between intervention and health system. I conclude here with three suggestions. Firstly, if it is misperceived that the Polio Eradication Initiative is neutral to the routine immunisation status of older children simply because missed shots could easily be followed up, this can become an obstacle to realising improvements and actually generating synergies between the programmes. Catch-up mechanisms for routine immunisation deserve particularly attention in this respect.

Secondly, the methodology used in this paper can be applied to assess the interactions between other programmes with a mass campaign design and public health services such as routine immunisation or antenatal care. Such analyses can guide corrective action for programme managers but should be complemented with qualitative research to examine the specific channels through which interferences and synergies arise. Such studies may go beyond the logistic regression framework with age-stratified results used in this paper to address the correlation between child age and campaign exposure, using for example multilevel or survival analysis frameworks.

Thirdly, prospective health initiatives can benefit from ex-ante appraisals of interactions with local health systems. In a recent report by the German KfW Development Bank, Haenssgen and Nohr [33] explore the applicability of these conclusions to social marketing in HIV/AIDS initiatives and argue that health interventions and national health systems can interact along various interfaces such as health workforce, finance, or service delivery [33]. Programme managers in consultation with stakeholders can draw on past project experiences to assess

both the level of integration and possible interactions of the health initiatives along these interfaces with the health system. Programmatic responses prior to implementing the initiatives can then potentially help to exploit synergies and minimise adverse side effects.

Abbreviations

AIC	Akaike Information Criterion
BCG	Bacillus Calmette-Guérin Vaccine
DLHS	District-Level Household and Facility Survey
DPT	Diphtheria, Pertussis, and Tetanus Vaccine
GHI	Global Health Initiative
GPEI	Global Polio Eradication Initiative
OPV	Oral Polio Vaccine
PEI	Polio Eradication Initiative
RI	Routine Immunisation

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Table 1. Variables Included in Logistic Regression Model

Variable / Vector	Variable / Vector Description	Included Variables
Dependent Variable		
***P*(*y* = 1)**	Child's probability to attain full vaccination status, ages 10 to 30 month, Uttar Pradesh and Bihar	• Vaccination status ([1] if BCG, DPT 1-3, and measles vaccine have been received)
Independent Variables		
pol	Polio campaign exposure	• Number of polio campaigns to which the child has been exposed throughout its life at time of survey
CHI	Child characteristics	• Age of child • Sex of child • [Age^2 of child] • [Birth order of child]
MOT	Maternal and paternal characteristics	• Level of education in years (mother, [father]) • Age of mother at birth • Motivation and awareness: ▪ Received ante- and post-natal care ▪ Possession of vaccination card ▪ Received advice to vaccinate child
HH	Household characteristics	• Standard of living index (quintiles) • Religion dummy • Caste dummy • [Household size]
INF	Health system characteristics	• Rural / urban location dummy • District dummy • Survey round dummy
INT	Interaction terms	• Polio campaign exposure x age of child (*POLxAGE*)

Source: Own elaboration.

Notes. Vectors indicated by *CAPITALISED ITALICS*. Dummy variables of "health system-level characteristics" capture effects beyond healthcare, e.g. political and other infrastructural differences. Variables [in brackets] have been estimated in full model but are not reported in this paper.

Table 2. Overall Regression Results in Uttar Pradesh and Bihar (Restricted Model)

Variable Name	Variable Description	Uttar Pradesh	Bihar
pol	Child's exposure to polio campaigns	-0.056*** (0.009)	0.042*** (0.010)
ch_sex	Sex of child (1 = girl)	-0.139*** (0.028)	-0.249*** (0.036)
ch_age	Age in months	0.075*** (0.005)	0.026*** (0.006)
m_age_at_birth	Age of mother in years at birth of child	0.011*** (0.003)	-0.001 (0.003)
m_school	Mother's years of schooling	0.079*** (0.004)	0.078*** (0.005)
m_anc	Mother received ante-natal care	0.805*** (0.038)	0.436*** (0.045)
m_pnc	Mother received post-natal care or assisted delivery	0.183*** (0.031)	0.269*** (0.040)
ch_VACCadv	Advice by health staff to vaccinate child	0.748*** (0.031)	0.512*** (0.040)
ch_healtc_seen	Has and presented vaccination card for child	1.877*** (0.038)	2.301*** (0.051)
ch_healtc_notseen	Has vaccination card for child (not presented)	1.121*** (0.034)	1.773*** (0.049)
hh_SLI_quint	Household standard of living (quintiles)	0.145*** (0.014)	0.137*** (0.019)
hh_rel_notmuslim	Religion of household head: other than Muslim	0.372*** (0.042)	0.629*** (0.058)
hh_caste_schedtribe	Caste group: Scheduled tribe	-0.062 (0.146)	-0.022 (0.152)
hh_caste_OBC	Caste Group: Other backward class	-0.027 (0.037)	0.289*** (0.048)
hh_caste_general	Caste Group: General caste	0.105* (0.046)	0.551*** (0.065)
hh_rur_urb	Rural / urban dummy (1 = urban)	0.110** (0.039)	0.005 (0.058)
survey_dummy	Survey dummy (1 = DLHS III)	0.189** (0.072)	0.463*** (0.082)
Constant	Constant	-4.827*** (0.166)	-5.944*** (0.200)
n		34 327	20 525
***p*-Value**		< 0.001	< 0.001
Pseudo R^2		0.248	0.293
Akaike Information Criterion		0.919	0.917

