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ABSTRACT

Early Life Access to Polio Vaccines and Declining Disability Rates in India*

We evaluate the impact of oral polio vaccines on the incidence of disabilities in India, focusing on polio-related disability. Polio was hyperendemic in India even as recently as the early 1990s but the country was declared wild polio virus-free in 2014. Average treatment effects on the treated from difference-in-differences with multiple time period models that condition on time-invariant demographic and socio-economic characteristics reveal that with access to oral polio vaccines in the year of birth, the incidence of any disability, locomotor disability and polio-related disability declined by 61.4%, 57.3% and 55.9%, respectively. We test for pre-trends and estimate alternate specifications that offer support for these results. Heterogeneity analyses show that in general, access to oral vaccines in the year of birth lowers the incidence of disabilities across gender, rural/urban and education stratifications. An exception is low-caste groups where there is some evidence that post-period average ATT rose. The eradication of polio saved a significant number of lives and brought measurable health and economic benefits to the country.

JEL Classification: I15, I12, I18, O12, J13, J14

Keywords: polio, locomotor, disability, acute flaccid paralysis, oral polio vaccines, early childhood, difference-in-differences with multiple time period models

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1. Introduction

Wild polio virus (WPV) was hyperendemic in India. Estimates note that even as late as the beginning years of the 1990s, on average 500 to 1000 Indian children developed polio-related paralysis *each day* (John and Vashishtha 2013). Evidence from 1980, which is the earliest year that reliable data is available, indicates that the cost to the national economy per paralyzed child was INR 150,000 (2022 USD 64,503.8) which translates into an annual loss of INR 450 million (2022 USD 193.5 million) or 0.1% of India's 1980 Gross National Product (GNP) in current prices (John 1981; World Bank 2013). This percentage constitutes about 7% of the government's relative allocation to healthcare in the 1980s (Government of India 2016), a sizeable fraction for a developing country. In contrast, polio had been essentially eradicated in the United States by 1980. Despite its clear disease burden in India, to the best of our knowledge, no study has used the tools of demography and economics to undertake a comprehensive analysis of the effectiveness of oral polio vaccines (OPVs) in reducing the incidence of acute flaccid paralysis (AFP) – the largest burden associated with polio, and which is caused by damage to lower motor neurons – which we term polio-related disability, or documented what the impact of OPVs on disabilities more broadly has been.

Our research answers the question: what was the impact of gaining access to OPVs at the district-level on the incidence of all disabilities in India, especially polio-related disability? This is important given the magnitude of costs that polio entailed, because the proportion vaccinated with OPVs is an incomplete measure of protection provided in terms of disabilities averted, and because there is relatively little research on disabilities in general in developing country contexts. We focus on any disability (which includes locomotor, hearing, visual, speech and mental), locomotor disability - the largest component of any disability (51.9% of those with any disability have a locomotor disability in our sample), and polio-related disability - the largest component of locomotor disability (19.9% of those with locomotor disability identify polio as the cause). A reason for considering any disability is because of evidence that the physical disabilities caused by polio (and embodied in locomotor challenges) may also become the source of mental health issues such as depression (Shiri et al. 2015, Bagcchi 2019). Another reason is because the availability of OPVs in a district may coincide with the availability of other vaccines such as those for tuberculosis and diphtheria, pertussis and tetanus (DPT). Hence, we want a catch-all measure of disability to understand comprehensively what overall vaccine access in childhood achieved.

We use multiple sources of representative data including those from the National Sample Survey Organization (NSSO), the National Family Health Surveys (NFHS), and Family Planning Statistics of India. Our preferred empirical approach leverages newly developed difference-in-differences (DD) with multiple time period methods and time-invariant regressors that exploit the staggered diffusion of OPVs across Indian districts but avoids the "forbidden" comparisons. John and Vashishtha (2013) notes that the spread of OPVs was dictated by financing and administrative stipulations decided by the World Health Organization (WHO), UNICEF, CDC - United States and Rotary International, which set up the National Polio Surveillance System (NPSP), a partnership between the WHO and the Government of India (GOI). The timing of which district receives OPVs was thus exogenous to any individual's control (random). We present tests for pre-trends and additional evidence for results from our preferred specification using alternate linear probability saturated fixed-effects models.

