Essays on the economics of childhood vaccinations

Amit Summan

Propositions

1. Basic child immunisation coverage improves wages and consumption expenditure in adulthood.
   (This thesis)
2. The distribution of public health resources is uneven among different socioeconomic and demographic groups and contributes to gaps in vaccination.
   (This thesis)
3. Every small contribution of individual studies is indispensable to build the large body of research that will drive policy change.
4. Scientific research and researchers should be valued according to their ability to contribute to positive real-world change.
5. Lack of cultural exchange, deprivation of education, and self-imposed restrictions on the flow of knowledge are at the roots of many contemporary societal failures.
6. To reach our full potential as a species, the means to pursue intellectual curiosities and knowledge should not be restricted to a privileged few.

Propositions belonging to the thesis, entitled

Essays on the economics of childhood vaccinations

Amit Summan
Wageningen, 22 November 2022

Essays on the economics of childhood vaccinations

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This research was conducted under the auspices of the Wageningen Graduate School of Social Sciences (WASS)

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Thesis
submitted in fulfilment of the requirements for the degree of doctor
at Wageningen University
by the authority of the Rector Magnificus,
Prof. Dr A.P.J. Mol,
in the presence of the
Thesis Committee appointed by the Academic Board
to be defended in public
on Tuesday 22 November 2022
at 1:30 p.m. in Omnia Auditorium.

Amit Summan
Essays on the economics of childhood vaccinations,
220 pages.

PhD thesis, Wageningen University, Wageningen, the Netherlands (2022)
With references, with summary in English

DOI https://doi.org/10.18174/579890
ISBN 978-94-6447-474-9

For Papa Ji, our beloved and dearly missed grandfather.

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CHAPTER 1

Introduction

Chapter 1

Introduction

1.1 Child health and child immunisation in India

Significant progress has been made in improving child and maternal health globally in the past three decades — under five child mortality has decreased from 12.6 million deaths in 1990 to five million deaths in 2020.[1] However, most of these improvements have been concentrated in upper-middle-income and high-income countries, and today 82% of total under-five deaths occur in the Sub-Saharan Africa and South Asia region.[2] India had an estimated 783,000 under-five deaths in 2020, the second highest after Nigeria.[1]

Targeted investments in key health programs such as immunisation, antenatal and postnatal care, and research and surveillance are critical to decrease under-five mortality in India and improving the quality and supply of healthcare.[2,3] The High Level Expert Group on Universal Health Coverage of the Indian Planning Commission recommends public health expenditure of 2.5-3% of gross domestic product (GDP) per year;[4] at 1.3% of GDP, prior to the COVID-19 pandemic, India's public financing of health falls substantially short of this target.[5] In 2018, India's per capita public health spending of $70 in purchasing power parity (PPP) terms was substantially lower than that of other large low- and middle-income countries (LMICs) such as China ($459), Brazil ($559), Mexico ($554), and Colombia ($923).[6] Low public health expenditure and a high disease burden contribute to high private out-of-pocket (OOP) medical expenditure in India — 65% of all health expenditure is OOP[7] and an estimated 25% of households annually experience health expenditure which is "catastrophic", i.e. exceeding 10% of household expenditure.[8] Substantial variation in health spending and disease burden across states presents additional challenges for India in meeting its health targets.

Indian children experienced 257 million disability-adjusted life years (DALYs) in 1990, which decreased to 80 million DALYS in 2019.[9] Table 1 below shows the top ten causes of morbidity and mortality in terms of DALYs in these time periods. While measles and tetanus were leading contributors to disease burden in 1990, they are not a part of the top ten causes of disease burden for under five children currently. There have also been substantial decreases in the burden caused by diarrheal diseases which decreased by 85%, protein energy malnutrition which decreased by 90%, whopping cough which decreased by 73%, and meningitis which decreased by 81%, relative to the 69% decrease in overall disease burden, from 1990 to 2019. The National Rural Health Mission (NHRM), launched in 2005, contributed to these reductions, by focusing on expanding basic health coverage in regions with poorer health outcomes — rural areas, the Empowered Action Group states — Bihar, Chhattisgarh, Jharkhand, Madhya Pradesh, Orissa, Rajasthan, Uttaranchal, and Uttar Pradesh — and North Eastern states.[10] Investment in immunisation services, also contributed to a substantial portion of the decline in under-five mortality since 2015.[11]

Table 1: Top ten causes of DALYs in India, 1990 to 2019

1990		2019	
Cause	DALYS	Cause	DALYS
Neonatal disorders	76,176,880	Neonatal disorders	39,564,441
Lower respiratory infections	45,908,080	Lower respiratory infections	11,356,707
Diarrheal diseases	32,802,439	Congenital birth defects	6,099,747
Protein-energy malnutrition	16,626,293	Diarrheal diseases	5,014,575
Measles	11,803,363	Protein-energy malnutrition	1,617,180
Congenital birth defects	10,947,096	Dietary iron deficiency	1,467,626
Tetanus	8,302,922	Whooping cough	1,396,952
Malaria	7,764,486	Meningitis	917,190
Whooping cough	5,995,193	Malaria	861,506
Meningitis	4,658,375	Acute hepatitis	728,890

Source: Global Burden of Disease Study.[9] *DALY* = disability-adjusted life year

While there has been success in increasing provision of maternal health services, gaps in primary and secondary care continue to exist and have led to continued significant private sector use.[12] Also despite the NRHM's focus on lagging regions, decreases in disease burden have not been experienced uniformly across Indian states. After 2000, there has been an increasing disparity across states in overall child disease burden; in higher under-five mortality states, two of the top three leading causes include infectious disease — pneumonia and diarrhoea.[11] immunisation is one of the most cost-effective child health interventions available against infectious disease,[13] yet one-third of Indian child deaths are from vaccine preventable diseases such as pneumonia, diarrheal diseases, measles, and meningitis.[14] Beyond its direct impacts on disease prevention, vaccination is also linked with improved long term health, cognition, and schooling outcomes, reduced antimicrobial resistance, and reduced health expenditure.[15]

Even in 2022, child immunisation remains far from universal. In India the full immunisation rate for under two children — vaccination of basic childhood vaccines against — Bacillus Calmette–Guérin (BCG), measles, and three doses each of diphtheria, pertussis, and tetanus (DPT)/Penta and polio vaccine (excluding polio vaccine given at birth)— remains at 76.6% according to a 2019-2021 national survey.[16] In addition to low coverage, failure to vaccinate children at recommended ages has remained a major challenge. In 2013, the proportion of delayed doses among under-5 children ranged from 35% for OPV first dose (OPV1) to 65% for DPT3.[17] Among 10-23 month old children in 2016, the proportion of delayed doses (i.e., more than 28 days after the minimum eligibility age) ranged from 23% for BCG to 35% for the measles vaccine.[18] Timely vaccination is important especially for highly contagious diseases such as measles which can rapidly affect a large number of children and retard long-term immunity against other diseases.[19,20] Furthermore, there are gaps in vaccination across socioeconomic and demographic groups, with female, lower caste and scheduled tribe, non-Hindu, and low-income households having lower vaccination rates than their counterparts in India.[16] There are also

severe state-level disparities, with full immunisation varying from 57.9% in Nagaland in the Northeast to 90.5% in Odisha[i] in East India.[16]

The COVID-19 pandemic has added to the existing challenges of reaching universal immunisation. Over 90% of countries that provide health systems information to the World Health Organization (WHO) were reporting disruptions to essential healthcare programs at the end of 2021, and the proportion of countries reporting disruptions in routine immunisation programs increased from 33% to almost 50% between the first and fourth quarters of 2021.[21] An estimated 23 million children did not receive DPT3 in 2020—3.7 million more than in 2019[22]—and 60% of these children lived in ten LMICs including India.[23] India had among the largest reductions in childhood vaccination coverage, e.g., DPT1 vaccination rates fell from 91% in 2019 to 85% in 2020.[22] A study using administered dose data found that DPT3 vaccination dropped 15.8% in 2020 in India, relative to the previously projected vaccination rate.[24]

1.2. Objectives

My overall research question is, "What are the broad economic effects of child immunisation and how can public resources be utilized to realize these benefits through universal child immunisation in India in the COVID-19 era?" The overarching objective of my thesis is to inform public policy in budgeting and finance, and health to improve allocations towards child immunisation efforts in India and more broadly in LMICs.

The main objective can be broken down into the following sub-objectives: 1) improve our understanding of the comprehensive benefits of vaccines, 2) identify the impacts of government resource allocation decisions on child immunisation services and vaccination rates, and 3) analyse the impacts of the COVID-19 pandemic on immunisation rates in India. The individual research questions for the Chapters are as follows:

1. What are the effects of vaccination coverage during childhood on economic outcomes in adulthood in India?
2. What are the impacts of a supplementary immunisation programs and/or periodic intensification of routine immunisation programs on child immunisation coverage and timeliness of vaccination coverage in India?
3. How does the quality of government health facilities affect child immunisation coverage and timeliness of coverage in India?
4. How has COVID-19 impacted child vaccination coverage and timeliness in India?

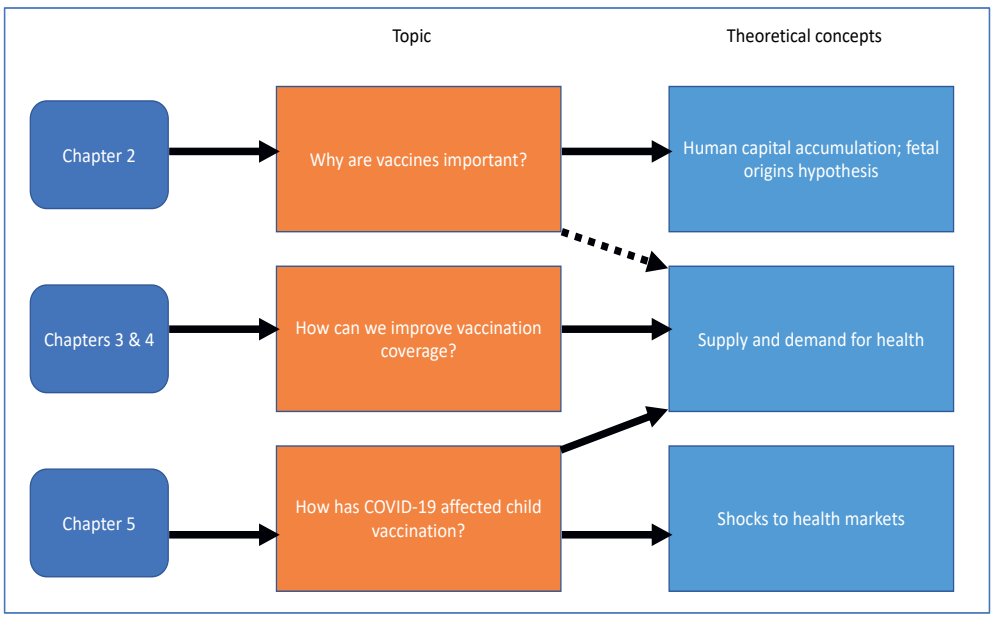
1.3. Theoretical and conceptual framework

The underlying conceptual framework of the thesis and connections between the chapters are depicted in Figure 1. Chapters 3 and 4 explore how vaccination coverage can currently be improved in India, specifically how supply-related factors may affect vaccination coverage. Vaccination coverage is based on the demand and supply for immunisation, which is guided by

[i]Dadra and Nagar Haveli has a 94.9% full immunisation rate, however Odisha is described given Dadra and Nagar Haveli's small population size — 465,999.

many of the same underlying economic principles and considerations as other health goods and services. Chapter 2 investigates the long-term economic benefits of vaccination building on a key hypothesis from epidemiology, the fetal origins hypothesis, where environmental factors during the first two years of life and prenatal stage can have substantial consequences for health and brain development in later life.[25–27] This hypothesis has been proven in social sciences and epidemiological research, including economics, where health in early life may be seen as an investment in later life. Knowledge of the full benefits of immunisation coverage affects both demand for coverage and supply of vaccination services — government investments and budget allocations. Chapter 5 is also based on underlying supply and demand principles from economics, but the focus is on the unprecedented shocks to healthcare seeking and supply of healthcare due to COVID-19.

Figure 1: Thesis conceptual framework



We can further elucidate some of these theoretical concepts from the perspective of the household using Becker's model,[28,29] where parents maximize utility subject to a household budget constraint. A basic depiction of their model relevant to this paper is as follows, utility is given by own consumption and the discounted sum of consumption of future generations:

$$U_t = \sum_{i=0}^{\infty} \partial^i u(Z_{t+i})$$

Where Z_{t+i} is consumption of next generation of descendants when $i > 0$ and consumption of parents when $i = 0$, and ∂ is a constant which measures the 'altruism' of parents.

Consumption is based on income, which is described as follows:

$$I_t = \gamma(T_t, f_t)H_t + \epsilon_t$$

Where I_t is income, γ is the earning of one unit of human capital which is a function of T_t, technical knowledge and f_t, the ratio of human capital to non-human capital in the market, H_t is human capital, and ϵ_t are random effects affecting income.

Adult earnings are a function of human capital accumulation in the first period of life, where human capital accumulation is described by the following equation:

$$H_t = \forall(x_{t-1}, s_{t-1}, E_t)$$

Where H_t is human capital accumulation, which is function of parental expenditure x and public expenditure s, and E_t is endowment received. In later work, Becker developed the concept of health itself is human capital.[28]

Therefore, parents maximize their utility by making budget allocations towards their own consumption and consumption of their children, where children's future consumption will be a function of current investments in health and education. Parents can make a decision to vaccinate children, increasing their health and future earnings and consumption, based on their budget constraint. Their decision to vaccinate will depend on the relative returns of human capital investment and the perceived costs of investments. Broadly, parents' decisions to vaccinate are based on their beliefs, preferences, and perceived returns from vaccination. However, there is a fundamental information asymmetry problem for healthcare products, and in particular vaccination, which results in an information deficit for households, and sometimes even vaccination hesitancy due to the belief that vaccination can be harmful. There may also be a lack of trust in institutions which affects the perceived benefits of vaccination. Basic vaccinations are provided free of charge under the Indian immunisation program, however, there are other costs, x, that parents, particularly low-income households must consider including: cost of transportation to the vaccination site, information seeking regarding vaccination, and lost wages from taking children to vaccination sites. The government has provided investments, s, in the form of free vaccination to children, however, they can further eliminate costs of parents by providing transportation or making vaccination convenient enough for parents to not lose work time. The government can increase the supply of vaccination, by increasing the number of health facilities in rural areas or frequency of regular vaccination camps to reduce financial and non-financial costs of vaccinating for caregivers. Government programs can also increase demand for vaccination by providing information to parents regarding the benefits of vaccination and availing fears of the risk of immunisation through positive media messages, building trust in institutions, proactive engagement from health care providers, targeting of high-risk groups, and engagement and dialogue with vaccine hesitant groups.[30]
However, due to a scarcity of resources, there are opportunity costs for the Ministry of Health to divert increased resources to immunisation from other health services and for the Ministry of Finance to divert resources towards health from other social programs such as education. Unfortunately, the broad social and economic benefits of vaccines are often not fully accounted

for; benefit-cost analyses underestimate the returns to vaccination, which may reduce overall funding allocations. There are additional steps the government may take to increase supply of vaccination given a fixed budget such as improving allocation of existing resources in a more efficient manner to produce the greatest quantity of vaccination services, reducing barriers to entry for vaccine manufacturers, and incentivizing research and development.

Some may argue that government intervention is unnecessary or undesired in markets and may lead to inefficiencies, however, the government has a critical role in the immunisation market due to the large positive externalities specific to immunisation. Like other disease prevention interventions, vaccination reduces health expenditures, increases quality of life, decreases caregiver costs, and increases productivity, however, vaccination additionally prevents the spread of infectious diseases. Any of these benefits which accrue to individuals not being vaccinated are the positive externalities to vaccination. Households will only take into account their marginal private benefit for vaccination services, whereas the government's goals may be protection of societal health. They would be concerned with the marginal social benefit of vaccination. When social marginal benefit exceeds the private marginal benefit (which determines private demand), government intervention will increase consumption to a socially optimal level. Other market failures in the health care market including imperfect competition which leads to inefficiencies and excess profits, or imperfect capital markets which do not allow households to borrow to invest in health, may also warrant government intervention. Lastly, government involvement can be justified on equity grounds consistent with the idea of health being a human right.

The COVID-19 pandemic has caused an unprecedented shock to both the supply and demand for health services. Possible demand-side factors include decreased care-seeking due to fear of risk of contagion, caregivers being infected with COVID-19, caregivers facing increased budget constraints for travel due to decreased livelihoods, and lockdowns limiting mobility. Supply-side factors include decreased supply of healthcare workers as they were infected with COVID-19; decreased overall resources —including healthcare workers, facility space, and financial resources — for general care as they were diverted towards COVID-19 related healthcare; and supply chain issues decreasing the availability of critical supplies and tools. The convergence of these factors may affect child vaccination coverage and the probability of infectious disease outbreaks in the future.

1.4 Contributions

Each of the individual chapters make several important contributions to the child immunisation literature and together form a body of work that will ideally inform both ministries of finance and health policy in India and across LMICs. The thesis as a whole underscores the importance of investments in childhood immunisation and identifies potential pathways to improve vaccination outcomes in the post-COVID-19 world. The chapter-by-chapter contributions are described below.

Chapter 2 makes several important contributions to the literature on the long-term economic effects of health interventions. First, studies estimating the economic benefits of vaccines address short-term forgone medical expenses (including cost savings to health care providers), financial

risk protection (e.g., value of insurance), and the monetized value of health gains (e.g., value of statistical life years) due to reduced disease incidence.[31–34] To the best of our knowledge, this is the first study of the long-term economic benefits of vaccines in LMICs, and one that evaluates the human capital development aspect of vaccines.[15] Previous studies of human capital development analyze only the link between vaccines and standardized test scores or schooling attainment, not earnings or consumption. Atwood[35] estimates a 1.1% increase in future income due to measles vaccinations, but in the context of the United States and not LMICs. A large volume of published work links nutrition or undernutrition, famine, air pollution, diseases, and war in early childhood with later-life economic outcomes,[27] and the literature on diseases focuses heavily on malaria eradication and deworming; little is known about the long-term effects of vaccines or other low-cost preventive health interventions.

Second, we contribute substantially to the understanding of how large-scale public health programs can aid long-term human capital development and economic growth in India and potentially other LMICs. Although previous studies have examined the educational benefits of India's national nutrition and early childhood development program (the Integrated Child Development Services program); [36,37] economic outcomes remain inadequately studied.

Lastly, our study informs the policy discussion surrounding universal routine childhood immunisation coverage in India and other LMICs. In the past two decades, routine childhood vaccination coverage increased from 50% to 80% in LMICs, followed by a sharp reduction due to the ongoing COVID-19 pandemic.[38] Additional challenges such as vaccine hesitancy have also become significant in the past few years. Our findings can help reinforce and revitalize the drive for universal immunisation and ensure sustained efforts in future years, even when major childhood diseases are on the verge of eradication.

By employing robust statistical techniques and addressing endogeneity concerns, Chapter 3 contributes to the gap in evidence on the causal impact of Mission Indradhanush on desired programmatic and immunisation outcomes. Data from the Integrated Child Health and Immunisation Survey (INCHIS) in 24 states showed an increase in full immunisation rates from 64.1% to 73.5% during April 2015 to October 2015.[39] In districts which were covered under phase 1, rates of oral polio vaccine third dose and DPT third dose increased substantially. However, these estimates did not control for potential confounding factors and secular time trends of vaccination coverage in MI and non-MI areas. A study found that the Intensified Mission Indradhanush (IMI) program – a successor of MI – may have increased coverage rates by 3.9 to 35.7% for different vaccines; however this study inferred coverage rates through vaccine delivery volume rather than data on administration of vaccine to individual children.[40] We estimated the association between exposure to MI phases 1 and 2, and child immunisation outcomes by comparing vaccination rates (overall, as well as at recommended ages) and timing in MI vis-à-vis non-MI districts. We used household survey data and employed difference-in-difference multivariate regression models which controlled for several possible confounders.

In Chapter 4 we examined the socioeconomic and healthcare quality determinants of coverage rates and timeliness of routine child immunisation in rural India. We also conducted in-depth analyses of the distribution of facility quality and its association with vaccination outcomes across income groups using decomposition methods. While parents report poor quality of

healthcare facilities as an important deterrent to child vaccination, healthcare quality itself – and its association with vaccination coverage – remains inadequately quantified in LMICs. Previous literature has instead focused mainly on access to healthcare. For example, a recent study in India found that the availability of health center (primary health sub-center [SC] or primary health center [PHC]) or health care workers (auxiliary nurse midwives or accredited social health activists) did not significantly reduce DPT vaccination dropout rates.[41] Another study found that rural Indian children who had a hospital within 2 km of their village were 4.8% less likely to miss non-polio vaccine doses.[42] The authors found no association between the availability of a community health worker in the village and vaccination rates. A third study focused on the availability of health facility near households within the slums of Agra, India and identified a positive association with vaccination coverage.[43] In the Indian state of West Bengal, availability of health workers and equipment at SCs was found to have a positive association with month-specific vaccine coverage.[44] A study in Burkina Faso found no associations between the availability of physical and human resources at the health facility serving a community and the community's vaccination coverage.[45]

These studies [41,42,44] have primarily focused on access to healthcare rather than the quality of healthcare. Three of the four India-focused studies referenced above looked at the availability of a public health facility or health worker within a household's village or district but did not account for the quality of those facilities or workers,[41–43] while a fourth which focused on a state within India included very limited measures of quality.[44] In LMICs, the quality of care is a better predictor of health outcomes than access to healthcare facilities.[46,47] Our study fills these gaps by focusing on measures of facility quality and quality of service delivery. Measurable indicators of quality that are related to vaccination coverage rates can inform policies for immunisation program funding in India and other LMICs.

In Chapter 5 we estimated the effect of COVID-19 on nine routine childhood vaccinations in Indian using data from a large, nationally representative household survey. We accounted for potentially confounding child and family characteristics using a mother fixed-effects (siblings) model to examine vaccination coverage and timeliness. Previous modelling studies have shown that India had among the largest reductions in childhood vaccination coverage, e.g., DPT1 vaccination rates fell from 91% in 2019 to 85% in 2020.[22] A study using administered dose data found that DPT3 vaccination dropped 15.8% in 2020 in India, relative to the previously projected vaccination rate.[24] Another study from Rajasthan conducted phone interviews for 2,144 children between January and October 2020, and found that children in heavily COVID-19–exposed areas were less than half as likely to get vaccinated by nine months of age, relative to unexposed children.[48]

These studies have limitations inherent in modelled and administrative data because they tend to present aggregate statistics without accounting for potential confounding factors, including underlying secular trends in coverage and differences in individual and household-level factors that influence vaccinations, such as age, sex, parental education, beliefs, and access to healthcare facilities. Additionally, the quality of administrative data, particularly at the subnational level, is limited by the lack of depth typically present in prospective surveys. Lastly, these studies focused on only DPT3 and MCV vaccinations and did not address other vaccines.

1.5 Methodological overview

This multidisciplinary thesis employs common empirical approaches from public health, health economics, and international development.

Data

All of the chapters primarily employ nationally representative cross-sectional household datasets or exploit variations in the timing of the rounds of the datasets to use them as repeated cross-sectional datasets. For Chapter 2 our data come from two sources. National Sample Surveys are routine, nationally representative surveys that collect data on an exhaustive set of socioeconomic characteristics. NSS round 68 (NSS-68) was conducted between July 2011 and June 2012 and contains the following outcome variables: wages, monthly per capita expenditure, and income source (agriculture versus non-agriculture) of household. NSS-68 collected data on 456,999 individuals from 101,724 households in 626 districts. The data for the year of UIP implementation—our treatment variable—were taken from our previous work.[49] We reviewed district bifurcations and creation of new districts and states and carefully matched the districts in NSS-68 data retrospectively with the phased district-wise rollout of UIP in 1985–1990.

Chapters 3 and 4 used data from the Integrated Child Health and Immunisation Survey (INCHIS), a stratified, nationally representative, cross-sectional household survey conducted in three rounds from March 2015 to April 2016.[39] The survey covered a total of 44,571 households across 260 districts in 24 states across the three rounds. Each round of INCHIS collected data from 12 states, where Bihar, Maharashtra, Madhya Pradesh, Rajasthan, Telangana, and Uttar Pradesh were fixed, and the six other states were rotated across rounds. The states were chosen to ensure representation from each geographical region and level of development. Data were obtained on socioeconomic and demographic indicators, and access to and quality of health facilities for households with children below the age of two years. Immunisation receipt and date information for the youngest under-2 child in each household were collected from either vaccination card or through maternal (or caregiver) recall if the card was unavailable.

For Chapter 5 we used data from the fifth round of the National Family Health Survey (NFHS-5), conducted between June 2019 and April 2021.[50] The survey was conducted in two phases. Phase 1 extended from June 2019 to January 2020, covering 22 states and union territories; phase 2 was from January 2020 to April 2021, covering the remaining 14 states and union territories. NFHS-5 covered 636,699 households in 707 districts across all 36 jurisdictions, and it included 232,920 children under the age of five years. The survey collected immunisation data on all children born after 2016, including vaccine dose and receipt date, from vaccination cards or from maternal recall when a card was unavailable. In our study we used data on 59,506 children and their siblings.

Methodological considerations

Randomized control trials (RCTs) are the ideal research design with the highest internal validity. In RCTs we conduct an experiment where certain subjects — whether individuals, health facilities, or geographical regions — receive a treatment or exposure and a control group does

not receive such a treatment. These subjects are randomly assigned to a treatment or control group, and observed and unobserved confounding variables are balanced across these two groups. However, RCTs are not always possible or desired. They may be impossible to implement, unethical, or prohibitively expensive. For example, to investigate the impacts of earthquakes on fertility it is impossible to simulate an earthquake in control and treatment regions, or to investigate the effects of alcohol consumption during prenatal stages on newborn health it would be unethical to instruct pregnant mothers to drink alcohol due to harms to the fetus.

In these circumstances, we can rely on '2nd best' options, using quasi-experiments or natural experiments. Although these terms are sometimes used interchangeably, I will discuss natural experiments as those where there is no deliberate manipulation of treatment by researchers. This does not, however, preclude human intervention, for example, a government policy may target a certain group of individuals and still be considered a natural experiment to analyze. Natural experiments also do not refer specifically to physical phenomena although they may also be investigated. In natural experiments there is no random assignment of participants as in experimental research. Without random assignment, there may be substantial underlying differences between the groups that affect the outcome of interest due to selection bias. There may also be other events that occur systematically differently across treatment and control groups during the exposure phase which affect the outcome of interest. These can limit our ability to make causal claims using natural experiments. However, if assignment to groups approximates 'as-if random', causal claims may be made.[51] Moreover, the potential effects of confounding factors in natural experiments can be accounted for and tested using statistical methods such as difference-in-difference, propensity score matching, interrupted time series, regression discontinuity, and fixed effects; the ability of these methods to control for unobserved or unmeasured confounding factors will determine our ability to make causal claims.[52] Following natural experiments, there is correlational research which has the lowest internal validity, due to factors such as omitted variable bias or reverse causality, which are difficult to control for with statistical methods. I primarily rely on natural experiments and quasi-experimental estimators in my methodological approach.

Methods

Chapter 2 employs age-district fixed effects regression models to compare the earnings and per capita household consumption spending of 21- to 26-year-old adults who were born in India's Universal Immunisation Program (UIP)-covered districts vis-à-vis non-UIP districts in 1985–1990. The model incorporates household and individual characteristics and district-and-time-varying factors. Treatment is assigned based on the birth year of individuals relative to UIP rollout year. The source of variation at the individual level is from the year of birth, controlling for district and age (people of same age but born in different years). Additionally, I look at household income source as another outcome. All models consist of control variables commonly found to affect wages.

In Chapter 3 we explored the association of MI (phases 1 and 2) and the binary indicators of 11 vaccination outcomes for each child: full immunisation, receipt of DPT1, DPT2, DPT3, oral polio vaccine dose 1 (OPV1), OPV2, OPV3, OPV birth dose (OPV0), measles first dose

(measles1), Bacillus Calmette–Guérin (BCG), hepatitis B birth dose (HepB0), and on-time vaccination. Each child that had reached the vaccination eligibility age before the end of the MI intervention was considered for analysis for that vaccine. The on-time vaccination (OTV) indicator considered the timely receipt of DPT1, DPT2, DPT3, and full immunisation (3 doses each of DPT and OPV, and one dose each of measles and BCG). We employed a difference-in-difference (DID) framework in which the average difference in outcomes before and after the MI program in each district was first estimated. Then, the difference between MI and control districts of this average difference was taken. Each model included binary indicators of location (whether an MI district), time (pre- or post-intervention), and an interaction between the two (DID indicator). We used linear probability models (LPM) and probit models for our analysis. Our regression models included a vector of household level socioeconomic indicators and mother and child characteristics as covariates.

In Chapter 4 we employed multiple correspondence analysis (MCA) to construct two indices of the quality of care related to immunisation services in sub-centers (SCs) – an infrastructure quality index and an immunisation service delivery index. We conducted probit regression analysis to evaluate the associations between each vaccination outcome and sub-center characteristics. We considered seven vaccination outcomes: full immunisation, DPT1, DPT2, DPT3, BCG, hepB0, and timely vaccination. The model included indicators of the top two terciles of the two SC quality indices and time taken to reach to immunisation facility as reported by households. The model covariates also included a set of household and socioeconomic indicators that have been found to affect vaccination outcomes. We then employed the Fairlie decomposition method to analyze factors contributing to gaps in immunisation between rich and poor households.

In Chapter 5 we employed a linear probability model (LPM) with mother fixed-effects to identify the differences in vaccination between siblings born before and after the COVID-19 pandemic. In our data, background characteristics of children can systematically differ between the groups affected or unaffected by COVID. If these differences are correlated with immunisation outcomes, simple group differences in the outcomes indicator or least squares-based regression results of the relationship between COVID-19 exposure and immunisation outcomes would yield biased estimates. To mitigate such biases, we included mother fixed-effects in our regression model, which accounted for all observed and unobserved characteristics at the level of the mother and above (e.g., household, district, and state). Nine vaccines were considered—BCG, hepB0, DPT1, DPT2, DPT3, polio1, polio2, polio3, and measles first dose (MCV1). Additionally, we controlled for sibling varying confounders. The source of variation in the variable of interest comes from mothers with multiple children under five years of age. A child was considered to have been timely vaccinated if they received the vaccine within 45 days of minimum eligibility. Children who were eligible for a vaccine after January 30, 2020 (date of the first COVID case in India) were included in the COVID-affected group.

1.6 Thesis outline

This thesis is organized as follows. Chapter 2 evaluates the long-term economic benefits of the Universal Immunisation Programme. Individual-level data is combined from the 68th round of

the National Sample Survey of India (2011–2012) with district-wise data on the rollout of UIP between 1985 and 1990 and age-district fixed effects regression models are used to compare the earnings and per capita household consumption spending of 21- to 26-year-old adults who were born in UIP-covered districts vis-à-vis non-UIP districts. Chapter 3 evaluates the effects of India's Mission Indradhanush program — a periodic intensification of the routine immunisation program — which was implemented in phases across districts between March 2015 and July 2017, and routine vaccination coverage and timeliness among children. Difference-in-difference regressions are employed to examine binary indicators of receipt of 11 vaccines, and whether vaccines were received at recommended ages. Chapter 4 examines the association between the quality of public health facilities and child vaccination outcomes in rural India using data from the nationally representative Integrated Child Health and Immunisation Survey (2015-2016). Using probit regression, the relationship between vaccination outcomes in children under 2 years of age and sub-center quality — using two constructed indices of sub-center quality — is analyzed. Additionally, we conduct Fairlie decomposition analysis by wealth group - bottom wealth quintile relative to the top four wealth quintiles- to examine factors contributing to gaps in immunisation between rich and poor households. Chapter 5 describes the effects of the COVID-19 pandemic on child immunisation rates in India. The effect of the pandemic on the timeliness and coverage of routine childhood immunisation in India using data from India's fifth National Family Health Survey, conducted between June 2019 and April 2021, is analyzed. We use a mother fixed-effects regression model – which accounted for secular trends and child-level varying confounders – to compare immunisation outcomes of COVID-affected and COVID-unaffected siblings. Chapters 2, 3, and 5 include supplementary appendices that primarily contain results from sensitivity or robustness analyses, or endogeneity tests. Chapter 6 presents a synthesis of the thesis, including its implications for public policy and limitations and possible steps for future research.

CHAPTER 2

2

Long-term effects of India's Universal Immunisation Program on economic outcomes

Routine childhood vaccinations are among the most cost-effective child health interventions. In recent years, the broader benefits of vaccines, which include improved cognitive and schooling outcomes, have also been established. This paper evaluates the long-term economic benefits of India's national program of childhood vaccinations, known as the Universal immunisation Programme (UIP). We combine individual-level data from the 68th round of the National Sample Survey of India (2011–2012) with district-wise data on the rollout of UIP from 1985 to 1990. We employ age-district fixed effects regression models to compare the earnings and per capita household consumer spending of 21- to 26-year-old adults who were born in UIP-covered districts vis-à-vis non-UIP districts between 1985 and 1990. We find that exposure to UIP in infancy increases weekly wages by 13.8% (95% CI: 7.6% to 20.3%, $p<0.01$) and monthly per capita household consumption expenditure by 2.9% (95% CI: 0.7% to 5.0%, $p<0.01$). Program exposure also reduces the probability that an individual's household relies on agriculture as the main source of income by 1.9% (95% CI: 0.0% to 3.5%, $p<0.01$). The findings are robust to several specifications including varying study duration and accounting for potential migration. The effects vary by sex, location, and caste group.

Based on: Summan, A., Nandi, A., Bloom, D. (2022). A Shot at Economic Prosperity: Long-term Effects of India's Childhood immunisation Program on Earnings and Consumption Expenditure

2.1 Introduction

Vaccination is one of the most cost-effective interventions for preventing childhood deaths, yet in 2020, 23 million children under the age of one year did not receive basic vaccines.[53] Vaccine-preventable diseases continue to kill approximately 700,000 children globally every year.[54] Vaccination rates decreased substantially during the COVID-19 pandemic, with poorer regions of the world, which already lagged in immunisation before the pandemic bearing the brunt of the burden: diphtheria, pertussis (whooping cough), and tetanus third dose (DPT-3) vaccination fell to 84% from 90% in South Asia,[55] for example. In 2020, India had the highest number of unvaccinated children, 3.5 million, up 1.4 million from the previous year.[56] The economic and health shocks from the COVID-19 pandemic and relative low priority given to health spending necessitate immediate and sustained increases in government funding for immunisation.

In addition to protecting against the specific disease for which a vaccine is administered, routine childhood immunisation may also have nonspecific effects such as providing broader immunity and reducing all cause-mortality.[19,57] Other benefits of vaccination include reduced out-of-pocket medical expenses; reduced antimicrobial resistance; and improved long-term health, cognition, and schooling outcomes.[15,58–61] The life-long benefits of vaccines are consistent with the fetal origins hypothesis, which posits that infectious disease episodes in the first two to three years of life can damage the long-term growth and cognitive development of children.[25–27] Interventions that prevent disease transmission or cure infections—vaccines, clean water, sanitation, drugs—may therefore also improve long-term health, learning, and economic outcomes.

Although the immediate health benefits and cost-effectiveness of vaccines are well established, the potential long-term human capital development benefits, such as cognitive gains or improved schooling, have been studied only to a limited extent. Such analysis requires longitudinal or long-term data that until recently were available mainly in high-income countries. At the same time, high-income countries have had near universal coverage of routine childhood vaccines for many years, and thus the control group for long-term vaccine benefit studies may not be large enough for analysis. In low- and middle-income countries (LMICs), a few studies have linked the receipt of measles and *Haemophilus influenzae* type B (Hib) vaccines with 0.1 to 0.2 points higher anthropometric z-scores, 1.7 to 4.5 percentage points higher standardized test scores, and an additional 0.2 to 0.3 years of schooling in Ethiopia, India, South Africa, and Vietnam, and a 7% increase in the male school enrollment rate in Bangladesh.[20,62–64] Full vaccination status or exposure to national immunisation programs in early childhood has similarly been linked with higher schooling attainment or improved cognitive test scores in China, India, and the Philippines.[49,65–68] Although the benefits of childhood vaccination on cognitive outcomes and schooling attainment have recently been quantified, estimates of the long-term economic effects of immunisation in LMICs are not available.

This paper examines the long-term effects of India's routine childhood vaccination program, known as the Universal immunisation Programme (UIP), on wages, consumption expenditure, and primary source of income. We combine data on the district-wise implementation of UIP from 1985 to 1990 with household and individual socioeconomic characteristics, wages, and consumption data drawn from the National Sample Survey of India 2011. We employ age-district fixed effects regression models to estimate the effect of exposure to UIP in the first year

of life on the wages and consumption expenditure of 21- to 26-year-old adults who were born during the five-year implementation phase. We find that those born after their district had UIP coverage have 14% higher wages and 3% higher consumption expenditure than those who were born before the program was implemented. Households of individuals who were treated under the program are also 2% less likely to rely on agriculture as their primary source of income (based on household head's occupation). Treatment effects vary substantially by sex and socioeconomic groups, and the findings are robust to several alternative specifications and variations in study periods.

2.2 Potential pathways of long-term effects of vaccines

Vaccination can improve long-term health and economic outcomes via multiple pathways. The *fetal origins* hypothesis, first proposed by David Barker in 1990 and widely researched and accepted later, is the main theoretical pathway.[26,69,70] Following this theory, stimuli in the first two to three years of life—disease or another stressor, for example—elicit a biological response that can alter "the structure and function of various organs".[70] Repeated episodes of infections can hinder physical growth and reduce adult height, which in turn has been linked with worse economic productivity.[27] Children attain 80–90% of their adult brain size within the first three years of life, and disease exposure during this phase can permanently alter brain development and reduce cognitive functioning.[71,72] Furthermore, seasonal influenza and other influenza-like illnesses, pneumonia, and diarrheal infections can result in school absenteeism, affecting longer-term learning and educational outcomes.[73–75]

Childhood vaccines can mitigate adverse long-term outcomes by preventing episodes of the specific disease that a vaccine targets. In addition, recent evidence shows that the measles vaccine can provide broad immunity against all infections. An episode of measles can reduce the innate immunity of children for a period of up to two years, making them vulnerable to other diseases.[19] A live attenuated measles vaccine can induce immune memory and reduce other infections.[76,77] The protection provided against measles infection and the broader immunity gain could translate into improved brain development, schooling, and economic outcomes.[20,35,62,64]

A large body of literature finds improved schooling outcomes from decreased disease exposure. Analysis of in utero exposure to the 1918 influenza pandemic in Taiwan finds that a 0.1% increase in the maternal mortality rateii reduces years of school completed by 2.5%.[78] Nelson[79] also looks at in utero exposure to the influenza pandemic and finds that those born in 1919 were 13% less likely to graduate from college and had 0.04 fewer years of schooling than those born in other years between 1912 and 1922 in Brazil. An unpublished study finds that those exposed to the influenza pandemic in utero were 1% to 1.5%iii less likely to graduate from high school in the United States.[80] Analysis of a deworming program for school-aged children in Kenya, where drugs were randomly phased into schools, estimates that the direct effect (excluding externalities created by the program) increased overall school participation by 0.14 years per pupil treated, but no effect is found on standardized test scores.[81] Ozier [82] also looks at a school deworming program in Kenya and finds that children under the age of one who lived in communities where

ii Maternal mortality rate at the region-year level was employed as a proxy for exposure to the pandemic.
iii This is the effect found for the average level of pandemic intensity.

the deworming program was implemented have 0.5 to 0.8 additional years of schooling. Bleakley[83] analyzes the hookworm eradication campaign implemented in the American South in the 1910s and finds that a child who was infected with hookworm disease attended on average 2.1 fewer years of school than an uninfected child. A study analyzes the effect of malaria exposure in Paraguay and Sri Lanka where malaria eradication programs were implemented and finds that a 10% decrease in malaria incidence results in a 0.1-year increase in completed schooling and increases the probability of being literate by 1%.[84] Finally, in an unpublished study, Bhalotra and Venkataramani[85] estimate that a one standard deviation decrease in childhood diarrhea mortality leads to a 0.1 standard deviation increase in test scores of girls.

In addition to schooling outcomes, a few studies examine the link between diseases and labor market outcomes, consumption, or economic growth. A study on early-life malaria exposure finds that boys covered by a malaria eradication program in the most malarious states of India have increases in household per capita expenditure of approximately 2% in adulthood.[86] Baird et al.[87] find that exposure to a deworming program in school-aged children in Kenya leads to log wage increases of 19.7 points 10 years after the intervention. Analysis of the effects of malaria eradication programs in Brazil, Colombia, Mexico, and the United States finds that childhood infection with malaria reduces adult income by 50%.[88] Beach et al.[89] find that eliminating early life exposure to typhoid fever increased income by 1% in later life in the United States. Nelson[79] finds that in utero exposure to the 1918 influenza pandemic in Brazil led to an 8.6% lower likelihood that individuals born in 1919 would have formal employment than those born in other years between 1912 and 1922.

Our paper makes several important contributions to the literature on the long-term economic effects of health interventions. First, studies estimating the economic benefits of vaccines address short-term forgone medical expenses (including cost savings to health care providers), financial risk protection (e.g., value of insurance), and the monetized value of health gains (e.g., value of statistical life years) due to reduced disease incidence.[31–34] To the best of our knowledge, this is the first study of the long-term economic benefits of vaccines in LMICs, and one that evaluates the human capital development aspect of vaccines.[15] Previous studies of human capital development analyze only the link between vaccines and standardized test scores or schooling attainment, not earnings or consumption. To the best of our knowledge, Atwood[35] is the only study to estimate a 1.1% increase in future income due to measles vaccinations, but in the context of the United States and not LMICs. A large volume of published work links nutrition or undernutrition, famine, air pollution, diseases, and war in early childhood with later-life economic outcomes,[27] and the literature on diseases focuses heavily on malaria eradication and deworming; little is known about the long-term effects of vaccines or other low-cost preventive health interventions.

Second, we contribute substantially to the understanding of how large-scale public health programs can aid long-term human capital development and economic growth in India and potentially other LMICs. Although previous studies have examined the educational benefits of India's national nutrition and early childhood development program (the Integrated Child Development Services);[36,37] economic outcomes remain inadequately studied.

Last, our study informs the policy discussion surrounding universal routine childhood immunisation coverage in India and other LMICs. In the past two decades, routine childhood vaccination coverage increased from 50% to 80% in LMICs, followed by a sharp reduction due to the ongoing COVID-19 pandemic.[38] Additional challenges such as vaccine hesitancy have also become significant in the past few years. Our findings can help reinforce and revitalize the drive for universal immunisation and ensure sustained efforts in future years, even when major childhood diseases are on the verge of eradication.

2.3 Background on the Universal immunisation Programme

The Universal immunisation Programme was launched in 1985 and implemented in phases; all districts were covered by 1990.[90] Prior to launch, some routine childhood vaccines were administered before 1985 but mainly in urban areas and with negligible coverage rates.[91] The measles vaccine—a key vaccine with potential long-term benefits—was not provided before 1985 because it was not yet available in India.

Figure 1 shows the rollout of UIP by district. Initially, the program administered vaccines for six diseases: diphtheria, pertussis, and tetanus (DPT); measles; polio; and Bacillus Calmette-Guérin (BCG) for tuberculosis.[90] UIP aimed for full coverage of 85% of infants by March 1990.[91] By the time the program was fully implemented, vaccination rates had risen considerably but were far from universal. DPT-3 coverage, which is commonly used as a performance measure of national immunisation programs, was estimated by UNICEF at 57% in 1991 and 61% in 1993.[91]

UIP is among the largest immunisation programs in the world, attempting to vaccinate an annual cohort of 26 million children with a budget of $2 billion.[92] A major success of the program was the 2014 elimination of polio through a special campaign that immunized 170 million under-five children.[93] Despite UIP's achievements, coverage has yet to be universal. DPT-3 coverage among 12-23-month-old Indian children was 85% in 2020.[16] To address delayed and missed vaccination, the Indian government recently implemented additional vaccination campaigns known as Mission Indradhanush and Intensified Mission Indradhanush, which together raised immunisation rates.[94,95] Currently, UIP provides vaccination for polio (oral polio vaccine); DPT; BCG; measles; hepatitis B; Hib containing pentavalent (DPT, hepatitis B, and Hib); inactivated polio vaccine; tetanus toxoid; and, in endemic areas, Japanese encephalitis.

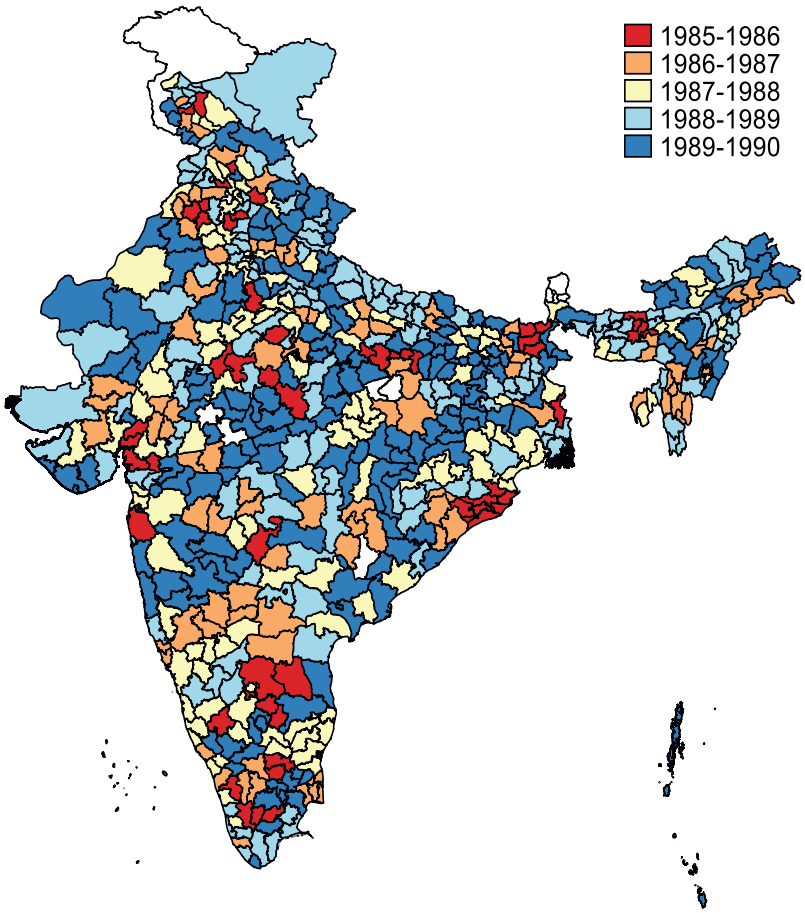
2.4 Data and descriptive statistics

2.4.1. Data sources

Data primarily come from two data sets. National Sample Surveys (NSS) are routine, nationally representative surveys that collect data on an exhaustive set of socioeconomic characteristics. NSS round 68 (NSS-68) was conducted between July 2011 and June 2012 and contains the following outcome variables: wages, monthly per capita expenditure, and income source (agriculture versus nonagriculture) of household. NSS-68 collected data on 456,999 individuals from 101,724 households in 626 districts. The data for the year of UIP implementation—our treatment variable—were taken from our previous work.[49] We reviewed district bifurcations and

creation of new districts and states and carefully matched the districts in NSS-68 data retrospectively with the phased district-wise rollout of UIP from 1985 to 1990. All control variables come from NSS-68 data except for the probability of being a migrant, which is predicted using the National Family Health Survey 4,[96] discussed further in a later section.

Figure 1: Rollout of the Universal immunisation Programme, by year and district



Note: Color codes denote the year of UIP implementation in a district. Districts with no data appear in white.

2.4.2. Outcome variables and sample selection

Our main outcome variable from NSS-68 is log weekly wages, measured in Indian rupees. Our sample includes individuals who were in the job market and had wage information. Because UIP implementation started in 1985 and ended by 1990, we include people born between 1985 and 1990 in our main analysis sample. Those born in this period would be between the ages of 21 and 26 when surveyed in 2011–2012. We select this study sample because in a sample with a wider age range, factors other than the immunisation program could affect wages. The likelihood of major generational economic and educational reforms increases with time and could affect wage growth among individuals. Therefore, someone born in 1995 and in the job market (at age 16) at the time of the survey may not have had access to the same education system and labor market as someone born in 1980 (age 31 at the time of the survey). Individuals who were attending school or enrolled in institutes of higher education in 2011–2012 are excluded from the analysis; this situation applies to 9% of our 21- to 26-year-old sample. Out of employed individuals, we include those who had salaried employment (33% of the sample) and exclude those who were self-employed or employed in a household enterprise because the survey did not collect wage data for them.