Source: Own estimation.

Notes. Coefficients reported. Standard errors in parentheses. District dummy variables not displayed. Coefficient values of different models cannot be immediately compared due to varying samples.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 3. Comparison of Age-Specific Model Results Uttar Pradesh and Bihar

Variable Name	Variable Description	Uttar Pradesh	Bihar
pol	Child's exposure to polio campaigns	0.037* (0.018)	0.119*** (0.02)
ch_age	Age in months	0.102*** (0.007)	0.054*** (0.009)
POLxAGE	Impact of child age on polio campaign exposure[a]	-0.003*** (0.001)	-0.003*** (0.001)
N		34 327	20 525
***p*-Value**		< 0.001	< 0.001
Pseudo R^2		0.249	0.294
Akaike Information Criterion		0.918	0.916

Source: Own estimation.

Notes. Coefficients reported. Standard errors in parentheses. Only main results displayed. Coefficient values of different models cannot be immediately compared due to varying samples.

[a]Suggested interpretation of interaction term.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

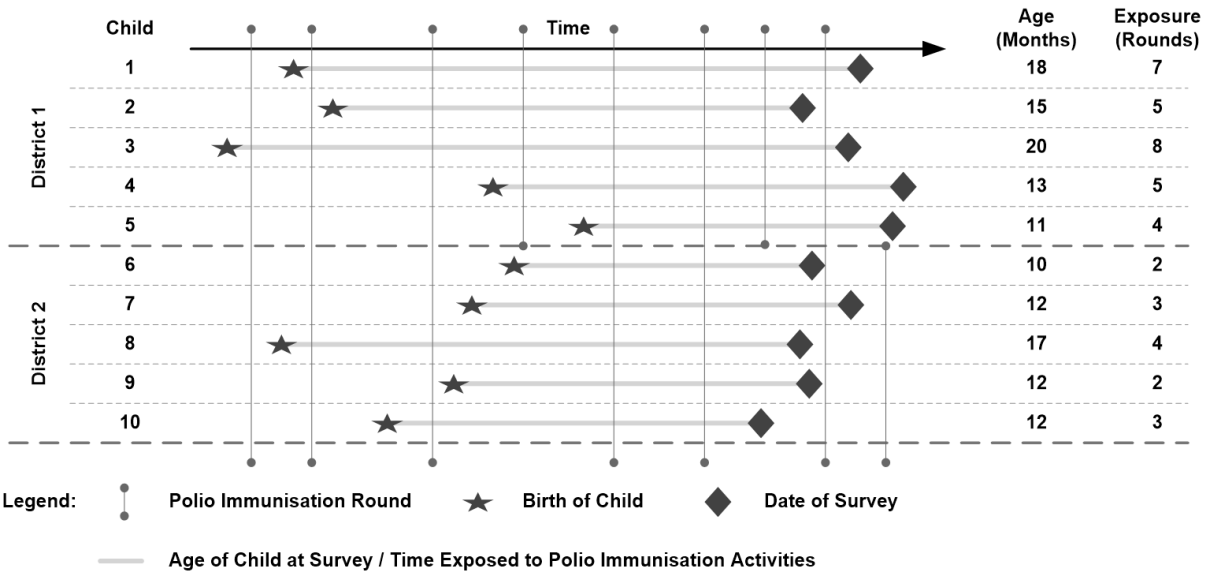
Table 4. Main Age-Stratified Regression Results in Uttar Pradesh and Bihar (Restricted Model)