Using information on the dissemination of OPVs to children in the 0-5 years age-group across the districts of India from 1985 onwards (the immunization program extends beyond urban centers for the first time in 1985), we document significant negative impacts of access in the year of birth on any disability, locomotor disability, and polio disability. More specifically, with controls for individual and household demographic and socio-economic characteristics, and state-level spending on polio campaigns, we estimate average treatment effects on the treated (ATTs) which show that the incidence of any disability declined by 61.4%, of locomotor disability declined by 57.3%, and of polio-related disability decreased by 55.9%. Even if the advantage of OPV access is gauged most accurately only in the cases of locomotor and polio-related disabilities, these are sizeable gains.

We next evaluate heterogeneity in estimated ATTs by considering samples that differ by gender, rural/urban status, caste status, and literacy. Overall, post-treatment average ATTs are either negative or smaller in magnitude as compared to pre-treatment average ATTs (implying that access to OPVs in the year of birth resulted in lower disability incidence). We note an exception for low-caste groups where post-period average ATTs actually rose. On the other hand, literate individuals have a negative pre-period average ATT which only gets more pronounced (retains sign and increases in magnitude) in the post-treatment periods.

Finally, we estimate an alternative specification that takes both exposure status (year of birth either coincides with or is after the year in which the district of residence gains access to OPVs), the number of years of exposure at the time of birth (difference between the year in which district gains access and year of birth), and their interactions into account (to allow for the fact that the impacts of exposure may differ in regions that have had longer access). These linear probability models condition on district fixed-effects, year fixed-effects, and their interactions. In general, both exposure and number of years of exposure have negative effects, but it is the latter that retains its significance across the various specifications in this class of models.[1] An advantage of this alternate form is that we can readily evaluate the impact of the rich set of demographic and socio-economic regressors we include.

Our study contributes to the literature by evaluating the efficacy of early life OPV access in reducing disabilities in a large developing country where the polio burden was consistently among the highest in the world. We provide results from multiple specifications to show that the benefits of OPV access in the year of birth have been significant.

2. Background of Polio in India

Poliomyelitis is an infectious disease that has existed since ancient times and that is caused by a virus which mainly infects children (polio is also known as "infant paralysis"). This virus is only found in humans, and is spread through the fecal-oral route mostly by exposure to contaminated drinking water and/or because of unsanitary conditions. In a proportion of cases, it can lead to irreversible AFP in limbs that waste away causing deformities in arms and legs and often resulting in death by affecting breathing muscles (Stafford and Gurney 1951). No cure exists, but effective (injectable) vaccines were developed in 1955 while the oral vaccine, the focus of this study and the most widely distributed version across the developing world given its ease of administration, was developed in 1962 (Ochmann and Roser 2017).

Despite the availability of vaccines, even as of 1980, 125 countries reported paralytic polio cases among which the largest proportion (38.2%) was reported in South East Asia; in this region, India had the dubious distinction of having 94.5% of this region's total (Ochmann and Roser 2017). To provide a different perspective, while the United States reported 0.03 paralytic

[1] These models result in estimates that are somewhat smaller than those from the DD with multiple time period models, as we detail below.

polio cases per one million in 1980, India reported 27.2 similar cases in the same year (Ochmann and Roser 2017).[2] Starting from this baseline, and thanks to a re-focus in international and national priorities and funding for programs such as 1978's Expanded Program on Immunization (EPI) and 1995's Pulse Polio vaccination campaigns that were conducted as often as ten times annually to carefully track and vaccinate every eligible child across all locations including state and district border transit points, India was declared WPV - free by WHO in 2014 (John and Vashishtha 2013; Bahl et al. 2014).