We also examine the log of monthly per capita expenditure (MPCE) as an outcome variable measuring standard of living. A special NSS module collects data on various goods and services consumed by the household. For common monthly expenditures such as food, personal care items, entertainment, and rent, the household is asked what it spent over the previous 30 days. For expenditures on durable goods, furniture, household items, and school fees, the household is asked for its spending estimate over the previous 365 days. This amount is divided by 12 and added to the monthly estimate to yield the total monthly household consumption expenditure. This number is then divided by the number of members in the household to arrive at the monthly per capita expenditure. We use MPCE data for the full sample, irrespective of employment status.

Finally, we examine household income source as an outcome variable. Specifically, we are interested in knowing whether the household receives income from agricultural or nonagricultural sources. Employment in agriculture could be less secure and less desirable than formal employment in other sectors. This variable was assigned a value of 1 if the head of the household depended primarily on agriculture for income and 0 if nonagricultural income was the primary source. Therefore, even those who did not have salaried work were included in this sample, unlike the analysis of wages.

2.4.3. Assignment of treatment status

UIP focuses on vaccination of infants (under the age of one year), following World Health Organization recommendations during the 1980s.[97,98] For each district, the residents born either after or during the year of UIP implementation in that district are included in the treatment group: they were potentially vaccinated by UIP during the first year of life. People living in districts without UIP by their year of birth year are in the control group. These data are not available as exact dates or months, so we assign treatment status based on the year of birth and the year of UIP implementation. UIP implementation proceeded in five one-year phases, starting

in 1985–1986 and ending in 1989–1990 (see Figure 1). We used the endpoint of this data range as the year of program implementation. For example, 1985–1986 districts were coded as having the program implemented in 1986, and 1989–1990 districts were coded as having the program implemented in 1990.

2.4.4. Effect of migration

NSS-68 has data on individuals' current district of residence but not their district of birth. Cutler et al.[86] suggest that current residence status often indicates birth location because of the low migration patterns in rural India. In 2011, at the time of NSS-68, 73% of the Indian population was rural, and out-of-district migration was only 15%.[99] However, we approach incorporating the potential effect of migration more thoroughly by conducting additional analysis using data from the National Family Health Survey, round 4 (NFHS-4).

NFHS-4 is a nationally representative cross-sectional survey conducted between 2015 and 2016. It surveyed 2.87 million individuals in 601,509 households in all states and union territories of India. Unlike NSS-68, NFHS-4 collected information on migration status (whether someone had lived in the same location since birth) of a subsample of adult men and women. First, we conduct a probit regression of migrant status in NFHS-4 (a person had not lived in the same location since birth) on a vector of background characteristics of individuals (born in 1985–1990), including sex, age, relationship to household head, age of household head, marital status, caste, religion, household size, and wealth quintiles. Then, using the estimated coefficients from this regression and the same set of explanatory variables from NSS-68,[iv] we predict the probability of migration for NSS-68 individuals. Our model uses the predicted probability as an explanatory variable, as discussed in Section 5. Additional robustness checks that exclude potential migrants are also conducted, as discussed in Section 5.6.

2.4.5. Background characteristics of the treatment and control groups

Table 1 shows the major socioeconomic and demographic characteristics, by control and treatment groups, for individuals whose birth year is between 1985 and 1990 (21- to 26-year-olds). Wages are significantly higher in the control group (INR 1,557 vs. INR 1,279 mean value, $p<0.01$), primarily due to outliers. Median wages were not statistically different between the two groups. UIP-covered households are more likely to have agriculture as the primary income source (23% vs. 25%, $p<0.01$). The control group is on average 2.23 years older than the treatment group (25.02 vs. 22.79 years, $p<0.01$). The age difference may also explain the higher rate of marriage (53% vs. 34%, $p<0.01$) in the control group. Another significant difference between the treatment and control groups is the mean probability of being a migrant (96% vs. 95%, $p<0.01$). The control group has a larger proportion of graduates (4% vs. 2%, $p<0.01$) and a smaller proportion of those who completed secondary education (14% vs. 20%, $p<0.01$). More people in the control group reside in the western and southern regions and fewer are from the central region. This would mean that the UIP program rolled out earlier in the central region (see

iv NFHS-4 collected data on assets such as televisions, radios, and cars, and housing condition indicators such as quality of roof and number of rooms in the house. Using these indicators, we create a wealth index in the spirit of Filmer and Pritchet[100]. We divide the wealth index into five quintiles. In NSS-68, we consider MPCE quintiles (no data on assets were available) as equivalent to NFHS wealth quintiles.

Figure 1). Also, the control group included significantly more Hindu and Christian households and fewer Muslim and Sikh households.

2.5 Empirical strategy

5.1. Testing for selective program placement

No administrative data are available on the selection criteria for districts in each UIP phase. An earlier study posited that UIP rollout was prioritized in districts with higher levels of health infrastructure and capacity to vaccinate but did not provide any evidence.[101] We systematically test for selective placement of UIP using additional village-level data. The 1991 Census of India was the first national census to publish data on demographic indicators (e.g., age and sex distribution) and infrastructure (e.g., availability of a primary health center or electricity) for all 634,000 Indian villages. We matched the UIP rollout data with the district indicators in Census 1991 data to determine the phase of UIP rollout for each village (assuming that a village was covered when its parent district was covered). Then, we examine if the village characteristics can predict early rollout sufficiently. We estimate the following probit model:

$$Phase1_k = \alpha_0 + \alpha_1 x_k + u_k \quad (1)$$

where $Phase1_k$ is the binary indicator of whether the district containing village *k* was selected in the first phase of UIP (1985–1986). The covariate set *x* included a series of village-level indicators such as log of population by age and sex, male and female literacy rates, share of socioeconomically disadvantaged groups (known as scheduled caste and scheduled tribe), and availability of different types of schools (e.g., primary or middle school), health care facilities (e.g., primary health center or sub-center), community health worker, private doctor, drinking water, paved road, and electricity. A second probit model similar to (1) repeats the analysis for villages that were in either phase 1 or 2 of UIP, as compared with the remaining villages across the country. Analysis is done for 20 major states of India (450,000 villages) using Census 1991 data obtained from Nandi and Deolaikar[102]. Standard errors were clustered at the district level.

Appendix Table A1 presents the results from the two regression models. We find that village health infrastructure is generally not associated with selection into UIP phases 1 or 2. Out of nine health indicators, only the availability of a private doctor is negatively linked with selection in phase 1, but not in the second model (phases 1 or 2). Except for one or two cases, the estimated coefficients of other demographics and infrastructure indicators are also statistically insignificant. Considering that improving health and other physical infrastructure is an expensive and slow process, we argue that the phase-wise UIP rollout was not determined by the underlying health systems capability of districts. Additionally, UIP rollout was also not associated with schooling infrastructure, reducing the possibility of unobserved biases (e.g., districts that are prioritized for UIP and also receiving greater schooling inputs that can affect future labor market outcomes).

Table 1: Socioeconomic characteristics, by control and treatment groups

	UIP-covered district		Control		Difference in means
	Mean	Standard deviation	Mean	Standard deviation	
Wages	1,278.88	1,145.20	1,556.96	1,605.97	-278.08**
MPCE (INR)	1,714.88	1,485.58	1,949.89	2,053.55	-235.00**
Agricultural occupation	0.15	0.36	0.13	0.34	0.02**
Age	22.79	1.29	25.02	1.30	-2.23**
Rural	0.55	0.50	0.52	0.50	0.03**
Female	0.19	0.39	0.21	0.41	-0.02*
Female head	0.14	0.35	0.12	0.32	0.02**
Married	0.34	0.48	0.53	0.50	-0.18**
Probability of being migrant	0.96	0.09	0.95	0.11	0.01**
Region					
Northeast	0.09	0.28	0.09	0.29	0.00
North	0.22	0.42	0.23	0.42	-0.01
West	0.24	0.42	0.19	0.40	0.04**
South	0.28	0.45	0.26	0.44	0.02*
Central	0.05	0.21	0.07	0.26	-0.03**
East	0.13	0.34	0.14	0.34	0.00
Caste					
General	0.26	0.44	0.28	0.45	-0.01
Scheduled caste	0.12	0.32	0.13	0.34	-0.01*
Scheduled tribe	0.23	0.42	0.21	0.41	0.01+
Other backward caste	0.40	0.49	0.38	0.49	0.01
Religion					
Hindu	0.75	0.43	0.77	0.42	-0.02*
Muslim	0.15	0.36	0.13	0.33	0.02**
Christian	0.05	0.22	0.06	0.24	-0.01*
Sikh	0.03	0.18	0.02	0.14	0.02**
Relationship to head of household					
Head of household	0.17	0.37	0.27	0.44	-0.1**
Spouse	0.05	0.21	0.08	0.27	-0.03**
Child	0.66	0.47	0.54	0.50	0.13**
Grandchild	0.02	0.14	0.01	0.11	0.01**
Parent	0.00	0.00	0.00	0.00	0**
Education					
Middle or lower	0.55	0.50	0.51	0.50	0.04**

Secondary	0.16	0.36	0.13	0.34	0.02**
Higher secondary	0.12	0.32	0.10	0.31	0.01*
Graduate	0.11	0.31	0.15	0.35	-0.04**
Postgraduate	0.02	0.15	0.06	0.24	-0.04**
Education of head of household					
Middle or lower	0.77	0.42	0.70	0.46	0.07**
Secondary	0.12	0.32	0.11	0.32	0.00
Higher secondary	0.05	0.21	0.06	0.23	-0.01**
Graduate	0.05	0.21	0.08	0.27	-0.03**
Postgraduate	0.01	0.11	0.03	0.17	-0.02**
Sample size		3,941		6,840	

Note: Data are from National Sample Survey, 68th round. The sample consists of 21- to 26-year-olds. Treatment group comprises individuals living in districts where the Universal immunisation Programme was implemented by the year of their birth or earlier. MPCE=monthly per capita expenditure. INR = Indian rupees. +p<0.1, *p<0.05, **p<0.01.

2.5.2. Main model specification

Characteristics of districts unobserved in the 1991 Census data, e.g., disease prevalence, population density, transportation infrastructure, or political factors, may still be associated with UIP rollout. Systematic differences between the treatment and control districts could bias ordinary least squared estimates of the effect of UIP coverage on labor market outcomes. Differences between the groups could also evolve over time. To account for such potential biases, we employ an age-district fixed effects model that incorporates household and individual characteristics and district-and-time-varying factors. Our fixed effects log wage regression model takes the following form:

$$log(w_{i,j}) = \beta_0 + \beta_1 UIP_{i,j} + \beta_2 X_{i,j} + \partial Age_i \times District_j + \epsilon_{i,j} \quad (2)$$

where w_{ij} are wages observed in 2011-2012 for individual i in district j, $UIP_{i,j}$ is a binary variable equal to 1 if UIP was implemented before or during the birth year of individual i and 0 otherwise, Age_i is age of individual i and $District_i$ is the current district of individual i, and $Age_i \times District_i$ is the vector of dummy variables for age and district fixed effects. The source of variation at the individual level is from the year of birth, controlling for district and age (people of same age but born in different years).

Similarly, the regression model for MPCE is as follows:

$$log(MPCE_{i,j}) = \beta_0 + \beta_1 UIP_{i,j} + \beta_2 X_{i,j} + \partial Age_i \times District_j + \epsilon_{i,j} \quad (3)$$

We estimate the probability that a household relies on agriculture using a fixed effects linear probability model:

$$\Pr\left(Agri_{i,j}\right) = \beta_0 + \beta_1 UIP_{i,j} + \beta_2 X_{i,j} + \partial Age_i \times District_j + \epsilon_{i,j} \quad (4)$$

Where $\Pr\left(Agri_{i,j}\right)$ indicates the probability that individual *i* is in an agriculture-supported household. In all three models, the vector $X_{i,j}$ consists of control variables commonly found to affect wages: locality (urban vs. rural), caste, sex, religion, household size, and education level. We also include the following: whether household head is female, education of household head, relationship to household head, and the predicted probability that the individual is a migrant.

We include education of household head to account for intergenerational transfer of resources. Because education is highly associated with income and wealth, higher education of the household head may mean greater transfer of resources to dependents and offspring, equivalent to greater investments in education and health. Alternatively, for poorly educated and low-income households, children may need to enter the job market earlier to support their families rather than invest in their own human capital.

Relationship to the household head is included as a measure of intrahousehold resource allocation. The relative position of a child in a household may affect resource allocation in early and later life, which can in turn affect wages. For example, with limited resources, some households in India invest more in the education and health of boys.[103,104] We also include an indicator of whether the household head is female. Female-headed households often differ socioeconomically from male-headed households, including being poorer.[105,106] Finally, the probability of being a migrant, as discussed in Section 4.4, is included in *X*. We cluster all standard errors at the district level.

2.5.3. Consideration of benefits of vaccination for older cohorts

In 2016, 24%, 29%, and 23% of Indian children between the ages of 10 and 23 months had delayed vaccination of measles, DPT-1, and BCG, respectively; where delay is defined as receiving the vaccine at least 28 days after the recommended eligibility age.[18] Delayed vaccination can occur for many reasons: extreme weather may prevent families from reaching vaccination sites, for example, or logistical issues may interrupt the vaccine supply chain. Implementation of UIP may not have been perfect during the early years—as evidenced by the less-than-universal coverage after full program rollout—and delays may have been common. However, even if delayed, vaccination may still have long-term benefits. Although the focus of UIP is vaccination during the first year of life, per the recommended schedule, infants living in districts where UIP was implemented later may have received delayed vaccinations. Although vaccines should be administered close to the recommended schedule, most vaccines do not have an upper age limit,[97] and the program could have administered "catch-up" vaccinations.

UIP may also have benefited nontarget cohorts through a second pathway in which reduced disease transmission from other vaccinated children in the household or the neighborhood protected unvaccinated children.[107–109] Vaccination of younger siblings has been previously shown to provide protective effects to unvaccinated older siblings and other older members of the household.[110–112] To test these pathways, we consider late or partial exposure of children to UIP by using three alternative definitions of treatment status. We repeat our analysis with

treatment status variables based on whether UIP was implemented one, two or three years, respectively, after the birth year, and code 0 otherwise.

2.5.4. Parallel trends analysis

The validity of our empirical strategy depends on the parallel trends assumption—that is, time trends in the outcome variable should be similar between UIP and non-UIP districts in years leading up to UIP implementation, even though the levels could be different. To test for parallel trends, we first divide our sample into four pairs of treatment and control group combinations based on the year of implementation: (i) individuals from districts in which UIP was introduced by 1986 (treatment) versus all other districts (control); (ii) individuals from districts in which UIP was introduced by 1987 (treatment) versus all other districts, excluding the 1986 UIP districts (control); (iii) individuals from districts in which UIP was introduced in 1988 (treatment) versus all other districts, excluding the 1986 and 1987 UIP districts (control); and (iv) individuals from districts in which UIP was introduced in 1989 (treatment) versus all other districts, excluding the 1986, 1987, and 1988 UIP districts (control). By the end of 1990, all districts had UIP, and no control group remained.

Then, we test for parallel trends for each treatment-control pair in two ways. First, we estimate the average annual residual log wages of those born between 1975 and the year before UIP introduction (e.g., born in 1975–1984 during the first subset before UIP was implemented in 1985–1986, born in 1975–1985 during the second subset, and so on), controlling for district fixed effects. Appendix Figures A1–A4 present the trends in residual log wages, separately for future treatment and control groups (e.g., those born in 1975–1984 separately in districts that will have UIP in 1985–1986 versus the remaining districts). We find that leading up to the introduction of UIP, the trends were similar across treatment and control groups in each of the four analysis subsamples, satisfying the parallel trends assumption.

Second, separately in each of the four data subsets, we regress log wages on the covariate set $X_{i,j}$, an indicator for the future treatment group (e.g., 1986 UIP districts in case of the first subset of 1975–1984 data), identifiers for year of birth, and interaction terms between year and the treatment indicator. The estimated coefficient of the future treatment and birth year interaction indicates whether wages were statistically different between the treatment and control groups year by year leading up to the introduction of UIP, controlling for observable characteristics of individuals. Appendix Figures A5–A8 present the estimated coefficients along with their 95% confidence intervals. Generally, no statistical differences appear in the year-by-year trends in wages between treatment and control groups in all four analysis subsets before UIP implementation in those districts, validating the parallel trends assumption. Parallel trend test results for MPCE and occupational choice are similar and therefore not presented separately.

2.5.5. Cohort size variations: selective mortality and fertility

Following Araujo et al.,[113] who evaluate the long-term benefits of an iodine supplementation program in Tanzania, we test for selection biases in the study sample by examining cohort sizes. First, UIP may affect parental fertility choice: some parents may have chosen to delay childbearing until after UIP was implemented in their home district. These parents could be

richer and more knowledgeable about public health programs and in turn may invest more in the human capital development of their children. This potentially creates an upward bias in the future wages of their children. A second issue is that death rates, especially from vaccine-preventable diseases, may be higher among children in the control group. As a result, the treatment group may have more "weaker" children who survive but have lower health and human capital than the control group children who went through "survival of the fittest," resulting in a possible downward bias in wages for the treatment group. We evaluate these issues by comparing the cohort sizes in NSS-68 in UIP 1985–1986 districts vis-à-vis other districts during 1975–1988. We exclude other treatment groups—that is, those born in UIP districts post 1985–1986—to keep the control group uncontaminated. The results, presented in Appendix Figure A9, show that the relative cohort sizes between the treatment and control group follow a parallel trend, and no divergence occurs after the introduction of UIP in 1985–1986. This implies that bias due to selective fertility or mortality in the study sample is unlikely.

2.5.6. Robustness checks and treatment heterogeneity

We conduct additional robustness checks. First, we exclude from our sample individuals who were most likely to be out-of-district migrants. We do this only for those born between 1986 and 1990, because migrants born before 1986 would all be in the control group and individuals born after 1990 would all be part of the treatment group. The 2011 Census of India estimates that among urban male, urban female, rural male, and rural female populations, 24%, 30%, 4%, and 15%, respectively, were out-of-district migrants.[99] We divide our data into these population subgroups and exclude the corresponding top part of the predicted probability distribution of being a migrant. For example, for urban males, we exclude those with values in the top 24% of the predicted probability distribution, and for rural females, we drop the top 15%. The exclusion of these observations is imperfect because being a migrant does not necessarily mean that treatment status is inaccurately assigned. For example, if individuals born in 1988 in a district where UIP was implemented in 1988 migrated to another district where implementation occurred between 1985 and 1988, their assigned treatment status would be correct despite their status as migrants and we would lose valid observations. However, conducting the analysis based on a sample of individuals least likely to be migrants was the best method to test for the robustness of our results.

Second, we examine whether our choice of study period matters. We consider two additional groups—those born between 1985 and 1995 (21- to 31-year-olds) and those born between 1980 and 1995 (16- to 31-year-olds)—and repeat our analysis. Third, we exclude education control variables. With education controls, our coefficient of interest measures differences in vaccination between UIP-exposed and non-exposed individuals with the same level of education. However, schooling attainment itself may be a function of UIP exposure.[49]

Finally, in addition to the robustness checks, we conduct heterogeneity analyses by gender, location (rural vs. urban and high-focus states vs. low-focus states), caste (scheduled caste, scheduled tribe, and other backward classes), occupation (salaried workers only), and religion (Hindu and non-Hindu). The Indian government designates the states of Assam, Bihar, Chhattisgarh, Jharkand, Madhya Pradesh, Orissa, Rajasthan, Uttar Pradesh, and Uttaranchal as

high-focus states (HFS) due to high levels of fertility and child mortality, while the remaining states are considered to be low-focus (LFS).

2.6 Results

2.6.1. Effect of UIP exposure on economic outcomes

Tables 2–4, models 1A–1C, present the coefficient of interest—the effect of UIP coverage on wages, MPCE, and income source, respectively. Appendix Table A2 provides the full model results for wage outcome, Appendix Table A3 for MPCE outcome, and Appendix Table A4 for household income source outcome. We find that exposure to UIP in infancy increases wages by 14% (95% CI: 8%–20%, $p<0.01$) in the principal model for those born between 1985 and 1990. This result is insensitive to changing the sample's age group, with models 1B (born 1980–1995) and model 1C (born 1985–1995) having identical coefficients. We find that UIP exposure in infancy increases MPCE by 3% (95% CI: 1%–5%, $p <0.01$) in model 1A for those born between 1985 and 1990, and this result is consistent in models 1B and 1C. Finally, we find that individuals exposed to UIP have a 2% (95% CI: 0%–4%, $p<0.05$) lower probability of being in households primarily supported by agriculture. These results are consistent in models 1B and 1C.

2.6.2. Benefits of vaccination for older cohorts

In Tables 2 and 3, models 2A–2C, we redefine the treatment variable, where those born one year before UIP implementation are considered to have received (weak) treatment as well. We find individuals who are partially exposed to UIP have wages only 7% higher (95% CI: 0%–15%, $p <0.01$) than those in the control group in model 2B (born 1985–1995). For MPCE outcomes the results are similar to those with exposure only at birth. In models 2A and 2C, expenditure increases by 4% (95% CI: 1%–6%, $p>0.01$). Appendix Tables A2 and A3 show the full model results. In Appendix Table A5, we present longer delays in exposure to UIP for only five-year birth cohorts. Specifically, we consider children exposed to UIP two and three years after birth as receiving treatment in these two sets of models. We find positive effects on wages for those born two years before UIP of 8% but not for those born three years prior to UIP. Those with delayed exposure two and three years after birth have a 5% and a 4% increase in MPCE, respectively. No significant effects are found on household income source outcome.

2.6.3. Exclusion of migrant populations

As a robustness check, we excluded the proportion of the sample within each sex-locality group that was most likely to be migrant, using predicted probabilities of being a migrant based on 2011 census rates of out-of-district migration. We find that the coefficients in all models remain the same, and the results are insensitive to exclusion of migrant populations for samples born in 1980–1995 and 1985–1995. Appendix Tables A2 and A3 provide the full results.

2.6.4. Heterogeneity across population groups

Models 4A–13A in Tables 2 and 3 show the coefficient of exposure on treatment status with age-district fixed effects for those born between 1985 and 1990, by subsample group. Appendix Tables A6–A13 provide the full model results. We see that the effect of UIP exposure during

Table 2: Summary results of effect of UIP exposure on wages

Model	Model description	Time period					
		A) 1985-90		B) 1980-95		C) 1985-95	
		Coefficient	Sample size	Coefficient	Sample size	Coefficient	Sample size
1	Main model	0.14** (0.03)	10,781	0.14** (0.03)	15,750	0.14** (0.03)	26,562
2	With partial effects	0.07+ (0.03)	10,781	0.07* (0.03)	15,750	0.06+ (0.03)	26,562
3	Without predicted migrants	0.16** (0.03)	8,963	0.16** (0.03)	13,932	0.16** (0.03)	24,744
4	Rural	0.14** (0.04)	5,716	0.14** (0.04)	8,582	0.14** (0.04)	14,284
5	Urban	0.08+ (0.05)	5,065	0.08+ (0.05)	7,168	0.09+ (0.05)	12,278
6	Male	0.16** (0.03)	8,618	0.16** (0.03)	12,660	0.15** (0.03)	21,140
7	Female	-0.05 (0.12)	2,163	-0.07 (0.12)	3,090	-0.07 (0.12)	5,422
8	SC/ST	0.2** (0.06)	15,798	0.2** (0.06)	16,385	0.2** (0.06)	17,855
9	OBC	0.05 (0.05)	4,178	0.05 (0.05)	6,169	0.06 (0.05)	10,252
10	Hindu	0.14** (0.03)	8,261	0.14** (0.03)	11,920	0.15** (0.04)	20,342
11	Non-Hindu	0.09 (0.08)	2,520	0.08 (0.08)	3,830	0.09 (0.08)	6,220
12	High focus states	0.21** (0.06)	3,119	0.23** (0.07)	7,941	0.22** (0.07)	4,884
13	Low focus states	0.12** (0.03)	7,662	0.12** (0.03)	18,621	0.12** (0.03)	10,866
14	No education control	0.12** (0.03)	10,781	0.12** (0.03)	26,562	0.12** (0.03)	15,750
15	Only salaried workers	0.13** (0.04)	5,699	0.14** (0.07)	13,644	0.13** (0.04)	7,529

Notes: Data are from National Sample Survey (68th round). The sample consists of 21- to 26-year-olds. The treatment group comprises individuals living in districts where the Universal immunisation Programme was implemented in the year of their birth or earlier. Standard errors clustered at district level. Includes age and district-level fixed effects. *OBC*=other backward caste; *ST*=scheduled tribe; *SC*=scheduled caste. Standard errors are clustered at the district level. +p<0.1, *p<0.05, **p<0.01.

Table 3: Summary results of effect of UIP exposure on consumption expenditure

Model	Model description	Time period					
		A) 1985-90		B) 1985-95		C) 1980-95	
		Coefficient	Sample size	Coefficient	Sample size	Coefficient	Sample size
1	Main model	0.03** (0.01)	46,557	0.03** (0.01)	91,191	0.03** (0.01)	129,980
2	With partial effects	0.04** (0.01)	46,557	0.03** (0.01)	91,191	0.04** (0.01)	129,980
3	Without predicted migrants	0.03** (0.01)	38,346	0.03* (0.01)	82,980	0.03* (0.01)	121,769
4	Rural	0.04** (0.01)	27,854	0.04** (0.01)	55,158	0.04** (0.01)	78,263
5	Urban	0.01 (0.02)	18,703	0.01 (0.02)	36,033	0.01 (0.02)	51,717
6	Male	0.01 (0.02)	22,813	0.01 (0.02)	46,297	0.01 (0.01)	65,008
7	Female	0.03* (0.01)	23,744	0.04* (0.01)	44,894	0.03* (0.01)	64,972
8	SC/ST	0.04+ (0.02)	76,076	0.04+ (0.02)	82,469	0.04+ (0.02)	87,720
9	OBC	0.03 (0.02)	18,058	0.03+ (0.02)	35,607	0.03+ (0.02)	50,827
10	Hindu	0.04** (0.01)	34,268	0.04** (0.01)	66,082	0.03** (0.01)	95,291
11	Non-Hindu	0.02 (0.02)	12,289	0.01 (0.02)	25,109	0.01 (0.02)	34,689
12	High focus states	0 (0.02)	17,278	0 (0.02)	49,887	0 (0.02)	35,379
13	Low focus states	0.04** (0.01)	29,279	0.04** (0.01)	80,093	0.04** (0.01)	55,812
14	No education control	0.03** (0.01)	46,564	0.03** (0.01)	129,988	0.03** (0.01)	91,198
15	Only salaried workers	0.02 (0.04)	5,802	0.02 (0.02)	13,883	0.02 (0.04)	7,665

Notes: Data are from National Sample Survey (68th round). The sample consists of 21- to 26-year-olds. The treatment group comprises individuals living in districts where the Universal immunisation Programme was implemented in the year of their birth or earlier. Includes age and district-level fixed effects. *OBC*=other backward caste; *ST*=scheduled tribe; *SC*=scheduled caste. Standard errors are clustered at the district level. +p<0.1, *p<0.05, **p<0.01.

Table 4: Summary results of effect of UIP exposure on agriculture as household income source

Model	Model description	Time period					
		A) 1985-90		B) 1985-95		C) 1980-95	
		Coefficient	Sample size	Coefficient	Sample size	Coefficient	Sample size
1	Main model	-0.02* (0.01)	46,557	-0.02* (0.01)	91,191	-0.02* (0.01)	129,980
2	With partial effects	-0.01 (0.01)	46,714	-0.02* (0.01)	90,025	-0.02* (0.01)	127,752
3	Without predicted migrants	-0.01 (0.01)	38,775	-0.01 (0.01)	83,409	-0.01 (0.01)	122,198

Notes: Data are from National Sample Survey (68th round). The sample consists of 21- to 26-year-olds. The treatment group comprises individuals living in districts where the Universal immunisation Programme was implemented in the year of their birth or earlier. Includes age and district-level fixed effects. +p<0.1, *p<0.05, **p<0.01.

infancy differs for various subsamples. For rural, male, scheduled caste or scheduled tribe, and Hindu households, UIP exposure during infancy has a significant and positive effect on wages. Individuals residing in rural areas and males who were exposed to UIP at birth have 14% (95% CI: 5%–23%, p<0.01) and 16% (95% CI: 9%–23%, p<0.01) higher wages than the control group, respectively. However, program exposure has no effect on urban, female, other backward caste, and non-Hindu individuals. Individuals exposed to UIP in high-focus states had 21% higher wages (95% CI: 7%–38%, p<0.01) and in low-focus states had 12% higher wages (95% CI: 5%–19%, p<0.01) than individuals in control groups. For the MPCE outcomes, we find that the coefficients are similar to the complete sample models for rural, female, and Hindu households, but insignificant for other household groups. UIP exposed adults in LFS had significantly higher MPCE, while no effect was found in HFS. Results were similar in samples across different time periods. In model 15A, which includes salaried workers, the treatment effect on wages is 13% (95% CI: 3%–23%, p<0.01).

2.6.5. Additional robustness checks

We perform additional robustness checks and present the results in Tables 2 and 3. In models 14A, for those born between 1985 and 1990 we show the results excluding education controls. We find that the coefficient of exposure decreases 2 percentage point from the main model, showing a 12% increase in wages (95% CI: 6%–19%, p<0.01) for the treatment group relative to the control group. For MPCE, model results without education controls are identical to the main model.

2.7 Discussion and conclusion

An estimated 400,000 Indian children under age five die yearly from vaccine-preventable diseases such as pneumonia, diarrheal diseases, measles, and meningitis.[114] Vaccines can not only save these lives but also improve cognitive outcomes and educational attainment.[20,49] Our study adds to the growing body of literature showing the substantial long-term economic benefits of immunisation in LMICs. We find that adults aged 21 to 26 in districts where the Universal immunisation Programme was implemented at the time of birth have 14% higher weekly wages. We also examine changes in monthly per capita household consumption expenditure and find a 3% higher MPCE for adults with UIP exposure. Finally, vaccination also influences livelihoods: treatment individuals' households are 2% less likely to rely on agriculture as their principal source of income. These results are robust to changing the sample size to include both 16- to 31-year-olds and 21- to 31-year-olds.

While there is a substantially large literature on the long-term economic benefits of disease reduction in LMICs,[25,27] the only published study of labor market effects of childhood vaccination is from the United States which linked measles vaccinations with 1.1% rise in future wages.[35] However, these estimates may not be generalizable to LMICs such as India which have a higher burden of vaccine preventable diseases and lower coverage of clean water and sanitation. In a yet unpublished study, Atwood and Pearlman[115] show that log wages were 2%-12% higher – depending upon the data and methods used – among adults in Mexico who had received the measles vaccine in childhood as compared with those who did not. These estimates are up to 10 times larger than the effects Atwood[35] found in the United States — and the authors

attribute these differences to the higher disease burden and lower access to healthcare in Mexico. Similarly, Hamory et al.[116] find that those with an additional two to three years of exposure to childhood deworming treatment in Kenya had 13% higher hourly earnings 20 years later. In addition to this recent evidence, there are a number of studies including on deworming programs, malaria eradication, and the influenza pandemic which show exposure effects on wages ranging from 8.6% to 50% in LMICs.[79,87,88]

The effects of exposure to UIP differ by population subgroup. Rural, male, scheduled caste and scheduled tribe, and Hindu adults experienced a positive effect of the program on wages, but urban, female, non-Hindu, and other backward caste adults did not. Similarly, for MPCE, we found that only rural, Hindu, and females experienced a rise in their consumption expenditure. Both HFS and low-focus states saw an increase in wages, with a higher increase in HFS, but no effect was found on MPCE for HFS. These differential effects have many plausible reasons.

First, we do not observe actual receipt of vaccines but conduct an intent-to-treat analysis. Underlying socioeconomic characteristics of individuals and supply-side factors may be associated with vaccination.[117] The first-ever population-based national vaccination estimates in India are available from the National Family Health Survey conducted in 1992–1993.[118] Coverage of DPT-3 vaccination was only 46.9% and measles vaccination was only 32.7% at that time. In rural areas, these rates were 41.8% and 28.7%, respectively; in urban areas, they were 64.2% and 32.7%, respectively. There was a difference by sex as well: 49.8% of females versus 53.8% of males received the DPT-3 dose. Among socioeconomic groups, the lowest vaccination rates were observed among Muslim and scheduled caste and tribe households. These groups have historically had lower vaccination rates, and contemporary estimates suggest these vaccination gaps, though narrower, persist even today.[96] Therefore, the lower rates of vaccination among some population subgroups may explain part of the difference in labor market outcomes

Second, known statistical discrimination exists against socioeconomically disadvantaged and minority groups in the Indian job market. Women and individuals from lower-caste groups may lack access to the same job opportunities conditional on their level of education and productivity.[119,120] This would reduce the potential benefits of UIP among these groups. High-focus states may have experienced greater increase in wages than low-focus states due to the overall higher level of disease, and therefore benefits of vaccination, relative to states with overall better health outcomes.

The primary mechanism for these effects is reduced disease exposure in childhood, which has long-lasting health effects. Although outside the scope of this paper, other work has confirmed the health effects of UIP. A study exploited the temporal rollout in UIP and found that the program led to higher child height-for-age and weight-for-age metrics, both common measures of overall health status for children.[62] These health outcomes are related to education outcomes. Studying UIP exposure, Nandi et al. show that children in UIP-exposed districts completed 0.18 more years of school compared with control groups.[49] Stunted child development reduced human capital accumulation, and poorer health and productivity of workers result in lower wages.

Our findings have important policy implications. Higher investment in UIP can pay very large returns in terms of increased per capita income, with vaccinated populations earning 14% higher

wages. A simple back-of-the-envelope calculation with the most recent Indian data—a 471 million labor force with 27% salaried workers,v 15% of them unvaccinated,vi and a gross domestic product per capita of $1,900[38] —would mean overall economic output could increase by 0.11% to 0.28%. This is a lower bound of the potential effect because we lack earnings data for all workers. If this rate were applied to all workers in the labor force, the effect of UIP could increase gross domestic product by 1.2%. Although the country's ministries of health are typically responsible for funding health programs, it is widely recognized that a multisectoral approach is required for effective change, and the support of ministries of finance is needed.[121] Our estimates show a direct link between vaccination and labor market outcomes and make a strong economic case for adequate funding for routine vaccines.

Globally, an additional 8.5 million and 8.9 million children did not receive their DTP-3 and meningococcal conjugate vaccine dose-1vaccine in 2020 relative to the number of missed doses projected.[24] The highest reductions in vaccination rates were in March and April 2020, during the beginning of the COVID-19 pandemic, and the regions hit the hardest were North Africa, the Middle East, South Asia, and Latin America and the Caribbean[24]—the same regions with the lowest overall vaccination rates prior to the pandemic.[55] A 2015 study estimated a global funding gap of $7.6 billion in 2016–2020 for delivery of full vaccination programs in 94 LMICs, which corresponds to 0.2% of general government expenditures.[122] For India's UIP an annual funding gap of $560 million was recently estimated to reach a 90% vaccination target.[123] The disruptions to immunisation and the persistent funding gaps not only lead to higher levels of preventable deaths but can also substantially lower standards of living and even compromise poverty reduction efforts in LMICs in the long term. The increased expenditure of 0.2% of the government budget is many times smaller than the future increase in economic output that an immunisation program could deliver.

India has the largest population of unvaccinated children in the world: the rate of full immunisation (BCG, measles, and three doses each of DPT and polio) was only 62% in 2016.[124] Although Mission Indradhanush and other programs have increased vaccination rates substantially,[94,95] their long-term sustainability is uncertain. A recent analysis found that the per dose cost of vaccination under Intensified Mission Indradhanush was substantially higher than the per cost dose of routine immunisation: $4.73 versus $1.31 in Bihar and $3.45 versus $1.43 in Uttar Pradesh.[125] This higher cost was attributed to the time required to identify children missed by UIP and the additional cost of vaccination in hard-to-reach areas. Routine immunisation budgets must incorporate the full costs of catch-up vaccination and have adequate funding to reach new birth cohorts.

To vaccinate children who missed vaccines because of COVID-19 or delays in immunisation campaigns, countries will have to engage in catch-up vaccination campaigns. The World Health Organization[13] states that a catch-up vaccination strategy is an integral part of any national immunisation program to ensure protection for individuals who may have missed doses. Ideally, vaccines should be administered on the recommended schedule, but most vaccines do not have

v Labor force includes salaried workers, self-employed, domestic worker/working in household enterprise, and unemployed individuals.

vi This is based on current DPT-3 vaccination rate in infants.

an upper age limit.[97] Early identification and vaccination of children who missed doses is the most practical approach, because identifying them at later ages is more challenging.[97] World Health Organization guidelines for interrupted or delayed routine immunisation do not set a maximum age limit for vaccines but rather recommend the time between vaccines and sometimes a different number of doses, depending on the age of the child.[98] Indian immunisation guidelines give an upper age limit for certain vaccines—five years of age for *Haemophilus influenzae*, pneumococcal vaccine, and BCG, and eight months for rotavirus.[126] However, they allow for delayed vaccination several years after the recommended age.

Catch-up vaccination campaigns have become common in LMICs. For example, although the first dose of measles vaccine should typically be administered at eight months of age, in China, children up to age seven are targeted for catch-up.[127] Hutton et al.[128] estimate that catch-up vaccination of children aged one to 19 years would be cost-effective at a cost of $2,500 per quality-adjusted life year gained and would remain cost-effective even if catch-up vaccination targets only children under two. Catch-up vaccination continues to be important as rates of newborn immunisation increase, depending on the level of coverage needed to achieve herd immunity, and as transmission decreases with the population of susceptible individuals.[129]

Our analysis has important limitations. First, because we lack data on place of birth and have only current residence data, individuals may be wrongly assigned to the treatment or control group if their current district had a different UIP implementation date than their birth district. However, as discussed earlier, the current rate of out-of-district migration is approximately 15%, according to the 2011 Census. We predict the probability of an individual being a migrant and dropped 15% of observations that were most likely to be migrants; our estimates were robust to this specification. Moreover, the treatment status of some migrants would not change, depending on the timing of UIP implementation in their birth and current districts even if birth district was known.

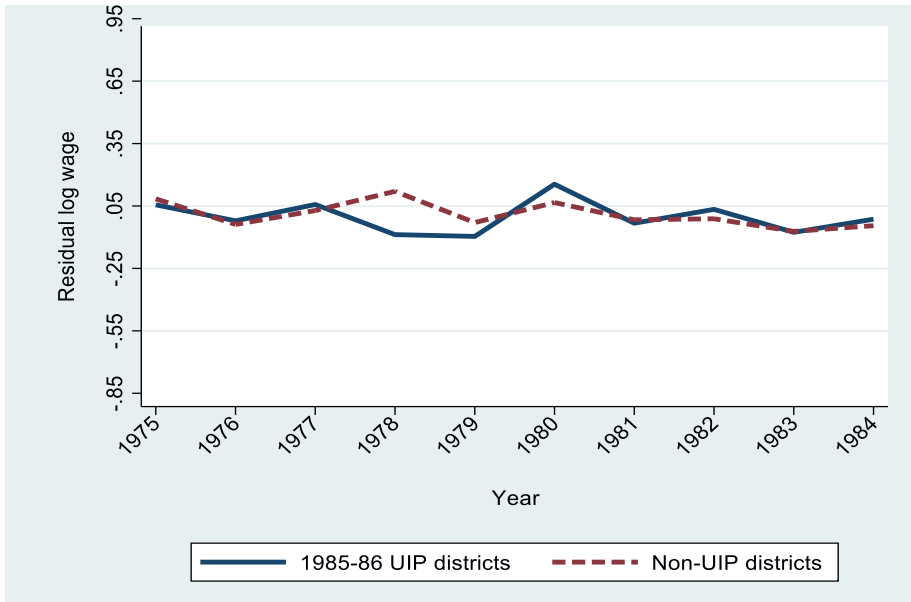
Second, vaccination benefits may be underestimated because we do not consider spillover effects to other household members. By reducing secondary transmission of disease, vaccination of infants may protect unvaccinated older siblings or neighborhood children. Our results may also be underestimates if residents of control districts traveled to treatment districts to receive the vaccine. In this case, some members of the treatment group were wrongly assigned to the control group and biased our coefficients downward.

A third limitation is that wage data, by definition, exist only for hired workers. If systematic differences exist between treatment or control group individuals who choose wage work rather than work for a household enterprise or self-employment, or those who choose to stay out of the job market, and their income differs from the current control and treatment groups, our results may be biased. For example, those who did not receive vaccines may have had more illness during childhood and been unable to find jobs as easily as the treatment group. In this example, the effect on wages would be biased downward. To account for individuals without wage data, we used monthly per capita household expenditure as an additional outcome variable. Although this is not a perfect variable to observe outcomes for the treatment group, it was the best proxy we could identify in our data set, and we find positive effects on MPCE from UIP coverage.

Immunization is the most cost-effective tool for decreasing mortality and morbidity in children. In addition to the well-established health and cognitive benefits, vaccination has substantial economic benefits. The recent pandemic shock to immunisation rates combined with already low vaccination rates in many LMICs will not only increase mortality and morbidity for these cohorts but also portend long-term harms in the form of lower incomes and standards of living. From an economic and a health perspective, it is critical that funding to immunisation programs increases.

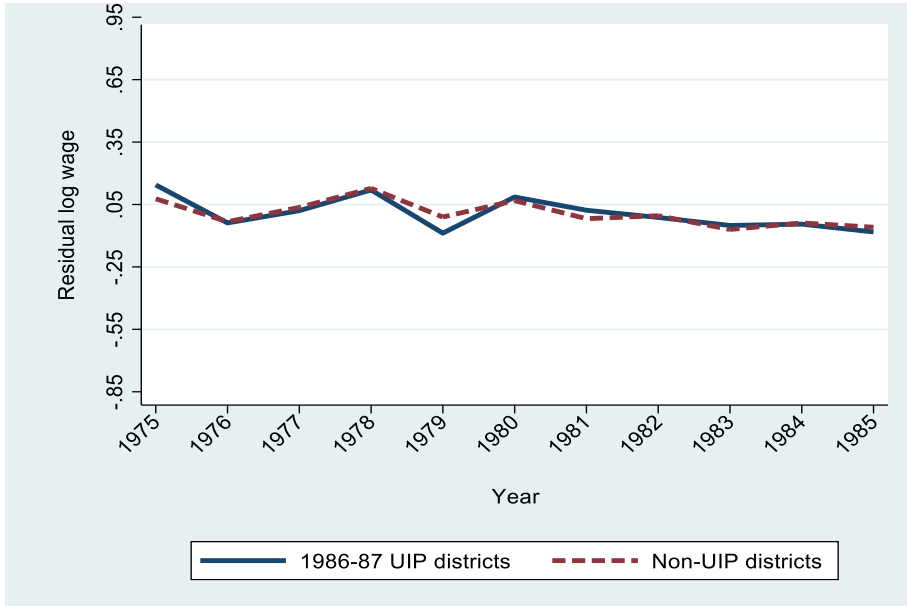
Appendix

Figure A1: Average annual residual log wages, in 1985–1986 UIP (treatment) and control districts, 1975–1984



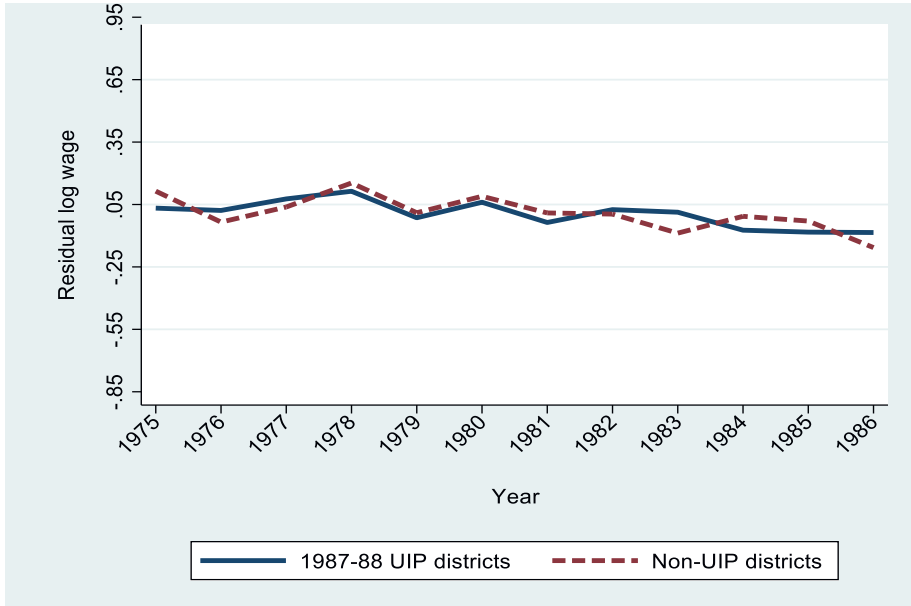
Notes: Data are from National Sample Survey 2011 (68th round). Treatment group comprises individuals born before 1985 in districts where UIP was introduced during 1985–1986. Control group comprises those born before 1985 in all other districts of India.

Figure A2: Average annual residual log wages, in 1986–1987 UIP (treatment) and control districts, 1975–1985



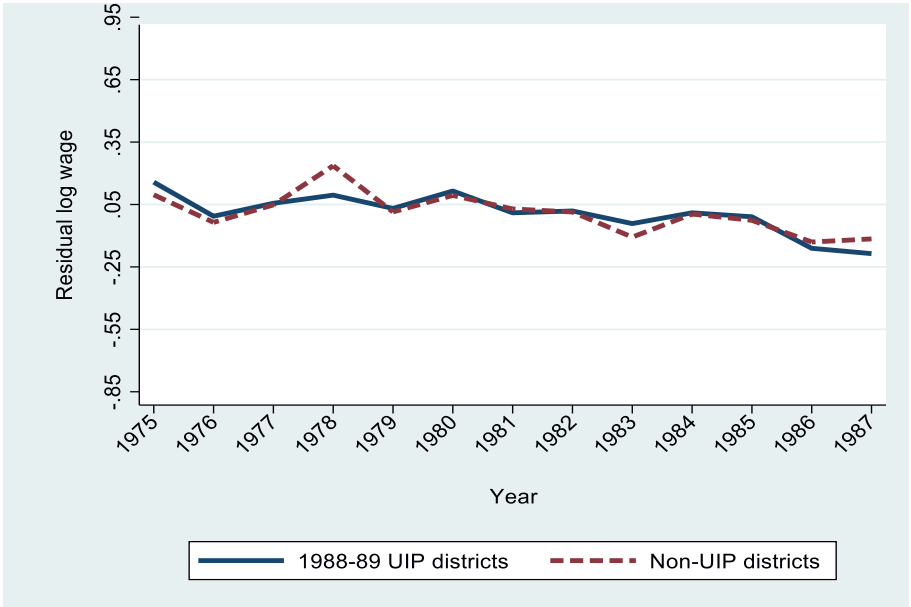
Notes: Data are from National Sample Survey 2011 (68th round). Treatment group comprises individuals born before 1986 in districts where UIP was introduced during 1986–1987. Control group comprises those born before 1986 in all other districts of India, excluding 1985–1986 UIP districts.