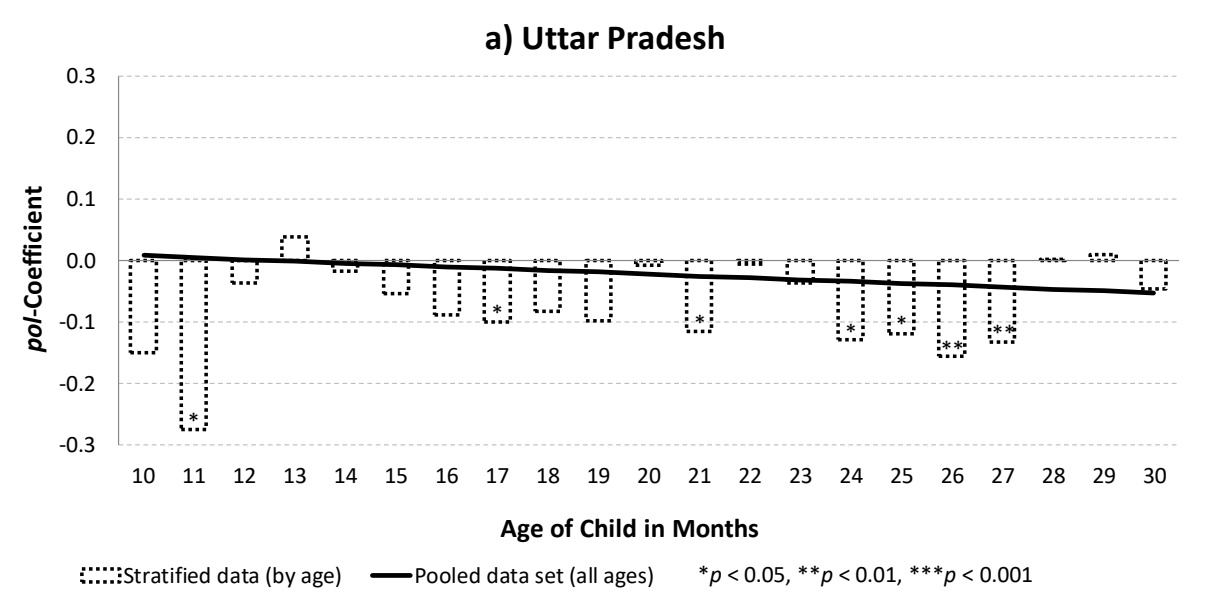
Child Age in Months	Uttar Pradesh					Bihar				
	***Pol* Coef. (Std. Err.)**	***n***	***p*-Value**	**Pseudo R^2**	**AIC**	***Pol* Coef. (Std. Err.)**	***n***	***p*-Value**	**Pseudo R^2**	**AIC**
10	-0.149 (0.122)	1 548	< 0.001	0.243	0.813	0.233 (0.129)	731	< 0.001	0.239	0.963
11	-0.274* (0.109)	1 324	< 0.001	0.263	0.903	0.069 (0.119)	568	< 0.001	0.332	0.992
12	-0.037 (0.096)	1 412	< 0.001	0.268	0.955	0.127 (0.076)	1 013	< 0.001	0.273	0.968
13	0.039 (0.072)	1 750	< 0.001	0.271	0.937	0.003 (0.067)	1 338	< 0.001	0.296	0.930
14	-0.017 (0.067)	1 564	< 0.001	0.300	0.933	0.010 (0.059)	1 301	< 0.001	0.331	0.911
15	-0.053 (0.057)	1 757	< 0.001	0.294	0.944	0.132* (0.062)	1 176	< 0.001	0.355	0.923
16	-0.089 (0.051)	1 818	< 0.001	0.295	0.961	0.048 (0.057)	1 244	< 0.001	0.343	0.929
17	-0.099* (0.046)	1 911	< 0.001	0.264	1.015	-0.001 (0.054)	1 160	< 0.001	0.304	1.005
18	-0.082 (0.048)	1 849	< 0.001	0.265	0.982	0.142* (0.060)	1 041	< 0.001	0.309	1.017
19	-0.097 (0.053)	1 850	< 0.001	0.332	0.936	0.002 (0.068)	891	< 0.001	0.338	0.992
20	-0.008 (0.055)	1 682	< 0.001	0.303	0.968	-0.115 (0.070)	736	< 0.001	0.319	1.042
21	-0.116* (0.057)	1 490	< 0.001	0.314	0.998	0.064 (0.066)	727	< 0.001	0.358	1.000
22	-0.005 (0.056)	1 391	< 0.001	0.304	0.996	0.086 (0.072)	685	< 0.001	0.350	0.987
23	-0.036 (0.052)	1 408	< 0.001	0.280	1.002	0.078 (0.065)	641	< 0.001	0.388	0.986
24	-0.129* (0.058)	1 459	< 0.001	0.335	0.947	0.051 (0.049)	973	< 0.001	0.409	0.872
25	-0.119* (0.049)	1 639	< 0.001	0.294	0.971	0.022 (0.045)	1 112	< 0.001	0.357	0.922
26	-0.156** (0.053)	1 567	< 0.001	0.315	0.952	0.045 (0.048)	1 063	< 0.001	0.375	0.899
27	-0.133** (0.051)	1 654	< 0.001	0.282	1.024	0.078 (0.044)	1 038	< 0.001	0.341	0.970
28	0.002 (0.060)	1 648	< 0.001	0.301	0.974	0.023 (0.042)	1 039	< 0.001	0.362	0.953
29	0.010 (0.062)	1 725	< 0.001	0.307	0.980	0.043 (0.059)	1 025	< 0.001	0.382	0.939
30	-0.045 (0.060)	1 749	< 0.001	0.285	0.990	0.066 (0.054)	954	< 0.001	0.332	1.005