Figure A3: Average annual residual log wages, in 1987–1988 UIP (treatment) and control districts, 1975–1986



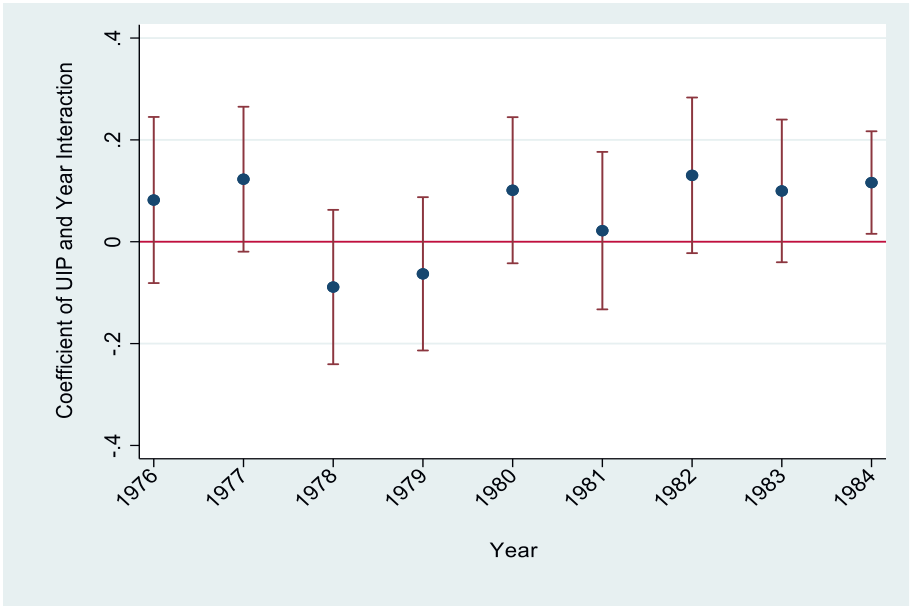
Notes: Data are from National Sample Survey 2011 (68th round). Treatment group comprises individuals born before 1987 in districts where UIP was introduced during 1987–1988. Control group comprises those born before 1987 in all other districts of India, excluding 1985–1986 and 1986–1987 UIP districts.

Figure A4: Average annual residual log wages, in 1988–1989 UIP (treatment) and control districts, 1975–1987



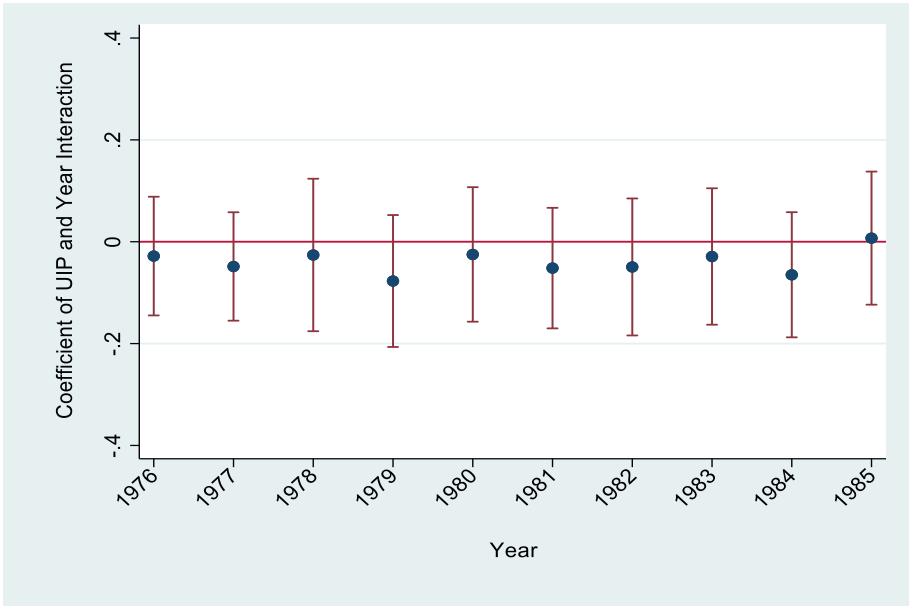
Notes: Data are from National Sample Survey 2011 (68th round). Treatment group comprises individuals born before 1988 in districts where UIP was introduced during 1988–1989. Control group comprises those born before 1988 in all other districts of India, excluding 1985–1986, 1986–1987, and 1987–1988 UIP districts.

Figure A5: Coefficient of interaction between UIP district status and birth year in regression of log wages, 1975–1984



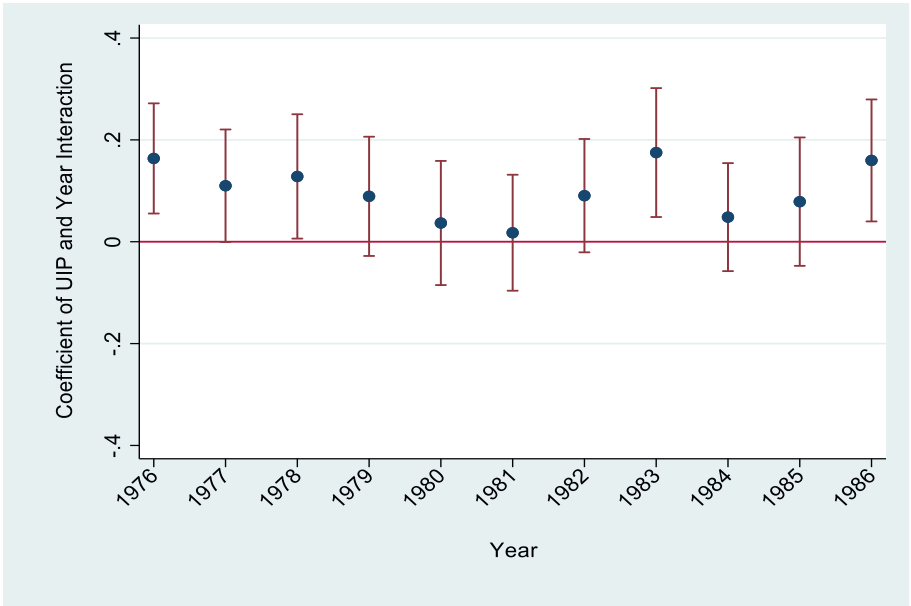
Notes: Data are from National Sample Survey 2011 (68th round). Treatment group comprises individuals born before 1985 in districts where UIP was introduced during 1985–1986. Control group comprises those born before 1985 in all other districts of India. Coefficients and 95% confidence intervals are shown.

Figure A6: Coefficient of interaction between UIP district status and birth year in regression of log wages, 1975–1985



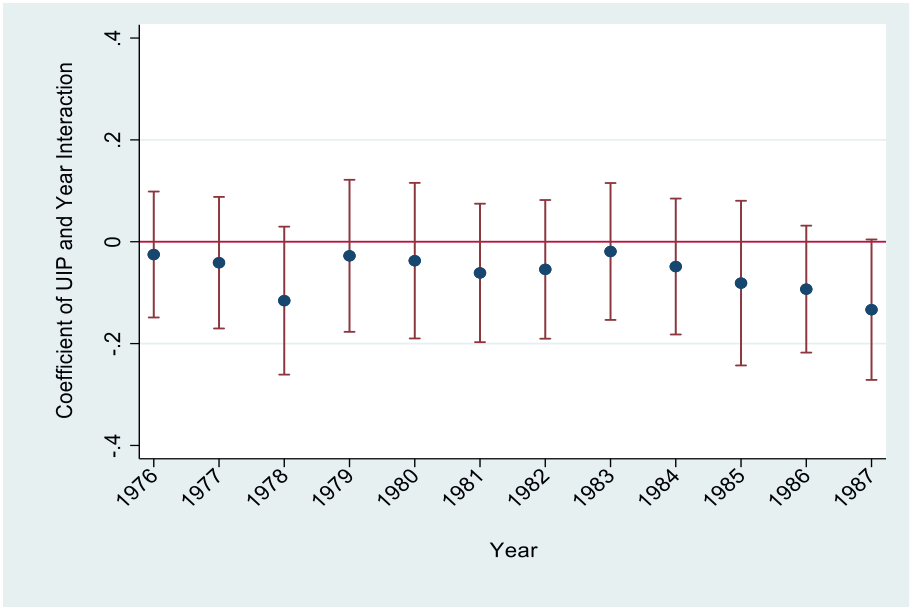
Notes: Data are from National Sample Survey 2011 (68th round). Treatment group comprises individuals born before 1986 in districts where UIP was introduced during 1986–1987. Control group comprises those born before 1986 in all other districts of India, excluding 1985–1986 UIP districts. Coefficients and 95% confidence intervals are shown.

Figure A7: Coefficient of interaction between UIP district status and birth year in regression of log wages, 1975–1986



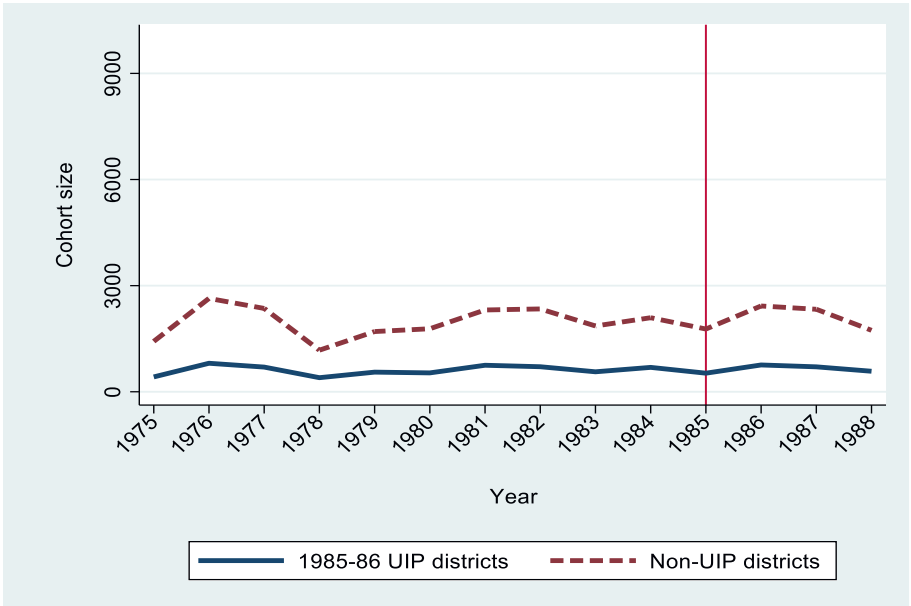
Notes: Data are from National Sample Survey 2011 (68th round). Treatment group comprises individuals born before 1987 in districts where UIP was introduced during 1987–1988. Control group comprises those born before 1987 in all other districts of India, excluding 1985–1986 and 1986–1987 UIP districts. Coefficients and 95% confidence intervals are shown.

Figure A8: Coefficient of interaction between UIP district status and birth year in regression of log wages, 1975–1987



Notes: Data are from National Sample Survey 2011 (68th round). Treatment group comprises individuals born before 1988 in districts where UIP was introduced during 1988–1989. Control group comprises those born before 1988 in all other districts of India, excluding 1985–1986, 1986–1987, and 1987–1988 UIP districts. Coefficients and 95% confidence intervals are shown.

Figure A9: Cohort sizes in 1985–1986 UIP districts and control districts before and after UIP introduction



Notes: Data are from National Sample Survey 2011 (68th round). Number of individuals born in districts where UIP was introduced during 1985–1986 vis-à-vis all other districts are presented year by year since 1975. Individuals born during other years of UIP introduction post 1985–1986 are excluded to keep the control group uncontaminated. The vertical line signifies the year of UIP introduction.

Table A1: Village-level probit model of selection into early phases of UIP, Census 1991

	Whether the village belonged to a UIP phase 1 district	Whether the village belonged to a UIP phase 1 or 2 district
Log adult male population	0.026	0.011
Log adult female population	0.000	0.000
Log population of boys aged 0–6 years	-0.014	-0.003
Log population of girls aged 0–6 years	-0.017	-0.011
Percentage of scheduled caste population	-0.012	-0.001
Percentage of scheduled tribe population	-0.056+	-0.002
Male literacy rate	0.044	-0.106
Female literacy rate	0.004	0.116
Share of agricultural laborers to all workers: male	0.179*	0.015
Share of agricultural laborers to all workers: female	-0.117+	0.031
Availability in the village of		
Primary school	-0.015	-0.005
Middle school	0.003	-0.002
College	-0.008	-0.013
Mother-child welfare center	-0.001	0.019
Maternity home	-0.011	-0.050
Health center	-0.009	-0.025
Primary health center	-0.010	-0.009
Primary health sub-center	0.015	0.018
Family welfare center	0.036	-0.005
Nursing home	-0.005	0.005
Private doctor	-0.040**	-0.048+
Community health worker	-0.011	0.019
Drinking water supply	0.014	0.051
Paved approach road	0.020	0.038+
Electricity	0.034+	0.070*
Sample size	450,078	450,078
Pseudo-R^2	0.03	0.01

Notes: Data are at the village level, obtained from 20 major states in Census 1991. +p<0.1, *p<0.05, **p<0.01

Table A2: Effect of vaccination coverage on log wages with age and district fixed effects

Model	1	2	3	4	5	6	7	8	9
Model description		Main			Includes partial effects			Non-migrant sample	
Time period	1985-90	1985-95	1980-95	1985-90	1985-95	1980-95	1985-90	1985-95	1980-95
UIP covered	0.13**	0.13**	0.13**				0.15**	0.15**	0.15**
	0.03	0.03	0.03				0.03	0.03	0.03
UIP covered partial				0.07+	0.07*	0.06+			
				0.03	0.03	0.03			
Locality (Urban=0)									
Rural	-0.03*	0	0.07**	-0.03*	0	0.06**	-0.07**	-0.02	0.06**
	0.02	0.01	0.02	0.02	0.01	0.02	0.02	0.02	0.02
Sex (Male=0)									
Female	-0.34**	-0.40**	-0.70**	-0.34**	-0.40**	-0.70**	-0.30**	-0.42**	-0.73**
	0.03	0.03	0.04	0.03	0.03	0.04	0.05	0.03	0.04
Married	0.03+	0	-0.04**	0.03+	0	-0.04**	0	-0.03	-0.05**
	0.02	0.02	0.01	0.02	0.02	0.01	0.02	0.02	0.02
Household size	0	0	0.01**	0	0	0.01**	0.01	0.01*	0.02**
	0	0	0	0	0	0	0.01	0	0
Age of household head	0	-0.00*	-0.00**	-0.00+	-0.00*	-0.00**	0	-0.00+	-0.00**
	0	0	0	0	0	0	0	0	0
Female head	0.03	0.01	-0.06**	0.03	0.01	-0.06**	0.02	0.01	-0.06**
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Probability of being a migrant	-0.73**	-0.77**	-1.42**	-0.73**	-0.77**	-1.42**	-0.67**	-0.80**	-1.43**
	0.19	0.14	0.11	0.19	0.14	0.11	0.21	0.14	0.13
Caste (General=0)									
Scheduled caste	-0.11*	-0.10**	-0.08*	-0.11*	-0.10**	-0.08*	-0.12*	-0.11**	-0.08*

	0.05	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.04
Scheduled tribe	-0.11**	-0.10**	-0.10**	-0.11**	-0.10**	-0.10**	-0.13**	-0.11**	-0.11**
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Other backward caste	-0.08**	-0.07**	-0.09**	-0.08**	-0.07**	-0.09**	-0.09**	-0.07**	-0.09**
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Religion (Hindu=0)									
Muslim	0.01	0.01	0.04**	0.01	0.01	0.04**	0.01	0.01	0.04*
	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02
Christian	0.03	0.02	-0.02	0.03	0.02	-0.02	0	0	-0.03
	0.04	0.04	0.03	0.04	0.04	0.03	0.05	0.04	0.04
Sikh	0.19**	0.19**	0.28**	0.19**	0.19**	0.28**	0.33**	0.26**	0.32**
	0.07	0.06	0.05	0.07	0.06	0.05	0.1	0.07	0.05
Relationship to head (Parent=0)									
Head	0.17**	0.22**	0.41**	0.16**	0.22**	0.41**	0.22**	0.25**	0.42**
	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Spouse	-0.40**	-0.46**	-0.43**	-0.41**	-0.46**	-0.44**	-0.37**	-0.42**	-0.41**
	0.06	0.05	0.04	0.06	0.05	0.04	0.06	0.05	0.04
Child	0.14**	0.21**	0.59**	0.14**	0.21**	0.59**	0.18**	0.22**	0.59**
	0.03	0.03	0.04	0.03	0.03	0.04	0.03	0.04	0.05
Grandchild	0.24**	0.26**	0.72**	0.23**	0.26**	0.72**	0.28**	0.24**	0.71**
	0.07	0.06	0.07	0.07	0.06	0.07	0.09	0.07	0.08
Education (Primary or lower=0)									
Secondary	0.01	0.02	0.04**	0.01	0.02	0.04**	0.02	0.02	0.05**
	0.02	0.02	0.01	0.02	0.02	0.01	0.02	0.02	0.01
Higher secondary	0.12**	0.11**	0.17**	0.12**	0.11**	0.17**	0.14**	0.12**	0.18**
	0.03	0.02	0.02	0.03	0.02	0.02	0.03	0.03	0.02
Graduate	0.44**	0.44**	0.53**	0.44**	0.44**	0.53**	0.46**	0.46**	0.55**
	0.03	0.03	0.02	0.03	0.03	0.02	0.04	0.03	0.03

Postgraduate	0.65**	0.67**	0.77**	0.65**	0.67**	0.77**	0.65**	0.67**	0.79**
	0.04	0.04	0.03	0.04	0.04	0.03	0.05	0.05	0.04
Education of household head (Primary or lower=0)									
Secondary	0.13**	0.12**	0.11**	0.13**	0.12**	0.11**	0.11**	0.10**	0.11**
	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02
Higher secondary	0.22**	0.21**	0.22**	0.23**	0.21**	0.22**	0.18**	0.17**	0.20**
	0.04	0.03	0.03	0.04	0.04	0.03	0.04	0.04	0.03
Graduate	0.45**	0.42**	0.38**	0.45**	0.42**	0.38**	0.40**	0.37**	0.35**
	0.04	0.04	0.03	0.04	0.04	0.03	0.05	0.05	0.03
Postgraduate	0.47**	0.44**	0.48**	0.47**	0.44**	0.48**	0.44**	0.41**	0.46**
	0.06	0.06	0.04	0.06	0.06	0.04	0.07	0.07	0.05
Observations	10,781	15,750	26,562	10,781	15,750	26,562	8,963	13,932	24,744
R^2	0.25	0.22	0.30	0.25	0.22	0.30	0.27	0.22	0.31

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Partial treatment refers to those born less than one year after the UIP was implemented in their district. Includes age-district-level fixed effects. Standard errors clustered at the district level. Standard errors below coefficients. +p<0.1, *p<0.05, **p<0.01

Table A3: Effect of vaccination coverage on log monthly per capita consumption expenditure with age and district fixed effects

Model	1	2	3	4	5	6	7	8	9
Model description		Main			Includes partial effects			Non-migrant sample	
Time period	1985-90	1985-95	1980-95	1985-90	1985-95	1980-95	1985-90	1985-95	1980-95
UIP covered	0.03**	0.03**	0.03**				0.03**	0.03*	0.03*
	0.01	0.01	0.01				0.01	0.01	0.01
UIP covered partial				0.03**	0.03**	0.04**			
				0.01	0.01	0.01			
Locality (Urban=0)									
Rural	-0.06**	-0.07**	0.12**	-0.06**	-0.07**	0.12**	-0.08**	-0.08**	0.11**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Sex (Male=0)									
Female	-0.07**	-0.08**	-0.50**	-0.07**	-0.08**	-0.50**	-0.04**	-0.08**	-0.50**
	0.01	0	0.01	0.01	0	0.01	0.01	0.01	0.01
Married	-0.11**	-0.12**	-0.26**	-0.11**	-0.12**	-0.26**	-0.14**	-0.14**	-0.27**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Household size	-0.05**	-0.05**	-0.02**	-0.05**	-0.05**	-0.02**	-0.05**	-0.05**	-0.02**
	0	0	0	0	0	0	0	0	0
Age of household head	0	0	-0.01**	0	0	-0.01**	-0.00+	0	-0.01**
	0	0	0	0	0	0	0	0	0
Female head	-0.03**	-0.03**	-0.14**	-0.03**	-0.03**	-0.14**	-0.05**	-0.03**	-0.14**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Probability of being a migrant	-0.98**	-1.00**	-2.40**	-0.98**	-1.00**	-2.40**	-0.97**	-0.96**	-2.38**
	0.05	0.04	0.06	0.05	0.04	0.06	0.05	0.04	0.05
Caste (General=0)									
Scheduled caste	-0.19**	-0.17**	-0.14**	-0.19**	-0.17**	-0.14**	-0.18**	-0.17**	-0.15**

	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Scheduled tribe	-0.16**	-0.17**	-0.16**	-0.16**	-0.17**	-0.16**	-0.15**	-0.17**	-0.16**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Other backward caste	-0.08**	-0.08**	-0.09**	-0.08**	-0.08**	-0.09**	-0.07**	-0.08**	-0.08**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Religion (Hindu=0)									
Muslim	0.03**	0.01	0.09**	0.03*	0.01	0.09**	0.05**	0.01	0.09**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Christian	0.01	0.01	-0.07**	0.01	0.01	-0.07**	0.01	0	-0.07**
	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02
Sikh	0.19**	0.22**	0.39**	0.19**	0.22**	0.39**	0.24**	0.23**	0.40**
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Relationship to head (Parent=0)									
Head	0.12**	0.26**	0.60**	0.12**	0.26**	0.60**	0.14**	0.26**	0.59**
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Spouse	-0.24**	-0.30**	-0.46**	-0.24**	-0.30**	-0.46**	-0.24**	-0.29**	-0.45**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Child	0.10**	0.18**	0.94**	0.10**	0.18**	0.94**	0.14**	0.18**	0.93**
	0.01	0.01	0.03	0.01	0.01	0.03	0.01	0.01	0.02
Grandchild	0.17**	0.26**	1.14**	0.17**	0.26**	1.14**	0.20**	0.26**	1.13**
	0.02	0.02	0.03	0.02	0.02	0.03	0.03	0.02	0.03
Education (Primary or lower=0)									
Secondary	0.07**	0.11**	0.09**	0.07**	0.11**	0.09**	0.08**	0.11**	0.09**
	0.01	0	0	0.01	0	0	0.01	0.01	0
Higher secondary	0.19**	0.21**	0.18**	0.19**	0.21**	0.18**	0.18**	0.21**	0.18**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Graduate	0.29**	0.28**	0.27**	0.29**	0.28**	0.27**	0.28**	0.28**	0.26**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Postgraduate	0.36**	0.35**	0.33**	0.36**	0.35**	0.33**	0.36**	0.34**	0.33**
	0.02	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.01
Education of household head (Primary or lower=0)									
Secondary	0.13**	0.14**	0.13**	0.13**	0.14**	0.13**	0.12**	0.14**	0.13**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Higher secondary	0.23**	0.26**	0.23**	0.23**	0.26**	0.23**	0.23**	0.26**	0.23**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Graduate	0.37**	0.40**	0.35**	0.37**	0.40**	0.35**	0.35**	0.39**	0.35**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Postgraduate	0.49**	0.51**	0.46**	0.49**	0.51**	0.46**	0.46**	0.50**	0.46**
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Observations	46,557	91,191	129,980	46,557	91,191	129,980	38,346	82,980	121,769
R^2	0.36	0.34	0.38	0.36	0.34	0.38	0.36	0.34	0.38

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Partial treatment refers to those born less than one year after the UIP was implemented in their district. Includes age-district-level fixed effects. Standard errors clustered at the district level. Standard errors below coefficients. +p<0.1, *p<0.05, **p<0.01

Table A4: Effect of vaccination coverage on household income source (agriculture vs. non-agriculture) with age and district fixed effects

Model	1	2	3	4	5	6	7	8	9
Model description		Main			Includes partial effects			Non-migrant sample	
Time period	1985-90	1985-95	1980-95	1985-90	1985-95	1980-95	1985-90	1985-95	1980-95
UIP covered	-0.02*	-0.02*	-0.02*				-0.01	-0.01	-0.01
	0.01	0.01	0.01				0.01	0.01	0.01
UIP covered partial				-0.01	-0.02*	-0.02*			
				0.01	0.01	0.01			
Locality (Urban=0)									
Rural	0.36**	0.37**	0.36**	0.35**	0.37**	0.36**	0.35**	0.37**	0.36**
	0	0	0	0	0	0	0.01	0	0
Sex (Male=0)									
Female	0	0	0	0	0	-0.01	0	0	0
	0.01	0	0.01	0.01	0	0.01	0.01	0	0.01
Married	-0.01*	-0.02**	-0.01*	-0.01+	-0.02**	-0.01**	-0.01*	-0.02**	-0.01*
	0.01	0	0	0.01	0	0	0.01	0.01	0
Household size	0.01**	0.01**	0.01**	0.01**	0.01**	0.01**	0.01**	0.01**	0.01**
	0	0	0	0	0	0	0	0	0
Age of household head	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**
	0	0	0	0	0	0	0	0	0
Female head	-0.05**	-0.04**	-0.04**	-0.05**	-0.04**	-0.05**	-0.04**	-0.04**	-0.04**
	0.01	0	0	0.01	0	0	0.01	0	0
Probability of being a migrant	-0.10**	-0.07**	-0.04	-0.09**	-0.07**	-0.04+	-0.08*	-0.07**	-0.02
	0.03	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.02

Caste (General=0)									
Scheduled caste	0.01+	0.01*	0.01**	0.01+	0.01*	0.01*	0.02*	0.02**	0.01**
	0.01	0.01	0	0.01	0.01	0	0.01	0.01	0
Scheduled tribe	-0.10**	-0.10**	-0.10**	-0.10**	-0.10**	-0.10**	-0.08**	-0.09**	-0.10**
	0.01	0	0	0.01	0	0	0.01	0	0
Other backward caste	-0.04**	-0.04**	-0.04**	-0.03**	-0.04**	-0.04**	-0.03**	-0.04**	-0.04**
	0	0	0	0	0	0	0.01	0	0
Religion (Hindu=0)									
Muslim	-0.09**	-0.09**	-0.08**	-0.08**	-0.09**	-0.08**	-0.08**	-0.08**	-0.08**
	0.01	0	0	0.01	0	0	0.01	0	0
Christian	-0.03**	-0.03**	-0.03**	-0.03**	-0.04**	-0.03**	-0.02+	-0.03**	-0.03**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Sikh	0.12**	0.09**	0.09**	0.11**	0.09**	0.09**	0.12**	0.09**	0.08**
	0.02	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.01
Relationship to head (Parent=0)									
Head	-0.01	0.01	0	-0.01	0.01	0	-0.01	0.01	-0.01
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Spouse	-0.05**	-0.04**	-0.03**	-0.05**	-0.05**	-0.03**	-0.05**	-0.04**	-0.03**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Child	0.01	0.01	0.01	0.01+	0.01	0.01	0	0	0
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Grandchild	0.03+	0.02+	0.02+	0.02	0.02+	0.02+	0.02	0.02	0.02
	0.02	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.01
Education (Primary or lower=0)									
Secondary	0.02**	0.01	0	0.01**	0.01+	0.01+	0.01*	0	0
	0.01	0	0	0.01	0	0	0.01	0	0
Higher secondary	0.01	0.01*	0	0.01	0.01*	0	0	0.01+	0
	0.01	0	0	0.01	0	0	0.01	0	0

Graduate	0	0	-0.01	0	0	-0.01+	0	0.01	0
	0.01	0.01	0	0.01	0.01	0	0.01	0.01	0
Postgraduate	0.01	0.02+	0.01	0	0.01	0	0.01	0.02+	0
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Education of household head (Primary or lower=0)									
Secondary	-0.06**	-0.06**	-0.05**	-0.05**	-0.05**	-0.05**	-0.05**	-0.05**	-0.05**
	0.01	0	0	0.01	0	0	0.01	0	0
Higher secondary	-0.08**	-0.08**	-0.08**	-0.07**	-0.08**	-0.08**	-0.07**	-0.08**	-0.08**
	0.01	0.01	0	0.01	0.01	0	0.01	0.01	0
Graduate	-0.11**	-0.12**	-0.11**	-0.10**	-0.12**	-0.11**	-0.09**	-0.12**	-0.11**
	0.01	0.01	0	0.01	0.01	0	0.01	0.01	0
Postgraduate	-0.14**	-0.16**	-0.14**	-0.14**	-0.16**	-0.14**	-0.12**	-0.15**	-0.13**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Observations	46,557	91,191	129,980	46,714	90,025	127,752	38,775	83,409	122,198
R^2	0.20	0.21	0.20	0.20	0.21	0.20	0.21	0.21	0.20

Notes: Data are from National Sample Survey (68th round). Dependent variable=1 if household head income source is agriculture, 0 otherwise. Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Partial treatment refers to those born less than one year after the UIP was implemented in their district. Includes age-district-level fixed effects. Standard errors clustered at the district level. Standard errors below coefficients. +p<0.1, *p<0.05, **p<0.01

Table A5: Effect of vaccination coverage on economic outcomes, delayed treatment exposure

Model	1	2	3	4	5	6
Outcome	Wage		MPCE		Agricultural income	
UIP covered (2 year delay)	0.08*		0.05**		-0.01	
	0.03		0.01		0.01	
UIP covered (3 year delay)		0.06+		0.04**		-0.01
		0.03		0.01		0.01
UIP covered (8 year delay)						
UIP covered (13 year delay)						
Locality (Urban=0)						
Rural	-0.05**	-0.07**	-0.05**	-0.05**	0.35**	0.34**
	0.02	0.02	0.01	0.01	0	0
Sex (Male=0)						
Female	-0.37**	-0.38**	-0.08**	-0.07**	0.01	0.01
	0.03	0.03	0.01	0.01	0.01	0.01
Married	0.03*	0.04*	-0.12**	-0.11**	0	0
	0.02	0.02	0.01	0.01	0.01	0.01
Household size	0	0	-0.04**	-0.04**	0.01**	0.01**
	0	0	0	0	0	0
Age of household head	0	0	-0.00**	-0.00**	0.00**	0.00**
	0	0	0	0	0	0
Female head	0.02	0.01	-0.04**	-0.05**	-0.05**	-0.06**
	0.02	0.02	0.01	0.01	0.01	0.01
Probability of being a migrant	-0.79**	-0.71**	-1.09**	-1.12**	-0.07*	-0.07*
	0.17	0.17	0.05	0.05	0.03	0.03

Caste (General=0)						
Scheduled caste	-0.10+	-0.09+	-0.17**	-0.16**	0.01	0.02*
	0.05	0.05	0.02	0.02	0.01	0.01
Scheduled tribe	-0.12**	-0.13**	-0.15**	-0.15**	-0.10**	-0.10**
	0.02	0.02	0.01	0.01	0.01	0.01
Other backward caste	-0.08**	-0.08**	-0.07**	-0.07**	-0.04**	-0.03**
	0.02	0.02	0.01	0.01	0	0
Religion (Hindu=0)						
Muslim	-0.01	-0.03	0.03**	0.04**	-0.08**	-0.08**
	0.02	0.02	0.01	0.01	0.01	0.01
Christian	0.05	0.01	-0.01	-0.02	-0.03*	-0.02*
	0.04	0.04	0.02	0.02	0.01	0.01
Sikh	0.20**	0.19**	0.21**	0.22**	0.11**	0.10**
	0.06	0.06	0.02	0.02	0.02	0.02
Relationship to head (Parent=0)						
Head	0.22**	0.23**	0.08**	0.07**	-0.02*	-0.03**
	0.03	0.03	0.02	0.02	0.01	0.01
Spouse	-0.36**	-0.30**	-0.27**	-0.27**	-0.06**	-0.06**
	0.05	0.05	0.01	0.01	0.01	0.01
Child	0.15**	0.16**	0.12**	0.13**	0.01	0.01
	0.03	0.03	0.01	0.01	0.01	0.01
Grandchild	0.20*	0.20*	0.26**	0.30**	0.02	0.03
	0.09	0.09	0.03	0.03	0.02	0.02
Education (Primary or lower=0)						
Secondary	0.05*	0.06**	0.08**	0.07**	0.01	0.01
	0.02	0.02	0.01	0.01	0.01	0.01
Higher secondary	0.19**	0.20**	0.16**	0.16**	0	-0.01
	0.03	0.03	0.01	0.01	0.01	0.01

Graduate	0.52**	0.56**	0.29**	0.30**	-0.01*	-0.02**
	0.03	0.03	0.01	0.01	0.01	0.01
Postgraduate	0.71**	0.76**	0.37**	0.38**	-0.01	-0.01
	0.04	0.04	0.01	0.01	0.01	0.01
Education of household head (Primary or lower=0)						
Secondary	0.11**	0.13**	0.13**	0.13**	-0.05**	-0.05**
	0.02	0.02	0.01	0.01	0.01	0.01
Higher secondary	0.21**	0.23**	0.21**	0.20**	-0.08**	-0.08**
	0.03	0.03	0.01	0.01	0.01	0.01
Graduate	0.42**	0.39**	0.34**	0.32**	-0.10**	-0.09**
	0.04	0.04	0.01	0.01	0.01	0.01
Postgraduate	0.55**	0.54**	0.46**	0.45**	-0.13**	-0.13**
	0.05	0.05	0.02	0.02	0.01	0.01
Observations	11,906	12,813	45,957	47,815	45,957	47,815
R^2	0.31	0.33	0.36	0.36	0.20	0.20

Notes: Data are from National Sample Survey (68th round). Includes age-district-level fixed effects. Standard errors below coefficients. *MPCE*=monthly per capita expenditure. p<0.1, *p<0.05, **p<0.01

Table A6: Effect of vaccination coverage on log wages with age-district fixed effects, by population subsample, ages 21–26 years

Model	1	2	3	4	5	6	7	8
Population	Rural	Urban	Male	Female	SC/ST	OBC	Hindu	Not Hindu
UIP covered	0.13**	0.08+	0.15**	-0.06	0.18**	0.05	0.13**	0.08
	0.04	0.05	0.03	0.12	0.06	0.05	0.03	0.08
Locality (Urban=0)								
Rural			-0.04+	-0.04	-0.13**	-0.09**	-0.06**	0.04
			0.02	0.08	0.02	0.03	0.02	0.04
Sex (Male=0)								
Female	-0.38**	-0.33**			-0.44**	-0.40**	-0.34**	-0.40**
	0.05	0.05			0.04	0.05	0.04	0.06
Married	0.03	0.05+	0.02	0.04	0.10**	0.02	0.02	0.08+
	0.03	0.03	0.02	0.11	0.02	0.03	0.02	0.05
Household size	0.01	0	0	-0.01	0	0	0	-0.01
	0.01	0.01	0	0.02	0	0.01	0	0.01
Age of household head	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0
Female head	0.05	0.02	0	0.12	-0.02	0.04	0.02	0.09+
	0.03	0.03	0.03	0.08	0.03	0.04	0.03	0.04
Probability of being a migrant	-1.15**	-0.72*	-1.52*	-0.11	-0.36*	-0.57*	-0.53**	-1.36**
	0.38	0.31	0.71	0.51	0.15	0.28	0.21	0.47
Caste (General=0)								
Scheduled caste	0.02	-0.26**	-0.15**	-0.08	0.06		-0.15**	0.1
	0.05	0.07	0.05	0.11	0.04		0.05	0.09
Scheduled tribe	-0.04	-0.17**	-0.11**	-0.11			-0.13**	-0.03

	0.04	0.03	0.02	0.08			0.03	0.09
Other backward caste	-0.01	-0.12**	-0.07**	-0.17*			-0.11**	0.06
	0.04	0.03	0.02	0.07			0.03	0.06
Religion (Hindu=0)								
Muslim	0.06	-0.04	0	-0.04	-0.24	-0.02		0.18+
	0.04	0.04	0.02	0.12	0.17	0.04		0.11
Christian	-0.01	0.08	0.03	-0.04	0.06	0.09		0.29**
	0.07	0.06	0.05	0.08	0.1	0.07		0.11
Sikh	0.21	0.17*	0.22**	0.04	0.15+	0.53**		0.51**
	0.14	0.08	0.06	0.15	0.08	0.15		0.14
Relationship to head (Parent=0)								
Head	0.23**	0.18**	0.17**	0.13	0.16**	0.19**	0.19**	0.14
	0.06	0.05	0.04	0.16	0.04	0.05	0.04	0.11
Spouse	-0.38**	-0.49**	-0.45**	-0.25+	-0.23**	-0.34**	-0.33**	-0.61**
	0.08	0.12	0.08	0.13	0.06	0.09	0.06	0.16
Child	0.22**	0.14*	0.13**	-0.02	0.10*	0.12+	0.12**	0.16*
	0.05	0.06	0.05	0.16	0.04	0.07	0.04	0.07
Grandchild	0.32**	0.33**	0.22*	0.09	0.28*	0.18	0.18*	0.38*
	0.11	0.12	0.09	0.25	0.12	0.14	0.09	0.15
Education (Primary or lower=0)								
Secondary	0.03	0.01	0.02	0.02	0.13**	-0.02	0.01	0.03
	0.03	0.03	0.02	0.08	0.03	0.04	0.03	0.05
Higher secondary	0.18**	0.11*	0.10**	0.21*	0.27**	0.10*	0.11**	0.13*
	0.05	0.04	0.03	0.1	0.04	0.05	0.03	0.06
Graduate	0.42**	0.47**	0.43**	0.59**	0.64**	0.38**	0.46**	0.38**
	0.05	0.04	0.04	0.09	0.05	0.05	0.04	0.07
Postgraduate	0.50**	0.76**	0.57**	0.91**	0.88**	0.68**	0.68**	0.50**
	0.09	0.05	0.06	0.09	0.08	0.08	0.05	0.09

Education of household head (Primary or lower=0)								
Secondary	0.09*	0.15**	0.12**	0.18*	0.16**	0.08*	0.08**	0.17*
	0.04	0.03	0.03	0.08	0.03	0.04	0.03	0.07
Higher secondary	0.1	0.29**	0.19**	0.35**	0.25**	0.15*	0.20**	0.25**
	0.06	0.06	0.04	0.1	0.05	0.07	0.05	0.08
Graduate	0.26**	0.49**	0.37**	0.57**	0.40**	0.37**	0.44**	0.40**
	0.08	0.05	0.05	0.09	0.06	0.08	0.05	0.1
Postgraduate	0.34*	0.48**	0.46**	0.46**	0.41**	0.23*	0.48**	0.27+
	0.14	0.07	0.08	0.11	0.09	0.1	0.07	0.15
Observations	5,716	5,065	8,618	2,163	15,798	4,178	8,261	2,520
R^2	0.18	0.32	0.18	0.36	0.31	0.24	0.27	0.20

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Includes age-district-level fixed effects. Sample comprises those born between 1985 and 1990. Standard errors below coefficients. *OBC*=other backward caste; *ST*=scheduled tribe; *SC*=scheduled caste. +p<0.1, *p<0.05, **p<0.01

Table A7: Effect of vaccination coverage on log wages with age-district fixed effects, by population subsample, ages 21–31 years

Model	1	2	3	4	5	6	7	8
Population	Rural	Urban	Male	Female	SC/ST	OBC	Hindu	Not Hindu
UIP covered	0.13**	0.08+	0.15**	-0.07	0.18**	0.05	0.13**	0.08
	0.04	0.05	0.03	0.12	0.06	0.05	0.03	0.08
Rural			0	0.01	-0.09**	-0.04+	-0.03+	0.06+
			0.02	0.07	0.02	0.02	0.02	0.04
Female	-0.43**	-0.38**			-0.48**	-0.44**	-0.39**	-0.43**
	0.04	0.05			0.04	0.05	0.03	0.06
Married	0.02	0	0	-0.01	0.09**	-0.01	-0.01	0.06
	0.02	0.03	0.02	0.1	0.02	0.03	0.02	0.05
Household size	0.01	0	0	-0.01	0.01*	0	0	0
	0	0.01	0	0.01	0	0.01	0	0.01
Age of household head	0	0	0	0	0	0	-0.00*	0
	0	0	0	0	0	0	0	0
Female head	0.03	0.01	-0.01	0.07	-0.05+	0	-0.02	0.10**
	0.03	0.03	0.02	0.06	0.03	0.03	0.02	0.04
Probability of being a migrant	-0.77**	-0.78**	-1.03**	-0.35	-0.73**	-0.73**	-0.71**	-0.81**
	0.25	0.25	0.28	0.47	0.16	0.22	0.16	0.31
Scheduled caste	-0.03	-0.19**	-0.14**	-0.13	0.03		-0.13**	0.04
	0.04	0.06	0.04	0.1	0.04		0.05	0.08
Scheduled tribe	-0.04	-0.15**	-0.09**	-0.14+			-0.10**	-0.07

Other backward caste	0	-0.11**	-0.06**	-0.16*			-0.09**	0.03
	0.03	0.03	0.02	0.07			0.02	0.05
Muslim	0.05	-0.03	0.01	-0.04	-0.17	-0.02		0.16+
	0.03	0.03	0.02	0.09	0.15	0.03		0.08
Christian	-0.01	0.03	0.01	-0.06	0.05	0.09		0.27**
	0.07	0.05	0.05	0.09	0.1	0.06		0.1
Sikh	0.25*	0.15*	0.21**	0.04	0.17*	0.29+		0.45**
	0.12	0.07	0.05	0.15	0.08	0.16		0.12
Head	0.23**	0.24**	0.22**	0.16	0.25**	0.24**	0.24**	0.20*
	0.05	0.05	0.04	0.15	0.04	0.05	0.03	0.09
Spouse	-0.38**	-0.53**	-0.55**	-0.34*	-0.37**	-0.42**	-0.41**	-0.55**
	0.09	0.11	0.07	0.13	0.06	0.09	0.06	0.16
Child	0.21**	0.23**	0.18**	0.1	0.25**	0.17**	0.21**	0.16*
	0.05	0.07	0.05	0.17	0.05	0.06	0.04	0.07
Grandchild	0.27**	0.35**	0.19**	0.19	0.42**	0.19	0.26**	0.27*
	0.09	0.11	0.07	0.21	0.11	0.12	0.08	0.12
Secondary	0.02	0.02	0.02	0.03	0.13**	0.02	0.02	0.03
	0.02	0.03	0.02	0.06	0.03	0.03	0.02	0.04
Higher secondary	0.16**	0.07+	0.09**	0.18*	0.27**	0.09*	0.10**	0.13*
	0.04	0.04	0.03	0.08	0.04	0.04	0.03	0.06
Graduate	0.40**	0.45**	0.41**	0.54**	0.65**	0.36**	0.45**	0.39**
	0.05	0.04	0.04	0.08	0.05	0.05	0.03	0.07
Postgraduate	0.49**	0.77**	0.57**	0.87**	0.88**	0.68**	0.68**	0.53**
	0.09	0.05	0.06	0.09	0.08	0.07	0.05	0.09

Secondary	0.10**	0.14**	0.11**	0.12+	0.16**	0.06+	0.09**	0.13*
	0.03	0.03	0.02	0.07	0.03	0.03	0.02	0.06
Higher secondary	0.09	0.30**	0.18**	0.39**	0.25**	0.18**	0.20**	0.21**
	0.06	0.06	0.04	0.1	0.05	0.06	0.04	0.07
Graduate	0.24**	0.48**	0.35**	0.54**	0.37**	0.37**	0.42**	0.34**
	0.08	0.05	0.05	0.08	0.06	0.07	0.05	0.1
Postgraduate	0.35**	0.45**	0.44**	0.45**	0.41**	0.23*	0.47**	0.25+
	0.13	0.07	0.08	0.11	0.09	0.09	0.06	0.14
Observations	8,582	7,168	12,660	3,090	16,385	6,169	11,920	3,830
R^2	0.16	0.28	0.14	0.32	0.30	0.20	0.24	0.17

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Includes age-district-level fixed effects. Sample comprises those born between 1985 and 1990. Standard errors below coefficients. *OBC*=other backward caste; *ST*=scheduled tribe; *SC*=scheduled caste. +p<0.1, *p<0.05, **p<0.01

Table A8: Effect of vaccination coverage on log wages with age-district fixed effects, by population subsample, ages 16–31 years

Model	1	2	3	4	5	6	7	8
Population	Rural	Urban	Male	Female	SC/ST	OBC	Hindu	Not Hindu
UIP covered	0.13**	0.08+	0.14**	-0.07	0.18**	0.05	0.14**	0.09
	0.04	0.05	0.03	0.12	0.06	0.05	0.04	0.08
Rural			0.09**	0.27**	0.02	0.05+	0.05**	0.10*
			0.02	0.08	0.03	0.03	0.02	0.04
Female	-0.60**	-0.86**			-0.74**	-0.76**	-0.71**	-0.64**
	0.05	0.07			0.06	0.06	0.05	0.09
Married	-0.02	-0.09**	-0.06**	-0.06	0.02	-0.03	-0.04*	-0.04
	0.02	0.03	0.02	0.08	0.02	0.02	0.02	0.04
Household size	0.01**	0.02**	0.02**	0.04**	0.02**	0.01	0.01**	0.01
	0	0.01	0	0.01	0	0.01	0	0.01
Age of household head	-0.00*	-0.00**	-0.00*	-0.01*	-0.00+	-0.00*	-0.00**	0
	0	0	0	0	0	0	0	0
Female head	-0.01	-0.10**	-0.06**	-0.08	-0.10**	-0.07**	-0.09**	0.02
	0.03	0.03	0.02	0.06	0.03	0.03	0.02	0.04
Probability of being a migrant	-1.00**	-2.00**	-1.78**	-2.54**	-1.45**	-1.38**	-1.44**	-1.18**
	0.16	0.23	0.16	0.46	0.17	0.19	0.14	0.26
Scheduled caste	-0.02	-0.14*	-0.10**	-0.03	0.03		-0.12**	0.03
	0.03	0.06	0.04	0.08	0.04		0.04	0.07
Scheduled tribe	-0.04	-0.15**	-0.09**	-0.09			-0.11**	-0.1

	0.02	0.03	0.02	0.06			0.02	0.07
Other backward caste	-0.01	-0.14**	-0.08**	-0.15**			-0.11**	-0.03
	0.02	0.02	0.02	0.05			0.02	0.04
Muslim	0.08**	0.03	0.06**	0.16*	-0.09	0.04+		0.12
	0.03	0.03	0.02	0.07	0.11	0.03		0.08
Christian	-0.02	-0.04	-0.07*	-0.1	0.02	0		0.1
	0.05	0.04	0.03	0.07	0.08	0.04		0.09
Sikh	0.25*	0.33**	0.30**	0.49**	0.25**	0.33*		0.38**
	0.1	0.07	0.05	0.14	0.08	0.15		0.09
Head	0.33**	0.54**	0.45**	0.61**	0.47**	0.38**	0.41**	0.41**
	0.05	0.06	0.04	0.12	0.05	0.05	0.04	0.08
Spouse	-0.37**	-0.46**	-0.14	-0.46**	-0.38**	-0.40**	-0.44**	-0.32**
	0.06	0.06	0.32	0.11	0.05	0.06	0.04	0.1
Child	0.43**	0.87**	0.62**	1.25**	0.62**	0.57**	0.61**	0.48**
	0.06	0.09	0.05	0.21	0.07	0.07	0.06	0.08
Grandchild	0.53**	1.09**	0.69**	1.61**	0.85**	0.64**	0.75**	0.61**
	0.09	0.11	0.07	0.3	0.13	0.12	0.09	0.13
Secondary	0.07**	0.02	0.03*	0.08	0.14**	0.02	0.04*	0.07+
	0.02	0.02	0.01	0.05	0.03	0.02	0.02	0.04
Higher secondary	0.21**	0.15**	0.15**	0.29**	0.32**	0.14**	0.16**	0.18**
	0.03	0.03	0.02	0.07	0.04	0.04	0.02	0.05
Graduate	0.54**	0.52**	0.50**	0.66**	0.69**	0.45**	0.54**	0.50**
	0.04	0.03	0.03	0.06	0.04	0.04	0.03	0.06
Postgraduate	0.73**	0.81**	0.73**	0.96**	0.93**	0.78**	0.76**	0.69**
	0.06	0.04	0.04	0.07	0.07	0.06	0.04	0.07

Secondary	0.10**	0.13**	0.11**	0.09+	0.15**	0.05*	0.10**	0.12**
	0.03	0.03	0.02	0.05	0.03	0.03	0.02	0.05
Higher secondary	0.22**	0.25**	0.19**	0.32**	0.22**	0.23**	0.22**	0.22**
	0.04	0.04	0.03	0.07	0.04	0.05	0.03	0.05
Graduate	0.23**	0.44**	0.35**	0.46**	0.32**	0.35**	0.37**	0.33**
	0.05	0.04	0.03	0.06	0.05	0.05	0.04	0.06
Postgraduate	0.43**	0.47**	0.38**	0.63**	0.39**	0.25**	0.51**	0.26*
	0.1	0.05	0.05	0.09	0.08	0.07	0.05	0.12
Observations	14,284	12,278	21,140	5,422	17,855	10,252	20,342	6,220
R^2	0.24	0.34	0.24	0.34	0.32	0.29	0.33	0.22

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Includes age-district-level fixed effects. Sample comprises those born between 1985 and 1990. Standard errors below coefficients. *OBC*=other backward caste; *ST*=scheduled tribe; *SC*=scheduled caste. +p<0.1, *p<0.05, **p<0.01

Table A9: Effect of vaccination coverage on log monthly per capita expenditure with age-district fixed effects, by population subsample, ages 21–26 years

Model	1	2	3	4	5	6	7	8
Population	Rural	Urban	Male	Female	SC/ST	OBC	Hindu	Not Hindu
UIP covered	0.04**	0.01	0.01	0.03*	0.04+	0.03	0.04**	0.02
	0.01	0.02	0.02	0.01	0.02	0.02	0.01	0.02
Locality (Urban=0)								
Rural			-0.09**	0.21**	-0.08**	-0.04**	-0.06**	-0.04*
			0.01	0.02	0.01	0.01	0.01	0.02
Sex (Male=0)								
Female	-0.10**	-0.12**			-0.07**	-0.10**	-0.08**	-0.05**
	0.01	0.01			0.01	0.01	0.01	0.01
Married	-0.12**	-0.15**	-0.09**	-0.17**	-0.04**	-0.10**	-0.13**	-0.05**
	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01
Household size	-0.03**	-0.06**	-0.06**	-0.02**	-0.05**	-0.04**	-0.05**	-0.05**
	0	0	0	0	0	0	0	0
Age of household head	-0.00**	-0.00**	0	-0.01**	0.00**	0	0	0
	0	0	0	0	0	0	0	0
Female head	-0.06**	-0.07**	-0.04**	-0.12**	-0.02+	-0.07**	-0.04**	-0.03*
	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02
Probability of being a migrant	-2.33**	-1.35**	-5.89**	-2.54**	-0.80**	-1.07**	-1.05**	-0.88**
	0.09	0.09	0.52	0.1	0.03	0.07	0.05	0.09
Caste (General=0)								
Scheduled caste	-0.15**	-0.14**	-0.22**	-0.11**	-0.05*		-0.21**	-0.10**
	0.02	0.03	0.02	0.02	0.02		0.02	0.03
Scheduled tribe	-0.13**	-0.14**	-0.18**	-0.09**			-0.16**	-0.29**

	0.01	0.02	0.01	0.01			0.01	0.03
Other backward caste	-0.06**	-0.09**	-0.08**	-0.07**			-0.08**	-0.07**
	0.01	0.01	0.01	0.01			0.01	0.02
Religion (Hindu=0)								
Muslim	0.08**	0.06**	0.01	0.16**	0.06	0.05**		-0.05
	0.01	0.02	0.01	0.01	0.06	0.02		0.04
Christian	-0.05	0.01	-0.01	-0.05	0.02	-0.02		-0.05
	0.03	0.03	0.03	0.03	0.03	0.05		0.04
Sikh	0.21**	0.20**	0.20**	0.35**	0.14**	0.28**		0.25**
	0.04	0.03	0.03	0.03	0.03	0.06		0.06
Relationship to head (Parent=0)								
Head	0.19**	0.20**	0.14**	0.43**	0.11**	0.15**	0.15**	0.02
	0.02	0.03	0.02	0.04	0.01	0.02	0.02	0.03
Spouse	-0.41**	-0.39**	-0.72**	-0.47**	-0.15**	-0.25**	-0.25**	-0.25**
	0.02	0.03	0.19	0.02	0.01	0.03	0.02	0.03
Child	0.26**	0.23**	0.17**	0.52**	0.08**	0.10**	0.11**	0.08**
	0.02	0.03	0.02	0.03	0.01	0.02	0.01	0.02
Grandchild	0.36**	0.40**	0.24**	0.63**	0.20**	0.12**	0.18**	0.19**
	0.03	0.05	0.04	0.04	0.02	0.04	0.03	0.05
Education (Primary or lower=0)								
Secondary	0.08**	0.06**	0.07**	0.07**	0.10**	0.05**	0.06**	0.09**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Higher secondary	0.17**	0.19**	0.19**	0.17**	0.18**	0.17**	0.17**	0.21**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Graduate	0.25**	0.29**	0.28**	0.31**	0.25**	0.29**	0.28**	0.28**
	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02
Postgraduate	0.37**	0.34**	0.34**	0.41**	0.34**	0.38**	0.36**	0.33**
	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.04

Education of household head (Primary or lower=0)								
Secondary	0.11**	0.16**	0.12**	0.13**	0.18**	0.11**	0.12**	0.14**
	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.02
Higher secondary	0.22**	0.25**	0.24**	0.21**	0.27**	0.22**	0.24**	0.20**
	0.01	0.02	0.02	0.01	0.02	0.02	0.01	0.02
Graduate	0.29**	0.40**	0.37**	0.34**	0.43**	0.33**	0.37**	0.33**
	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02
Postgraduate	0.36**	0.56**	0.47**	0.47**	0.54**	0.41**	0.49**	0.47**
	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.05
Observations	27,854	18,703	22,813	23,744	76,076	18,058	34,268	12,289
R^2	0.27	0.40	0.36	0.40	0.25	0.29	0.37	0.31

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Includes age-district-level fixed effects. Sample comprises those born between 1985 and 1990. Standard errors below coefficients. *OBC*=other backward caste; *ST*=scheduled tribe; *SC*=scheduled caste. +p<0.1, *p<0.05, **p<0.01

Table A10: Effect of vaccination coverage on log monthly per capita expenditure with age-district fixed effects, by population subsample, ages 21–31 years

Model	1	2	3	4	5	6	7	8
Population	Rural	Urban	Male	Female	SC/ST	OBC	Hindu	Not Hindu
UIP covered	0.04**	0.01	0.01	0.03*	0.04+	0.03+	0.04**	0.01
	0.01	0.02	0.02	0.01	0.02	0.02	0.01	0.02
Rural			-0.06**	0.11**	-0.05**	-0.05**	-0.07**	-0.04**
			0.01	0.01	0.01	0.01	0.01	0.02
Female	-0.09**	-0.15**			-0.11**	-0.09**	-0.09**	-0.05**
	0.01	0.01			0.01	0.01	0.01	0.01
Married	-0.13**	-0.19**	-0.10**	-0.18**	-0.06**	-0.11**	-0.14**	-0.07**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Household size	-0.03**	-0.06**	-0.05**	-0.02**	-0.04**	-0.04**	-0.05**	-0.05**
	0	0	0	0	0	0	0	0
Age of household head	-0.00**	-0.00**	0.00**	-0.00**	0.00*	0	0	0
	0	0	0	0	0	0	0	0
Female head	-0.03**	-0.07**	-0.02*	-0.08**	-0.05**	-0.05**	-0.03**	-0.03*
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Probability of being a migrant	-1.60**	-1.46**	-3.56**	-2.12**	-1.20**	-1.04**	-1.09**	-0.88**
	0.05	0.08	0.2	0.07	0.04	0.06	0.04	0.07
Scheduled caste	-0.15**	-0.12**	-0.19**	-0.12**	-0.03		-0.20**	-0.07*
	0.02	0.02	0.02	0.02	0.02		0.02	0.03
Scheduled tribe	-0.16**	-0.16**	-0.18**	-0.14**			-0.17**	-0.30**

	0.01	0.01	0.01	0.01			0.01	0.03
Other backward caste	-0.06**	-0.09**	-0.08**	-0.07**			-0.08**	-0.10**
	0.01	0.01	0.01	0.01			0.01	0.02
Muslim	0.05**	0.04**	0.01	0.11**	0.12*	0.03**		-0.04
	0.01	0.01	0.01	0.01	0.06	0.01		0.03
Christian	-0.03	0	-0.02	-0.04+	-0.02	-0.02		-0.05
	0.03	0.02	0.02	0.02	0.02	0.04		0.03
Sikh	0.23**	0.21**	0.24**	0.33**	0.18**	0.29**		0.28**
	0.03	0.03	0.02	0.02	0.03	0.06		0.05
Head	0.28**	0.38**	0.32**	0.56**	0.25**	0.30**	0.31**	0.16**
	0.02	0.03	0.02	0.04	0.01	0.02	0.02	0.03
Spouse	-0.43**	-0.48**	-1.14**	-0.52**	-0.31**	-0.32**	-0.32**	-0.30**
	0.02	0.03	0.13	0.02	0.01	0.02	0.02	0.03
Child	0.30**	0.39**	0.33**	0.61**	0.27**	0.20**	0.22**	0.14**
	0.02	0.03	0.02	0.02	0.01	0.02	0.01	0.02
Grandchild	0.40**	0.54**	0.39**	0.72**	0.39**	0.25**	0.30**	0.22**
	0.02	0.04	0.03	0.03	0.02	0.03	0.02	0.04
Secondary	0.11**	0.10**	0.11**	0.10**	0.10**	0.08**	0.10**	0.11**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Higher secondary	0.19**	0.22**	0.21**	0.20**	0.19**	0.19**	0.20**	0.22**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Graduate	0.26**	0.29**	0.28**	0.29**	0.25**	0.28**	0.27**	0.28**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Postgraduate	0.37**	0.32**	0.33**	0.37**	0.34**	0.36**	0.34**	0.33**

Secondary	0.13**	0.16**	0.13**	0.14**	0.18**	0.12**	0.14**	0.15**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Higher secondary	0.23**	0.27**	0.26**	0.24**	0.28**	0.24**	0.27**	0.23**
	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.02
Graduate	0.32**	0.44**	0.40**	0.38**	0.43**	0.36**	0.41**	0.36**
	0.01	0.02	0.01	0.02	0.02	0.02	0.01	0.02
Postgraduate	0.38**	0.60**	0.50**	0.50**	0.54**	0.45**	0.52**	0.48**
	0.03	0.03	0.03	0.02	0.03	0.03	0.02	0.04
Observations	55,158	36,033	46,297	44,894	82,469	35,607	66,082	25,109
R^2	0.25	0.39	0.35	0.37	0.27	0.27	0.36	0.30

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Includes age-district-level fixed effects. Sample comprises those born between 1985 and 1990. Standard errors below coefficients. *OBC*=other backward caste; *ST*=scheduled tribe; *SC*=scheduled caste. +p<0.1, *p<0.05, **p<0.01

Table A11: Effect of vaccination coverage on log monthly per capita expenditure with age-district fixed effects, by population subsample, ages 16–31 years

Model	1	2	3	4	5	6	7	8
Population	Rural	Urban	Male	Female	SC/ST	OBC	Hindu	Not Hindu
UIP covered	0.04**	0.01	0.01	0.03*	0.03+	0.03+	0.03**	0.01
	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.02
Rural			0.17**	0.81**	0.08**	0.15**	0.15**	0.09**
			0.01	0.02	0.01	0.01	0.01	0.02
Female	-0.37**	-1.16**			-0.40**	-0.53**	-0.59**	-0.33**
	0.01	0.03			0.01	0.02	0.01	0.02
Married	-0.21**	-0.47**	-0.26**	-0.63**	-0.15**	-0.25**	-0.30**	-0.17**
	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01
Household size	-0.02**	0	-0.03**	0.08**	-0.03**	-0.01**	-0.02**	-0.03**
	0	0	0	0	0	0	0	0
Age of household head	-0.01**	-0.01**	-0.00**	-0.02**	-0.00**	-0.01**	-0.01**	-0.00**
	0	0	0	0	0	0	0	0
Female head	-0.11**	-0.29**	-0.10**	-0.40**	-0.15**	-0.17**	-0.16**	-0.11**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Probability of being a migrant	-2.10**	-4.64**	-3.90**	-7.00**	-2.13**	-2.55**	-2.76**	-1.81**
	0.06	0.14	0.11	0.13	0.05	0.08	0.06	0.09
Scheduled caste	-0.14**	-0.06**	-0.15**	-0.02	-0.02		-0.17**	-0.05*
	0.02	0.02	0.02	0.02	0.02		0.02	0.03
Scheduled tribe	-0.15**	-0.12**	-0.16**	-0.09**			-0.15**	-0.29**
	0.01	0.01	0.01	0.01			0.01	0.03

Other backward caste	-0.07**	-0.10**	-0.09**	-0.09**			-0.09**	-0.10**
	0.01	0.01	0.01	0.01			0.01	0.02
Muslim	0.08**	0.23**	0.10**	0.42**	0.18**	0.11**		0.02
	0.01	0.01	0.01	0.01	0.05	0.01		0.03
Christian	-0.07**	-0.19**	-0.11**	-0.30**	-0.08**	-0.10**		-0.11**
	0.02	0.02	0.02	0.02	0.02	0.03		0.03
Sikh	0.34**	0.59**	0.40**	1.04**	0.27**	0.44**		0.38**
	0.03	0.02	0.02	0.02	0.03	0.05		0.05
Head	0.52**	1.08**	0.61**	1.42**	0.54**	0.65**	0.70**	0.42**
	0.02	0.04	0.02	0.03	0.02	0.02	0.02	0.03
Spouse	-0.46**	-0.68**	-1.06**	-0.94**	-0.41**	-0.48**	-0.50**	-0.41**
	0.02	0.02	0.12	0.02	0.02	0.02	0.01	0.02
Child	0.81**	1.94**	1.06**	3.20**	0.86**	1.01**	1.10**	0.67**
	0.03	0.06	0.03	0.06	0.03	0.04	0.03	0.04
Grandchild	1.00**	2.32**	1.20**	3.67**	1.07**	1.19**	1.32**	0.83**
	0.04	0.07	0.04	0.07	0.04	0.05	0.04	0.05
Secondary	0.09**	0.09**	0.09**	0.08**	0.10**	0.07**	0.08**	0.10**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Higher secondary	0.18**	0.19**	0.18**	0.16**	0.18**	0.17**	0.17**	0.20**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Graduate	0.25**	0.27**	0.24**	0.25**	0.24**	0.26**	0.26**	0.25**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Postgraduate	0.34**	0.32**	0.29**	0.33**	0.36**	0.33**	0.31**	0.35**
	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02

Secondary	0.12**	0.13**	0.12**	0.10**	0.17**	0.11**	0.13**	0.13**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Higher secondary	0.21**	0.22**	0.22**	0.17**	0.26**	0.21**	0.23**	0.21**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Graduate	0.29**	0.36**	0.34**	0.29**	0.40**	0.32**	0.36**	0.32**
	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.02
Postgraduate	0.35**	0.50**	0.44**	0.41**	0.52**	0.41**	0.46**	0.45**
	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.03
Observations	78,263	51,717	65,008	64,972	87,720	50,827	95,291	34,689
R^2	0.27	0.45	0.39	0.50	0.31	0.31	0.39	0.33

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Includes age-district-level fixed effects. Sample comprises those born between 1985 and 1990. Standard errors below coefficients. *OBC*=other backward caste; *ST*=scheduled tribe; *SC*=scheduled caste. +p<0.1, *p<0.05, **p<0.01

Table A12: Effect of vaccination coverage on log monthly per capita expenditure with age-district fixed effects, by population subsample

Model	1	2	3	4	5	6	7	8	9	10	11	12
Birth year	1985-1990				1985-1995				1980-1995			
Population	HFS	LFS	No educ control	Only salaried	HFS	LFS	No educ control	Only salaried	HFS	LFS	No educ control	Only salaried
UIP covered	0.19**	0.11**	0.12**	0.12**	0.20**	0.11**	0.12**	0.13**	0.20**	0.11**	0.12**	0.12**
	0.06	0.03	0.03	0.04	0.07	0.03	0.03	0.04	0.07	0.03	0.03	0.04
Locality (Urban=0)												
Rural	-0.09**	-0.01	-0.04*	-0.03	0.01	0.09**	0.07**	0.12**	-0.02	0.11**	0.07**	0.11**
	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.03	0.03	0.02	0.02	0.03
Sex (Male=0)												
Female	-0.28**	-0.36**	-0.23**	-0.32**	-0.67**	-0.74**	-0.64**	-0.76**	-0.47**	-0.65**	-0.53**	-0.63**
	0.06	0.03	0.03	0.04	0.07	0.04	0.04	0.05	0.08	0.04	0.04	0.06
Married	0.03	0.04+	0	0.06*	-0.03	-0.04*	-0.07**	-0.05*	-0.02	-0.06**	-0.08**	-0.06+
	0.03	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.03
Household size	0	0	0	-0.01+	0.01	0.02**	0.01**	0.01**	0	0.02**	0.01**	0.01*
	0.01	0	0	0.01	0	0	0	0	0.01	0	0	0.01
Age of household head	0	0	0	0	-0.00**	-0.00**	-0.00**	-0.00*	-0.00+	-0.00**	-0.00**	-0.00*
	0	0	0	0	0	0	0	0	0	0	0	0
Female head	0.07	0.02	0.02	0.06*	-0.04	-0.07**	-0.08**	-0.08**	0.02	-0.04+	-0.04*	-0.03
	0.05	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.04	0.02	0.02	0.03
Probability of being a migrant	-0.43	-0.80**	-0.76**	-0.53+	-1.42**	-1.50**	-1.53**	-1.75**	-0.74**	-1.35**	-1.25**	-1.41**
	0.44	0.21	0.2	0.27	0.2	0.13	0.12	0.17	0.24	0.15	0.13	0.2
Caste (General=0)												
Scheduled caste	-0.02	-0.14*	-0.15**	-0.11+	-0.03	-0.10*	-0.12**	0	-0.02	-0.12*	-0.12**	-0.10+
	0.06	0.06	0.05	0.06	0.04	0.05	0.04	0.05	0.05	0.05	0.04	0.05
Scheduled tribe	-0.09	-0.12**	-0.16**	-0.21**	-0.08+	-0.11**	-0.15**	-0.16**	-0.06	-0.11**	-0.13**	-0.18**
	0.05	0.03	0.02	0.03	0.04	0.02	0.02	0.02	0.05	0.02	0.02	0.03
Other backward caste	-0.03	-0.09**	-0.10**	-0.13**	-0.07*	-0.09**	-0.11**	-0.12**	-0.03	-0.09**	-0.09**	-0.13**
	0.04	0.03	0.02	0.03	0.03	0.02	0.02	0.02	0.04	0.02	0.02	0.02
Religion (Hindu=0)												
Muslim	0.05	-0.01	-0.02	-0.03	0.08*	0.03	0.02	0.03	0.04	0.03	0.02	0.02
	0.04	0.03	0.03	0.04	0.03	0.02	0.02	0.03	0.04	0.02	0.02	0.03
Christian	-0.25+	0.05	0.02	0.01	-0.07	-0.02	-0.02	-0.05	-0.18	-0.01	-0.02	-0.05
	0.14	0.04	0.04	0.05	0.08	0.03	0.03	0.04	0.12	0.04	0.04	0.05

Sikh	-0.17	0.20**	0.21**	0.16*	0.14	0.29**	0.31**	0.29**	0.04	0.27**	0.28**	0.25**
	0.19	0.07	0.07	0.07	0.1	0.05	0.05	0.05	0.22	0.06	0.06	0.06
Relationship to head (Parent=0)												
Head	0.17**	0.17**	0.15**	0.08+	0.31**	0.45**	0.40**	0.46**	0.26**	0.39**	0.35**	0.34**
	0.06	0.04	0.03	0.05	0.05	0.04	0.03	0.04	0.07	0.04	0.04	0.05
Spouse	-0.29*	-0.43**	-0.52**	-0.39**	-0.52**	-0.43**	-0.56**	-0.44**	-0.31**	-0.49**	-0.56**	-0.50**
	0.12	0.06	0.06	0.11	0.07	0.04	0.04	0.06	0.1	0.05	0.05	0.09
Child	0.14+	0.15**	0.20**	0.08	0.49**	0.65**	0.70**	0.72**	0.31**	0.55**	0.56**	0.55**
	0.07	0.04	0.03	0.05	0.08	0.05	0.05	0.07	0.1	0.06	0.05	0.09
Grandchild	0.27	0.24**	0.34**	0.22*	0.52**	0.80**	0.87**	0.91**	0.38*	0.65**	0.68**	0.71**
	0.19	0.08	0.08	0.11	0.14	0.08	0.07	0.1	0.16	0.08	0.07	0.12
Education (Primary or lower=0)												
Secondary	0.02	0.02		0.01	0.05	0.04**		0.04	0.02	0.02		0.04
	0.05	0.02		0.03	0.03	0.02		0.02	0.04	0.02		0.03
Higher secondary	0.07	0.14**		0.09*	0.16**	0.17**		0.16**	0.08	0.11**		0.12**
	0.06	0.03		0.04	0.04	0.02		0.03	0.05	0.03		0.03
Graduate	0.44**	0.44**		0.38**	0.48**	0.54**		0.45**	0.41**	0.44**		0.39**
	0.07	0.04		0.04	0.05	0.03		0.03	0.06	0.03		0.03
Postgraduate	0.49**	0.69**		0.61**	0.67**	0.79**		0.68**	0.51**	0.70**		0.62**
	0.11	0.04		0.05	0.07	0.04		0.04	0.1	0.04		0.05
Education of household head (Primary or lower=0)												
Secondary	0.09+	0.14**	0.21**	0.13**	0.12**	0.11**	0.20**	0.13**	0.13**	0.12**	0.18**	0.12**
	0.05	0.03	0.02	0.03	0.04	0.02	0.02	0.02	0.05	0.03	0.02	0.03
Higher secondary	0.17*	0.24**	0.38**	0.22**	0.20**	0.23**	0.41**	0.24**	0.14+	0.23**	0.34**	0.20**
	0.08	0.04	0.04	0.05	0.06	0.03	0.02	0.03	0.08	0.04	0.03	0.04
Graduate	0.30**	0.49**	0.76**	0.47**	0.34**	0.39**	0.77**	0.40**	0.31**	0.43**	0.69**	0.43**
	0.1	0.05	0.05	0.05	0.05	0.04	0.03	0.03	0.09	0.05	0.04	0.04
Postgraduate	0.50**	0.48**	0.87**	0.50**	0.47**	0.50**	1.03**	0.50**	0.46**	0.44**	0.79**	0.46**
	0.11	0.07	0.06	0.07	0.08	0.05	0.04	0.05	0.1	0.07	0.06	0.07
Observations	3,119	7,662	10,781	5,699	7,941	18,621	26,562	13,644	4,884	10,866	15,750	7,529
R^2	0.22	0.27	0.20	0.26	0.29	0.31	0.25	0.29	0.17	0.24	0.18	0.24

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Includes age-district-level fixed effects. Standard errors below coefficients. *HFS*=High focus states; *LFS*=Low focus states. +p<0.1, *p<0.05, **p<0.01

Table A13: Effect of vaccination coverage on log monthly per capita expenditure with age-district fixed effects, by population subsample

Model	1	2	3	4	5	6	7	8	9	10	11	12
Birth year	1985-1990				1985-1995				1980-1995			
Population	HFS	LFS	No educ control	Only salaried	HFS	LFS	No educ control	Only salaried	HFS	LFS	No educ control	Only salaried
UIP covered	0	0.04**	0.03**	0.02	0	0.04**	0.03**	0.02	0	0.04**	0.03**	0.02
	0.02	0.01	0.01	0.04	0.02	0.01	0.01	0.04	0.02	0.01	0.01	0.04
Locality (Urban=0)												
Rural	-0.07**	-0.06**	-0.07**	-0.11**	0.09**	0.14**	0.12**	0.19**	0.07**	0.12**	0.10**	0.15**
	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Sex (Male=0)												
Female	-0.09**	-0.06**	-0.05**	-0.06*	-0.46**	-0.53**	-0.51**	-0.82**	-0.40**	-0.47**	-0.46**	-0.69**
	0.01	0.01	0.01	0.03	0.01	0.02	0.01	0.04	0.01	0.02	0.01	0.05
Married	-0.10**	-0.10**	-0.14**	-0.10**	-0.24**	-0.26**	-0.29**	-0.32**	-0.23**	-0.28**	-0.31**	-0.30**
	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Household size	-0.04**	-0.05**	-0.05**	-0.08**	-0.01**	-0.03**	-0.02**	-0.05**	-0.02**	-0.03**	-0.03**	-0.05**
	0	0	0	0.01	0	0	0	0	0	0	0	0
Age of household head	0	-0.00+	0	0	-0.00**	-0.01**	-0.01**	-0.01**	-0.00**	-0.00**	-0.00**	-0.00**
	0	0	0	0	0	0	0	0	0	0	0	0
Female head	0.01	-0.06**	-0.04**	-0.01	-0.10**	-0.16**	-0.15**	-0.21**	-0.06**	-0.14**	-0.12**	-0.17**
	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Probability of being a migrant	-1.14**	-0.96**	-1.07**	-0.87**	-2.31**	-2.51**	-2.54**	-3.15**	-2.13**	-2.37**	-2.40**	-2.77**
	0.06	0.06	0.05	0.14	0.07	0.09	0.06	0.15	0.07	0.09	0.06	0.19
Caste (General=0)												
Scheduled caste	-0.19**	-0.19**	-0.21**	-0.12**	-0.15**	-0.14**	-0.17**	-0.04	-0.16**	-0.14**	-0.17**	-0.09**
	0.02	0.03	0.02	0.04	0.02	0.03	0.02	0.03	0.02	0.03	0.02	0.03
Scheduled tribe	-0.14**	-0.16**	-0.19**	-0.15**	-0.15**	-0.16**	-0.18**	-0.13**	-0.15**	-0.17**	-0.19**	-0.13**
	0.02	0.01	0.01	0.03	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Other backward caste	-0.08**	-0.07**	-0.10**	-0.07*	-0.09**	-0.08**	-0.10**	-0.10**	-0.09**	-0.08**	-0.10**	-0.09**
	0.01	0.01	0.01	0.03	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Religion (Hindu=0)												
Muslim	0.02	0.04*	0	0.05	0.07**	0.11**	0.07**	0.17**	0.06**	0.10**	0.06**	0.16**
	0.01	0.01	0.01	0.03	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.03
Christian	-0.02	0.02	0.01	-0.06	-0.12**	-0.07**	-0.08**	-0.17**	-0.08*	-0.06**	-0.07**	-0.16**
	0.04	0.03	0.02	0.05	0.03	0.02	0.02	0.03	0.04	0.02	0.02	0.05

Sikh	0.22*	0.19**	0.21**	0.18**	0.40**	0.40**	0.41**	0.42**	0.38**	0.36**	0.38**	0.42**
	0.09	0.02	0.02	0.05	0.06	0.02	0.02	0.04	0.07	0.02	0.02	0.06
Relationship to head (Parent=0)												
Head	0.17**	0.10**	0.12**	0.03	0.62**	0.60**	0.62**	0.54**	0.67**	0.64**	0.67**	0.52**
	0.02	0.02	0.02	0.05	0.02	0.02	0.02	0.04	0.03	0.03	0.02	0.05
Spouse	-0.19**	-0.28**	-0.30**	-0.37**	-0.43**	-0.49**	-0.53**	-0.61**	-0.37**	-0.46**	-0.49**	-0.61**
	0.02	0.02	0.01	0.07	0.02	0.02	0.01	0.04	0.02	0.02	0.01	0.06
Child	0.08**	0.11**	0.14**	0.07	0.87**	1.00**	1.02**	1.16**	0.79**	0.93**	0.95**	0.98**
	0.02	0.02	0.01	0.05	0.03	0.04	0.03	0.07	0.03	0.04	0.03	0.08
Grandchild	0.14**	0.20**	0.27**	0.11	1.05**	1.22**	1.25**	1.41**	0.95**	1.12**	1.15**	1.17**
	0.04	0.03	0.03	0.09	0.04	0.05	0.03	0.09	0.04	0.05	0.03	0.11
Education (Primary or lower=0)												
Secondary	0.10**	0.06**		0.01	0.12**	0.08**		0.02	0.12**	0.09**		0.02
	0.01	0.01		0.03	0.01	0.01		0.02	0.01	0.01		0.02
Higher secondary	0.21**	0.17**		0.07*	0.20**	0.17**		0.09**	0.22**	0.18**		0.08**
	0.01	0.01		0.03	0.01	0.01		0.02	0.01	0.01		0.02
Graduate	0.31**	0.28**		0.15**	0.28**	0.26**		0.19**	0.28**	0.25**		0.15**
	0.02	0.01		0.03	0.01	0.01		0.02	0.01	0.01		0.03
Postgraduate	0.39**	0.35**		0.23**	0.36**	0.31**		0.27**	0.35**	0.31**		0.22**
	0.03	0.02		0.04	0.02	0.01		0.03	0.03	0.02		0.04
Education of household head (Primary or lower=0)												
Secondary	0.10**	0.14**	0.19**	0.14**	0.11**	0.14**	0.18**	0.13**	0.12**	0.14**	0.18**	0.13**
	0.02	0.01	0.01	0.03	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Higher secondary	0.24**	0.23**	0.33**	0.22**	0.22**	0.23**	0.31**	0.21**	0.24**	0.25**	0.32**	0.22**
	0.02	0.02	0.01	0.03	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.03
Graduate	0.32**	0.39**	0.50**	0.43**	0.32**	0.36**	0.46**	0.34**	0.35**	0.39**	0.47**	0.40**
	0.02	0.02	0.01	0.04	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.03
Postgraduate	0.44**	0.53**	0.66**	0.64**	0.40**	0.51**	0.61**	0.51**	0.43**	0.55**	0.61**	0.61**
	0.03	0.03	0.02	0.07	0.02	0.02	0.02	0.04	0.03	0.03	0.02	0.06
Observations	17,278	29,279	46,564	5,802	49,887	80,093	129,988	13,883	35,379	55,812	91,198	7,665
R^2	0.37	0.35	0.32	0.38	0.39	0.37	0.35	0.43	0.39	0.37	0.35	0.40

Notes: Data are from National Sample Survey (68th round). Treatment group comprises individuals who had the Universal immunisation Programme implemented by the year of their birth or earlier. Includes age-district-level fixed effects. Standard errors below coefficients. *HFS*=High focus states; *LFS*=Low focus states. +p<0.1, *p<0.05, **p<0.01

CHAPTER 3

Improving vaccination coverage and timeliness through periodic intensification of routine immunisation: Evidence from Mission Indradhanush

Only an estimated 83% of Indian children under the age of two years are fully immunized. We examined the association between India's Mission Indradhanush (MI) — a periodic intensification of the routine immunisation program — which was implemented in phases across districts between March 2015 and July 2017, and routine vaccination coverage and timeliness among children. We used data from a 2015-2016 national survey of children (n=29,532) and employed difference-in-difference regressions to examine binary indicators of receipt of 11 vaccines, and whether vaccines were received at recommended ages. Full immunisation rate was 27% higher among under-2 children residing in MI phase 1 and 2 districts (intervention group) as compared with those residing elsewhere (control group). The rate of receiving all vaccines at recommended ages was 8% higher in the intervention group. Receiving doses of oral polio vaccine (OPV) birth dose, OPV dose 1 (OPV1), OPV2, OPV3, Bacillus Calmette–Guérin, and Hepatitis B birth dose vaccines were 9%, 9%, 11%, 16%, 5%, and 19% higher in the intervention group than the control group, respectively. More research is required on the costeffectiveness of investing in MI-type programs as compared with routine immunisation.

Based on: Summan, A., Nandi, A., Deo, S., Laxminarayan, R. (2021). Improving vaccination coverage and timeliness through periodic intensification of routine immunisation: evidence from Mission Indradhanush. Annals of the New York Academy of Sciences, 1502(1). https://doi.org/10.1111/nyas.14657

3.1 Introduction

An estimated 400,000 Indian children under the age of five years die annually from vaccine preventable diseases such as pneumonia, diarrhoea, and measles. [130] India's Universal immunisation Programme (UIP), is among the largest routine childhood immunisation programs in the world. With an annual budget of $2 billion, the UIP aims to immunize 26 million newborn children every year. [131,132] The program currently provides the following vaccines: oral polio vaccine (OPV), Diphtheria-Pertussis-Tetanus (DPT), Bacillus Calmette–Guérin (BCG), measles, hepatitis B, Haemophilus influenzae type B (Hib) containing pentavalent (DPT, hepatitis B, and Hib), inactivated polio vaccine (IPV), tetanus toxoid, and in endemic areas, Japanese encephalitis. Rotavirus, pneumococcal, and measles-rubella vaccines have also been introduced in select high-burden areas.[133]

Despite the scale of the UIP, India has yet to achieve universal coverage of routine childhood vaccines. In 2018, only 83% of 12-23 month old Indian children received full immunisation (BCG, measles, and 3 doses each of polio and DPT), although the coverage rate increased substantially from 62% in 2016. [134–137] In addition to low coverage, failure to vaccinate children at recommended ages has remained a major challenge. In 2013, the proportion of delayed doses among under-5 children ranged from 35% for OPV first dose (OPV1) to 65% for DPT3.[17] Among 10-23 month old children in 2016, the proportion of delayed doses (i.e., more than 28 days after the minimum eligibility age) ranged from 23% for BCG to 35% for the measles vaccine.[18] Timely vaccination is important especially for highly contagious diseases such as measles which can rapidly affect a large number of children and retard long-term immunity against other diseases.[19,20]

In December 2014, the Government of India launched Mission Indradhanush (MI), with the objective of increasing full immunisation coverage.[138] MI was a periodic intensification of the routine immunisation (PIRI) program which targeted unvaccinated and under-vaccinated children by allocating more resources to under-served areas. The program was implemented in 528 districts – with low initial full immunisation coverage and high dropout rates – in four phases during April 2015 to July 2017.[133] An estimated 25.5 million children across India were vaccinated under MI in this time.[138]

Evidence on the impact of MI on desired programmatic and immunisation outcomes is limited. Data from the Integrated Child Health and immunisation Survey (INCHIS) in 24 states showed an increase in full immunisation rates from 64.1% to 73.5% during April 2015 to October 2015.[39] In districts which were covered under phase 1, rates of OPV third dose and DPT third dose increased substantially. However, these estimates did not control for potential confounding factors and secular time trends of vaccination coverage in MI and non-MI areas. A study found that the Intensified Mission Indradhanush (IMI) program – a successor of MI – may have increased coverage rates by 3.9–35.7% for different vaccines; however this study inferred coverage rates through vaccine delivery volume rather than data on administration of vaccine to individual children.[40]

We estimated the association between exposure to MI phases 1 and 2, and child immunisation outcomes by comparing vaccination rates (overall, as well as at recommended ages) and timing

in MI vis-à-vis non-MI districts. We used household survey data and employed difference-in-difference multivariate regression models which controlled for several possible confounders.

3.2 Data and methods

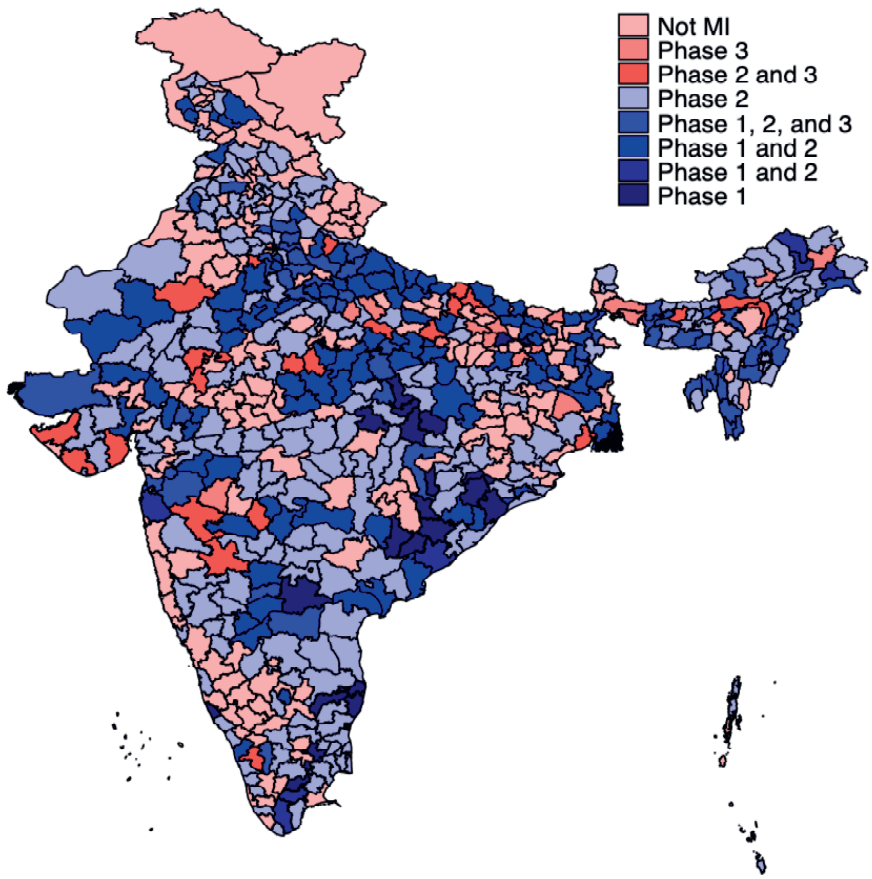
INCHIS survey data

We used data from the Integrated Child Health and immunisation Survey (INCHIS), a stratified, nationally representative, cross-sectional household survey conducted in three rounds from March 2015 to April 2016.[39] The survey covered a total of 44,571 households across 260 districts in 24 states across the three rounds. Data were obtained on socioeconomic and demographic indicators, and access to and quality of health facilities for households with children below the age of two years. immunisation receipt and date information for the youngest under-2 child in each household were collected from either vaccination card or through maternal (or caregiver) recall if the card was unavailable.

Each round of INCHIS collected data from 12 states, where Bihar, Maharashtra, Madhya Pradesh, Rajasthan, Telangana, and Uttar Pradesh were fixed, and the six other states were rotated across rounds. The states were chosen to ensure representation from each geographical region and level of development. Within each state, a three-stage stratified sampling design was employed where district, cluster (village/urban ward) and households were selected at three different stages. Districts were stratified into 3 or 4 groups based on a composite index using the following district-level indicators: proportion of urban households, percentage of scheduled caste/tribe population, literacy rate, proportion of households with latrine facility, and availability of banking facilities. Within each stratum, 1 to 3 districts were chosen based on the population of the state. Within a selected district, systematic sampling was used to draw clusters where the sampling frame (2011 census data) of clusters was ordered by female literacy rate. Probability sampling was used to select the household where households with at least 1 child between the ages of 0-23 months were eligible for selection within the cluster.[39]

Initially, MI was rolled out across India in two phases. Some districts were included in the program during both phases 1 and 2, while others were included only in either phase. We analyzed the impact of the first two phases of the MI program (April to July 2015, and October 2015 to January 2016, respectively) using data from the first and last rounds of INCHIS. INCHIS-1 was conducted before the MI program, INCHIS-2 was conducted in between MI phases 1 and 2, and INCHIS-3 was conducted after the conclusion of MI phase 2. MI phases 1 and 2 covered 480 districts of India, 77 of which were included in the INCHIS-1 and INCHIS-3 rounds. Figure 1 shows the MI phases across districts in a map of India and Figure A1 in the Appendix shows the timing of INCHIS rounds and MI phases.

Figure 1: District wise implementation of Mission Indradhanush Phases 1, 2, and 3



Note: Map coordinate data are from Database of Global Administrative Areas, version 2.8 (2015), combined with district identifiers from the National Family and Health Survey of India 2015–2016. Colors denote the phases of Mission Indradhanush (MI) implemented in each district. Districts with no data are marked with white color. Map is for illustration only and may not depict correct international boundaries.

In our study, children from districts included in phases 1 and 2 (P1&2) of MI were considered as the intervention group. The control group included children from districts that were not covered in either MI phase. Children in INCHIS-1 were considered pre-intervention observations, while children in INCHIS-3 were post-intervention observations. There were 48 P1&2 districts eligible for analysis — 21 MI districts, 13 before the intervention and 8 post the intervention; and 27 non-MI districts, 8 surveyed before the intervention and 19 post intervention. This resulted in data on 9,674 children available for analysis, 3,929 in the MI group and 5,745 in the non-MI group.

Analysis

We explored the association of MI (phases 1 and 2) and the binary indicators of 11 vaccination outcomes for each child: full immunisation, receipt of Diphtheria-Pertussis-Tetanus dose 1 (DPT1), DPT2, DPT3, oral polio vaccine dose 1 (OPV1), OPV2, OPV3, OPV birth dose (OPV0), measles first dose (measles1), Bacillus Calmette–Guérin (BCG), hepatitis B birth dose (HepB0), and on-time vaccination. The inactivated polio vaccine (IPV) was introduced into the UIP in 2016 after MI phase 3 and is therefore not included in our analysis. The eligibility age for each vaccine was taken from the Indian Academy of Pediatrics and World Health Organization guidelines.[139,140] Table A1 in Appendix describes each vaccine and its earliest eligibility age for a child. Each child that had reached the vaccination eligibility age before the end of the MI intervention was considered for analysis for that vaccine. We excluded children who were reported as vaccinated before the eligibility age (0.6% of the sample) to reduce potential measurement errors.

The on-time vaccination (OTV) indicator considered the timely receipt of DPT1, DPT2, DPT3, and full immunisation (3 doses each of DPT and OPV, and one dose each of measles and BCG). Each child was evaluated for timely vaccination of the latest vaccine dose they were eligible for, resulting in one observation per child for OTV. The indicator had a value of 1 if the child had received the dose within 28 days after the earliest age of eligibility described in Table A1. Previous studies have considered vaccination as timely if done within 28 days to 30 days after eligibility. [141–143]

We employed a difference-in-difference (DID) framework in which the average difference in outcomes before and after the MI program in each district was first estimated. Then, the difference between MI and control districts of this average difference was taken. Each model included binary indicators of location (whether an MI district), time (pre- or post-intervention), and an interaction between the two (DID indicator). We used linear probability models (LPM) and probit models for our analysis.

Our regression models included the following household level socioeconomic indicators and mother and child characteristics as covariates: locality (urban), caste (scheduled caste, scheduled tribe, and other backward classes), religion (Muslim, Christian, Sikh, and other religions), household size, wealth quintiles, age of the mother, mother's schooling attainment (primary or lower, middle to secondary, and graduate and above), child's age, sex, and place of birth (health facility or home). We also included the distance to the nearest public health sub-center (SC). SC

is the first point of contact between the primary health system and patients, and is used as a measure of accessibility to health services.[144] Finally, we used principal component analysis to create a wealth index of physical household characteristics and asset ownership. We included indicators of the top four wealth index quintiles in the model, keeping the bottom quintile as the reference category. A detailed description of the construction of the wealth index is provided in the Appendix. All covariates were obtained from the INCHIS data. Standard errors were clustered at the district level and survey weights were applied. Data were analyzed using STATA version 14.2 and we considered $p<0.05$ for statistical significance.

Parallel trends test

The parallel trends test is an important measure of methodological validity in DID analyses. If the parallel trends test were to be satisfied, child vaccination status in MI and non-MI districts should follow a similar trend in the years leading up to MI introduction. We used data from the National Family Health Survey 2015-2016 (NFHS-4) to test if trends in vaccination status in MI and non-MI districts were statistically indistinguishable between 2011 and 2014. NFHS-4 is a nationally representative survey which collected vaccination history information of 259,627 under-5 Indian children. Data were taken from vaccination card or from caregiver when vaccination card was unavailable. We compared DPT3 child vaccination rate trends between intervention and control districts. DPT3 is a widely used indicator for vaccination coverage, timely vaccination, and the overall performance of the system. For children who did not have a vaccination date recorded, we assumed that the child was vaccinated at the DPT3 eligibility age (14 weeks since birth).

We tested for parallel trends in two ways.[145] First, we estimated district fixed effect regression models of DPT3 vaccination rates for children from 2011 to 2014. We examined if the time trends of the estimated residual error terms of these models were parallel across MI and non-MI districts. Second, we regressed the rate of DPT3 vaccination on year identifiers, binary indicator of whether a district was included in MI, and interaction terms of the year and MI identifiers. If the estimated regression coefficients of the interaction terms were not statistically significant, the parallel trends assumption would be satisfied, i.e., trends in DPT3 vaccination rates would be similar between MI and non-MI districts leading up to the implementation of MI.

3.3 Results

Summary statistics of the study sample

Table A2 in the Appendix shows differences in vaccination rates, and socioeconomic and demographic characteristics of children across intervention and control groups for the baseline period. Vaccination rates were higher in the control group for all 11 vaccines. The largest unadjusted differences in vaccination rates between P1&2 intervention and control groups were for full immunisation (55% vs. 77%, $p<0.01$), measles1 (75% vs 85%, $p<0.01$), and DPT3 (62% vs. 75%, $p<0.01$). Figure 2 shows vaccination outcomes between control and intervention groups before and after the MI program. The unadjusted gap between MI and non-MI districts reduced substantially from the before- to after-MI period for most vaccination outcomes, except for slight increases for DPT1, DPT2, OPV0, HepB0, and OTV. Among covariates, the largest unadjusted

baseline differences were for children who were not born at health facilities (31% in MI vs. 15% in non-MI districts, p<0.01) and proportion of minority religion households (11% in MI vs. 38% in non-MI districts, p<0.01).

Table A3 in the Appendix shows the distribution of children by immunisation status and socioeconomic characteristics. Rates of vaccination were higher among children in richer and urban households, Sikh and general caste households, those born in health facilities, and those with more educated mothers, as compared with the respective reference groups. Among the outcome indicators, the differences across socioeconomic groups were the largest for full immunisation and OTV rates.

Parallel Trends Test Results

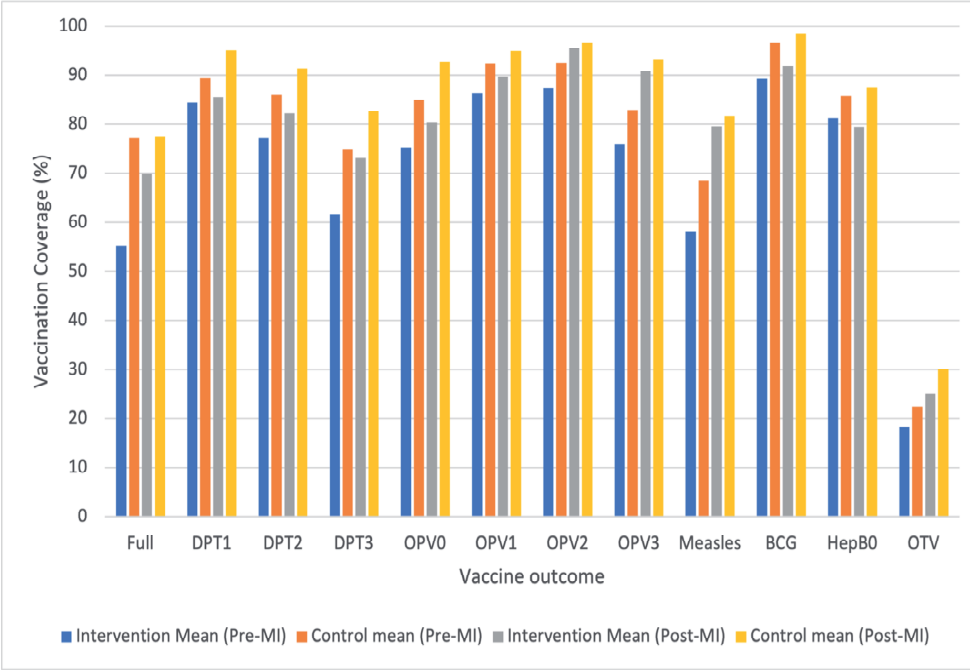
Figure 3 shows the residual probability of DPT3 vaccination rate between MI P1&2 districts and non-MI districts from 2011 to 2014. Time trends of the residual DPT3 vaccination probability was similar for MI and non-MI districts. Figure 4 presents the estimated coefficients (with 95% confidence intervals) of the interaction terms between year and MI indicators in the regression of DPT3 vaccination rate. Leading up to the introduction of MI in 2015, there was no statistical difference between DTP3 vaccination rates in intervention and control districts. Therefore, the parallel trends assumption was satisfied.

Regression Results

Table 1 presents summary results of the DID analysis, showing only the estimated coefficients of the DID indicator for both the LPM and probit model. The DID likelihood of receiving full immunisation was 27% (95% confidence interval [CI]: 0.11 – 0.42, p <0.01, LPM) higher among under-2 children residing in MI phase 1 and 2 districts (intervention group) as compared with those residing elsewhere (control group).