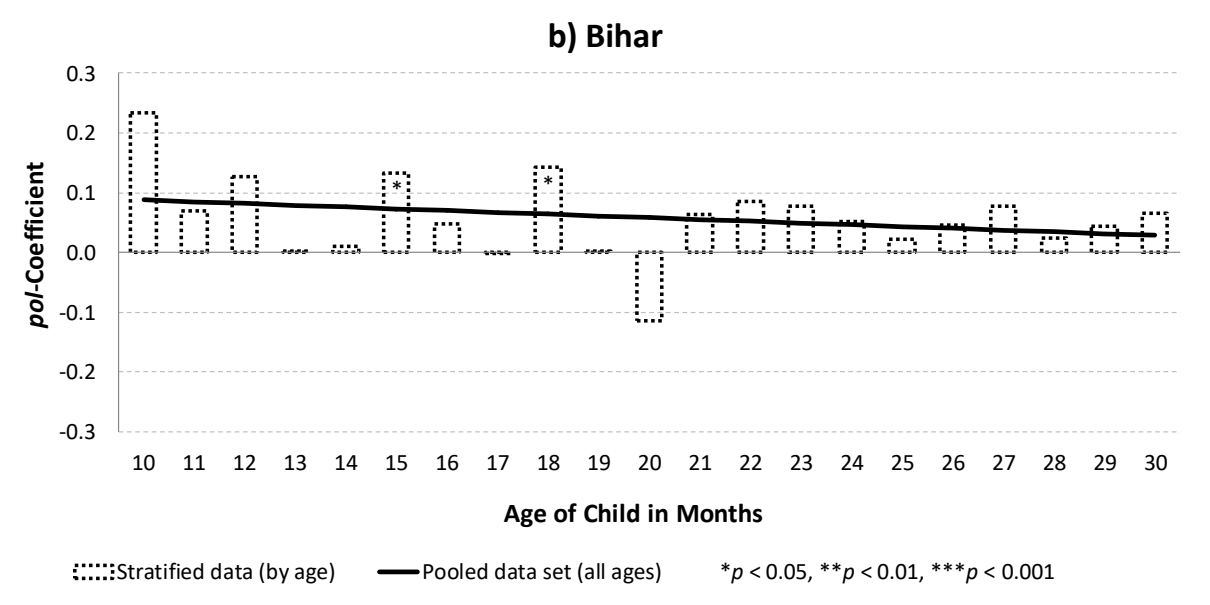
Source: Own estimation.

Notes. Coefficients reported. Standard errors in parentheses. Control variables (restricted model) not displayed. Coefficient values of different models cannot be immediately compared due to varying samples.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.


Child
Time
Age (Months)
Exposure (Rounds)
District 1
District 2
1
2
3
4
5
6
7
8
9
10
18
15
20
13
11
10
12
17
12
12
7
5
8
5
4
2
3
4
2
3
Legend:
Polio Immunisation Round
Birth of Child
Date of Survey
Age of Child at Survey / Time Exposed to Polio Immunisation Activities


a) Uttar Pradesh
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
pol-Coefficient
10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
Age of Child in Months
Stratified data (by age)
Pooled data set (all ages)
*p < 0.05, **p < 0.01, ***p < 0.001


b) Bihar
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
pol-Coefficient
10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
Age of Child in Months
Stratified data (by age)
Pooled data set (all ages)
*p < 0.05, **p < 0.01, ***p < 0.001