Table A4 in the Appendix presents the full LPM results. The DID likelihood of children in P1&2 intervention groups was also 9% higher for OPV0 (CI: 0.02 – 0.15, p<0.05, LPM), 9% higher for OPV1 (CI: 0.04 – 0.14, p<0.01, LPM), 11% higher for OPV2 (CI: 0.02 – 0.19, p<0.05, LPM), 16% higher for OPV3 (CI: 0.04 – 0.27, p<0.01, LPM), 5% higher for BCG (CI: 0.01 – 0.09, p<0.05, LPM) and 19% higher for hepatitis B birth dose (CI: 0.11 – 0.28, p<0.01, LPM). The DID likelihood in P1&2 intervention group to have received age-appropriate vaccines as per recommended schedule (OTV) was 8% higher (CI: 0.00 – 0.15, p<0.05, LPM) than the control group.

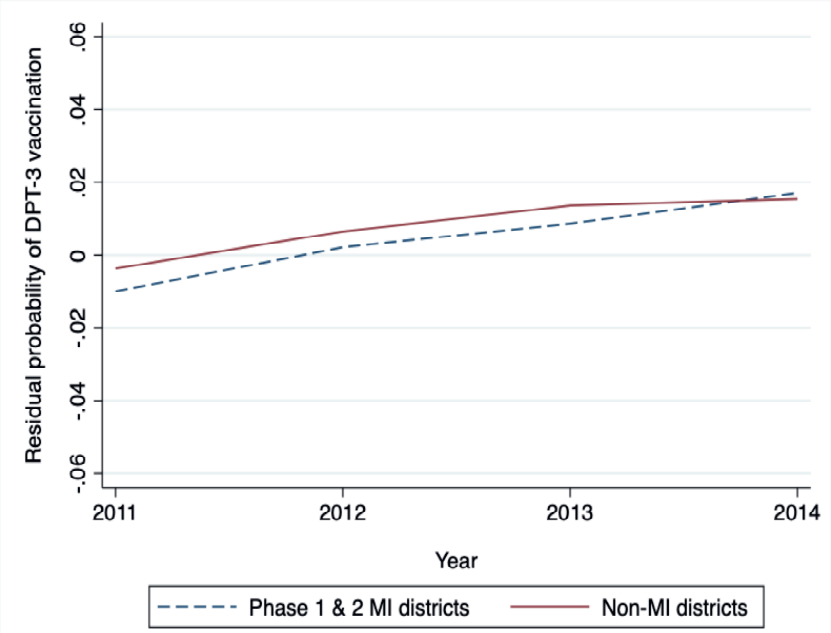
Figure 2: Vaccination outcomes by control and intervention groups before and after MI implementation



Note: *Full=* 1 dose BCG and measles, 3 doses of DPT and polio*; HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin; *OPV=Oral Polio Vaccine; OPV0=OPV* birth dose*; Measles1*: First dose of measles; *OTV*: On-time vaccination – considers timely vaccination of DPT and full immunisation.

The coefficients on the DID indicator in the probit model were almost identical to those in the LPM. The DID likelihood of children in P1&2 intervention groups was 26% higher for full immunisation (CI: 0.12 – 0.34, p<0.01), 7% higher for OPV0 (CI: 0.00 – 0.26, p<0.05), 6% higher for OPV1 (CI: 0.04 – 0.14, p<0.05), 9% higher for OPV2 (CI: 0.02 – 0.19, p<0.05), 15% higher for OPV3 (CI: 0.04 – 0.27, p<0.01), 16% higher for hepatitis B birth dose (CI: 0.01 – 0.37, p<0.01), and 9% higher for OTV (CI: 0.03 – 0.13, p<0.05) than children in the control group. However, the results were not significant for measles1 in the probit model. Figures A2 to Figures A9 in Appendix show the distribution of coefficients and significance levels for the estimated DID indicators from the probit models. For full immunisation, hepatitis B birth dose, and OTV, the DID indicator coefficients are significant for all observations. In additional analysis, we found vaccination outcomes were not statistically different in districts which were covered by either MI Phase 1 or Phase 2, but not both, as compared with non-MI control districts (Tables A5 and A6 in the Appendix).

Figure 3: Average annual residual probability of DPT vaccination in MI and non-MI districts, 2011-2014



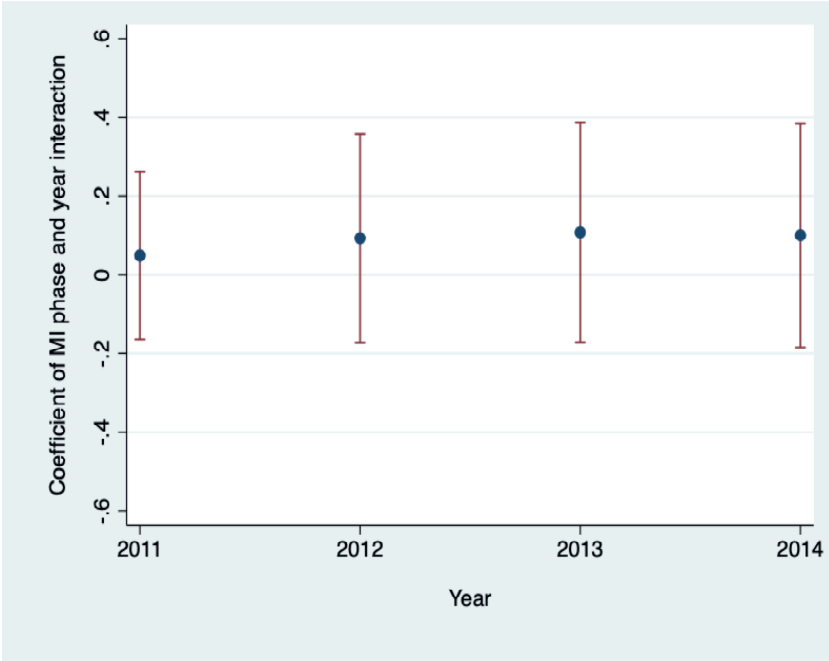
Note: N=178 districts; 126 non-MI districts and 52 MI districts. *DPT*=Diphtheria, Pertussis, Tetanus. Time trends of the estimated residual error terms of district fixed effect regression of DPT3 vaccination rates on year from 2011 to 2014.

The covariates indicated that children in higher wealth quintiles were more likely to be vaccinated compared with the lowest wealth quintile. The magnitude of the estimated association increased with the household's wealth quintile. Maternal schooling level was positively associated with vaccination for all vaccines except for DPT3 and measles1, and institutional delivery was positively associated with vaccination outcomes across all vaccines.

3.4 Discussion

In 2018, there were 882,000 deaths among Indian children under the age of five years;[146] an estimated 500,000 of these deaths could have been prevented with childhood vaccines.[130] Significant disparities in mortality rates across states — in 2016, under-five mortality rates varied from 65 per 1,000 live births in Madhya Pradesh to 7 per 1,000 live births in Kerala[96] — mirror the vaccination disparities across states. Only 83% of Indian children under the age of 23 months were fully vaccinated in 2018.[136] Furthermore, of those that were vaccinated, vaccination was often delayed — only 35% of Indian children in 2012 reported receiving DPT3 vaccination within a month of the recommended age[17], and only 23% of children received BCG vaccination within 28 days of the recommended age during 2015-16.[141]

Figure 4: Coefficient of interaction between MI districts and year in regression of DPT vaccination, 2011-2014



Note: N=178 districts; 126 non-MI districts and 52 MI districts. *DPT*=Diphtheria, Pertussis, Tetanus. Coefficient of MI phase year interaction term with 95% confidence interval from district fixed effects regression of the rate of DPT3 vaccination on year identifiers, binary indicator of whether a district was included in MI, and interaction terms of the year and MI identifiers.

Vaccination timing is critical especially for reducing the burden for highly infectious diseases. A child infected with measles can infect another 12 to 18 individuals, whereas someone with polio can infect another 5 to 7 individuals.[147,148] Timely vaccination can provide protection at the individual level and stop rapid outbreaks of these diseases through secondary protection. A study from 45 low- and middle-income countries (LMICs) found large variations in timely vaccination and estimated that in approximately 25% of countries children were vaccinated close to their vaccination schedule.[149] However, analysis of vaccination timeliness may be difficult in LMICs due to lack of good quality data on vaccination dates.

Our findings suggest that periodic intensification of routine immunisation (PIRI) activities, through programs such as MI, could play an important role in improving vaccination outcomes. We found under-2 children in Mission Indradhanush districts (those under both Phases 1 and 2) had higher rates of full immunisation, OPV0, OPV1, OPV2, OPV3, hepatitis B birth dose, BCG,

Table 1: Summary Linear Probability Regression Results - immunisation Outcomes and Mission Indradhanush Phase 1 & 2

Model	Vaccine	Liner Probability Model		Probit Model		N
		Coefficient	R^2	Coefficient	Pseudo R^2	
1	Full	**0.27****	0.155	**0.26****	0.155	4474
		0.08		0.08		
2	DPT1	0.02	0.107	0.02	0.107	8603
		0.03		0.03		
3	DPT2	0.07+	0.133	0.06	0.133	8272
		0.04		0.03		
4	DPT3	0.15+	0.164	0.14	0.164	7917
		0.08		0.08		
5	OPV0	**0.09***	0.131	**0.07***	0.131	9033
		0.03		0.03		
6	OPV1	**0.09****	0.126	**0.06***	0.126	8699
		0.02		0.02		
7	OPV2	**0.11***	0.183	**0.09***	0.183	8501
		0.04		0.04		
8	OPV3	**0.16****	0.219	**0.15****	0.219	8282
		0.06		0.05		
9	Measles1	0.05	0.129	0.04	0.129	5651
		0.05		0.05		
10	BCG	**0.05***	0.1	0.04	0.1	9033
		0.02		0.02		
11	HepB0	**0.19****	0.167	**0.16****	0.167	9033
		0.04		0.04		
12	OTV	**0.08***	0.178	**0.09***	0.178	8315
		0.04		0.04		

Note: Include district level fixed effects. Probit model shows average marginal effects. Standard errors below coefficients. *Full=* 1 dose BCG and measles, 3 doses of DPT and polio*; HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin; *OPV=Oral Polio Vaccine; OPV0=OPV* birth dose*; Measles1*: First dose of measles; *OTV*: On-time vaccination – considers timely vaccination of DPT and full immunisation. +p<0.1, *p<0.05, **p<0.0

and on-time vaccination as compared with children residing in non-MI districts. We found vaccination outcomes were not statistically different in districts which were covered by either MI Phase 1 or Phase 2, but not both, as compared with non-MI control districts. This indicates that program duration may be a key factor for success.

Extensions of MI and other future PIRI activities can potentially follow the success of the Pulse Polio program.[150,151] The pulse polio immunisation program included supplementary immunisation sessions that achieved success through engagement with local stakeholders and effective tracking of beneficiaries.[150] In 1995, the program was introduced nationwide, providing polio vaccines to 88 million children under the age of 3 years, and eventually covering all under-5 children.[151] Between 1999 and 2018, the coverage of polio vaccine third dose among 12-23 month old Indian children increased from 57% to 89%,[137] and India was declared polio free in 2011[151].

While our results suggest that PIRI activities can be successful, their long-term effectiveness and financial viability are unclear. [152] MI was succeeded by Intensified Mission Indradhanush (IMI), with a goal of reaching 90% full immunisation coverage in the poorest performing districts by December 2018,[133,138] but it is unknown if this target was attained. A survey study showed an increase in full immunisation rates in IMI districts.[138] Another new study used administrative data on vaccine doses delivered and found increased delivery of doses to IMI districts during the intervention period for 13 vaccines, but reduced volume of vaccine delivery at the end of IMI.[40] This suggests further research is needed to evaluate the longer-term effects of PIRI activities. While the IMI study used data on doses delivered to districts, child level data on vaccinations received before, during, and after a PIRI program may be more suitable for evaluating the program's effectiveness. The cost of the PIRI program per dose delivered needs to be compared to the routine immunisation cost to evaluate its cost-effectiveness. Future evaluations of MI should consider this.

PIRI activities can compensate for the inability of UIP to reach underserved communities but may not be a long-term replacement for routine immunisation. A health systems approach for improving routine immunisation coverage and timeliness requires focus on the following four areas: financing, service delivery, stewardship, and creating and maintaining human resources.[153]

Adequate financial resources must be provided to UIP to improve long-term vaccination outcomes. Although immunisation budgets have increased in response to the introduction of new vaccines in the UIP, they have not kept pace with resource requirements —UIP suffered from estimated annual budgetary shortfalls of $9 to $544 million during 2013-2017,[132] which may be responsible for current gaps in vaccination coverage. The UIP budget is projected to increase by 41% from 2018 to 2022,[154] but this is primarily to facilitate the introduction or universalization of new vaccines (e.g. pneumococcal),[155] and to compensate for reductions in funding from Gavi, The Vaccine Alliance, [156] — which pays for 3% of India's immunisation program budget at present.[132]

Resource allocation for immunisation programs including PIRI activities should focus on fixing key supply side gaps in the UIP that affect service delivery.[157] Post-MI surveys suggest that inadequate and poor-quality infrastructure, and lack of human resources are among the most

important supply-side factors leading to lower attendance in MI sessions.[138] These factors have also slowed the rollout of newer vaccines such as the Hepatitis B vaccine.[158] It will be important to integrate overall best practices in record keeping and vaccine management from high performing districts to poorer performing districts, in addition to providing additional investments in vaccine delivery systems and infrastructure in these districts.

India's shortage of a skilled health workforce affects child immunisation, stretching community level health workers who serve as shared personnel for multiple tasks.[157,159] Greater allocation of staff resources towards routine immunisation activities including regularly updating immunisation records should be a priority.[138] A recent study of MI from western India showed that 10% of study sites did not have an updated list of beneficiaries (known as due list), 13% of auxiliary nurse midwives did not give all key messages about immunisation, and 17% of community health workers were not aware about the incentive pay structure under the MI program.[160] Investments in training programs with a focus on these particular tasks can help improve service delivery.

Strong governance and political commitment are critical for universal routine childhood vaccine coverage.[153,161,162] To secure financing, build and retain skilled public health workers, and improve vaccination coverage, there must be a robust policy decision-making process, sensible regulation, and a high level of health intelligence.[153] Evidence-based policymaking should be aided by efficient surveillance system akin to the highly successful acute flaccid paralysis surveillance.[153] Greater power devolution to the National Technical Advisory Group on immunisation can expedite the policy making process on urgent matters, such as the introduction of new vaccines.[153]

Finally, it is important to consider the demand-side drivers of vaccination to improve program success. Post-MI surveys revealed the main demand side factors contributing to families not attending immunisation sessions were lack of awareness, concerns about adverse effects of vaccines, and lack of time of the mother and child illness.[138,163] To address these barriers, information campaigns should be used to promote the life-saving benefits of vaccines, as well as their secondary and longer-term positive effects on overall health, cognitive and educational outcomes, and reductions in potential medical expenditure.[15,20,34,49,63,66,164] A recent systematic review of interventions to improve immunisation coverage in low- and middle- income countries found health education through home or village level meetings to be successful.[163] Our results and findings from previous studies, showed maternal schooling to be significantly positively associated with child vaccination rates.[165] Therefore, health education interventions should target parents with lower levels of education.

Our analysis has important limitations. Our estimated associations of MI with vaccination outcomes may not be causal in the presence of unobserved covariates. For example, parents may decide to vaccinate their children based on perceived likelihood of survival or nutritional status, or they may be influenced by health workers to vaccinate certain children at higher rates. If such factors are correlated with MI status (e.g., frequent contact with health workers in MI districts), our estimated associations may be biased. However, we included a wide range of covariates in our regression models that are important determinants of vaccination outcomes and which have been used commonly in this type of analysis.

In INCHIS-1 and INCHIS-3, 40% and 34% of households did not have a vaccination card available or did not show vaccination card to the surveyor, and the vaccination outcomes of the child were reported by the mother or caregiver. These observations can be susceptible to measurement errors if there were systematic differences in vaccination status of missing observations between intervention and control districts. We conducted additional analysis by only including households that had vaccination card available and where verification was completed by the surveyor. The results were similar to the main results.

Finally, INCHIS did not survey the same districts in multiple rounds. Therefore, our analysis could not compare changes over time in the same intervention and control districts, although we did control for confounding variables. Analysis of later MI phases can investigate richer datasets that do not have this limitation, more specifically following the same households over time would provide the most robust estimates of MI program effects.

Our study shows that large scale PIRI activities such as Mission Indradhanush can potentially improve vaccination coverage and on-time vaccination rates in India. Further research using longer-term data may provide more robust estimates of the potential effects of the program. Research on the cost-effectiveness of PIRI programs could help inform resource allocation for routine immunisation vis-à-vis supplementary programs such as Mission Indradhanush in the long term.

Appendix

Construction of Wealth Index

A wealth index is a composite measure of a household's economic status and commonly used as a proxy of the long-term economic well-being of a household.[166] Principal component analysis (PCA) was used to construct the wealth index. PCA is widely used method to reduce dimensionality through orthogonal linear transformation of the underlying data.[167] The orthogonal unit eigenvectors calculated from a covariance matrix of data are known as the principal components in a multivariate setting. The following variables from the Integrated Child Health immunisation Survey (INCHIS) were used to construct the PCA: type of household structure; number of persons sharing a room for sleeping; availability of separate room used for kitchen, type of cooking fuel used; availability of electricity; toilet facility type; and ownership of clock, television, laptop, internet, refrigerator, washing machine, air cooler/air conditioner, motorcycle/scooter and car/jeep/van/tractor. We considered the first principal component, which captures most of the variance in data, as an index of wealth. The index was then divided into quintiles

Table A1: Description of vaccination indicators

Vaccine	Definition	Recommended age
Fully vaccinated	A child is considered fully immunized when they receive one dose of Bacillus Calmette–Guérin, three doses of DPT and polio and one dose of measles. Full immunisation can occur in children as early as 12 months of age.	12 months
DPT1	Provides vaccination against diphtheria, pertussis (whooping cough), and tetanus, and requires three doses and a fourth booster dose.	6 weeks
DPT2		10 weeks
DPT3		14 weeks
OPV0	Provides vaccination against poliomyelitis (polio). Requires one birth dose and three follow-up doses. As of 2018, OPV has been replaced by inactivated polio vaccine (IPV) in the immunisation schedule.	at birth
OPV1		6 weeks
OPV2		10 weeks
OPV3		14 weeks
Hep B0	Hepatitis B	at birth
Measles1	First dose of measles vaccine	9 months
BCG	Bacillus Calmette–Guérin	at birth
OTV	The on-time vaccination indicator considered the timely receipt of DPT1, DPT2, DPT3, and full immunisation. Each child was evaluated for timely vaccination of the most recent vaccine they were eligible for. The indicator had a value of 1 if the child had received one of these vaccines within 28 days after the earliest age of eligibility.	See above

Source: Indian Academy of Pediatrics[139]

Table A2: Distribution of households by outcome variables and socioeconomic and demographic characteristics for P1&2 intervention and control groups before intervention (%)

	Intervention Mean	Intervention SD	Control mean	Control SD	Difference
Vaccine					
Full	0.553	0.498	0.773	0.419	-0.22**
DPT1	0.845	0.362	0.894	0.309	-0.049**
DPT2	0.773	0.419	0.859	0.348	-0.086**
DPT3	0.617	0.486	0.750	0.433	-0.133**
OPV0	0.752	0.432	0.850	0.357	-0.098**
OPV1	0.865	0.342	0.924	0.265	-0.06**
OPV2	0.874	0.332	0.925	0.263	-0.051**
OPV3	0.760	0.427	0.829	0.376	-0.069**
Measles	0.582	0.493	0.684	0.465	-0.103**
BCG	0.893	0.310	0.967	0.180	-0.074**
HepB0	0.812	0.391	0.858	0.350	-0.045**
OTV	0.183	0.387	0.225	0.418	-0.042**
Sex					
Female	0.487	0.500	0.466	0.499	0.020
Locality					
Urban	0.344	0.475	0.298	0.457	0.046**
Wealth Quintile					
1	0.166	0.372	0.143	0.350	0.024*
2	0.186	0.389	0.193	0.394	-0.007
3	0.160	0.367	0.259	0.438	-0.099**
4	0.220	0.414	0.224	0.417	-0.004
5	0.265	0.441	0.179	0.383	0.086**
Religion					
Hindu	0.618	0.486	0.889	0.314	-0.271**
Muslim	0.138	0.345	0.057	0.231	0.081**
Christian	0.235	0.424	0.009	0.095	0.226**
Sikh	0.006	0.080	0.039	0.193	-0.032**
Other	0.000	0.000	0.004	0.060	-0.004**
Caste					
General	0.217	0.412	0.274	0.446	-0.057**
Scheduled Tribe	0.260	0.439	0.054	0.227	0.206**
Other Backward Caste	0.386	0.487	0.306	0.461	0.08**
Scheduled Caste	0.134	0.341	0.363	0.481	-0.229**

Education					
No Schooling	0.262	0.440	0.234	0.423	0.029*
Primary Or Lower	0.211	0.408	0.148	0.355	0.063**
Middle To Secondary	0.417	0.493	0.503	0.500	-0.086**
Graduate	0.106	0.308	0.112	0.316	-0.006
Household Size					
> 5	0.667	0.471	0.700	0.458	-0.034*
Place of Birth					
Non-Institutional	0.308	0.462	0.146	0.353	0.163**
Distance to Sub-Center					
< 15 Minutes	0.255	0.436	0.243	0.429	0.012
15 To 30 Minutes	0.464	0.499	0.565	0.496	-0.101**
> 30 Minutes	0.272	0.445	0.190	0.392	0.082**

Note: Data are from INCHIS-1 with 13 districts in intervention group and 8 districts in control group. Numbers are proportion of households within each group. *Full*=1 dose BCG and measles, 3 doses of DPT and polio; *HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *OPV=Oral Polio Vaccine, OPV0=OPV* birth dose, *BCG*=Bacillus Calmette–Guérin; *Measles1*= First dose of measles; *OTV*= On-time vaccination – considers timely vaccination of DPT and full immunisation; Wealth Quintile 1 refers to the poorest wealth quintile; Control group = Children that were not covered by phase 1 or 2 of Mission Indradhanush; +p<0.1, *p<0.05, **p<0.01

Table A3: Background characteristics of study children by vaccination status (%)

	Full		DPT1		DPT2		DPT3		OPV0		OPV1		OPV2		OPV3		Measles		BCG		Hepatitis B	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Sex																						
Male	28	72	13	87	20	80	32	68	8	92	10	90	21	79	37	63	18	82	5	95	15	85
Female	36	64	14	86	20	80	35	65	10	90	11	89	23	77	40	60	21	79	6	94	17	83
Locality																						
Rural	35	65	14	86	20	80	34	66	10	90	11	89	23	77	39	61	21	79	6	94	16	84
Urban	25	75	12	88	20	80	33	67	9	91	10	90	20	80	37	63	17	83	6	94	15	85
Wealth Quintile																						
1	44	56	27	73	31	69	43	57	16	84	16	84	32	68	47	53	29	71	11	89	25	75
2	34	66	11	89	19	81	35	65	7	93	10	90	21	79	40	60	22	78	4	96	15	85
3	29	71	11	89	14	86	25	75	8	92	9	91	19	81	36	64	15	85	4	96	13	87
4	28	72	10	90	17	83	30	70	8	92	10	90	20	80	35	65	19	81	6	94	11	89
5	20	80	7	93	18	82	32	68	7	93	9	91	19	81	34	66	10	90	3	97	14	86
Religion																						
Hindu	31	69	13	87	19	81	32	68	9	91	10	90	21	79	37	63	20	80	5	95	16	84
Muslim	40	60	20	80	31	69	47	53	14	86	22	78	32	68	48	52	20	80	10	90	19	81
Christian	39	61	13	87	19	81	36	64	19	81	5	95	17	83	35	65	18	82	15	85	23	77
Sikh	20	80	7	93	13	87	23	77	8	92	9	91	13	87	30	70	11	89	8	92	7	93
Other	0	100	0	100	0	100	3	97	10	90	0	100	4	96	4	96	0	100	0	100	17	83
Caste																						
General	35	65	15	85	21	79	33	67	11	89	12	88	24	76	43	57	21	79	6	94	21	79
Scheduled Tribe	49	51	18	82	24	76	43	57	14	86	8	92	26	74	46	54	19	81	8	92	14	86
Other Backward Caste	27	73	12	88	18	82	31	69	8	92	11	89	21	79	35	65	16	84	5	95	13	87
Scheduled Caste	33	67	14	86	21	79	36	64	10	90	10	90	22	78	39	61	24	76	6	94	18	82
Education																						
No Schooling	41	59	23	77	29	71	40	60	16	84	17	83	30	70	45	55	22	78	10	90	25	75

Primary Or Lower	32	68	11	89	17	83	35	65	10	90	10	90	19	81	39	61	25	75	9	91	14	86
Middle To Secondary	25	75	10	90	16	84	30	70	6	94	8	92	20	80	34	66	17	83	3	97	11	89
Graduate	25	75	3	97	11	89	27	73	5	95	4	96	14	86	34	66	14	86	1	99	11	89
Household size																						
< 5	29	71	11	89	16	84	29	71	6	94	8	92	21	79	37	63	19	81	4	96	12	88
> 5	32	68	14	86	21	79	35	65	11	89	12	88	22	78	39	61	20	80	6	94	17	83
Place Of Birth																						
Institutional	25	75	10	90	16	84	28	72	6	94	8	92	19	81	34	66	16	84	4	96	12	88
Non-Institutional	60	40	28	72	39	61	57	43	25	75	23	77	38	62	59	41	35	65	16	84	34	66
Distance to vaccination site																						
< 15 Minutes	24	76	13	87	19	81	31	69	8	92	11	89	22	78	37	63	18	82	7	93	14	86
15 To 30 Minutes	34	66	14	86	21	79	34	66	10	90	10	90	21	79	39	61	20	80	6	94	17	83
> 30 Minutes	37	63	13	87	20	80	35	65	8	92	12	88	26	74	42	58	22	78	4	96	15	85
Observations	7,494		14,892		14,356		13,829		15,304		15,304		15,304		15,304		10,095		15,304		15,304	

Note: Data are from INCHIS-1. Numbers are percentages for each binary vaccination outcome e.g., whether fully vaccinated (yes/no). F*ull*= 1 dose BCG and measles, 3 doses of DPT and polio; *HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *OPV*=Oral Polio Vaccine, *OPV0=OPV* birth dose, *BCG*=Bacillus Calmette–Guérin; *Measles1*= First dose of measles; *OTV*= On-time vaccination – considers timely receipt of all three DPT vaccines and full immunisation; Wealth Quintile 1 refers to the poorest wealth quintile.

Table A4: immunisation Outcomes and Phase 1 and 2 Mission Indradhanush Treatment

Model	1	2	3	4	5	6	7	8	9	10	11	12
Vaccine	Full	DPT1	DPT2	DPT3	OPV0	OPV1	OPV2	OPV3	DPT3	BCG	HepB0	OTV
Phase 1&2=1	-0.23**	-0.04	-0.06*	-0.11+	-0.01	-0.07*	-0.08**	-0.08*	-0.01	-0.05*	-0.07+	-0.07*
	0.03	0.03	0.02	0.06	0.02	0.03	0.03	0.03	0.05	0.02	0.04	0.03
Post-Intervention=1	-0.02	0.03	0.02	0.03	0	0	0.03	0.04	0.05	0	-0.11**	-0.02
	0.03	0.02	0.03	0.05	0.02	0.01	0.02	0.04	0.03	0.01	0.03	0.04
DID Indicator	0.27**	0.02	0.07+	0.15+	0.09*	0.09**	0.11*	0.16**	0.05	0.05*	0.19**	0.08*
	0.08	0.03	0.04	0.08	0.03	0.02	0.04	0.06	0.05	0.02	0.04	0.04
Age of Mother	0	0	0	0	0	0	0	0	0	0	0	-0.00+
	0	0	0	0	0	0	0	0	0	0	0	0
Sex (Male=1)												
Female	-0.06+	0	0.01	0	-0.01	0	0	-0.02	-0.02	0	-0.01	0.01
	0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02
Locality (Rural=1)												
Urban	0.01	-0.01	-0.02	0	0.01	0.01	0	0.01	0	-0.01	0.02	0.01
	0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.02
Age of Child	0	0.00**	0.00**	0.00**	0.00*	0.00**	0.00**	0.01**	0.00**	0.00**	0.00**	0.01**
	0	0	0	0	0	0	0	0	0	0	0	0

Wealth Quintile (1=1)												
2	0.06**	0.08**	0.06	0.05**	0.05**	0.05**	0.08*	0.06**	0.04+	0.03+	0.05+	0.02
	0.02	0.03	0.04	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.03	0.02
3	0.09**	0.06+	0.06	0.06**	0.03	0.03	0.07*	0.06*	0.05**	0.02	0.03	0.02
	0.02	0.03	0.04	0.02	0.02	0.02	0.03	0.03	0.02	0.02	0.03	0.03
4	0.11**	0.07*	0.05	0.05+	0.02	0.03	0.06+	0.09**	0.06+	0.01	0.05	0.05
	0.02	0.03	0.04	0.03	0.02	0.02	0.04	0.03	0.03	0.03	0.03	0.03
5	0.17**	0.09*	0.06	0.07*	0.05	0.06+	0.09*	0.12**	0.11*	0.05+	0.05	0.04+
	0.03	0.04	0.04	0.03	0.03	0.03	0.03	0.02	0.04	0.03	0.03	0.02
Religion (Hindu=1)												
Muslim	0.01	0	-0.02	0	0	-0.02	-0.01	0	-0.02	0	0.04+	-0.01
	0.02	0.03	0.02	0.03	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.03
Christian	0.1	0.01	0.02	0.05	0.02	0.01	0	0.04	0.05	-0.03	0.03	-0.06
	0.06	0.02	0.03	0.04	0.02	0.03	0.03	0.04	0.04	0.03	0.04	0.06
Sikh	-0.03	0	-0.03	0	-0.01	-0.04	-0.01	-0.05	0.03	-0.03	0.01	0.07
	0.04	0.02	0.05	0.04	0.03	0.03	0.03	0.05	0.03	0.03	0.02	0.08
Other	0.01	0	0.01	0.02	0.02	-0.01	-0.02	0.01	-0.06	-0.01	-0.04	-0.10*
	0.05	0.01	0.01	0.04	0.02	0.02	0.03	0.05	0.04	0.01	0.06	0.04
Caste (General=1)												
Scheduled tribe	-0.02	0.02	0.01	-0.03	-0.01	0.02	0	-0.01	0.01	0	0.01	0
	0.05	0.02	0.02	0.04	0.02	0.01	0.03	0.03	0.03	0.01	0.02	0.03
Other backward caste	0.07+	0.03+	0.02	0.01	0.02+	0.02	0.03	0.06*	0.03	0	0.04*	0.04
	0.04	0.01	0.02	0.03	0.01	0.01	0.02	0.03	0.03	0.01	0.02	0.02
Scheduled caste	0.09**	0.07**	0.05*	0.04	0.04+	0.05*	0.05+	0.07**	0.05*	0.02+	0.05+	0.01
	0.03	0.02	0.02	0.03	0.02	0.02	0.03	0.03	0.02	0.01	0.02	0.02
No schooling												

	0.03	0.01	0.01	0.02	0.02	0.01	0.02	0.02	0.03	0.01	0.02	0.02
Middle to Secondary	0.07**	0.05**	0.05*	0.03	0.04*	0.04*	0.04*	0.04*	0	0.03*	0.05*	0.09**
	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
Graduate	0.06+	0.09**	0.09*	0.04	0.05	0.07*	0.08**	0.05*	0	0.04+	0.08*	0.13**
	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.02	0.03	0.04
Household size (<5=1)												
> 5	0	-0.01	-0.01	0	0	0.01	0.02	0.03	0.01	0	0.01	0.02
	0.03	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.02
Institutional Delivery (Institutional=1)												
Non-Institutional	-0.17**	-0.09**	-0.13**	-0.13**	-0.14**	-0.07**	-0.09**	-0.12**	-0.13**	-0.07**	-0.15**	-0.08**
	0.04	0.02	0.03	0.02	0.02	0.01	0.02	0.02	0.04	0.01	0.03	0.02
Distance to Vaccination Site (< 15 minutes=1)												
15 to 30 minutes	-0.05+	-0.02+	-0.02	-0.03	0	0	-0.01	-0.01	0	0	0	-0.04*
	0.03	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.02
> 30 minutes	-0.11*	-0.03**	-0.05*	-0.06*	0.01	-0.02	-0.05**	-0.07*	-0.05	0.01	0	-0.05+
	0.04	0.01	0.02	0.03	0.02	0.01	0.02	0.03	0.04	0.01	0.02	0.03
Observations	4474	8603	8272	7917	9033	8699	8501	8282	5651	9033	9033	8315
Pseudo R^2	0.155	0.107	0.133	0.164	0.131	0.126	0.183	0.219	0.129	0.1	0.167	0.178

Note: *Full*= 1 dose BCG and measles, 3 doses of DPT and polio*; HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin; *OPV=Oral Polio Vaccine; OPV0=OPV* birth dose*; Measles1*= First dose of measles; *OTV*= On-time vaccination – considers timely vaccination of DPT and full immunisation.*; Phase 1 and 2 control*: did not receive treatment in phase 1 or phase 2; +p-value<0.10, *p-value<0.05, **p-value<0.01; Standard errors below coefficients.

Table A5: immunisation Outcomes and Phase 1 Mission Indradhanush Treatment

Model	1	2	3	4	5	6	7	8	9	10	11	12
Vaccine	Full	DPT1	DPT2	DPT3	OPV0	OPV1	OPV2	OPV3	DPT3	BCG	HepB0	OTV
Phase 1&2=1	-0.11**	-0.04+	-0.04*	-0.08*	-0.04*	-0.03*	-0.03+	-0.06*	-0.02	-0.03+	-0.05*	-0.07**
	0.04	0.02	0.02	0.03	0.02	0.02	0.02	0.03	0.03	0.02	0.02	0.03
Post-Intervention=1	0.09*	0.06**	0.08**	0.10**	0.02*	0.04**	0.11**	0.14**	0.09**	0.03**	0.01	0.02
	0.04	0.01	0.01	0.03	0.01	0.01	0.01	0.02	0.03	0.01	0.02	0.03
DID Indicator	0.04	0	0	0.02	0.01	0	-0.01	0	-0.04	0.01	0.01	0.01
	0.05	0.03	0.03	0.04	0.02	0.02	0.02	0.04	0.03	0.02	0.04	0.03
Age of Mother	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0
Sex (Male=1)												
Female	0.01	0	0.01	0	0	0	0.01	-0.01	0.01	0	0	-0.01
	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0	0.01	0.01
Locality (Rural=1)												
Urban	0.03	-0.01	-0.01	0.01	-0.01	-0.01	-0.01	0.02	0	-0.01+	-0.02	0.02+
	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Age of Child	0	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**	0.01**	0.00**	0.00**	0.00**	0.00**
	0	0	0	0	0	0	0	0	0	0	0	0
Wealth Quintile (1=1)												

	2	0.06**	0.05**	0.04**	0.04*	0	0.04**	0.04**	0.04**	0.03+	0.02	0.05**	0.03*
		0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02
	3	0.03	0.04**	0.04*	0.02	0	0.05**	0.05**	0.03+	0.01	0.02+	0.03	0.03*
		0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.01	0.02	0.01
	4	0.06*	0.06**	0.07**	0.05*	0.01	0.05**	0.06**	0.04+	0.02	0.04**	0.07**	0.04*
		0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
	5	0.11**	0.08**	0.08**	0.08**	0.01	0.07**	0.07**	0.08**	0.07**	0.05**	0.08**	0.07**
		0.03	0.02	0.03	0.02	0.03	0.02	0.02	0.02	0.02	0.01	0.03	0.02
Religion (Hindu=1)													
Muslim		-0.08**	-0.03	-0.06*	-0.06*	-0.03	-0.02	-0.05*	-0.06*	-0.08**	-0.03	-0.05**	-0.05**
		0.03	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.01
Christian		-0.06	0	-0.02	0.01	0.01	0.02+	0.01	0	-0.04	0	-0.01	0
		0.05	0.01	0.02	0.03	0.01	0.01	0.01	0.03	0.03	0.01	0.03	0.03
Sikh		0.09*	0.03+	0.01	0.03	0.03*	-0.02	0.02	0	0.03	0	0.02	0.08
		0.04	0.02	0.04	0.03	0.01	0.02	0.03	0.04	0.02	0.01	0.02	0.08
Other		-0.02	0.01	-0.02	-0.01	0	-0.01	-0.04*	-0.01	-0.06	-0.02+	-0.05	-0.07
		0.05	0.01	0.02	0.03	0.01	0.01	0.02	0.02	0.04	0.01	0.03	0.05
Caste (General=1)													
Scheduled tribe		-0.04	0.02	0.02	-0.06+	0.01	0.03	-0.01	-0.06+	0.02	0.03+	0.04*	-0.06*
		0.05	0.02	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.02	0.02	0.03
Other backward caste		0.02	0.02	0.01	0	0	0.02	0.01	0.01	0.03	0.02	0.03	-0.01
		0.03	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02
Scheduled caste		0.01	0.05**	0.02	0	0.01	0.03+	0.02	0	0.03	0.02+	0.05**	-0.02
		0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.01	0.02	0.02
No schooling													
Primary or lower		0.04+	0.02*	0.05**	0.04**	0.02	0.02*	0.04**	0.05**	0.04*	0.02*	0.05**	0.04**

	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.01
Middle to Secondary	0.03+	0.04**	0.05**	0.04**	0.02	0.02	0.04*	0.04**	0.04**	0.02*	0.03*	0.04**
	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.02
Graduate	0.04	0.07**	0.08**	0.06**	0.05**	0.04*	0.06**	0.04*	0.08**	0.04**	0.07*	0.07**
	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.03	0.02
Household size (<5=1)												
> 5	0	-0.01	0	0.01	-0.02*	-0.01	0.01	0.01	0	-0.01	-0.01	-0.02
	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0	0.01	0.01
Institutional Delivery (Institutional=1)												
Non-Institutional	-0.11**	-0.06**	-0.08**	-0.10**	-0.11**	-0.08**	-0.08**	-0.11**	-0.09**	-0.07**	-0.13**	-0.04**
	0.03	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.01
Distance to Vaccination Site (< 15 minutes=1)												
15 to 30 minutes	-0.06**	-0.02	-0.02	-0.02+	0	0	-0.01	-0.03*	-0.04*	0	0	-0.02*
	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01
> 30 minutes	-0.10**	-0.07**	-0.06**	-0.07**	-0.02	-0.05**	-0.07**	-0.08**	-0.07**	-0.02	-0.02	-0.03
	0.03	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
Observations	8813	17720	17036	16388	18574	17931	17530	17166	11793	18574	18574	17068
Pseudo R^2	0.133	0.105	0.138	0.151	0.121	0.13	0.208	0.234	0.141	0.098	0.173	0.147

Note: Analysis based on INCHIS-1 and INCHIS-2. *Full*= 1 dose BCG and measles, 3 doses of DPT and polio*; HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin; *OPV=Oral Polio Vaccine; OPV0=OPV* birth dose*; Measles1*= First dose of measles; *OTV*= On-time vaccination – considers timely vaccination of DPT and full immunisation.; +p-value<0.10, *p-value<0.05, **p-value<0.01; Standard errors below coefficients.

Table A6: immunisation Outcomes and Phase 2 Mission Indradhanush Treatment

Model	1	2	3	4	5	6	7	8	9	10	11	12
Vaccine	Full	DPT1	DPT2	DPT3	OPV0	OPV1	OPV2	OPV3	DPT3	BCG	HepB0	OTV
Phase 1&2=1	-0.04	-0.02	-0.03+	-0.05**	-0.02	-0.02+	-0.03	-0.04**	-0.02	0	-0.03+	-0.04+
	0.02	0.01	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.02
Post-Intervention=1	-0.11**	-0.02	-0.05*	-0.08**	-0.02	-0.02	-0.04+	-0.08**	-0.03	-0.01	-0.07**	0
	0.03	0.01	0.03	0.03	0.01	0.01	0.03	0.02	0.03	0.01	0.02	0.03
DID Indicator	0	0.01	0.02	0.01	0.03	0.01	0.02	0.01	0	0	0.04	-0.04
	0.04	0.02	0.03	0.03	0.02	0.02	0.03	0.03	0.02	0.01	0.03	0.03
Age of Mother	0.00+	0	0	0.00**	-0.00+	0	0	0.00+	0	-0.00+	0	0
	0	0	0	0	0	0	0	0	0	0	0	0
Sex (Male=1)												
Female	0.02+	0	0	0	0.01	0	-0.01+	-0.01	0	0	0	0.01
	0.01	0	0.01	0.01	0	0	0.01	0.01	0.01	0	0.01	0.01
Locality (Rural=1)												
Urban	-0.01	-0.02*	-0.03**	-0.02	0	-0.01	-0.02+	0	-0.04**	-0.01	-0.01	0.01
	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Age of Child	0	0	0.00**	0.00**	0	0	0.00**	0.00**	0.00**	0	0.00*	0.01**
	0	0	0	0	0	0	0	0	0	0	0	0
Wealth Quintile (1=1)												

	2	0.02	0.02+	0.02	0.02	0.04**	0.02*	0.02	0.01	0.03**	0.01	0.02	0.01
		0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
	3	0.05+	0.02	0.01	0.02	0.04**	0.02*	0.01	0.04*	0.02	0.02+	0.01	0.02
		0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02
	4	0.04	0.02	0.04+	0.04	0.05**	0.02*	0.03*	0.05*	0.03+	0.02*	0.02	0.03
		0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02
	5	0.08**	0.03+	0.05*	0.06*	0.05**	0.02+	0.04**	0.07**	0.05**	0.02*	0.03	0.08**
		0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02
Religion (Hindu=1)													
Muslim		-0.02	-0.01	-0.02	-0.02	0.01	0	0	-0.03	0	0	0.01	0
		0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Christian		-0.06	0.01	0.01	0	0	0	0	0	-0.03	0	0	-0.05
		0.05	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.03	0.01	0.02	0.04
Sikh		0.07**	0	-0.01	0.02	0.01	0	-0.01	0.01	0.02+	0.01	0.02**	0.08*
		0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.04
Other		-0.04	0.01*	0.02+	0.01	0.02	0	0.01	0.01	-0.08*	0	-0.05	-0.08*
		0.04	0.01	0.01	0.03	0.01	0.01	0.02	0.02	0.04	0	0.04	0.03
Caste (General=1)													
Scheduled tribe		-0.08*	-0.02	-0.01	-0.04+	-0.03*	-0.03**	-0.02+	-0.06**	-0.04**	-0.01+	-0.05+	-0.03
		0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.02
Other backward caste		-0.02	0	0	-0.01	0	0	0	0	-0.02	0	0	0
		0.03	0.01	0.01	0.01	0.01	0	0.01	0.01	0.01	0	0.01	0.02
Scheduled caste		-0.01	0.01	0	-0.03+	-0.01	0	0	-0.02	0	0	0	-0.02
		0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0	0.01	0.02
No schooling													
Primary or lower		0.06**	0.02+	0.03+	0.03+	0	0.01	0.02	0.03+	0.04**	0.01**	0.02	0.02

Middle to Secondary	0.07**	0.04**	0.05**	0.07**	0	0.02*	0.03*	0.05**	0.04**	0.02**	-0.01	0.07**
	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0	0.01	0.02
Graduate	0.10**	0.05**	0.06**	0.08**	0.01	0.02*	0.03+	0.02	0.06**	0.02**	0.01	0.05+
	0.03	0.01	0.02	0.03	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.03
Household size (<5=1)												
> 5	-0.01	0	0	0	0	0	-0.01+	0	-0.01	-0.01*	0	0
	0.02	0.01	0.01	0.01	0.01	0	0	0.01	0.01	0	0.01	0.01
Institutional Delivery (Institutional=1)												
Non-Institutional	-0.11**	-0.03+	-0.04+	-0.04	-0.08**	-0.04*	-0.05**	-0.06*	-0.09**	-0.05**	-0.16**	-0.05**
	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.01	0.03	0.01
Distance to Vaccination Site (< 15 minutes=1)												
15 to 30 minutes	-0.03+	-0.01	-0.01	-0.01	0.01	0	0	-0.01	0	0	0.01	-0.04**
	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0	0.01	0.02
> 30 minutes	-0.05*	-0.03+	-0.04*	-0.02	0	-0.02	-0.03	-0.04*	-0.01	0	-0.01	-0.04
	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.02
Observations	6770	12973	12454	11973	13786	12973	12454	11973	8602	13786	13786	12595
Pseudo R^2	0.077	0.041	0.05	0.072	0.071	0.047	0.065	0.093	0.061	0.045	0.111	0.19

Note: *Full*= 1 dose BCG and measles, 3 doses of DPT and polio*; HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin; *OPV=Oral Polio Vaccine; OPV0=OPV* birth dose*; Measles1*: First dose of measles; *OTV*: On-time vaccination – considers timely vaccination of DPT and full immunisation.; +p-value<0.10, *p-value<0.05, **p-value<0.01; Standard errors below coefficients.

Table A7: immunisation Outcomes and Phase 1 and 2 Mission Indradhanush Treatment, Vaccination Card Seen

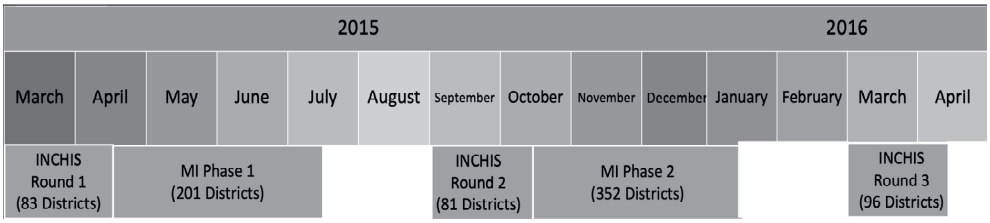
Model	1	2	3	4	5	6	7	8	9	10	11	12
Vaccine	Full	DPT1	DPT2	DPT3	OPV0	OPV1	OPV2	OPV3	DPT3	BCG	HepB0	OTV
Phase 1&2=1	-0.73**	-0.06	-0.16	-0.36+	0.23+	-0.24	-0.25*	-0.23*	0.02	-0.66*	-0.29*	-0.14
	0.19	0.13	0.1	0.18	0.13	0.18	0.13	0.1	0.16	0.26	0.13	0.15
Post-Intervention=1	-0.08	0.27	0.06	0.1	-0.09	-0.05	-0.04	0.04	0.25+	-0.35+	-0.66**	-0.07
	0.15	0.18	0.15	0.18	0.22	0.18	0.13	0.15	0.13	0.19	0.14	0.15
DID Indicator	0.76*	0.19	0.36+	0.47	0.78**	1.03**	0.79**	0.63**	0.41+	0.73*	0.96**	0.3
	0.35	0.27	0.21	0.33	0.23	0.24	0.24	0.24	0.23	0.31	0.16	0.21
Age of Mother	0.01+	0.02*	0.02*	0.02*	0	0.02	0.02*	0.01	0.02+	-0.01	0	-0.01
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Sex (Male=1)												
Female	-0.16	0.15	0.15+	0.02	-0.04	-0.03	0.01	-0.05	-0.14	-0.11	-0.04	0.02
	0.12	0.09	0.08	0.08	0.1	0.11	0.09	0.07	0.1	0.14	0.1	0.05
Locality (Rural=1)												
Urban	-0.1	-0.08	-0.11	-0.1	0.31*	0.15+	0.03	0	-0.06	0.54**	0.28**	0
	0.11	0.13	0.07	0.08	0.13	0.09	0.06	0.09	0.12	0.2	0.1	0.07
Age of Child	0	0.01**	0.02**	0.01**	0	0.02**	0.02**	0.02**	0.02**	0.01**	0.01**	0.02**
	0	0	0	0	0	0	0	0	0	0	0	0
Wealth Quintile (1=1)												

		0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
	3	0.05+	0.02	0.01	0.02	0.04**	0.02*	0.01	0.04*	0.02	0.02+	0.01	0.02
		0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02
	4	0.04	0.02	0.04+	0.04	0.05**	0.02*	0.03*	0.05*	0.03+	0.02*	0.02	0.03
		0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02
	5	0.08**	0.03+	0.05*	0.06*	0.05**	0.02+	0.04**	0.07**	0.05**	0.02*	0.03	0.08**
		0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02
Religion (Hindu=1)													
Muslim		-0.02	-0.01	-0.02	-0.02	0.01	0	0	-0.03	0	0	0.01	0
		0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Christian		-0.06	0.01	0.01	0	0	0	0	0	-0.03	0	0	-0.05
		0.05	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.03	0.01	0.02	0.04
Sikh		0.07**	0	-0.01	0.02	0.01	0	-0.01	0.01	0.02+	0.01	0.02**	0.08*
		0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.04
Other		-0.04	0.01*	0.02+	0.01	0.02	0	0.01	0.01	-0.08*	0	-0.05	-0.08*
		0.04	0.01	0.01	0.03	0.01	0.01	0.02	0.02	0.04	0	0.04	0.03
Caste (General=1)													
Scheduled tribe		-0.08*	-0.02	-0.01	-0.04+	-0.03*	-0.03**	-0.02+	-0.06**	-0.04**	-0.01+	-0.05+	-0.03
		0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.02
Other backward caste		-0.02	0	0	-0.01	0	0	0	0	-0.02	0	0	0
		0.03	0.01	0.01	0.01	0.01	0	0.01	0.01	0.01	0	0.01	0.02
Scheduled caste		-0.01	0.01	0	-0.03+	-0.01	0	0	-0.02	0	0	0	-0.02
		0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0	0.01	0.02
No schooling													
Primary or lower		0.06**	0.02+	0.03+	0.03+	0	0.01	0.02	0.03+	0.04**	0.01**	0.02	0.02

	0.15	0.22	0.11	0.11	0.14	0.14	0.1	0.11	0.22	0.2	0.14	0.1
Middle to Secondary	0.16	0.36	0.19	0.08	0.29+	0.21	0.18+	0.11	0	0.34	0.16	0.30**
	0.13	0.25	0.15	0.11	0.17	0.18	0.11	0.09	0.19	0.28	0.14	0.08
Graduate	0.1	0.63+	0.31	0.17	0.2	0.45*	0.24	0.08	-0.12	0.44	0.19	0.41**
	0.15	0.32	0.21	0.14	0.24	0.19	0.15	0.1	0.19	0.47	0.19	0.15
Household size (<5=1)												
> 5	0.05	-0.13	-0.15+	0.02	-0.03	-0.04	0.15*	0.19*	0.1	-0.22	0.02	0.07
	0.1	0.09	0.08	0.08	0.12	0.1	0.06	0.08	0.11	0.18	0.08	0.06
Institutional Delivery (Institutional=1)												
Non-Institutional	-0.44**	-0.18+	-0.32**	-0.26**	-0.74**	-0.16	-0.19+	-0.25*	-0.54**	-0.46**	-0.47**	-0.28**
	0.1	0.1	0.12	0.09	0.11	0.13	0.11	0.1	0.14	0.13	0.11	0.09
Distance to Vaccination Site (< 15 minutes=1)												
15 to 30 minutes	-0.15+	-0.16	-0.11	-0.09+	0.04	0.08	0	-0.05	0	-0.01	-0.03	-0.12
	0.09	0.11	0.07	0.05	0.14	0.11	0.1	0.06	0.11	0.21	0.13	0.08
> 30 minutes	-0.41**	-0.38**	-0.38**	-0.24**	-0.16	-0.27+	-0.35**	-0.36**	-0.27+	0.17	-0.15	-0.15
	0.15	0.09	0.11	0.09	0.15	0.16	0.1	0.11	0.16	0.25	0.17	0.1
Observations	3689	7210	7048	6925	7333	6845	7230	7221	4645	6375	7905	7259
Pseudo R^2	0.124	0.163	0.165	0.137	0.228	0.211	0.244	0.199	0.161	0.236	0.198	0.172

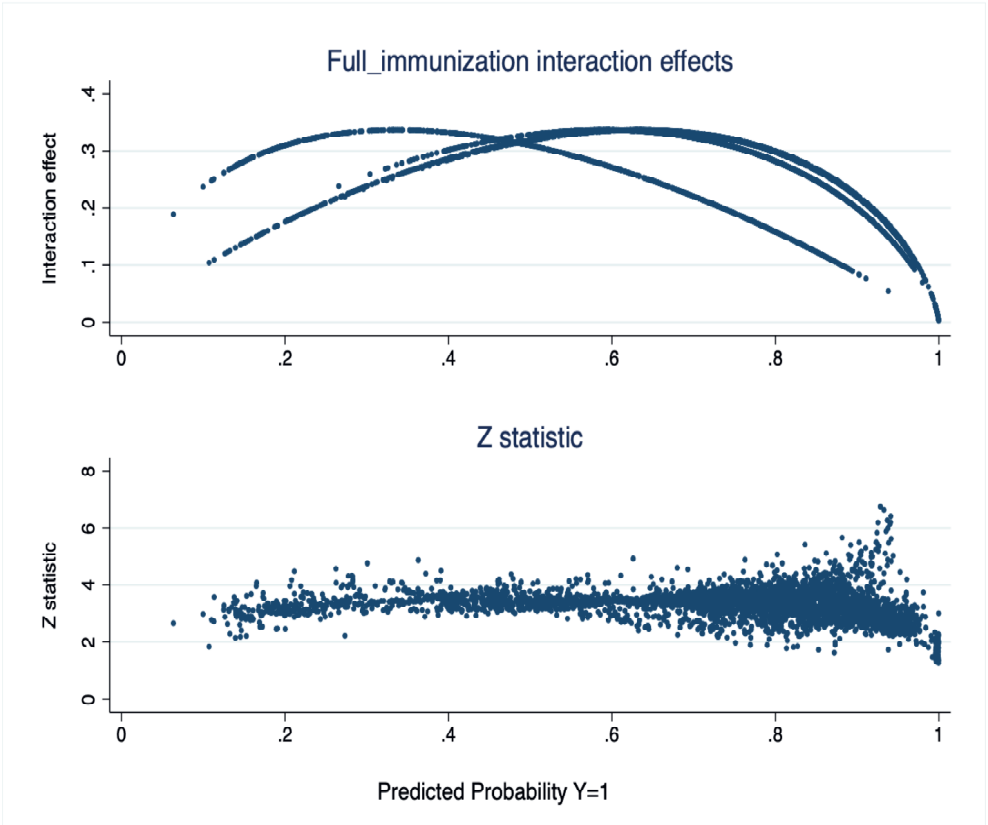
Note: *Full*= 1 dose BCG and measles, 3 doses of DPT and polio*; HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin; *OPV=Oral Polio Vaccine; OPV0=OPV* birth dose*; Measles1*= First dose of measles; *OTV*= On-time vaccination – considers timely vaccination of DPT and full immunisation.; +p-value<0.10, *p-value<0.05, **p-value<0.01; Standard errors below coefficients.

Figure A1: Timeline of MI and INCHIS phases



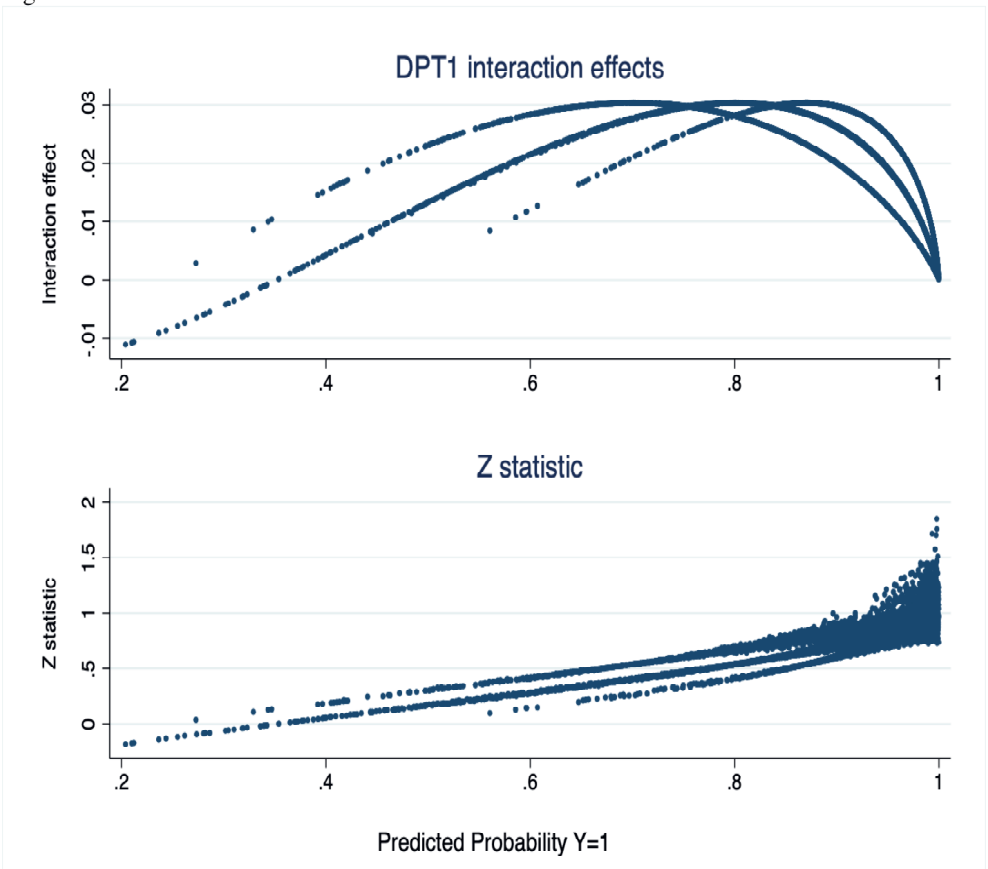
Note: *INCHIS* = Integrated Child Health and immunisation Survey.

Figure A2: Full immunisation Interaction Effects



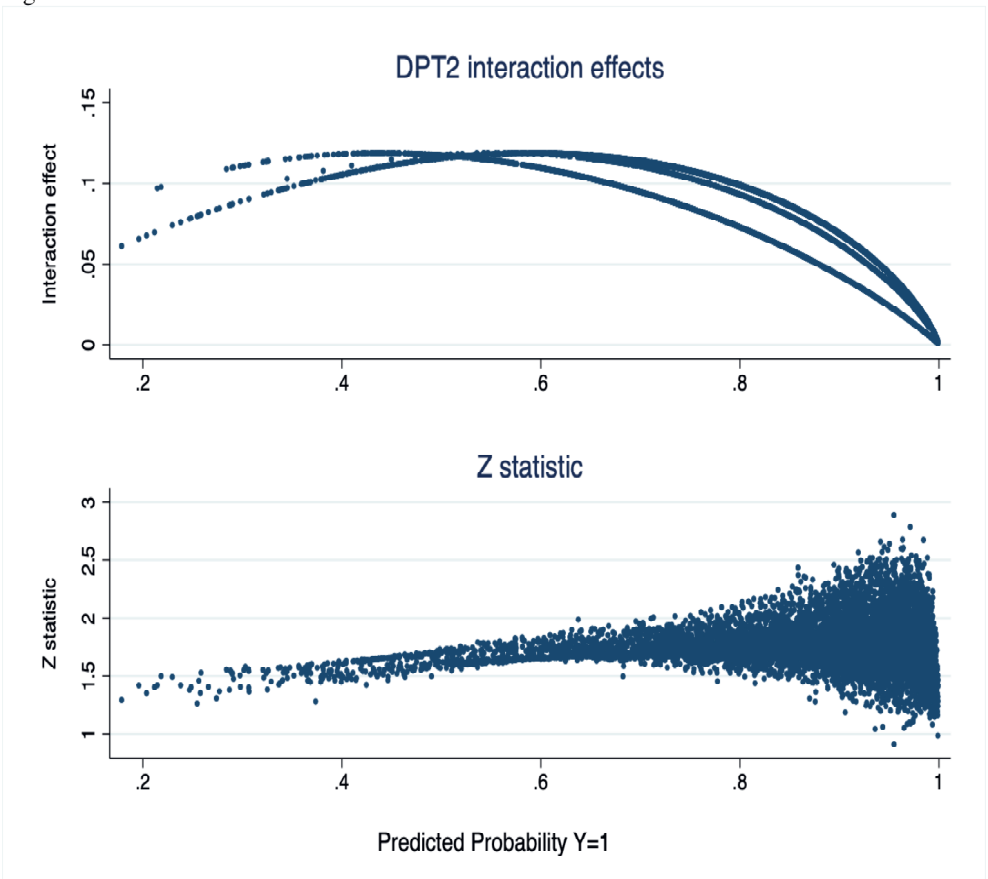
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *Full=* 1 dose BCG and measles, 3 doses of DPT and polio*; HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin.

Figure A3: DPT1 Interaction Effects



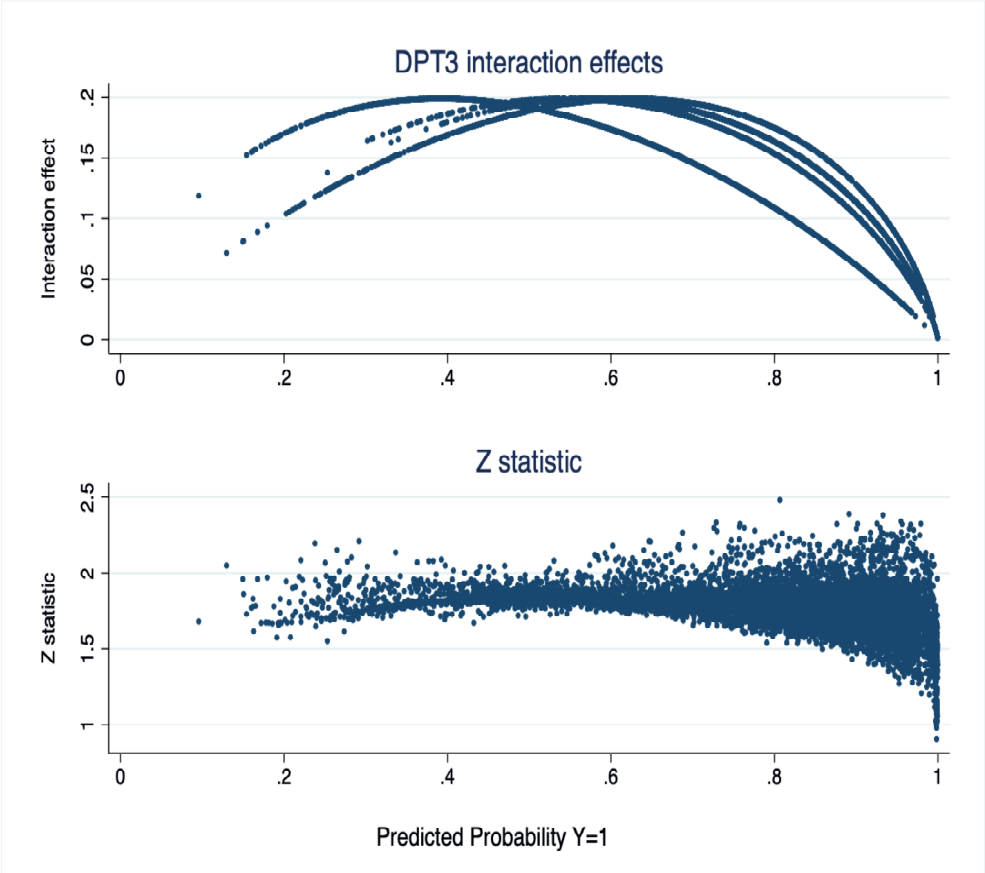
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *DPT1*=Diphtheria, Pertussis, Tetanus, dose 1.

Figure A4: DPT2 Interaction Effects



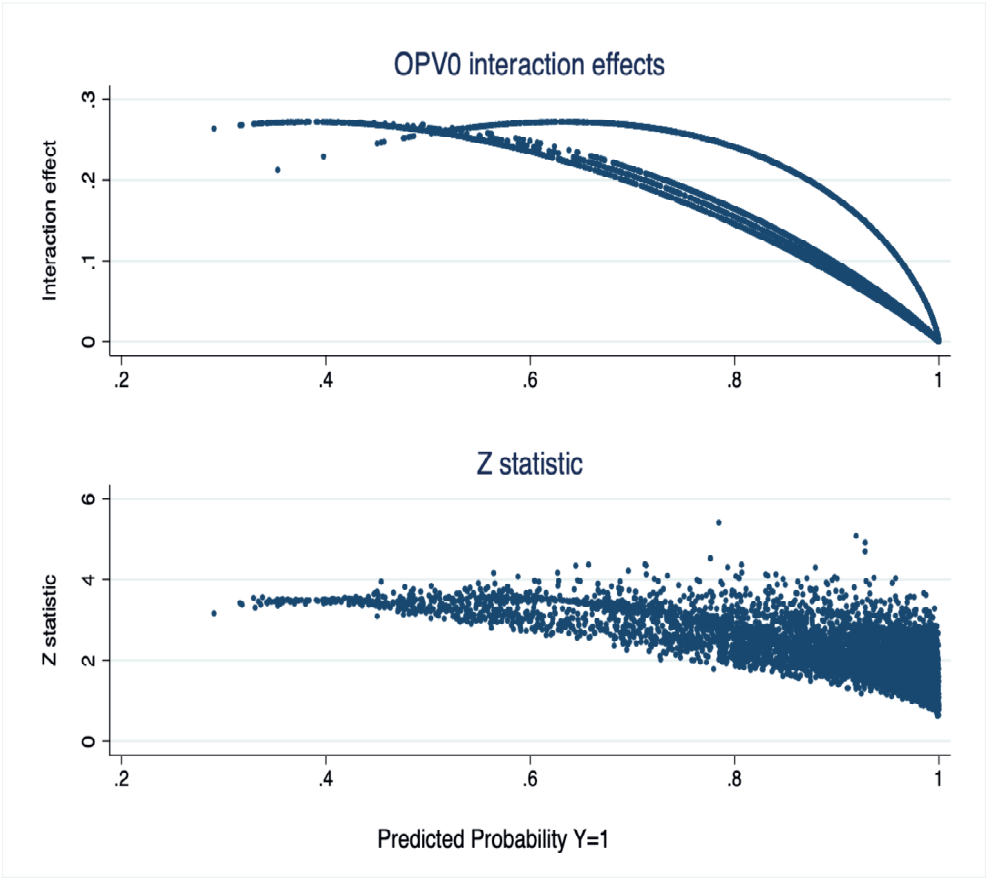
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *DPT2*=Diphtheria, Pertussis, Tetanus, dose 2.

Figure A5: DPT3 Interaction Effects



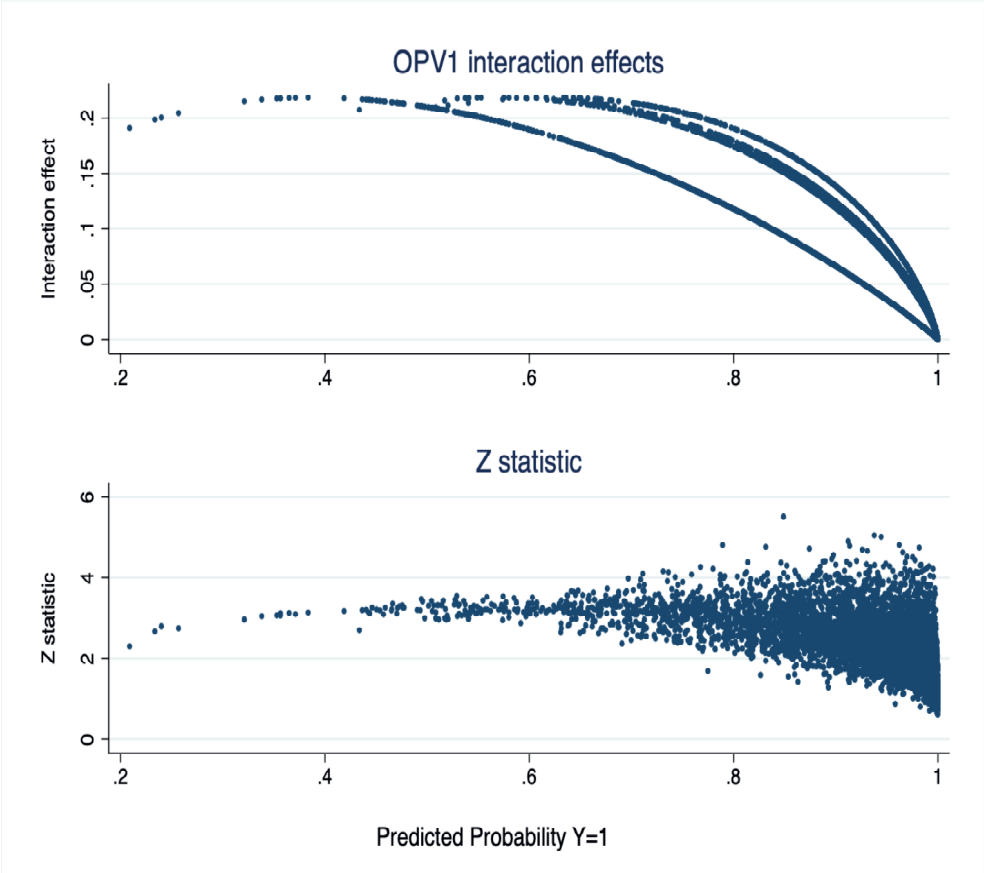
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *DPT3*=Diphtheria, Pertussis, Tetanus, dose 3.

Figure A6: OPV0 Interaction Effects



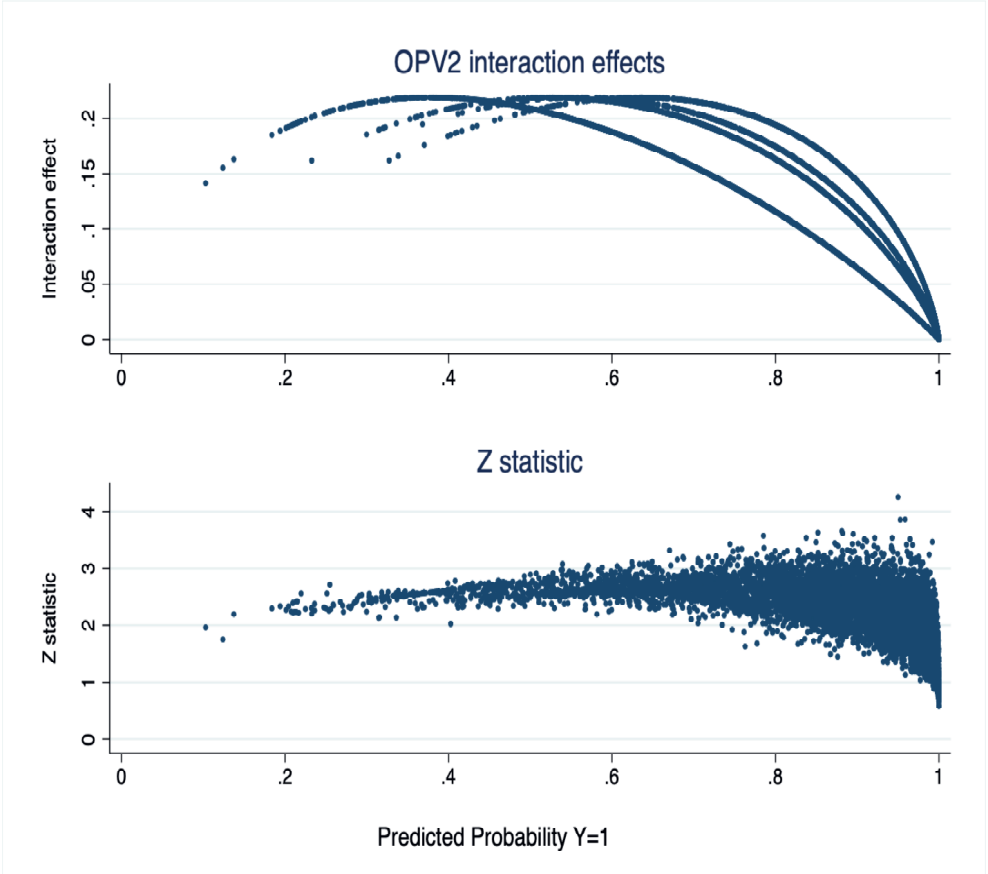
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *OPV0*=Oral Polio Vaccine, birth dose.

Figure A7: OPV1 Interaction Effects



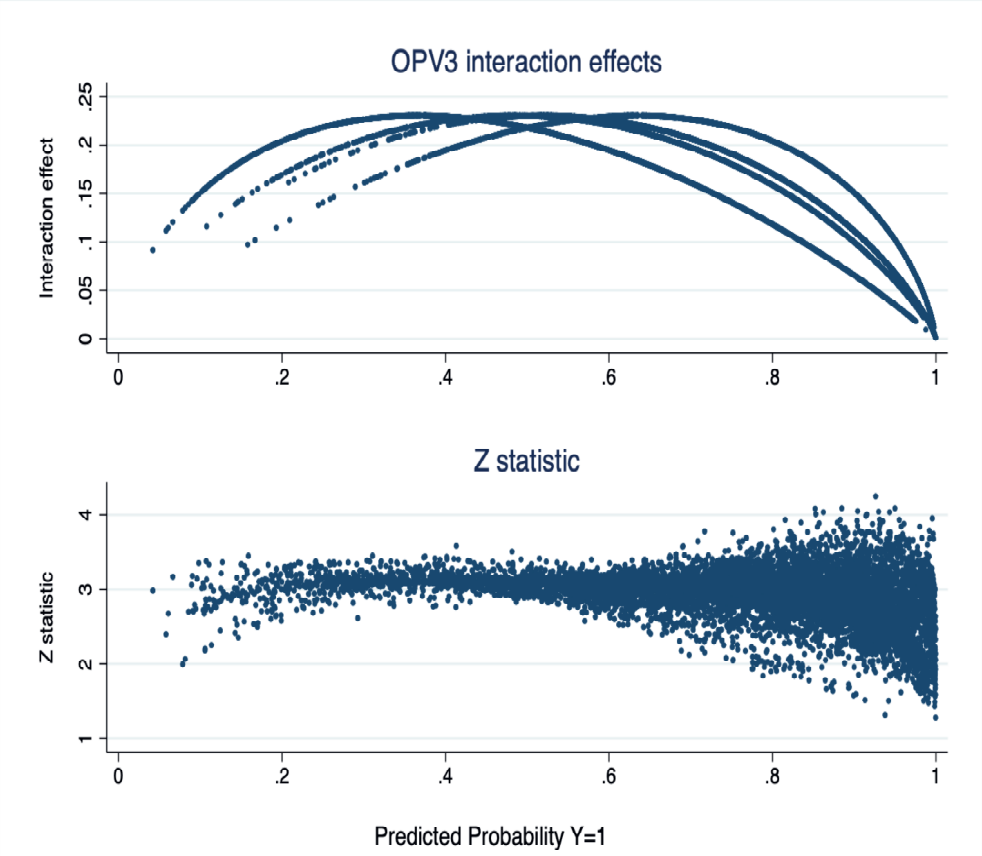
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *OPV1*=Oral Polio Vaccine, dose 1.

Figure A8: OPV2 Interaction Effects



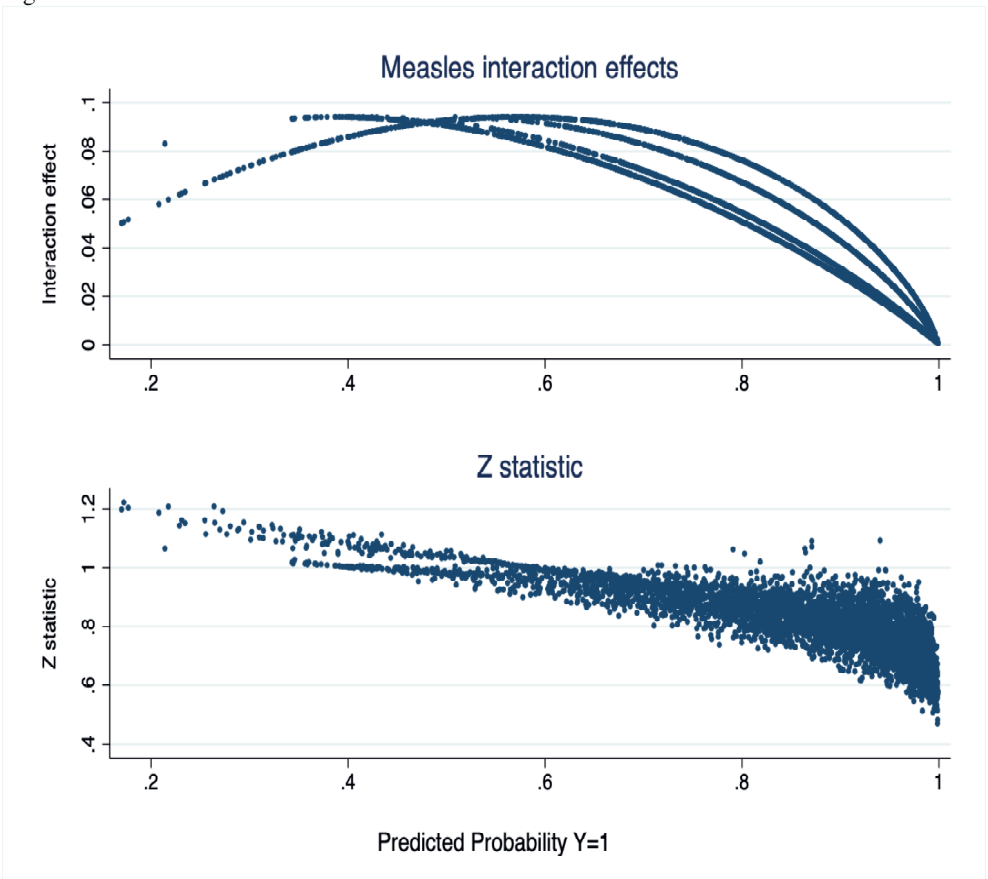
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *OPV2*=Oral Polio Vaccine, dose 2.

Figure A9: OPV3 Interaction Effects



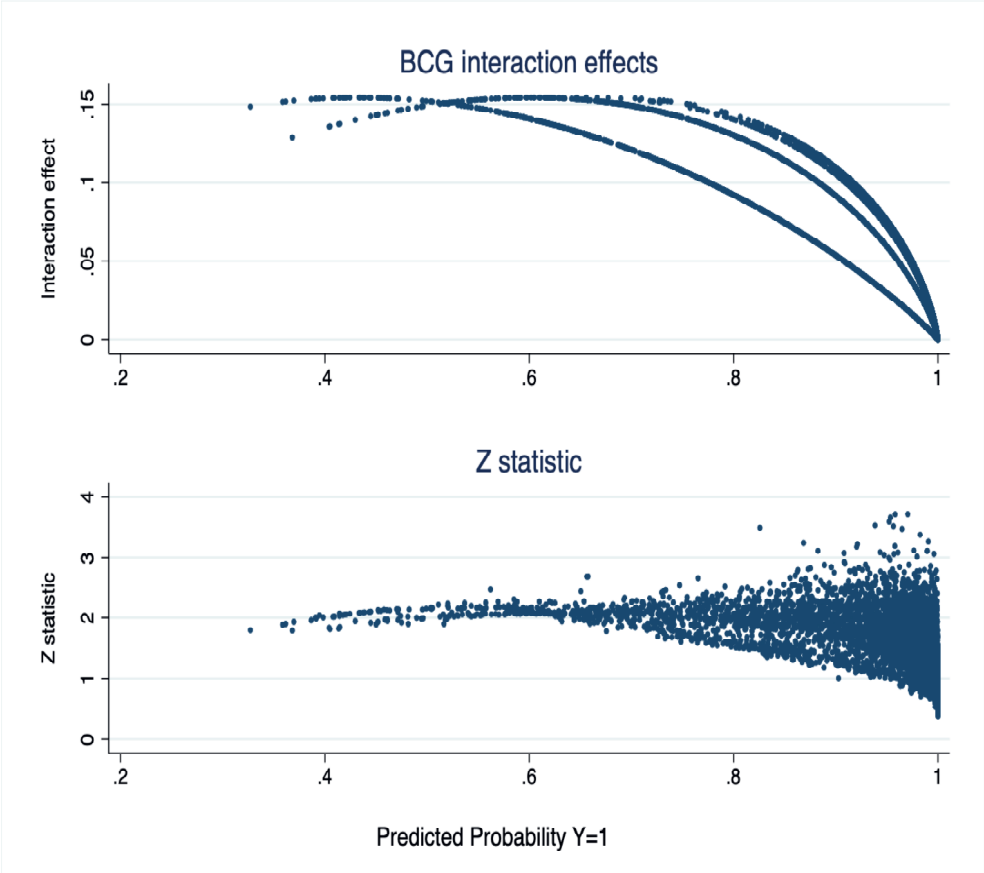
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *OPV3*=Oral Polio Vaccine, dose 3.

Figure A10: Measles Interaction Effects



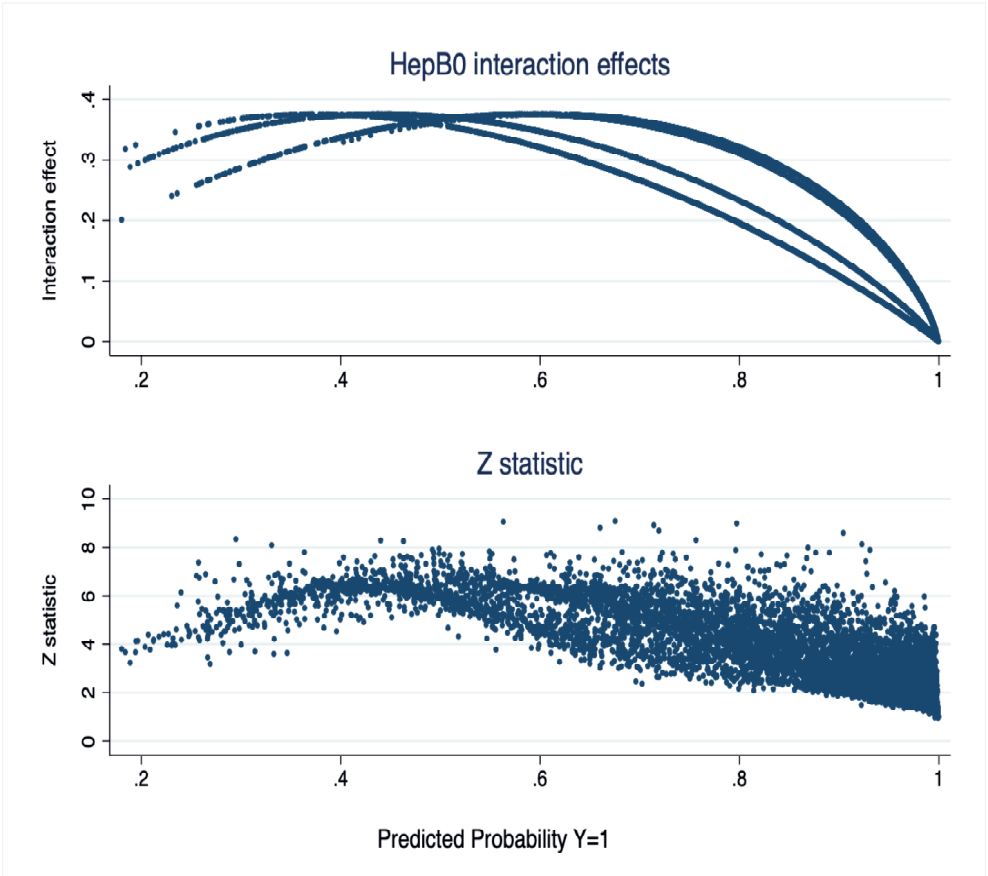
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects.

Figure A11: BCG Interaction Effects



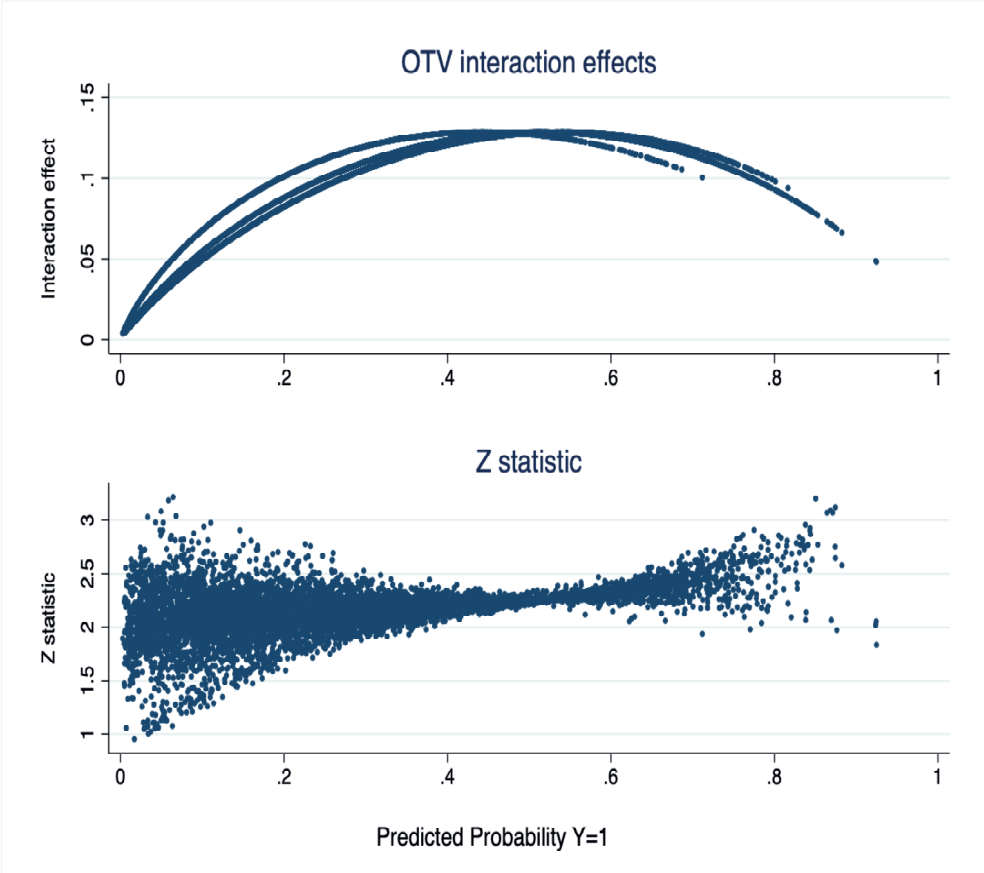
Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *BCG*=Bacillus Calmette–Guérin.

Figure A12: Hepatitis B Birth Dose Interaction Effects



Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects.

Figure A13: OTV Interaction Effects



Note: Interaction effects and significance levels from probit regression of receipt of vaccine on difference-in-difference indicators and vector of household control variables; includes district level fixed effects. *OTV*= on-time vaccination.

CHAPTER 4

4

Public health facility quality and child immunisation: A decomposition analysis

Universal coverage of routine childhood vaccines remains a challenge in many lowand middle-income countries (LMICs). In India, vaccination campaigns have increased full immunisation coverage among 12–23-month-old children from an estimated 62% in 2015-2016 to 76% in 2019-2020. Long-term improvements in coverage will likely require systemic changes to both the supply and demand sides of immunisation programs. However, the effect of health system inputs on child vaccination outcomes remains poorly quantified in India. We examined the association between the quality of public health facilities and child vaccination outcomes in rural India using data from the nationally representative Integrated Child Health and immunisation Survey (2015-2016) which covered 1,346 public primary health sub-centers and 44,571 households. We constructed two indices of sub-center quality using multiple correspondence analysis: one related to the general health infrastructure quality and the other measuring vaccine service delivery. Using probit regression, we analyzed the relationship between vaccination outcomes in children under 2 years of age and sub-center quality, controlling for household socioeconomic characteristics. Additionally, we conducted Fairlie decomposition analysis by wealth group — bottom wealth quintile relative to the top four wealth quintiles— to examine factors contributing to gaps in immunisation between rich and poor households. Infrastructure quality index was positively associated with completion of seven vaccination outcomes: full immunisation, DPT-1 (first dose of diphtheria, pertussis, and tetanus), DPT-2, DPT-3, Bacillus Calmette–Guérin (BCG), hepatitis B (birth dose), and on-time vaccination (OTV). Vaccine service delivery index was positively associated with completion of measles vaccination. The distribution of infrastructure quality contributed to increased gaps in full immunisation and OTV between rich and poor households, while greater proximity to vaccination site for poorer households reduced these gaps. Improved quality of health facilities, particularly facilities used by low-income households, may improve vaccination outcomes.

Based on: Summan, A., Nandi, A., Schueller, E., Laxminarayan, R. (2022). Child immunisation Outcomes and Public Health Facility Quality in India: A Decomposition Analysis. Vaccine, 40(16).

4.1 Introduction

Despite significant spending on childhood immunisation, many low-and middle-income countries (LMICs) have not achieved universal coverage of routine childhood vaccines. In India, vaccine-preventable diseases such as pneumonia, diarrheal diseases, measles, and meningitis accounted for more than 400,000 under-five deaths in 2015 alone.[168] Understanding the obstacles to vaccination at a local level is crucial for improving child mortality and health outcomes in India and other LMICs. Important demand-side determinants of child vaccination coverage in LMICs include household income and social status, parental knowledge, and religious and cultural beliefs.[169–177] In terms of supply-side factors, distance to immunisation session site, low quality of services, and lack of facility resources are known reasons for non-vaccination of children.[178,179] Recent policy efforts in India such as Mission Indradhanush, an effort to use a campaign mode to increase routine immunisation coverage in India have increased full immunisation coverage to an estimated 76%, [16,95] but gaps in coverage driven by both supply-side and demand-side factors persist. Rural areas of India — where 94% of children received the majority of vaccines in public health facilities — continue to lag urban areas for all vaccines.[96]

While parents report poor quality of healthcare facilities as an important deterrent to child vaccination, healthcare quality itself – and its association with vaccination coverage – remains inadequately quantified in LMICs. Previous literature has instead focused mainly on access to healthcare. For example, a recent study in India found that the availability of health center (primary health sub-center [SC] or primary health center [PHC]) or health care workers (auxiliary nurse midwives or accredited social health activists) did not significantly reduce Diphtheria, Pertussis, Tetanus (DPT) vaccination dropout rates.[41] Another study found that rural Indian children who had a hospital within 2 km of their village were 4.8% less likely to miss non-polio vaccine doses.[42] The authors found no association between the availability of a community health worker in the village and vaccination rates. A third study focused on the availability of health facility near households within the slums of Agra, India and identified a positive association with vaccination coverage.[43] In the Indian state of West Bengal, availability of health workers and equipment at SCs was found to have a positive association with month-specific vaccine coverage.[44] A study in Burkina Faso found no associations between the availability of physical and human resources at the health facility serving a community and the community's vaccination coverage.[45]

Previous studies [41,42,44] have primarily focused on access to healthcare rather than the quality of healthcare. Three of the four India-focused studies referenced above looked at the availability of a public health facility or health worker within a household's village or district but did not account for the quality of those facilities or workers,[41–43] while a fourth which focused on a state within India included very limited measures of quality[44]. In LMICs, the quality of care is a better predictor of health outcomes than access to healthcare facilities.[46,47] In 2016, an estimated five million excess deaths in LMICs were attributable to poor quality of health care alone.[46]

Measurable indicators of quality that are related to vaccination coverage rates can inform policies for immunisation program funding in India and other LMICs. We

examined the socioeconomic and healthcare quality determinants of coverage rates and timeliness of routine child immunisation in rural India. We also conducted in-depth analyses of the distribution of facility quality and its association with vaccination outcomes across income groups using decomposition methods.

4.2 Data and methods

Data

We used data from India's Integrated Child Health and immunisation Survey (INCHIS), a nationally representative, stratified, cross-sectional household survey conducted over three two-month rounds between March 2015 and April 2016.[180] INCHIS collected data on vaccination outcomes and access to public health facilities for children below the age of 24 months, and the quality of health facilities at the village level. It covered 44,571 households and 1,346 primary health SCs in 24 states. The first, second, and third rounds covered 11,683, 15,039, and 17,849 households, and 402, 436, and 508 SCs, in 83, 81, and 96 districts, respectively. Each INCHIS round collected data from 12 states; six states— Bihar, Maharashtra, Madhya Pradesh, Rajasthan, Telangana, and Uttar Pradesh — were fixed for every round and six states were rotated each survey round. States were selected to ensure representation from each region and income level. INCHIS employed three-stage stratified sampling design within each state where district, cluster (village/urban ward), and households were selected at three different stages.

We matched each household to its nearest SC. While SCs were primarily located in rural areas, some peri-urban households were reported as being served by SCs. immunisation status information of the youngest child in the household was collected from vaccination cards and through caregiver recall when cards were unavailable.

We analyzed the relationship between eight binary vaccination outcomes of children and health facility characteristics, controlling for socioeconomic indicators. Vaccination outcomes included: DPT-1 (first dose of diphtheria, pertussis, and tetanus), DPT-2, DPT-3, first dose of measles, hepatitis B given at birth (HepB), Bacillus Calmette–Guérin (BCG), full vaccination, and a measure of on-time vaccination (OTV). Table 1 describes each vaccine and the appropriate age for vaccination, according to the Indian Academy of Pediatrics.[139] We excluded children who were reported as being vaccinated before the eligibility age for a vaccine (0.6% of the sample) to reduce potential measurement errors.

A child was considered fully vaccinated if they received one dose of BCG, three doses of DPT and polio, and one dose of the measles vaccine. The OTV indicator examined the appropriate timing of the child's vaccination. We considered timely vaccination

Table 1: Description of vaccination indicators

Vaccine	Definition	Recommended age
BCG	Bacillus Calmette–Guérin	at birth
Hep B0	Hepatitis B	at birth
DPT-1	Provides vaccination against diphtheria, pertussis (whooping cough), and tetanus, and requires three doses and a fourth booster dose.	6 weeks
DPT-2		10 weeks
DPT-3		14 weeks
Measles1	First dose of measles vaccine	9 to 12 months
Fully vaccinated	A child is considered fully vaccinated when they receive one dose of Bacillus Calmette–Guérin, three doses of DPT and polio and one dose of measles. Full immunisation can occur in children as early as 9 months of age and is typically evaluated at 12 months of age.	12 months
OTV	On-time vaccination defined as child eligible for DPT-1, DPT-2, DPT-3, and full immunisation having been vaccinated 28 days after becoming eligible for the respective vaccine. Child evaluated for last vaccination they were eligible for.	See above

Source: Indian Academy of Pediatrics[139]

of DPT-1, DPT-2, DPT-3, and full immunisation. OTV had a value of 1 if the child had received the respective vaccine within 28 days after the recommended age for vaccination as described in Table 1. This is consistent with previous studies which have considered vaccination to be timely if it was done within 30 days of eligibility.[142,143] Each child was evaluated for the vaccine they were most recently eligible for resulting in one observation per child. Consider a child who was 19 weeks of age at the time of the survey. The last vaccine for which they were eligible for would be the DPT-3 dose which has an eligibility age of 14 weeks. If the child received the vaccine between 14 and 18 weeks of age, the child would be considered timely immunized for DPT-3 according to our definition. Their value of OTV would be 1. They would not be evaluated for timely vaccination of DPT-1 and DPT-2 under this definition, but only DPT-3 as it was the most recent vaccine for which they were eligible. We evaluated children who were above the age of 12 months for full vaccination; although a child can be fully immunized as early as 9 months —earliest recommended age for the measles vaccine (last vaccine received to be considered fully immunized) — the highest recommended age for measles is 12 months. In additional sensitivity analysis, we also examined the timeliness of receiving all past doses, not just the most recent dose. We constructed a composite *OTV_Cd* variable which had a value of 1 only if all four vaccinations, DPT-1, DPT-2, DPT-3, and full immunisation, were received within 28 days of eligibility age, and 0 otherwise. Also, a continuous variable varying between 0 and 1, *OTV_C*, was constructed which received an incremental value of 0.25 for each vaccine that was a received on-time.

Measures of Quality of Care at Primary Health Sub-centers

SCs are the first contact point with the public health system in rural India. There is one SC mandated for every 5,000 people (or 3,000 people for tribal or remote areas). In 2018, there were 158,417 SCs serving rural India at the rate of approximately 5,600 people per SC.[181] Each SC is staffed with at least one auxiliary nurse midwife (ANM) whose responsibilities include child immunisation activities under the UIP.[182,183] Vaccines are not always administered on-site at SCs; SC workers may be responsible for conducting immunisation sessions at outreach facilities such as an *Anganwadi* (maternal and child health and welfare center) or community health events such as the village health and nutrition day.[184,185] In INCHIS, 68% of child vaccinations were reported to be through SCs or *Anganwadi* (mother-child nutrition and welfare) centers.[183]

We employed multiple correspondence analysis (MCA) to construct two indices of the quality of care related to immunisation services in SCs – an infrastructure quality index and an immunisation service delivery index. MCA is a dimension reduction technique analogous to the commonly employed principal component analysis but for categorical data.[186] It has been applied widely to construct health and asset indices in earlier studies.[187–189] MCA analyzes the association between groups of variables by transforming all data to a matrix of all two-way cross tabulations across categorical variables (Burt matrix) or to an indicator matrix where possible variable levels are coded as binary variables.[190] The transformed data can be represented in multi-dimensional space where associations between variables are determined by the chi-squared distance across groups of variables and observations.[190] MCA identifies the key dimensions underlying this data; the first dimension can be considered as an unobserved latent variable which captures the greatest variance (known as inertia)

from the original variables.[191] The second dimension is orthogonal to the first dimension and contains the second most amount of variance, and so on. We obtained the indicator score for each facility by taking the weighted average of all categorical variables, from weights generated by MCA for the first dimension. Based on the MCA generated index scores, we assigned SCs to a tercile for each index.

The first index measured SC infrastructure quality and resource availability. This index modelled the following indicators: the cleanliness of the facility (good, fair, or poor), availability of a telephone, availability of toilet, the quality and reliability of water source (piped, bore/tube well, hand pump, well, external well, no water supply, or other water supply), and the availability of regular power supply (regular power supply, irregular power supply, regular power supply with power cut in summer, regular power cut, or no electricity). We included the following schooling indicators of village health workers who are known as the accredited social health activists (ASHAs) and tasked with improving child vaccination rates – illiterate, literate but no formal schooling, less than 8th standard (grade), 8th standard to higher secondary, and graduate or above.

The second index evaluated immunisation service delivery from 23 binary variables, each identifying whether the auxiliary nurse midwife (ANM) had experienced a shortage of essential items required for vaccination such as vaccines, syringe, and diluents, along with two basic medications (zinc tablet and paracetamol), in the last six months. Table 2 describes the variables included in the estimation of the indices. All variables used to construct the quality indices and other control variables for analysis, described below, were drawn from INCHIS data.

Probit and Fractional Probit Regression Analysis

We conducted probit regression analyses to evaluate the associations between each vaccination outcome and sub-center characteristics. The model included indicators of the top two terciles of the two SC quality indices and time taken to reach to immunisation facility as reported by households (15 to 30 minutes, and greater than 30 minutes). The model covariates also included a set of household and socioeconomic indicators that have been found to affect vaccination outcomes: region (east, north, northeast, south, or west), locality (rural or urban), wealth quintile (top four wealth quintiles), religion (Christian, Muslim, Sikh, or other religion), caste (scheduled caste, schedule tribe, or other backward caste), household size (greater than five), mother's education level (primary or lower, middle to secondary, and graduate and above), mother's age, child's age and gender, and whether the child was born in a health facility. Wealth quintile was constructed using MCA on 18 binary variables measuring ownership of assets.[180]

In sensitivity analysis we replaced the main OTV variable with the *OTV_Cd* variable which had a stricter definition of timeliness as discussed in the previous section. In addition to the probit model, we conducted a fractional probit regression

Table 2: Index components

Index	Infrastructure quality	Vaccine and equipment availability*+	
Indicators measured	ASHA education	BCG/ BCG diluent	5 ml reconstitution syringes
	Building type	DPT	Auto disable syringes
	Cleanliness	Hepatitis B	IFA Tablet (adult/kids)
	Electricity source	JE/ JE diluent	MCP Card
	Infrastructure condition	Measles/ Measles diluent	ORS Packet
	Telephone availability*	OPV	Paracetamol
	Toilet availability*	Pentavalent	Plastic spoon/cap
	Water source	TT	Red and black bags
		Zinc tablet/syrup	Vitamin A solution
Total index inputs	8	23	

*Binary variables coded yes and no indicating availability of item. +Shortage in last 6 months.
Note: *ASHA*= Accredited Social Health Activists; *BCG*= Bacillus Calmette–Guérin; *OPV*= Oral Polio Vaccine; *DPT*= Diphtheria, Pertussis, Tetanus; *TT*=Tetanus Toxoid; *JE*= Japanese encephalitis; *MCP*=Mother and Child Protection Card; *ORS*=Oral Rehydration Salt; *IFA*=Iron Folic Acid.

of *OTV_C*, the continuous composite variable evaluating timely vaccination of all vaccines, as a sensitivity analysis to the simple OTV variable, on the above variables. Standard errors were clustered at the district level, and survey weights for the child were applied to account for sampling design. Data were analyzed using STATA version 14.2, and we considered $p<0.05$ for statistical significance.

Fairlie Decomposition of Standard of Living

Standard of living - as measured by wealth quintile – is an important determinant of health and access to healthcare in LMICs.[172,183,192] Individuals in lower wealth quintiles are more likely to belong to minority caste groups, religious groups, live in rural areas, or have lower schooling levels. Public health facilities are meant to reduce such inequities in access and quality of care however, unequal distribution of public resources may be reflected in unequal distribution of health facility quality across wealth groups and exacerbate rather than reduce vaccination gaps.

We employed the Fairlie decomposition method[193] to further analyze vaccination outcomes of households in the bottom wealth quintile relative to the top four wealth quintiles. The Fairlie decomposition method is an extension of the Oaxaca-Blinder decomposition method, but for variables with binary outcomes.[194,195] It has been used to analyze differences in outcomes between groups (e.g., sex or race) for health and labor outcomes,[196–198] including in immunisation studies.[199,200] We decomposed full immunisation and timely vaccination differences between the lowest and the top 4 wealth quintile groups. The methodology is briefly described below.

We started with a probit regression model as follows:

$$\Pr\left(I_i^j = 1|X_i\right) = \omega\left(X_i{}'B^j\right) = \frac{e^{X_i{}'B^j}}{1 + e^{X_i{}'B^j}} \quad (1)$$

Where ω is the cumulative standard normal distribution function and $\mathrm{PR}(I_i)$ indicates the probability that child *i* received vaccine *j*, which is regressed upon the covariate set *X*. Regression coefficients are denoted by *B*.

Following Eq. 1, the difference in vaccination outcomes for rich and poor households can be written as follows:

$$\overline{I^R} - \overline{I^P} = \omega\left(\bar{X}^{R'}B^R\right) - \omega\left(\bar{X}^{P'}B^P\right) \quad (2)$$

Where $\overline{I^i}$ is the average probability of being vaccinated for type *i* households, $\bar{X}^{i'}$ is a vector of mean values of explanatory covariates for type *i* households and B^i is the vector of estimated coefficients for type *i* households. The two types of households considered are rich, *R*, and poor, *P*, households. By adding and subtracting counterfactual immunisation outcomes for poor households with a distribution of explanatory variables equivalent to rich households, $\omega\left(\bar{X}^{R'}B^P\right)$, Eq. 2 can be rewritten as:

$$\bar{I}^R - \bar{I}^P = \left[\omega\left(\bar{X}^{R\prime} B^R\right) - \omega\left(\bar{X}^{P\prime} B^R\right)\right] + \left[\omega\left(\bar{X}^{R\prime} B^R\right) - \omega\left(\bar{X}^{R\prime} B^P\right)\right] \quad (3)$$

The Fairlie decomposition method estimates the difference attributable to the two components. The first term in Eq. 3 is the endowment component, which is the explained difference in outcomes due to differences in distribution of the explanatory variables. It measures the difference in predicted probability of immunisation after replacing the distribution of explanatory variables in rich households to be equal to those of poorer households. The second term in Eq. 3 is the return individuals or households receive to these endowments. In health systems studies, this latter component can be attributed to structural differences in how health systems benefit different groups.[196–198]

4.3 Results

3.1. Summary statistics of the study sample

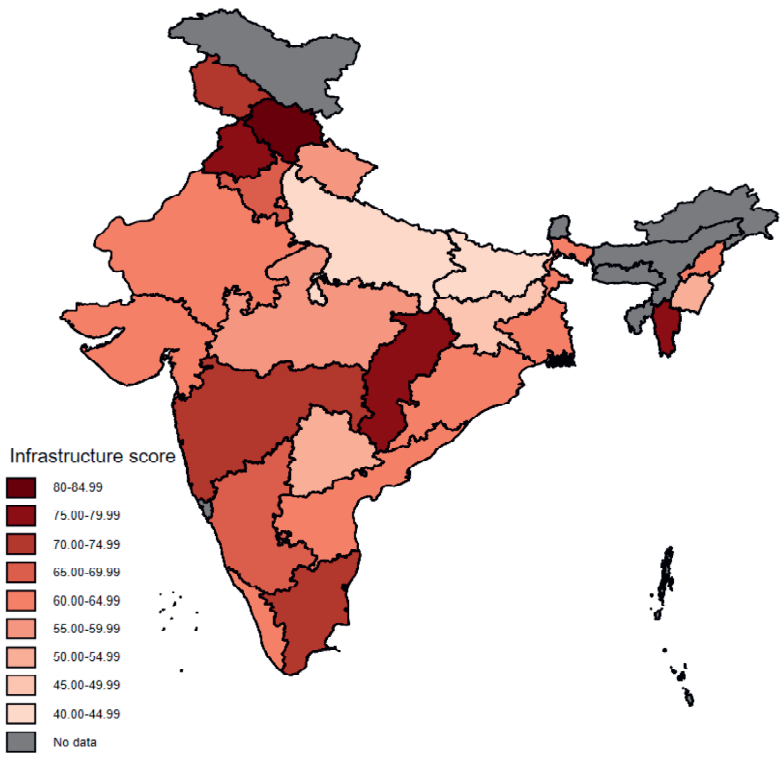
Table 3 shows vaccination status by background socioeconomic and demographic characteristics and quality of household's SC. Children in the highest and lowest wealth quintiles had substantial differences in full vaccination rates, 80% and 58%, respectively. Children with mothers who had graduate degrees had 75% coverage of full vaccination as compared with 59% among children whose mothers had no schooling. There was also a large urban-rural divide in vaccination rates — rural children had 80% full vaccination coverage as compared with 66% among urban (peri-urban areas) children. Children with access to an SC in the highest tercile for vaccine service delivery and infrastructure quality index had full vaccination rates of 69% and 74%, in comparison with 67% and 63% full vaccination coverage, respectively, for children who had access to an SC in the lowest tercile. Infants from socioeconomically disadvantaged tribal groups (scheduled tribe), Muslim, and Christian households, and those born at home also had lower vaccination rates when compared with the respective reference groups.

Figures 1 and 2 show the distribution of infrastructure quality score and vaccine delivery score of SCs across states. The MCA score was standardized between 0 and 100 and averaged using state household weighting for the figures. The infrastructure quality score ranged from 42 in Uttar Pradesh to 83 in Himachal Pradesh, and the vaccine service delivery score varied from 43 in Manipur to 100 in Delhi.

3.2. Probit Regression Results

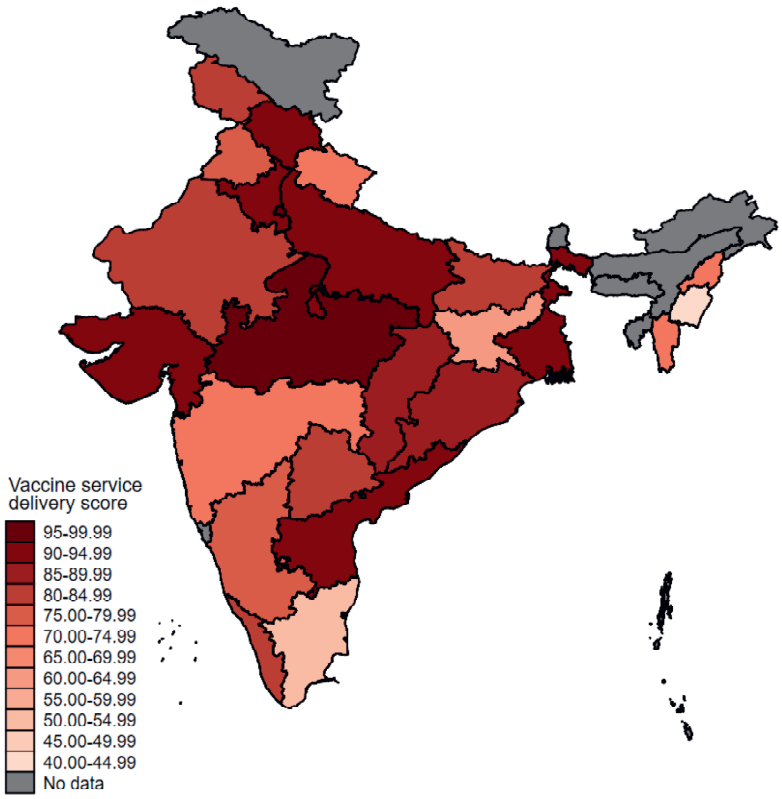
Table 4 presents the results of the probit regression. In comparison with children whose SC's infrastructure quality index score was in the lowest tercile, children whose SC's score was in the highest tercile had significantly higher rates vaccination for all vaccines except for measles. Full vaccination and OTV were 1.19 (95% confidence interval [CI]: 1.02 - 1.38, $p<0.05$) times and 1.2 (CI: 1.06 - 1.37, $p<0.05$) times higher for children residing in districts with SC in highest tercile of infrastructure index relative to those in the first tercile, respectively. Children whose SC's infrastructure quality index score was in the second tercile had significantly

Figure 1: Infrastructure quality score of sub-centers across states in India



Note: Map coordinate data are from Database of Global Administrative Areas, version 2.8 (2015). Colors denote the mean state score of infrastructure quality constructed using multiple correspondence analysis, where sub-center scores were standardized to be between 0 and 100. Scores were averaged using state household weights.

Figure 2: Vaccine service delivery score of sub-centers across states in India



Note: Map coordinate data are from Database of Global Administrative Areas, version 2.8 (2015). Colors denote the mean state score of vaccine service delivery score constructed using multiple correspondence analysis, where scores were standardized to be between 0 and 100. Scores were averaged using state household weights.

Table 3: Background characteristics of study children by vaccination status (%)

	Full		DPT-1		DPT-2		DPT-3		Measles		BCG		Hepatitis B		OTV	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Vaccine Availability Score																
1	33	67	14	86	20	80	30	70	21	79	6	94	20	80	39	61
2	34	66	16	84	23	77	35	65	22	78	8	92	21	79	42	58
3	31	69	12	88	19	81	30	70	17	83	5	95	16	84	38	62
Infrastructure Score																
1	37	63	18	82	25	75	38	62	24	76	9	91	26	74	46	54
2	30	70	13	87	19	81	30	70	19	81	5	95	17	83	37	63
3	26	74	9	91	14	86	24	76	16	84	3	97	10	90	32	68
Region																
Central	35	65	10	90	19	81	33	67	14	86	3	97	11	89	41	59
East	24	76	12	88	16	84	25	75	14	86	3	97	17	83	32	68
North	43	57	21	79	29	71	43	57	29	71	12	88	30	70	51	49
Northeast	41	59	16	84	22	78	33	67	25	75	10	90	32	68	44	56
South	22	78	4	96	8	92	17	83	17	83	1	99	2	98	25	75
West	30	70	13	87	19	81	30	70	20	80	6	94	14	86	36	64
Sex																
Male	32	68	14	86	20	80	32	68	20	80	6	94	19	81	39	61
Female	33	67	15	85	21	79	32	68	21	79	6	94	19	81	40	60
Locality																
Rural	34	66	15	85	21	79	33	67	21	79	7	93	20	80	41	59
Urban	20	80	8	92	13	87	20	80	15	85	2	98	12	88	27	73
Wealth Quintile																
1	42	58	21	79	29	71	41	59	27	73	10	90	28	72	49	51
2	31	69	13	87	20	80	32	68	18	82	6	94	18	82	39	61
3	28	72	10	90	16	84	27	73	18	82	4	96	14	86	34	66
4	25	75	8	92	13	87	23	77	16	84	2	98	10	90	31	69
5	20	80	7	93	12	88	21	79	12	88	2	98	10	90	28	72
Religion																

Hindu	31	69	13	87	20	80	31	69	19	81	6	94	18	82	39	61
Muslim	40	60	20	80	27	73	38	62	29	71	10	90	26	74	46	54
Christian	38	62	14	86	20	80	29	71	20	80	7	93	20	80	38	62
Sikh	12	88	5	95	11	89	18	82	6	94	4	96	6	94	22	78
Other	30	70	6	94	14	86	27	73	15	85	3	97	22	78	36	64
Caste																
General	28	72	13	87	18	82	28	72	18	82	6	94	18	82	35	65
Scheduled Tribe	39	61	15	85	22	78	36	64	18	82	5	95	17	83	44	56
Other Backward Caste	33	67	15	85	21	79	33	67	22	78	7	93	20	80	40	60
Scheduled Caste	33	67	13	87	21	79	32	68	21	79	6	94	19	81	40	60
Education																
No Schooling	41	59	21	79	28	72	40	60	26	74	10	90	27	73	48	52
Primary Or Lower	31	69	12	88	19	81	31	69	18	82	5	95	15	85	38	62
Middle To Secondary	25	75	10	90	15	85	25	75	16	84	4	96	15	85	33	67
Graduate	25	75	6	94	12	88	23	77	14	86	2	98	11	89	33	67
Household Size																
< 5	29	71	12	88	18	82	29	71	19	81	5	95	16	84	37	63
> 5	34	66	15	85	21	79	33	67	21	79	7	93	20	80	41	59
Place of Birth																
Institutional	29	71	12	88	18	82	29	71	17	83	4	96	14	86	37	63
Non-Institutional	45	55	24	76	32	68	45	55	31	69	14	86	37	63	52	48
Distance to Vaccination Site																
< 15 Minutes	30	70	13	87	19	81	30	70	18	82	6	94	19	81	37	63
15 To 30 Minutes	34	66	14	86	21	79	32	68	21	79	6	94	19	81	40	60
> 30 Minutes	36	64	20	80	25	75	35	65	22	78	7	93	20	80	43	57
Observations	11898		23863		23092		22302		16259		24508		24508		22139	

Note: Data are from INCHIS 1, 2, and 3 surveys. Numbers are percentages for each vaccination outcome binary indicator e.g., whether fully vaccinated (yes/ no). *Full*= 1 dose BCG and measles, 3 doses of DPT and polio; *HepB*=Hepatitis B given at birth; *DPT*=Diphtheria, Pertussis, Tetanus; *BCG*=Bacillus Calmette–Guérin; *OTV*= On-time vaccination – considers timely vaccination of DPT and full immunisation.

Table 4: Probit Results of Immunisation and Health Facility Characteristics

Model	1	2	3	4	5	6	7	8
Vaccine	Full	DPT-1	DPT-2	DPT-3	Measles	BCG	HepB	OTV
Vaccine availability score = 1								
2	1.11	1.04	1.01	1.02	1.13	1.02	1.1	1.08
	0.09	0.07	0.07	0.06	0.09	0.1	0.07	0.06
3	1.17+	1.11+	1.09	1.09	1.21*	1.13	1.13	1.07
	0.1	0.07	0.07	0.07	0.1	0.09	0.08	0.07
Infrastructure score = 1								
2	1.14	1.15*	1.12+	1.14*	1.11	1.27**	1.24**	1.12
	0.1	0.06	0.07	0.07	0.07	0.11	0.07	0.08
3	1.19*	1.17*	1.18**	1.20**	1.13	1.22*	1.34**	1.20**
	0.09	0.07	0.07	0.07	0.09	0.12	0.09	0.08
Region (Central=1)								
East	1.60**	1.1	1.27*	1.42**	1.37**	1.39**	0.95	1.50**
	0.19	0.11	0.13	0.16	0.12	0.16	0.08	0.15
North	0.93	0.75**	0.83+	0.85	0.78**	0.68**	0.61**	1.05
	0.11	0.07	0.08	0.1	0.07	0.08	0.05	0.11
Northeast	0.96	1.02	1.06	1.07	0.78+	0.77	0.50**	1.42*
	0.17	0.17	0.17	0.16	0.12	0.2	0.11	0.22
South	1.25	1.44*	1.48**	1.45*	0.92	1.35	1.74**	1.13
	0.24	0.21	0.21	0.22	0.16	0.25	0.28	0.15
West	1.12	0.82	0.89	0.99	0.84+	0.67**	0.77*	1.08
	0.13	0.1	0.1	0.11	0.08	0.1	0.09	0.12
Age of Mother	1	1	1	1	1	1	1	1.01
	0	0	0	0	0.01	0.01	0	0
Sex (Male=1)								
Female	0.99	1	1.03	1	0.98	1.09*	1.02	0.97
	0.04	0.04	0.03	0.02	0.03	0.04	0.04	0.03
Locality (Rural=1)								
Urban	1.22+	1.06	1.07	1.13	1.09	1.02	0.96	1.08
	0.13	0.1	0.09	0.12	0.11	0.16	0.09	0.08
Age of Child	1	1.01**	1.01**	1.01**	1.02**	1.01**	1.01**	1.03**
	0	0	0	0	0	0	0	0
Wealth Quintile (1=1)								
2	1.22**	1.19**	1.18**	1.14**	1.20**	1.11+	1.16**	1.21**
	0.06	0.06	0.06	0.05	0.05	0.07	0.05	0.06
3	1.19**	1.16*	1.19**	1.12**	1.18**	1.27**	1.17*	1.15*
	0.08	0.07	0.07	0.05	0.07	0.08	0.07	0.07
4	1.23*	1.30**	1.32**	1.24**	1.26**	1.47**	1.35**	1.22**
	0.1	0.11	0.1	0.09	0.1	0.14	0.11	0.08
5	1.54**	1.33**	1.39**	1.34**	1.53**	1.48**	1.40**	1.35**
	0.15	0.11	0.12	0.09	0.14	0.16	0.12	0.09
Religion (Hindu=1)								
Muslim	0.83*	0.84*	0.82*	0.9	0.78**	0.85	0.84*	0.83**
	0.06	0.07	0.07	0.07	0.06	0.11	0.06	0.05
Christian	0.76*	0.79+	0.74**	0.84	0.91	0.64*	0.85	0.84*
	0.09	0.1	0.08	0.09	0.11	0.13	0.13	0.07
Sikh	1.62*	1.44*	1.23	1.43+	1.58+	1.09	1.54*	1.20+

	0.35	0.25	0.24	0.3	0.41	0.18	0.27	0.11
Other	0.84	1.19	1.01	0.9	0.82	0.82	0.59*	0.9
	0.13	0.21	0.2	0.12	0.17	0.16	0.14	0.13
Caste (General=1)								
Scheduled tribe	0.84	0.88	0.92	0.82*	1.11	1.24+	1.01	0.80*
	0.09	0.09	0.08	0.07	0.11	0.16	0.09	0.07
Other backward caste	1.01	1.03	1	0.98	0.99	1.06	1.04	0.95
	0.08	0.09	0.06	0.06	0.08	0.14	0.08	0.05
Scheduled caste	0.97	1.09	0.98	0.98	0.98	1.13+	1.08	0.92
	0.06	0.07	0.06	0.06	0.09	0.08	0.06	0.05
Education (No schooling =1)								
Primary or lower	1.15**	1.20**	1.20**	1.14**	1.16**	1.17**	1.23**	1.10*
	0.06	0.06	0.06	0.05	0.06	0.07	0.07	0.05
Middle to Secondary	1.22**	1.28**	1.27**	1.22**	1.13**	1.25**	1.12*	1.16**
	0.07	0.07	0.06	0.06	0.05	0.08	0.06	0.06
Graduate	1.17	1.67**	1.43**	1.26**	1.20+	1.47*	1.26*	1.11
	0.13	0.15	0.13	0.1	0.12	0.23	0.13	0.09
Household size (<5=1)								
> 5	0.93+	0.99	1.01	1.01	0.97	0.94	0.95	0.96
	0.04	0.04	0.04	0.03	0.05	0.05	0.04	0.03
Institutional Delivery (Institutional=1)								
Non-Institutional	0.80**	0.77**	0.78**	0.78**	0.73**	0.62**	0.57**	0.84**
	0.05	0.04	0.04	0.04	0.04	0.06	0.04	0.05
Distance to vaccination center (< 15 minutes=1)								
15 to 30 minutes	0.86**	0.92+	0.92*	0.92*	0.85**	0.98	0.99	0.89**
	0.05	0.04	0.03	0.03	0.05	0.05	0.04	0.04
> 30 minutes	0.77**	0.71**	0.78**	0.85**	0.78**	0.87+	0.96	0.86**
	0.06	0.04	0.05	0.05	0.06	0.07	0.06	0.04
Observations	11461	22104	21333	20543	15179	22749	22749	20613
Pseudo R^2	0.063	0.111	0.114	0.094	0.098	0.156	0.141	0.269
P-value for c2	0	0	0	0	0	0	0	0

Note: *Full*= 1 dose BCG and measles, 3 doses of DPT and polio*; HepB*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin; *OTV*= On-time vaccination – considers timely vaccination of DPT and full immunisation. Standard errors are below coefficients. +p<0.1, *p<0.05, **p<0.01

higher vaccination rates for DPT-1, DPT-3, BCG, and HepB relative to the lowest tercile. In comparison with the same reference group, children whose SC's vaccine service delivery index score was in the third tercile had significantly higher rates of vaccination for measles (adjusted odds ratio [AOR]=1.21, CI: 1.03 - 1.42, p<0.05) Regarding other covariates, wealth quintile of household and maternal education level showed a significantly positive association with child vaccination outcomes. Non-institutional delivery of child and greater distance to vaccination site of household were significantly negatively associated with vaccination outcomes. Children from Muslim and Christian households had significantly lower levels of vaccination relative to Hindu households.

Sensitivity Analysis

Analysis with alternative definitions of the OTV variable, where timely receipt of all eligible DPT vaccines and full immunisation was evaluated instead of the last eligible vaccine, found infrastructure quality index continued to be significantly positively associated with these alternative definitions of OTV — with AORs of 1.19 (95% CI: 1.02 – 1.38) and 1.11 (95% CI: 1.05-1.17), respectively. Across the three INCHIS rounds, 37% of households did not have a verified vaccination card for the child and vaccination outcomes were reported by the mother or caregiver. In additional analyses, we excluded these observations and found that the infrastructure quality index was still significantly associated with DPT-2, DPT-3, BCG, HepB, and OTV vaccine outcomes. However, infrastructure quality index was not significantly associated with full vaccination and DPT-1 vaccination, and the vaccine service delivery index was not significantly associated with measles vaccination anymore.

Fairlie Decomposition Results

Table 5 shows the results of the Fairlie decomposition analysis for the poorest households (those in wealth quintile 1, or WQ1) relative to other households (WQ2-WQ5) for full immunisation and OTV. The difference in full vaccination and OTV rates between WQ1 and WQ2-WQ5 was 13% for full immunisation and 5% for OTV. The unexplained gap — gap not explained by differences in the distribution of included covariates — between WQ1 and WQ2-WQ5 households was 56% and 29% for full immunisation and OTV, respectively. The unexplained gap is due to structural differences in the returns to covariates across wealth groups.

The infrastructure quality index score of household's SC contributed to a widening gap in full immunisation and OTV rates between WQ1 and WQ2-WQ5 households, 5% and 11% of the total gap, respectively. For full immunisation and OTV, differences in locality (urban vs. rural residence), institutional delivery rates, and maternal education levels, contributed to a wider gap between WQ1 and WQ2-WQ5 households. Differences in maternal education between rich and poor households contributed most to explaining vaccination differences, 22% of the total gap for full immunisation and 25% for OTV. Differences in distance to vaccination site contributed to a decreased gap (1%) in full vaccination outcomes and age of child contributed to a reduction in gap in OTV between WQ1 and WQ2-WQ5 households.

4.4 Discussion

Missed child vaccinations in India continue to cause large burdens of preventable mortality and morbidity. In 2019-20, 76% of Indian children of age 12-23 months were fully vaccinated; state-wise, full vaccination rates ranged from 58% in Nagaland to 91% in Odisha.[16] Sub-national differences in vaccination rates contribute to higher child mortality in some states – in 2015, there were 10 deaths per 1,000 under-5 children in the Southern states, as compared with 40 deaths per 1,000 under-5 children in Northeastern states.[168] It is critical to understand the modifiable drivers of under-vaccination in India to decrease premature mortality.

Table 5: Decomposition of rural-urban gap in vaccination outcomes

Covariates	Full	OTV
Region	0.0080+	-0.0071*
	0.0047	0.0032
Locality	0.0074**	0.0038*
	0.0026	0.0019
Religion	0.0009	0.0012+
	0.0011	0.0007
Caste	0.0029	0.0034+
	0.0027	0.0019
Age of Mother	-0.0039+	-0.0022+
	0.0022	0.0012
Sex	0	0
	0.0002	0.0001
Age of Child	0	-0.0177**
	0.0001	0.0004
Distance to sub-center	-0.0018*	-0.0005
	0.0007	0.0003
Maternal Education	0.0295**	0.0178**
	0.0066	0.005
Household Size	-0.0002	0.0001
	0.0002	0.0001
Institutional Delivery	0.0102*	0.0068*
	0.0044	0.0031
Infrastructure score	0.0073*	0.0077**
	0.0033	0.0022
Vaccine availability score	-0.0008	0.0004
	0.0021	0.0012
Total Gap	0.13	0.07
Explained Gap	0.059571	0.01
Explained Gap (%)	44	21
Sample size	12793	23000

Note: *Full*= 1 dose BCG and measles, 3 doses of DPT and polio*; OTV*: On-time vaccination – considers timely vaccination of DPT and full immunisation. Standard errors are below coefficients. +p<0.1, *p<0.05, **p<0.01

While parents often report poor healthcare facility quality as a reason for not vaccinating their children, the association of health facility quality and vaccination remains largely unquantified in LMICs. Past studies have focused on access to care — availability of health facility or health workers — whereas the quality of care is known to be a more appropriate indicator of health outcomes.[46,47] For example, a recent study in India looked at the proximal availability of a health facility and health care workers and found no effect on DPT vaccination dropout rates.[41] Another

study in rural India looked at household proximity to a hospital and found a positive effect on vaccination rates but no effects of availability of community health workers on vaccination rates.[42] A third study focused on the slums of Agra, India, and found availability of health facility near households was positively associated with vaccination coverage.[43] In West Bengal, authors found that the availability of health workers and equipment at SCs was positively associated with month-specific vaccine coverage, while they found no effect of recent visit of supervisor to SC and the proportion of auxiliary nurses and midwives with immunisation training in the SC.[44] In Burkina Faso, a study found no association between physical and human resources availability in health facilities and the community's vaccination coverage.[45] Our findings move beyond these indicators of access and show that indicators of quality of health facilities are associated positively with vaccination outcomes.

A study similar to ours conducted in Pakistan found no association between district level indicators of healthcare staff availability and their knowledge, budget, and equipment, and child vaccination rates.[175] While our analysis is at the household level, the Pakistan study used aggregated district level data which may have omitted important variations at the household or individual level. Another major difference between our studies is their use of individual facility indicators as independent variables (e.g., syringe availability, budget, and number of staff visits made), whereas we used a composite index to measure infrastructure quality and equipment and vaccine availability.

An additional contribution of our study is examining the interplay of facility quality and household standard of living using a decomposition technique. While public health resources are meant to aid the most underserved communities which cannot access private sector healthcare, we found that lower income households had access to lower quality health facilities than higher income households, demonstrating a failure in the equitable distribution of public health resources. We did however find that the average distance to the closest health facility was smaller for lower income households and it decreased the gap in vaccination between income groups.

Our results have several policy implications. Health infrastructure quality in our study — measured by components of physical infrastructure (availability of regular power source, washroom, and building materials), observational assessment of the building by the surveyor, and ASHA education —was a proxy for overall facility resource availability and was positively associated with vaccination outcomes. The estimated associations were similar in magnitude to those of wealth quintile and maternal education indicators. This suggests that health infrastructure, including well-trained health workers, equipment, and facilities, could improve vaccination outcomes at the same rate as improvements in standard of living or maternal schooling.[169] In addition, vaccine service delivery quality – as measured by the availability of vaccines and associated medical supplies – may improve the coverage of measles vaccine more as compared with the physical infrastructure of SCs. This might be related to the timing of vaccine doses – in our analysis, the measles vaccine is the last vaccine (at age 9-12 months). One hypothesis may be that receipt of vaccines later in the series may depend more on the availability of vaccines and associated supplies instead of the general infrastructure of the SC as households have lesser contact with the health system as a child ages.

On the demand side, access to health facilities may play an important role in the household decision-making process related to child immunisation. Over 24% of respondents gave one of

the following as a reason for not vaccinating their children in INCHIS: not knowing benefits of vaccines, vaccination schedule, or distance to the vaccination site; and not having enough time to take child to vaccination site. Reasons directly related to health infrastructure for not vaccinating their child were vaccination site was too far (9%), vaccination site was unhygienic (3%), vaccine was not available (11%), and the ANM was not available (10%).

In our decomposition analysis, overall infrastructure quality contributed to an increasing gap in full immunisation and OTV between rich and poor households. This suggests that richer households are serviced by SCs that have greater overall infrastructure and financing relative to SCs near poorest households. The distance to SC, which is associated positively with vaccination, was shorter for the poorest households on average and decreased the gap in vaccination. Therefore, while greater proximity of facilities to poorer households or a greater number of facilities existing in low-income districts contributes to decreasing vaccination disparities, there needs to be an increased investment in the infrastructure of these facilities. However, the UIP annual budget currently at $2 billion[131] is underfunded — estimates suggest annual budgetary shortfalls ranging from $7.9 to $50.2 million (INR 56 crore to INR 3,537 crore, 1 USD= INR 70.52) during 2013-2017.[132] More recent estimates from a 2021 study suggest an additional $560 million would be required annually to increase child vaccination rates to 90%.[123] These shortfalls may increase as new vaccines are introduced (e.g. pneumococcal conjugate vaccine) and universalized, and as GAVI funding to the immunisation program decreases annually post-2017.[132]

Travel time to vaccination site was negatively associated with vaccination status in our results. Therefore, construction of more SCs to ensure easy access for all populations should be considered. These can be supplemented with more outreach immunisation sessions for hard-to-reach populations. Furthermore, to reduce travel time to vaccination sites investments in physical infrastructure such as paved roads and the availability of public transportation should be assessed, especially for rural areas.[201] The opportunity cost to travel to these vaccinations sites, particularly for the poor who lag in vaccination the most, may be too high if the site is prohibitively far.[179] These considerations should inform the location and timing of future vaccination centers to ensure equitable and timely access to vaccination in underserved communities. Additionally, we found large gaps in vaccination coverage across socio-economic subgroups in our study, consistent with past research.[172,183,192] Low-income and poorly educated households, as well as Muslim, Christian, and scheduled tribe households, continue to have worse vaccination outcomes, and vaccination efforts should target these groups.

Our study has important limitations. First, we used cross-sectional data which could be biased by selective program placement. For example, low-initial immunisation coverage districts may have received additional resources to improve infrastructure to bolster vaccination rates, which could bias our coefficient on infrastructure quality index downwards. Conversely, richer communities with more political clout may have received more infrastructural resources — previous research have shown that public goods allocation in India can be often political.[202,203] This would bias the estimated coefficients upwards as wealthier households tend to have higher levels of immunisation. Future research should use longitudinal data to identify causal effects.

Second, we examined the quality of SC primarily through physical infrastructure quality and equipment availability, with the exception of ASHA education. Other measures of immunisation delivery quality such as process quality can be included in future research.[204]

Third, we matched each household with the sub-center in its own geographical cluster. This is the officially designated SC serving that household; however, it may be possible that households went to SC in other clusters if those centers were geographically closer to them. Use of data where the actual SC visited is identified may be desirable in future research. Lasty, there may have been measurement error due to surveyor bias. While many of the facility quality indicators were based on objective measures (e.g., availability of vaccines), some indicators were based on the surveyor's objective assessment of the state of the facility (e.g., cleanliness of the facility). However, potential inconsistencies across interviewers should have been minimized by training —all surveyors were presented with extensive instruction on the administration of the questionnaire and a training manual to specifically ensure uniformity across surveyor methods.[180]

Immunization is a cost-effective tool for decreasing the high child mortality burden in India and other LMICs. This paper provides recent data on immunisation outcomes and an analysis of the socio-economic and demographic groups that remain most vulnerable to being unvaccinated. It also adds to the limited research on the association of immunisation outcomes with health infrastructure quality, showing that health facility quality could be an important determinant of immunisation and the distribution of resources for health facilities can be better targeted towards more vulnerable groups.

CHAPTER 5

The effects of COVID-19 on child vaccination in India

The COVID-19 pandemic has disrupted health systems, including childhood immunisation delivery, globally. We estimated the effect of the pandemic on the timeliness and coverage of routine childhood immunisation in India using data from India's fifth National Family Health Survey (NFHS-5), conducted between June 2019 and April 2021. NFHS-5 included immunisation data on under-five children from a nationally representative sample of households. We used a mother fixed-effects regression model – which accounted for secular trends and household-level varying confounders – to compare immunisation outcomes of COVID-affected and COVID-unaffected siblings (n=59,506). Children who were eligible for a vaccine after January 30, 2020 (date of the first COVID case in India) were considered as the COVID-affected group and those eligible for a vaccine before this date were included in the COVID-unaffected group. Nine vaccines were considered—Bacillus Calmette–Guérin (BCG), hepatitis B birth dose (hepB0), DPT1 (diphtheria, pertussis, and tetanus, first dose), DPT2, DPT3, polio1, polio2, polio3, and measles first dose (MCV1). A child was considered to have been timely vaccinated if they received the vaccine within 45 days of minimum eligibility. Children who were eligible for a vaccine after January 30, 2020 (date of the first COVID case in India) were included in the COVID-affected group. Coverage rates were significantly lower in COVID-affected children for all vaccines except for MCV1 which did not have a significant change, and ranged from 2% lower for BCG and hepB0 to 9% for DPT3 and 10% for polio3, as compared with the unaffected children. Reduction in coverage rates were greater for higher dose vaccines. The likelihood of timely vaccination was lower among COVID-affected children relative to unaffected children for the polio and DPT vaccines, ranging from 3% to 5%. Reduction in vaccination coverage rates in the COVID-affected group were highest among male children and those from rural areas, relative to their unaffected counterparts. Indian children experienced lower routine immunisation coverage and higher delays in vaccination during the COVID-19 pandemic.

Based on: Summan, A., Nandi, A., Shet, A., Laxminarayan, R. (2022). The effect of the COVID- 19 pandemic on routine child immunization coverage and timeliness in India: Retrospective analysis of the National Family Health Survey of 2019–2021 data. The Lancet Regional Health – Southeast Asia

5.1 Introduction

The COVID-19 pandemic has adversely affected healthcare access around the world, with 15 million excess deaths attributed to its direct and indirect effects.[205] Over 90% of countries that provide health systems information to the World Health Organization (WHO) were reporting disruptions to essential healthcare programs at the end of 2021, and the proportion of countries reporting disruptions in routine immunisation programs increased from 33% to almost 50% between the first and fourth quarters of 2021.[21]

Childhood immunisation prevents the spread of infectious diseases, reducing associated morbidity and mortality. By preventing disease episodes during the first 1000 days of life – a crucial developmental phase for young children – immunisation can also improve cognitive, education, and economic outcomes in later life.[15,27,49,206] However, an estimated 23 million children did not receive DPT3 (diphtheria, pertussis, and tetanus vaccine, third dose) in 2020—3.7 million more than in 2019[22]—and 60% of these children lived in 10 low- and middle-income countries (LMICs) including India.[23] An analysis of 170 countries using administrative vaccination data found reduced coverage of DPT3 and measles-containing vaccine first dose (MCV1) in the first half of 2020 with a rebound in the latter half.[207] In the WHO South-East Asia region, administered DPT3 doses dropped by 57% in April 2020 compared with April 2019.

India had among the largest reductions in childhood vaccination coverage. The WHO estimated that DPT3 vaccination rates in India fell from 91% in 2019 to 85% in 2020.[22] A study using administered dose data similarly estimated that DPT3 vaccination dropped 15.8% in 2020 in India, relative to the previously projected vaccination rate.[24] Another study from Rajasthan conducted phone interviews for 2,144 children between January and October 2020, and found that children in heavily COVID-19–exposed areas were less than half as likely to get vaccinated by nine months of age, relative to unexposed children.[48]

These studies have limitations inherent in modelled and administrative data because they tend to present aggregate statistics without accounting for potential confounding factors, including underlying secular trends in coverage and differences in individual and household-level factors that influence vaccinations, such as age, sex, parental education, beliefs, and access to healthcare facilities. Additionally, the quality of administrative data, particularly at the subnational level, is limited as compared with in-depth retrospective household surveys. Lastly, these studies focused on only DPT3 and MCV vaccinations and did not address the coverage of other vaccines or the timely receipt of doses. Considering that DPT3 coverage rate in India increased rapidly from 78% in 2015-2016 to 91% in 2019[22,124] – aided by special immunisation drives[94,95] – it is important to understand and quantify the backsliding in progress due to the pandemic.

Aiming to estimate the effect of the COVID-19 pandemic on routine childhood immunisation coverage and timeliness in India, we examined the status of standard routine childhood vaccines given in the first year of life in India using data from a large, nationally representative household survey.

5.2. Data and methods

Data

We used data from the fifth round of the National Family Health Survey (NFHS-5), conducted between June 2019 and April 2021.[50] The survey was conducted in two phases. Phase 1 extended from June 2019 to January 2020, covering 22 states and union territories; phase 2 was from January 2020 to April 2021, covering the remaining 14 states and union territories. NFHS-5 covered 636,699 households in 707 districts across all 36 jurisdictions, and it included 232,920 children under the age of five years. The survey collected immunisation data on all children born after 2016, including vaccine dose and receipt date, from vaccination cards or from maternal recall when a card was unavailable. We included all 232,920 under-five children from both phases of the survey in our analysis. Of these, children from phase 2 states who had at least one sibling (n=59,144) contributed to the variation in outcomes, as discussed in the next section.

We examined nine vaccine doses that are recommended during the first year of life: Bacillus Calmette–Guérin (BCG), hepatitis B birth dose (hepB0), DPT1 (diphtheria, pertussis, and tetanus, first dose), DPT2, DPT3, polio1 (polio, first dose), polio2, polio3, and first dose of measles conjugate vaccine (MCV1).[126] The recommended age for administering MCV1 is nine to 12 months; all the other vaccines are given within 14 weeks following birth. Newer vaccines (rotavirus vaccine and pneumococcal conjugate vaccines) were not included. We analyzed three sets of outcome variables. The first is a binary coverage indicator: (i) receipt of a vaccine dose vs. non-receipt. The two others are delay indicators: (ii) receipt of a vaccine dose within 28 of the minimum eligibility age vs. receipt after 28 days of minimum eligibility or non-receipt, and (iii) receipt of a vaccine dose within 45 days of the minimum eligibility vs. receipt after 45 days of minimum eligibility or non-receipt. Previous studies have used similar 28-day and 45-day definitions of delay to assess vaccination timeliness.[95,117,142]

We excluded children with implausible data, such as having been immunized prior to their birth date. Additionally, if vaccination of a higher dose was reported but previous doses were marked as not received, we changed the value of the higher-dose vaccine to missing; this accounts for 0.14% of observations. For example, if DPT3 was reported as being received but the child did not receive DPT1, the child would receive a missing value of DPT3 to account for measurement errors. For the delay indicators, we excluded children for whom vaccination receipt was reported more than one week prior to their minimum eligibility age.

Empirical approach

We employed a linear probability model (LPM) with mother fixed-effects to identify the differences in vaccination between siblings born before and after the COVID-19 pandemic. Household or mother fixed-effects have commonly been used in public health studies to assess the variation in health outcomes between siblings of different sex or age.[62,145] In our data, background characteristics of children—such as household standard of living; demographic, health, and educational indicators of parents; and community-level access to healthcare and quality of service delivery, including immunisation—can systematically differ between the groups affected or unaffected by COVID. If these differences are correlated with immunisation

outcomes, simple group differences in the outcomes indicator or least squares-based regression results of the relationship between COVID-19 exposure and immunisation outcomes would yield biased estimates. To mitigate such biases, we included mother fixed-effects in our regression model, which accounted for all observed and unobserved characteristics at the level of the mother and above (e.g., household, district, and state). Additionally, we controlled for the following sibling varying confounders: child's age in months, sex, birth order (first, second, third, fourth, or higher), and a binary indicator of institutional delivery. The source of variation in the variable of interest comes from mothers with multiple children under five years of age. However, all children with and without siblings are included in our model, following previous mother fixed-effects studies[62], to improve the goodness of fit of the model (e.g., the R^2 statistic).

The COVID-affected period start date is the date of the first reported COVID-19 case in India, January 30, 2020. Children were assigned to the COVID-affected or COVID-unaffected group for each vaccine outcome as follows:

$$T_x = 1 \; if \; age < eligibility_{age_x} + delay_x, and \; 0 \; otherwise$$

Where T_x is a binary indicator for vaccine x, age is the age of the child at the start of COVID-19 period, and $eligibility_{age_x}$ is the age of eligibility for the child for vaccine x, and $delay_x$ is the median delay (days) with which children in India received that vaccine x in 2019. For example, consider a child who was 9 weeks old on January 30, 2020, when the first case of COVID-19 was detected. The child was older than the minimum eligibility age for DPT1 (6 weeks) plus the median 2019 delay in DPT1 vaccination (2 weeks) and therefore was assigned to the control (COVID-unaffected) group for DPT1 analysis. In comparison, a child who was 7 weeks old on January 30, 2020, would be assigned to the COVID-affected group since they had not reached the minimum eligibility plus median delay age (6 + 2 = 8 weeks) for DPT1. Our definition of COVID-affected group was based on age and vaccine eligibility and was unrelated to COVID-19 infection or exposure of a child (to another infected individual) for which NFHS-5 did not collect data.

We conducted additional analysis by subgroup: rural vs. urban, female vs. male, and low-wealth vs. high-wealth households. High-wealth households were in the top three wealth quintiles and low-wealth households were in the bottom two wealth quintiles. STATA version 14.2 was used for all analysis. Standard errors were robust and clustered at the mother level and p-value of <0.05 was considered for statistical significance.

5.3 Results

Summary statistics

Table 1 presents the difference between the COVID-affected and COVID-unaffected groups for DPT3 coverage and delay and sample characteristics. Summary statistics for other vaccine doses were similar and are not presented separately. There were 18,803 children in the affected group and 214,117 children in the unaffected group (including children without siblings). COVID-

Table 1: Differences in socioeconomic characteristics between COVID-affected and COVID-unaffected groups for DPT3 vaccination

	Affected mean	Affected SD	Unaffected mean	Unaffected SD	Difference	P-value
DPT-3	0.70	0.46	0.84	0.37	-0.13**	0.00
DPT-3 delay	0.57	0.49	0.59	0.49	-0.01	0.01
Region						
North	0.23	0.42	0.18	0.38	0.05**	0.00
Central	0.50	0.50	0.23	0.42	0.26**	0.00
East	0.16	0.37	0.20	0.40	-0.03**	0.00
Northeast	0.05	0.21	0.16	0.36	-0.11**	0.00
West	0.00	0.04	0.10	0.30	-0.1**	0.00
South	0.06	0.24	0.13	0.34	-0.07**	0.00
Locality						
Urban	0.19	0.39	0.20	0.40	-0.01**	0.00
Religion						
Hindu	0.81	0.39	0.73	0.45	0.08**	0.00
Muslim	0.11	0.31	0.15	0.36	-0.04**	0.00
Sikh	0.03	0.18	0.09	0.28	-0.05**	0.00
Christian	0.03	0.16	0.02	0.13	0.01**	0.00
Other	0.02	0.15	0.02	0.15	0.00	0.86
Caste						
SC	0.23	0.42	0.20	0.40	0.02**	0.00
ST	0.20	0.40	0.20	0.40	0.00	0.13
OBC	0.41	0.49	0.38	0.49	0.03**	0.00
Other	0.16	0.37	0.22	0.41	-0.05**	0.00
Household size						
>4	0.78	0.42	0.74	0.44	0.04**	0.00
Head age						
< 21	0.01	0.09	0.01	0.07	0**	0.00
21 to 31	0.23	0.42	0.24	0.42	-0.01**	0.00
31 to 41	0.17	0.37	0.24	0.43	-0.08**	0.00
>41	0.60	0.49	0.51	0.50	0.08**	0.00
Head sex						
Female	0.14	0.35	0.15	0.36	-0.01**	0.00
Marital status						
Married	0.99	0.08	0.98	0.13	0.01**	0.00
Mother education						
No education	0.20	0.40	0.22	0.42	-0.02**	0.00
Primary	0.11	0.32	0.13	0.34	-0.02**	0.00

Secondary	0.51	0.50	0.51	0.50	0.00	0.95
Higher	0.17	0.38	0.13	0.34	0.04**	0.00
Child sex						
Female	0.48	0.50	0.48	0.50	0.00	0.38
Child age (months)						
<3	0.39	0.49	0.03	0.18	0.36**	0.00
3 to 6	0.18	0.38	0.04	0.19	0.14**	0.00
6 to 12	0.29	0.45	0.08	0.26	0.21**	0.00
>12	0.14	0.35	0.85	0.35	-0.72**	0.00
Birth order						
1	0.40	0.49	0.38	0.49	0.02**	0.00
2	0.32	0.47	0.33	0.47	-0.01**	0.00
3	0.16	0.36	0.16	0.36	0.00	0.64
>3	0.13	0.33	0.13	0.34	-0.01**	0.00
Delivery place						
Institutional	0.89	0.31	0.86	0.35	0.03**	0.00
Sample size	18,803		214,117			

Note: *HepB0*=hepatitis B given at birth, *DPT*=diphtheria, pertussis, tetanus, *BCG*=Bacillus Calmette–Guérin; standard errors are below coefficients. +p<0.1, *p<0.05, **p<0.01. Treatment group comprises children who did not reach eligibility age for DPT3 at time of first COVID-19 lockdown.

unaffected children had higher DPT3 vaccination rates than COVID-affected children (84% vs. 70%, p-value<0.01) and less delay in vaccination based on the 45-day measure (57% vs. 59%, p<0.01).

For background characteristics indicators, there were geographical differences driven by the timing of the survey in the specific area. The largest difference was the greater proportion of COVID-affected children vs. unaffected-COVID children in the Central region (50% vs. 23%, p<0.00) and a lower proportion in Northeast region (5% vs. 16%, p<0.01). Other major differences were a higher number of COVID-affected children from Hindu households and children with institutional delivery. The mean age of children in the affected group was lower than the unaffected group (5.7 months vs. 31.9 months, p<0.01).

Regression results: Vaccination coverage

Table 2, column A, presents the summary of the mother fixed-effects LPM results presenting the coefficient on the intervention (COVID-affected) variable for each vaccine. Full results are shown in Appendix Table A1. Coverage among COVID-19 affected children were lower than

their unaffected siblings who were born before the pandemic (2015-2019) for all vaccines except for MCV1. For doses given at birth, the likelihood of receiving BCG and hepB0 was 2% lower among COVID-affected children as compared with their unaffected counterparts. The decrease in vaccination probability for later doses of DPT and polio was greater than for earlier doses. There was a 7% decrease in probability for DPT1 and polio1 vaccination and a 10% decrease for polio3.

Regression results: Delay in vaccination

Table 2, columns B and C, presents the summary of the LPM results presenting the coefficient on the intervention variable for each vaccination delay variable. Full results are presented in Appendix Table A2 and A3. In the main delay model (vaccination within 45 days of eligibility vs. after 45 days or no vaccination), the probability of timely vaccination among COVID-affected children was lower by 3% for DPT3, 4% for polio3, and 5% for DPT1, DPT2, polio1, and polio2 for as compared with COVID-unaffected children. No significant effect was found for the doses given at birth or for MCV1. For vaccination within 28 days vs. after 28 days or no vaccination, only polio doses had a significant reduction in the probability of timely vaccination for COVID-affected children, ranging from 3% to 4%.

Subsample analysis

Appendix Table A4 presents the summary results for the subsample analysis for vaccination receipt and delay in vaccination, respectively. For vaccination receipt, results vary across vaccines. Reduction in vaccination coverage rates in the COVID-affected group were highest among male children and those from rural areas, relative to their unaffected counterparts. For DPT3, for example, there was a decrease in probability of vaccination of 15% vs 8% for rural vs. urban households. For delay in DPT1, polio1, polio2, and polio3 vaccination, COVID-affected children in rural households experienced a greater delay in vaccination than urban households after the pandemic. For DPT1, DPT2, and polio2, COVID-affected children in high-wealth households had a greater increase in delay than unaffected children, relative to COVID-affected children in low-wealth households. Similar to whole sample models, no significant effect was found for birth doses and measles in the delay variables.

5.4 Discussion

The adverse effects of the COVID-19 pandemic are likely to go far beyond the more immediate health and economic damage. The indirect effects from the pandemic and our policy response will become apparent only over the next several years and decades. Healthcare seeking decreased during the pandemic globally.[208,209] Two global studies[24,207] using administered dose data found substantial decreases in routine child immunisation; these findings were confirmed in many LMIC country specific studies which used varying data sources including in Lebanon,[210] Pakistan,[211] Equador,[212] and the sub-Saharan Africa region.[213] The effect of the COVID-19

Table 2. Summary results of effects of COVID-19 on vaccination outcomes

	Receipt of vaccination (A)			Receipt of vaccination within 45 days of eligibility (B)			Receipt of vaccination within 28 days of eligibility (C)		
Vaccine	Coefficient*	N	N (siblings)	Coefficient*	N	N (siblings)	Coefficient*	N	N (siblings)
BCG	-1.94** (0.006)	132,335	59,506	-0.47 (0.01)	113,421	50,121	0.15 (0.011)	113,421	50,121
HepB0	-2.49* (0.01)	131,240	58,972	-1.69 (0.011)	115,589	51,620	-1.28 (0.011)	115,589	51,620
DPT1	-7.06** (0.009)	127,232	56,885	-5.4** (0.015)	107,661	47,440	-2.83+ (0.016)	107,661	47,440
DPT2	-7.9** (0.011)	123,278	54,942	-4.59** (0.015)	105,649	46,504	-2.3 (0.015)	105,649	46,504
DPT3	-9.27** (0.012)	120,074	53,317	-3.38* (0.015)	104,550	45,883	-2.43+ (0.014)	104,550	45,883
Polio1	-6.98** (0.009)	127,618	57,063	-4.94** (0.014)	108,685	47,976	-2.97* (0.015)	108,685	47,976
Polio2	-8.21** (0.011)	123,368	55,011	-5.19** (0.014)	108,904	48,014	-3.79* (0.015)	108,904	48,014
Polio3	-10.28** (0.012)	120,282	53,433	-3.91** (0.014)	110,970	48,982	-3.05* (0.013)	110,970	48,982
Measles	1.68 (0.017)	99,223	43,513	1.85 (0.023)	82,161	35,443	2.26 (0.022)	82,161	35,443

Note: *Coefficient of COVID affected indicator. *BCG*=Bacillus Calmette–Guérin*; HepB0*=hepatitis B given at birth, *DPT*=diphtheria, pertussis, tetanus; standard errors in parentheses. +p<0.1, *p<0.05, **p<0.01

pandemic on child vaccination mirrors the experience of many countries in the west Africa region during the Ebola outbreak, where basic vaccination coverage dropped.[214,215] These lower vaccination rates were linked to increased measles incidence and measles outbreaks in affected countries post-Ebola.[216]

Our study shows that children born in India after COVID-19 had 2% to 10% lower probability of immunisation and 3% to 5% lower probability of timely vaccination as compared with their siblings who were born prior to the pandemic. For overall vaccination receipt, vaccines given later in the immunisation schedule had greater delay than early-dose vaccines. For timely vaccination, the birth doses did not show a significant difference between COVID-affected and COVID-unaffected children. These results may be due to the gradual increase in institutional delivery rates across children—from 83% of children born in 2015 to 89% of children born in 2020. Infants born in institutional facilities have direct access to birth-dose vaccines and more antenatal care interactions, which can increase demand for vaccination. For later-dose vaccines, however, households must make a separate trip to a health center or immunisation session site.

Reduced vaccination will substantially increase the already large preventable morbidity and mortality burden in children. Estimates suggest that vaccine-preventable diseases, including pneumonia, diarrheal diseases, measles, and meningitis, were responsible for more than 400,000 under-five deaths in India in 2015.[114] Vaccination also affects children's cognitive and education outcomes[15] and has recently been linked to labor market outcomes, which can have implications for economic growth.[35]

A previous modelling study estimated a decrease in DPT3 vaccination of 16% in 2020 in India relative to what rates may have been without COVID-19.[24] A second global study[207] found that DPT3 doses decreased by 57% in the South-East Asia region. Our estimates suggest a 9% decrease in the DPT3 vaccination rate of children born after the pandemic. The smaller magnitude decrease may be driven by a potential recovery as our study includes children sampled between January and April 2021 or may be driven by our empirical approach. The previous studies[24,207] used administered dose data to estimate the effects of COVID-19 on vaccination, while we used household survey data. Second, our methodological approach employed a robust modelling framework with the mother fixed-effects model to account for potential confounding factors.

These results have implications for India's immunisation campaigns and its COVID-19 and general pandemic response policies. An estimated 32 million children were born in India between February 2020 and April 2021.[217] Assuming an 89.5% pre-pandemic DPT3 vaccination rate and a 9% lower probability of vaccination in the exposed population, we calculate that more than 2.5 million doses of DPT3 were missed during this COVID-19 period. In recent years, India's Mission Indradhanush (MI) campaign has raised immunisation rates,[95] improving overall vaccination rates and reducing delays in vaccination.[95] Future iterations of MI and other campaigns need to consider the additional resources required to immunize the millions of children missed during the pandemic. Our results indicate that children in rural areas may have suffered the greatest decrease in vaccination rates. Funding for catch-up vaccination will need to be in addition to the estimated more than $560 million gap that already exists to reach 90% vaccination rates.[123] Health facilities should have enough capacity to handle routine health

services; research has shown that prior to the pandemic, health facility quality was significantly associated with child vaccination outcomes in India.[117,218]

It will also be important to evaluate pandemic preparedness and response policies in terms of their broad costs and benefits. A 2020 modelling analysis found that continued routine immunisation service provision in Africa would have resulted in greater deaths averted than the deaths caused by increased disease transmission from these visits.[219] Similar analysis is needed for other regions and throughout a pandemic as virus strains evolve or individuals get protection through vaccination. Broadly, lockdowns and pandemic policy should encourage and allow safe access to routine immunisation services.

Our analysis has important limitations. First, our identification strategy only allows for the comparison of outcomes between siblings — therefore, we do not capture the change in vaccination from children that did not have a sibling, even though they may have experienced a decrease in vaccination. However, the mother fixed-effects model allows for robust estimates of the effect of COVID-19 on vaccination status by examining siblings that would share all household level characteristics. Second, not all children had complete vaccination cards, and data based on the mother's recollections can be subject to recall error. To check for potential bias, we ran our main models only for children with vaccination cards, but the results remained largely unchanged. Third, it is possible that some children who became eligible for a vaccine close to the pandemic start date were assigned to the control group in error. This might happen for children with larger-than-median delay in vaccination. For example, consider a child nine weeks old at pandemic start date. They have passed the minimum eligibility date for DPT1 plus the median delay period for DPT1 of two weeks and therefore are assigned to the control group. However, if this household typically has a delay of four weeks in vaccinations, the child may have been affected by COVID-19 and should be in the treatment group. Such children constitute only a very small portion of our sample, but the effect of their misassignment would be to decrease the vaccination rate and increase the delay of COVID-affected children, essentially decreasing the coefficient of interest. Finally, evaluation of vaccines which were recently introduced in the national program, such as pneumococcal and rotavirus vaccines, was not included in our analysis as they were not available nationally before 2020.[220]

Child immunisation is one of the most cost-effective health interventions. Missed vaccinations will increase preventable child mortality and morbidity and have important secondary effects— poorer cognitive, education, and economic outcomes for children in later life. Future immunisation resources in India must consider the additional cost of catch-up vaccination for children who have missed doses. Future pandemic response and preparedness policies must ensure that routine health services, including child immunisation services, remain robust during infectious disease outbreaks.

Appendix

Table A1: Effect of COVID-19 on vaccination receipt

Model	1	2	3	4	5	6	7	8	9
Vaccine	BCG	hepb0	DPT1	DPT2	DPT3	polio1	polio2	polio3	MCV1
COVID-affected =1	-0.03**	-0.04**	-0.11**	-0.16**	-0.17**	-0.11**	-0.16**	-0.20**	-0.08**
	0.01	0.02	0.01	0.01	0.02	0.01	0.01	0.02	0.03
Female child	0	0.01	0	0	0	0	0	0	0
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Institutional delivery	0.06**	0.20**	0.01	0.05*	0.06**	0.02	0.04+	0.04+	0.02
	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Birth order									
Second	0.02**	0.04**	0.04**	0.05**	0.05**	0.02*	0.04**	0.04**	0.03+
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Third	0.03+	0.07**	0.07**	0.08**	0.09**	0.04*	0.07**	0.07**	0.02
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Fourth or higher	0.05*	0.12**	0.11**	0.11**	0.08*	0.07**	0.09**	0.06+	-0.01
Observations	95,731	94,842	93,515	91,993	91,024	93,744	92,027	91,183	81,727
Pseudo R^2	0.009	0.025	0.055	0.1	0.147	0.034	0.077	0.085	0.113

Note: *HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin, *MCV1*=Measles Conjugative Vaccine, dose 1; Standard errors are below coefficients. +p<0.1, *p<0.05, **p<0.01.

Table A2: Effect of COVID-19 on vaccination receipt within 45 days of eligibility

Model	1	2	3	4	5	6	7	8	9
Vaccine	BCG	hepb0	DPT1	DPT2	DPT3	polio1	polio2	polio3	MCV1
COVID-affected =1	0	-0.02	-0.05**	-0.05**	-0.03*	-0.05**	-0.05**	-0.04**	0.02
	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Female child	0	0	0	0	0.01	-0.01	-0.01	0	0.01
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Institutional delivery	0.15**	0.24**	0.01	-0.01	0.02	0	0.01	0.03+	0.04
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Birth order									
Second	0	0.01	0.01	0	-0.03*	-0.01	-0.01	-0.02	0.03
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Third	0	0.01	0.02	0.02	-0.05*	-0.02	-0.02	-0.04	0.01
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Fourth or higher	0.01	0.03	0.09*	0.05	-0.04	0.02	0.01	-0.01	0.05
Observations	113,421	115,589	107,661	105,649	104,550	108,685	108,904	110,970	82,161
R^2	0.014	0.029	0.006	0.021	0.025	0.012	0.018	0.015	0.017

Note: *HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin, *MCV1*=Measles Conjugative Vaccine, dose 1; Standard errors are below coefficients. +p<0.1, *p<0.05, **p<0.01.

Table A3: Effect of COVID-19 on vaccination receipt within 28 days of eligibility

Model	1	2	3	4	5	6	7	8	9
Vaccine	BCG	hepb0	DPT1	DPT2	DPT3	polio1	polio2	polio3	MCV1
COVID-affected =1	0	-0.01	-0.03+	-0.02	-0.02+	-0.03*	-0.04*	-0.03*	0.02
	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.02
Female child	0	0	-0.01	0	0	-0.01	-0.01	0	0.01
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Institutional delivery	0.18**	0.24**	0.03	-0.01	0.02	0.03	0.01	0.02	0
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Birth order									
Second	0	0.01	-0.01	-0.01	-0.03*	-0.02+	-0.02+	-0.02+	0
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Third	0	0.01	-0.01	0	-0.04	-0.04	-0.02	-0.03	0.01
	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.03
Fourth or higher	0.03	0.02	0.03	0.04	-0.03	-0.01	0	-0.03	0.04
Observations	113,421	115,589	107,661	105,649	104,550	108,685	108,904	110,970	82,161
R^2	0.018	0.029	0.004	0.016	0.016	0.007	0.013	0.01	0.012

Note: *HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin, *MCV1*=Measles Conjugative Vaccine, dose 1; Standard errors are below coefficients. +p<0.1, *p<0.05, **p<0.01.

Table A4: Summary results of effect of COVID-19 on vaccination receipt and timely vaccination, subsample analysis

		Receipt of vaccination within 30 days of eligibility		Receipt of vaccination within 45 days of eligibility	
Vaccine	Subsample	Coefficient	Sample size	Coefficient	Sample size
BCG	Urban	-0.03** (0.01)	76,345	0 (0.012)	90,692
BCG	Rural	-0.05* (0.02)	19,386	-0.01 (0.025)	22,729
BCG	Poor	-0.03* (0.012)	47,941	0.01 (0.015)	55,756
BCG	Rich	-0.04** (0.013)	47,790	-0.01 (0.016)	57,665
BCG	Male	-0.04* (0.017)	46,377	0.03 (0.022)	54,926
BCG	Female	-0.04* (0.018)	49354	0.01 (0.024)	58,495
hepb0	Urban	-0.04* (0.017)	75630	-0.02 (0.013)	92,487
hepb0	Rural	-0.06 (0.038)	19212	0.01 (0.028)	23,102
hepb0	Poor	-0.03+ (0.02)	47401	-0.01 (0.015)	57,360
hepb0	Rich	-0.06** (0.024)	47441	-0.01 (0.018)	58,229
hepb0	Male	-0.07* (0.03)	45938	-0.01 (0.022)	55,917
hepb0	Female	-0.08* (0.031)	48904	-0.01 (0.024)	59,672
DPT1	Urban	-0.11** (0.013)	74519	-0.02 (0.017)	85,784
DPT1	Rural	-0.14** (0.028)	18996	-0.07* (0.036)	21,877
DPT1	Poor	-0.12** (0.016)	46744	0 (0.021)	52,567
DPT1	Rich	-0.11** (0.018)	46771	-0.06** (0.023)	55,094
DPT1	Male	-0.13** (0.023)	45254	-0.04 (0.031)	52,015
DPT1	Female	-0.1** (0.025)	48261	-0.01 (0.032)	55,646

DPT2	Urban	-0.15** (0.015)	73282	-0.02 (0.017)	84,171
DPT2	Rural	-0.2** (0.034)	18711	-0.04 (0.036)	21,478
DPT2	Poor	-0.17** (0.019)	45952	-0.01 (0.02)	51,659
DPT2	Rich	-0.15** (0.02)	46041	-0.04 (0.023)	53,990
DPT2	Male	-0.18** (0.027)	44519	-0.05+ (0.03)	51,040
DPT2	Female	-0.11** (0.029)	47474	-0.03 (0.032)	54,609
DPT3	Urban	-0.16** (0.018)	72488	-0.02 (0.015)	83,269
DPT3	Rural	-0.22** (0.039)	18536	-0.06+ (0.034)	21,281
DPT3	Poor	-0.19** (0.022)	45526	-0.01 (0.018)	51,372
DPT3	Rich	-0.15** (0.024)	45498	-0.04+ (0.022)	53,178
DPT3	Male	-0.19** (0.031)	44049	-0.06* (0.027)	50,521
DPT3	Female	-0.14** (0.034)	46975	-0.02 (0.029)	54,029
polio1	Urban	-0.1** (0.013)	74710	-0.03+ (0.017)	86,725
polio1	Rural	-0.11** (0.028)	19034	-0.04 (0.035)	21,960
polio1	Poor	-0.12** (0.015)	46891	-0.01 (0.021)	53,141
polio1	Rich	-0.09** (0.017)	46853	-0.05* (0.022)	55,544
polio1	Male	-0.11** (0.023)	45376	-0.05 (0.03)	52,516
polio1	Female	-0.08** (0.024)	48368	0.02 (0.031)	56,169
polio2	Urban	-0.16** (0.016)	73329	-0.03* (0.016)	86,886

polio2	Rural	-0.2** (0.035)	18698	-0.06+ (0.035)	22,018
polio2	Poor	-0.19** (0.019)	46020	-0.02 (0.02)	53,490
polio2	Rich	-0.13** (0.021)	46007	-0.06** (0.022)	55,414
polio2	Male	-0.18** (0.028)	44555	-0.07* (0.029)	52,675
polio2	Female	-0.09** (0.03)	47472	-0.02 (0.031)	56,229
polio3	Urban	-0.18** (0.019)	72629	-0.02+ (0.014)	88,457
polio3	Rural	-0.29** (0.043)	18554	-0.06* (0.031)	22,513
polio3	Poor	-0.21** (0.023)	45636	-0.02 (0.017)	54,821
polio3	Rich	-0.18** (0.026)	45547	-0.04* (0.02)	56,149
polio3	Male	-0.21** (0.034)	44131	-0.08** (0.026)	53,662
polio3	Female	-0.16** (0.037)	47052	-0.02 (0.027)	57,308
MCV1	Urban	-0.09** (0.03)	64983	0.02 (0.024)	65,336
MCV1	Rural	-0.06 (0.066)	16744	0.01 (0.058)	16,825
MCV1	Poor	-0.11** (0.036)	40745	0.03 (0.031)	40,489
MCV1	Rich	-0.06 (0.04)	40982	0.01 (0.033)	41,672
MCV1	Male	-0.1+ (0.053)	39464	-0.02 (0.045)	39,643
MCV1	Female	-0.11+ (0.058)	42263	0.05 (0.047)	42,518

Note: *HepB0*=Hepatitis B given at birth, *DPT*=Diphtheria, Pertussis, Tetanus, *BCG*=Bacillus Calmette–Guérin, *MCV1*=Measles Conjugative Vaccine, dose 1; Standard errors are below coefficients. +p<0.1, *p<0.05, **p<0.01.

CHAPTER 6

Synthesis

Chapter 6

Synthesis

6.1 Child immunisation in India

India delivers vaccines to children through the Universal Immunisation Program (UIP) which targets approximately 27 million infants and 30 million pregnant women each year.[221] Since 2018, UIP has included the following vaccines: oral polio vaccine (OPV), Diphtheria-Pertussis-Tetanus (DPT), Bacillus Calmette–Guérin (BCG), measles, hepatitis B, Haemophilus influenzae type B (Hib) containing pentavalent (DPT, hepatitis B, and Hib), inactivated polio vaccine (IPV), measles rubella (MR), tetanus toxoid, and in endemic areas, Japanese encephalitis.[221] UIP has been recently expanded to include additional vaccines, such as rotavirus and pneumococcal conjugate vaccine (PCV), as well as planned scale-up of pentavalent, IPV, and MR vaccines.[221] Scale up of these vaccines will reduce under-five deaths further — rotavirus and pneumococcal pneumonia cause an annual estimated 854,000 and 105,000 child deaths, respectively.[222,223] A major success of the UIP has been the elimination of polio through a special campaign that immunized 170 million under-five children in 2014.[93] The UIP has recently included vaccination campaigns designed to increase vaccination rates in underserved areas including Mission Indradhanush (MI) and Intensified Mission Indradhanush (IMI), which were launched in 2014 and 2017, respectively.[224] These programs employed a multisectoral approach to improve access to and demand for childhood vaccinations. MI vaccinated approximately 25.5 million children and 6.9 million pregnant women, leading to an estimated 6.7% increase in the national full immunisation coverage rate.[224] Our results confirmed that these increases were specifically caused by the MI program. Roughly 6 million children were vaccinated through IMI, increasing full immunisation coverage rates by an estimated 18.5% in targeted districts.[224]

Despite the accomplishments of the UIP, currently one-third of Indian child deaths are from vaccine preventable diseases such as pneumonia, diarrheal diseases, measles, and meningitis.[14] Beyond its direct impacts on disease prevention, lower vaccination can result in poorer long term health, cognition, and schooling outcomes, increased antimicrobial resistance, and increased health expenditure.[15] Child immunisation remains far from universal in India. The full immunisation rate for under two children — vaccination of basic childhood vaccines against — BCG, measles, and three doses of DPT/Penta and polio vaccine (excluding polio vaccine given at birth)— remains at 76.6% according to a 2019-2021 national survey.[16] The targets of UIP are listed in the National Health Policy as 90% full immunisation rate of newborns by age of one year by 2025.[225] In addition to low coverage, failure to vaccinate children at recommended ages has remained a major challenge. In 2013, the proportion of delayed doses among under-5 children ranged from 35% for OPV first dose (OPV1) to 65% for DPT3.[17] Among 10-23 month old children in 2016, the proportion of delayed doses (i.e., more than 28 days after the minimum eligibility age) ranged from 23% for BCG to 35% for the measles vaccine.[18] Timely vaccination is important especially for highly contagious diseases such as measles which can rapidly affect a large number of children and retard long-term immunity against other diseases.[19,20] Furthermore, there are gaps in vaccination by socioeconomic and demographic groups, with female, lower

caste and scheduled tribe, non-Hindu, and low-income households having lower vaccination rates than their counterparts in India.[16] There are also severe state-level disparities, with full immunisation varying from 57.9% in Nagaland in the Northeast to 90.5% in Odisha[vii] in East India.[16]

6.2 Summary of findings

As depicted in the conceptual framework in Figure 1, my research has identified the value of vaccination, the means through which vaccination rates can be improved, and what challenges may exist in a post-COVID-19 environment. Chapter 2 identified the broader unexplored benefits of child immunisation, specifically on economic outcomes in later life. Higher investment in UIP can pay very large returns in terms of increased per capita income, with vaccinated populations earning 14% higher wages and increased monthly per capita household consumption expenditure (MPCE) by 2.9%. Program exposure also reduces the probability that an individual's household relies on agriculture as the main source of income by 1.9%. The effects vary by sex, location, and caste groups. For rural, male, scheduled caste or scheduled tribe, and Hindu households, UIP exposure during infancy has a significant and positive effect on wages. Individuals residing in rural areas and males who were exposed to UIP at birth have 14% and 16% higher wages than the control group, respectively. However, program exposure has no effect on urban, female, other backward caste, and non-Hindu individuals. Individuals exposed to UIP in high-focus states had 21% higher wages and in low-focus states had 12% higher wages than individuals in control groups. For the MPCE outcomes, we find that the coefficients are similar to the complete sample models for rural, female, and Hindu households, but insignificant for other household groups.

Next in Chapter 3 we showed that supplementary immunisation programs and periodic intensification of routine immunisation program activities can be used to realize these benefits. We found under-2 children in Mission Indradhanush districts (those under both Phases 1 and 2) had higher rates of full immunisation, OPV0, OPV1, OPV2, OPV3, hepatitis B birth dose (hepB0), BCG, and on-time vaccination (OTV) as compared with children residing in non-MI districts. Full immunisation rate was 27% higher among under-2 children residing in MI phase 1 and 2 districts (intervention group) as compared with those residing elsewhere (control group). The rate of receiving all vaccines at recommended ages was 8% higher in the intervention group. Receiving doses of OPV birth dose, OPV1, OPV2, OPV3, BCG, and hepatitis B birth dose vaccines were 9%, 9%, 11%, 16%, 5%, and 19% higher in the intervention group than the control group, respectively. We found vaccination outcomes were not statistically different in districts which were covered by either MI Phase 1 or Phase 2, but not both, as compared with non-MI control districts. This indicates that program duration may be a key factor for success.

In Chapter 4, we highlighted the role of public health facility investment in improving vaccination coverage and timeliness, and vaccination equity. We found that the constructed infrastructure quality index was positively associated with the completion of seven vaccination outcomes: full immunisation, DPT1, DPT2, BCG, hepatitis B (birth dose), and on-time

[vii]Dadra and Nagar Haveli has a 94.9% full immunisation rate, but Odisha is describe here given Dadra and Nagar Haveli's small population size — 465,999.

vaccination. Full vaccination and OTV were 1.19 times and 1.2 times higher for children residing in districts with a sub-center (SC) in the highest tercile of infrastructure index relative to those in the first tercile, respectively. The vaccine service delivery index was positively associated with completion of measles vaccination. In comparison with the same reference group, children whose SC's vaccine service delivery index score was in the third tercile had 1.12 times higher likelihood of vaccination for measles.

The distribution of infrastructure quality contributed to increased gaps in full immunisation and OTV between rich and poor households, while greater proximity to vaccination site for poorer households reduced these gaps. The difference in full vaccination and OTV rates between low-wealth and high-wealth households was 13% for full immunisation and 5% for OTV. The unexplained gap — gap not explained by differences in the distribution of included covariates — between low-wealth and high-wealth households was 56% and 89% for full immunisation and OTV of these differences, respectively. The infrastructure quality index score of household's SC contributed to a widening gap in full immunisation and OTV rates between low and high wealth households, 5% and 11% of the total gap, respectively. Differences in distance to vaccination site decreased the gap by 1% for full vaccination outcomes.

Chapter 5 found coverage rates were significantly lower in COVID-affected children for all vaccines except for MCV1 which did not have a significant change, and ranged from 2% lower for BCG and hepB0 to 9% for DPT3 and 10% for polio3, as compared with the unaffected children. Reduction in coverage rates were greater for higher dose vaccines. The likelihood of timely vaccination was lower among COVID-affected children relative to unaffected children for the polio and DPT vaccines, ranging from 3% to 5%.

6.3 Implications of findings for public policy

The findings of this thesis have several implications for health policy and financing in India and other LMICs.

Underfunded immunisation programs mean untapped economic growth potential

Taking the increased wages we identified from child immunisation coverage, a simple back-of-the-envelope calculation with the most recent Indian data—a 471 million labor force with 27% salaried workers,[viii] 15% of them unvaccinated,[ix] and a gross domestic product per capita of $1,900[38]—would mean overall economic output could increase by 0.11% to 0.28% in India. This is a lower bound of the potential effect because we lack earnings data for all workers. If this rate were applied to all workers in the labor force, the effect of UIP could increase gross domestic product by 1.2%. Although the country's ministries of health are typically responsible for funding health programs, it is widely recognized that a multisectoral approach is required for effective change, and the support of ministries of finance is needed.[121] Our estimates show a

[viii] Labor force includes salaried workers, self-employed, domestic worker/working in household enterprise, and unemployed individuals.
[ix] This is based on current DPT-3 vaccination rate in infants.

direct link between vaccination and labor market outcomes and make a strong economic case for adequate funding for routine vaccines.

Globally, an additional 8.5 million and 8.9 million children did not receive their DTP-3 and meningococcal conjugate vaccine dose-1 vaccines in 2020, relative to the number of missed doses projected.[24] The highest reductions in vaccination rates were in March and April 2020, during the beginning of the COVID-19 pandemic, and the regions hit the hardest were North Africa, the Middle East, South Asia, and Latin America and the Caribbean[24]—the same regions with the lowest overall vaccination rates prior to the pandemic.[55] A 2015 study estimated a global funding gap of $7.6 billion in 2016–2020 for delivery of full vaccination programs in 94 LMICs, which corresponds to 0.2% of general government expenditures.[122] For India's UIP an annual funding gap of $560 million was estimated to reach a 90% vaccination target.[123] The disruptions to immunisation and the persistent funding gaps not only lead to higher levels of preventable deaths but can also substantially lower standards of living and even compromise poverty reduction efforts in LMICs in the long term. The increased expenditure of 0.2% of the government budget is many times smaller than the future increase in economic output that an immunisation program could deliver.

SIAs and PIRIs can be used to boost immunisation and catch-up vaccination in the short run

Our findings suggest that periodic intensification of routine immunisation (PIRI) activities and supplementary immunisation activities (SIAs), through programs such as MI, could play an important role in improving vaccination outcomes. Extensions of MI and other future PIRI activities can potentially follow the success of the Pulse Polio program.[150,151] The pulse polio immunisation program included supplementary immunisation sessions that achieved success through engagement with local stakeholders and effective tracking of beneficiaries.[150] In 1995, the program was introduced nationwide, providing polio vaccines to 88 million children under the age of 3 years, and eventually covering all under-5 children.[151] Between 1999 and 2018, the coverage of polio vaccine third dose among 12-23 month old Indian children increased from 57% to 89%,[137] and India was declared polio free in 2011.[151]

While our results suggest that PIRI activities can be successful, their long-term effectiveness and financial viability are unclear.[152] MI was succeeded by Intensified Mission Indradhanush (IMI), with a goal of reaching 90% full immunisation coverage in the poorest performing districts by December 2018,[133,138] but it is unknown if this target was attained. A survey study showed an increase in full immunisation rates in IMI districts, but did not compare these rate changes to non-IMI districts.[138] Another new study used administrative data on vaccine doses delivered and found increased delivery of doses to IMI districts during the intervention period for 13 vaccines, but reduced volume of vaccine delivery at the end of IMI.[40] This suggests further research is needed to evaluate the longer-term effects of PIRI activities. While the IMI study used data on doses delivered to districts, child level data on vaccinations received before, during, and after a PIRI program may be more suitable for evaluating the program's effectiveness. The cost of the PIRI program per dose delivered needs to be compared to the routine immunisation cost to evaluate its cost-effectiveness. Future evaluations of MI should consider this.

PIRI activities can compensate for the inability of UIP to reach underserved communities but may not be a long-term replacement for routine immunisation. A health systems approach for improving routine immunisation coverage and timeliness requires focus on the following four areas: financing, service delivery, stewardship, and creating and maintaining human resources.[153]

Increase investments in immunisation services and sites; increase equity in service access for vulnerable groups

Health infrastructure quality in Chapter 4 — measured by components of physical infrastructure (availability of regular power source, washroom, and building materials), observational assessment of the building by the surveyor, and ASHA education —was a proxy for overall facility resource availability and was positively associated with vaccination outcomes. The estimated associations were similar in magnitude to those of wealth quintile and maternal education indicators. This suggests that health infrastructure, including well-trained health workers, equipment, and facilities, could improve vaccination outcomes at the same rate as improvements in standard of living or maternal schooling.[169] In addition, vaccine service delivery quality – as measured by the availability of vaccines and associated medical supplies – may improve the coverage of measles vaccine more as compared with the physical infrastructure of SCs.

In our decomposition analysis, overall infrastructure quality contributed to an increasing gap in full immunisation and timely vaccination between rich and poor households. This suggests that richer households are serviced by SCs that have greater overall infrastructure and financing relative to SCs near poorest households. The distance to SC, which is associated positively with vaccination, was shorter for the poorest households on average and decreased the gap in vaccination. Therefore, while greater proximity of facilities to poorer households or a greater number of facilities existing in low-income districts contributes to decreasing vaccination disparities, there needs to be an increased investment in the infrastructure of these facilities. Additionally, our findings suggested that rural, non-Hindu, and scheduled caste and tribe households — traits which may be correlated with low-income — have greater barriers to accessing high quality vaccination services; these gaps should be addressed as well.

Post-MI surveys suggest that inadequate and poor-quality infrastructure, and lack of human resources are among the most important supply-side factors leading to lower attendance in MI sessions.[138] In INCHIS, parents' reasons directly related to health infrastructure for not vaccinating their child were vaccination site was too far (9%), vaccination site was unhygienic (3%), vaccine was not available (11%), and the ANM was not available (10%). India's shortage of a skilled health workforce affects child immunisation, stretching community level health workers who serve as shared personnel for multiple tasks.[157,159] Greater allocation of staff resources towards routine immunisation activities including regularly updating immunisation records should be a priority.[138] A recent study of MI from western India showed that 10% of study sites did not have an updated list of beneficiaries (known as due list), 13% of auxiliary nurse midwives did not give all key messages about immunisation, and 17% of community health workers were not aware about the incentive pay structure under the MI program.[160] Investments in training programs with a focus on these particular tasks can help improve service delivery.

These factors have also slowed the rollout of newer vaccines such as the Hepatitis B vaccine.[158] It will be important to integrate overall best practices in record keeping and vaccine management from high performing districts to poorer performing districts, in addition to providing additional investments in vaccine delivery systems, human resources, and infrastructure in these districts.

Demand-side factors constrain vaccination rates

It is important to consider the demand-side drivers of vaccination to improve program success. Post-MI surveys revealed the main demand side factors contributing to families not attending immunisation sessions were lack of awareness, concerns about adverse effects of vaccines, and lack of time of the mother, and child illness.[138,163] Over 24% of respondents gave one of the following as a reason for not vaccinating their children: not knowing about benefits of vaccines, vaccination schedule, or vaccination site; and not having enough time to take child to vaccination site. To address these barriers, information campaigns should be used to promote the life-saving benefits of vaccines, as well as their secondary and longer-term positive effects on overall health, cognitive and educational outcomes, and reductions in potential medical expenditure.[15,20,34,49,63,66,164] A recent systematic review of interventions to improve immunisation coverage in LMICs found health education through home or village level meetings to be successful.[163] Our results and findings from previous studies, showed maternal schooling to be significantly positively associated with child vaccination rates.[165] Therefore, health education interventions should target parents with lower levels of education. Our findings also indicated that certain groups including low-wealth, rural, and scheduled caste and tribe households have greater barriers to vaccination and should be specifically targeted to improve knowledge of benefits of vaccination and build trust in public health institutions.

Increased funding for routine immunization is necessary

Adequate financial resources must be provided to UIP to improve long-term vaccination outcomes. Although immunisation budgets have increased in response to the introduction of new vaccines in the UIP, they have not kept pace with resource requirements. The UIP annual budget currently at $2 billion[131] is underfunded — estimates suggest annual budgetary shortfalls ranging from $7.9 to $50.2 million (INR 56 crore to INR 3,537 crore, 1 USD= INR 70.52) during 2013-2017.[132] The UIP budget is projected to increase by 41% from 2018 to 2022,[154] but this is primarily to facilitate the introduction or universalization of new vaccines (e.g. pneumococcal),[155] and to compensate for reductions in funding from Gavi, The Vaccine Alliance,[156] — which pays for 3% of India's immunisation program budget at present.[132] More recent estimates from a 2021 study suggest an additional $560 million would be required annually to increase child vaccination rates to 90%.[123]

High level political commitment; decentralized decision making and surveillance

Strong governance and political commitment are critical for universal routine childhood vaccine coverage.[153,161,162] To secure financing, build and retain skilled public health workers, and improve vaccination coverage, there must be a robust policy decision-making process, sensible regulation, and a high level of health intelligence.[153] Evidence-based policymaking should be

aided by efficient surveillance system akin to the highly successful acute flaccid paralysis surveillance.[153] Greater power devolution to the National Technical Advisory Group on Immunisation can expedite the policy making process on urgent matters, such as the introduction of new vaccines.[153]

Given large variations in state and district level mortality, a decentralised approach driven by district level data using a robust uniform surveillance program and analysis of local gaps in health service coverage including education and training, equipment, transportation services for mothers and children with the inclusion of all stakeholders is necessary; this would be a departure from planning in India that typically occurs at a central level.

COVID-19 shocks necessitate an increase in resources

An estimated 32 million children were born in India between February 2020 and April 2021.[217] Assuming an 89.5% pre-pandemic DPT3 vaccination rate and a 9% lower probability of vaccination in the exposed population identified in Chapter 5, we estimate that more than 2.5 million doses of DPT3 were missed during this COVID-19 period. In recent years, India's MI campaign has raised immunisation rates,[95] improving overall vaccination rates and reducing delays in vaccination.[95] Future iterations of MI and other campaigns need to consider the additional resources required to immunize the millions of children missed during the pandemic. Our results indicate that children in rural areas may have suffered the greatest decrease in vaccination rates. Funding for catch-up vaccination will need to be in addition to previously estimated gaps.[123] Health facilities should have enough capacity to handle routine health services; research has shown that prior to the pandemic, health facility quality was significantly associated with child vaccination outcomes in India.[117,218]

Build resilience of systems to public health crises and other shocks

Health systems and programs should have risk management and contingency plans to respond to public health crises and other shocks. This should also include the use of buffer resources or the rapid mobilisation of resources to ensure continued services. It will be important to evaluate pandemic preparedness and response policies in terms of their broad costs and benefits. A 2020 modelling analysis found that continued routine immunisation service provision in Africa would have resulted in greater deaths averted than the deaths caused by increased disease transmission from these visits.[219] Similar analysis will be needed for future pandemics, throughout all of its stages, as virus strains evolve or individuals get protection through vaccination. Ideally, lockdowns and pandemic policy should encourage and allow safe access to routine immunisation or other critical health services.

6.4 Limitations and suggestions for future research

This thesis has important limitations inherent to the type of data and methods that are employed. We do our best to address these challenges or suggest the possible impacts they may have on our findings with sensitivity analysis and robustness tests whenever possible. These limitations and their implications for future research are discussed below chapter-by-chapter.

Chapter 2

Assignment to treatment and control group in Chapter 2 was based on current place of residence rather than place of birth. As we lack data on place of birth and have only current residence data, individuals may be wrongly assigned to the treatment or control group if their current district had a different UIP implementation date than their birth district. However, as discussed, the current rate of out-of-district migration is approximately 15%, according to the 2011 Census. We predict the probability of an individual being a migrant and dropped 15% of observations most likely to be migrants; our estimates were robust to this specification. Moreover, the treatment status of some migrants would not change, depending on the timing of UIP implementation in their birth and current districts. Future research with data on place of birth or actual vaccination status is recommended.

Second, vaccination benefits may have been underestimated because we do not consider spillover effects to other household members. By reducing secondary transmission of disease, vaccination of infants may protect unvaccinated older siblings or neighbourhood children. Our results may also be underestimates if residents of control districts travelled to treatment districts to receive the vaccine. In this case, some members of the treatment group were wrongly assigned to the control group and biased our coefficients downward.

A third limitation is that the wage data we use, by definition, exist only for hired workers. If systematic differences exist between treatment or control group individuals who choose wage work rather than work for a household enterprise or self-employment, or those who choose to stay out of the job market, and their income differs from the current control and treatment groups, our results may be biased. For example, those who did not receive vaccines may have had more illness during childhood and been unable to find jobs as easily as the treatment group. In this example, the effect on wages would be biased downward. To account for individuals without wage data, we used monthly per capita household expenditure as an additional outcome variable. Although this is not a perfect variable to observe outcomes for the treatment group, it was the best proxy we could identify in our data set, and we find positive effects on MPCE from UIP coverage.

Chapter 3

In Chapter 3 our estimated associations of MI with vaccination outcomes may not be causal in the presence of unobserved covariates. For example, parents may decide to vaccinate their children based on perceived likelihood of survival or nutritional status, or they may be influenced by health workers to vaccinate certain children at higher rates. If such factors are correlated with MI status (e.g., frequent contact with health workers in MI districts), our estimated associations may be biased. However, we included a wide range of covariates in our regression models that are important determinants of vaccination outcomes which have been used commonly in this type of analysis.

The survey rounds used from INCHIS data, INCHIS-1 and INCHIS-3, had 40% and 34% households not having a vaccination card available or not showing vaccination card to the

surveyor, and the vaccination outcomes of the child were reported by the mother or caregiver, respectively. These observations can be susceptible to measurement errors if there were systematic differences in vaccination status of missing observations between intervention and control districts. We conducted additional analysis by only including households that had vaccination card available and where verification was completed by the surveyor and the results were similar to the main results.

Finally, INCHIS did not survey the same districts in multiple rounds. Therefore, our analysis could not compare changes over time in the same intervention and control districts, although we did control for confounding variables. Analysis of later MI phases can investigate richer datasets that do not have this limitation, more specifically following the same households over time would provide the most robust estimates of MI program effects.

Chapter 4

In Chapter 4 we used cross-sectional data which could be biased by selective program placement. For example, low-initial immunisation coverage districts may have received additional resources to improve infrastructure to bolster vaccination rates, which could bias our coefficient on infrastructure quality index downwards. Conversely, richer communities with more political clout may have received more infrastructural resources — previous research have shown that public goods allocation decisions in India can often be political.[202,203] This would bias the estimated coefficients upwards as wealthier households tend to have higher levels of immunisation. Future research should use longitudinal data to identify causal effects.

Second, we examined the quality of SC primarily through physical infrastructure quality and equipment availability, with the exception of health worker education. Other measures of immunisation delivery quality such as process quality can be included in future research.[204]
Third, we matched each household with the sub-center in its own geographical cluster. This is the officially designated SC serving that household; however, it may be possible that households went to SC in other clusters if those centers were geographically closer to them. Use of data where the actual SC visited is identified may be desirable in future research.
Lasty, there may have been measurement error due to surveyor bias. While many of the facility quality indicators were based on objective measures (e.g., availability of vaccines), some indicators were based on the surveyor's objective assessment of the state of the facility (e.g., cleanliness of the facility). However, potential inconsistencies across interviewers should have been minimized by training —all surveyors were presented with extensive instruction on the administration of the questionnaire and a training manual to specifically ensure uniformity across surveyor methods.[180]

Chapter 5

In Chapter 5, our identification strategy only allows for the comparison of outcomes between siblings — therefore, we do not capture the change in vaccination from children that were 'only childs', even though they may have experienced a decrease in vaccination. However, the siblings model allows for robust estimates of the effect of COVID-19 on vaccination status by examining siblings that would share all household level characteristics. Other models, for example, with

district or state-level fixed effects may also be explored in the future. Second, not all children had complete vaccination cards, and data based on the mother's recollections can be subject to recall error. To check for potential bias, we ran our main models only for children with vaccination cards, but our main results remained largely unchanged.

Third, it is possible that some children who became eligible for a vaccine close to the pandemic start date were assigned to the control group in error. This might happen for children with larger-than-median delay in vaccination. For example, consider a child nine weeks old at pandemic start date. They have passed the minimum eligibility date for DPT1 plus the median delay period for DPT1 of two weeks and are therefore assigned to the control group. However, if this household typically has a delay of four weeks in vaccinations, the child may have been affected by COVID-19 and should be in the treatment group. Such children constitute only a very small proportion of our sample, but the effect of their misassignment would be to decrease the vaccination rate and increase the delay of COVID-affected children, essentially decreasing the coefficient of interest.

Future research

Above I have discussed future research to address limitations of the current work. Here I discuss possible extensions to the current thesis and complementary research that would contribute to informing future public health policy to improve child health outcomes.

1. Age of mother at child's birth and birth spacing of children are important determinants of child's health at birth and later life.[226] Overall health and economic status may have an impact on marriage and reproductive decisions.[227] Therefore, in future research I propose to investigate the effect of UIP exposure in childhood on future fertility and reproductive health decisions.
2. As the COVID-19 pandemic has affected child vaccination rates, it would be interesting to investigate secondary health outcomes related to immunisation such as anthropometric outcomes of children[15] who were of vaccination age during the COVID-19 period. These effects may be compounded by the general reduction in health services, shocks to the food system, and other stressors associated with the pandemic (e.g., lockdowns and economic activity reductions).
3. Further research may conduct extensive unit costing analysis of various SIA, PIRI activities, and public health facility investment interventions. Public health facility interventions may also be done in a randomized control trial where the effects of childhood immunisations and other health service delivery outcomes are measured. Such research along with our estimates of the benefits of PIRI activities and health facility quality may be used to estimate cost-effectiveness ratios that inform resource allocation decisions.

6.5 Concluding remarks

Immunization is the most cost-effective tool for decreasing morbidity and mortality in children in low- and middle-income countries. The recent pandemic shock to immunisation rates combined with already low vaccination rates in many LMICs will not only increase mortality and morbidity for these cohorts but also portend long-term harms in the form of poorer cognitive and schooling outcomes, and lower incomes and standards of living. From an economic and a

health perspective, it is critical that a strong political commitment from governments to improve immunisation drives increased funding towards vaccination programs to fill past gaps in funding and cover the additional cost of catch-up vaccination for children who have missed doses. Investments in supply-side factors that increase quality of health facilities and availability of vaccinations, and demand creation activities should be invested in particularly. Supplementary vaccination campaigns should be considered to increase catch-up vaccination in the hardest hit districts. Future pandemic response and preparedness policies must ensure that routine health services, including child immunisation services, remain robust during infectious disease outbreaks.

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Acknowledgements

It is surreal how a modest idea can be nourished and transformed, how a goal that seemed so far out of reach can be realized with discipline, passion, and the support of wonderful people. First of all, I could not have asked for better promotors and thesis supervisors than Dr. Erwin Bulte and Dr. Robert Sparrow — I was very fortunate to work under their guidance. Their understanding, patience, breadth of knowledge, and good humour, which I felt from my very first interaction, made this difficult journey rewarding and enjoyable.

I would like to thank my supervisor Dr. Arindam Nandi. Arindam is not only a gifted researcher and ideal mentor, but also has become a great friend. I hope to emulate him as a researcher and more importantly as a mentor, to help someone in the way he has helped me and I am sure other junior researchers and reach his level of professionalism and people skills. His support and encouragement allowed me to take the first steps towards enrolling in this program.

Finally, I thank my amazing parents. Through their example and love I was able to pursue a path true to me, albeit very foreign to them. Without their patience, support, and the values they have instilled in me, I would not have been able to reach this monumental professional and personal milestone.

The research described in this thesis was financially supported by the Centre for Disease Dynamics, Economics, and Policy.

Financial support from Wageningen University for printing this thesis is gratefully acknowledged.