Panel A in Figure 1 shows that across the years of our data from 1985 onwards, the incidence of any disability has declined from 16.6% in the 1980s to 10% in the 2010-2018 years. The proportion of those with locomotor disability among those with any disability declined from 59.0% in the 1980s to 45.1% in the first decade of 2000, with an uptick to 49.8% in the most recent decade. Polio-related disability constituted almost 33.0% of all locomotor disability in the 1980s. This proportion declined to 27.5% in the 1990s with significant gains from then on (reflecting a renewed immunization effort including 1995's Pulse Polio campaign noted above) such that this disease constituted 8.5% of locomotor disabilities in the later years of our sample. The renewed immunization effort in the 1990s is also reflected in Panel B of Figure 1 which plots the proportion of children 0-5 years who had access to OPVs in their year of birth. As is clear, there is significant increase in access from the late 1980s onwards, another evident jump after 1995 when Pulse Polio begins, and some plateauing in this proportion between 2000 and 2010. From around 2012 onwards, almost every child has access.

3. Empirical Methodology

3.1. Naïve Specification

[2] A reason for this was that at independence, India invested in control of tuberculosis, malaria and leprosy, ignoring polio as a low priority disease with a high cost of eradication (John and Vashishtha 2013).

Our study of the impacts of OPVs is undertaken by leveraging both the timing of when access is gained and the identity of districts that gain access. As districts gain access in different years, the standard method to estimate impacts is a staggered difference-in-differences (DD) design of the following form:

$$y_{ijt} = \alpha_j + \theta_t + \beta \times Exp_{ijt} + \varepsilon_{it} \qquad (1)$$

Where y_{ijt} is an indicator for the presence of various types of disabilities (any, locomotor or polio-related) for individual i in district j in year of birth t, α_j are district fixed-effects, θ_t are year of birth fixed-effects, and Exp_{ijt} is an indicator that takes the value of one for an individual if she/he is born either in the same year or in a year after which her/his district gains access to OPVs (and thus was "Exposed" to OPVs). Results from equation (1) are reported in Appendix Table 1.

New developments note that if treatment effects vary over time and across units of analysis, then two-way fixed-effects (TWFE) models of this nature can yield biased results where the coefficient of interest β differs from the true average treatment effect on the treated (ATT). This is especially the case when earlier treated units are used as controls for later treated units, the so-called "forbidden" comparisons. We undertake diagnostics using methods developed in Golding (2019) and Goodman-Bacon (2021) to gauge the extent to which this is an issue in our case. Results reveal that such inappropriate comparisons potentially affect a relatively large part of our sample (details reported below).

3.2. Difference-in-Differences with Multiple Time Period Models

Given the results of diagnostic tests, we adopt newly developed methods in Callway and Sant'Anna (2021) as our preferred specification which allows the estimation of group-time specific ATTs that are insulated against the "forbidden" comparisons by using "never treated" and/or "not yet treated" units as the control group in a staggered implementation design where once the "treatment" turns on, it remains on. Given the widespread diffusion of OPVs across the districts of India during our time-period of analysis, the size of the "never treated" group in our case is relatively small (there is only one district in our sample that constitutes this group). We thus follow guidelines in Callway and Sant'Anna (2021) and use both never treated and not yet treated units as the control group. For purposes of this study, we report the "simple" aggregation of these group-time specific ATTs that uses the size of the group-year cell as weights, however, averages across time for a group or averages across groups for specific time periods are also obtained.[3] We present two sets of results from these models; results without controls (conditioning only on the variable that denotes the earliest year in which a district gains access) and results with controls (conditioning on year of earliest access and time-invariant individual, household and state-level characteristics). Including controls is important in our context as studies suggest that socio-economic inequalities are major barriers to childhood vaccination in low and middle income countries (Hajizadeh 2018, Pande and Yazbek 2003, Shrivastwa et al. 2015). Models are weighted using weights provided in the NSSO and standard errors are clustered at the district-level. Results from these models are reported in Table 2.

The identifying assumption for the Callway and Sant'Anna (2021) estimator's "not yet treated" version is that the trajectory in potential outcomes evolves in the same way for treated cohorts/groups and never treated and/or not yet treated cohorts/groups. We provide two pieces of evidence to show that this is the case in our analysis. First, we plot the the dynamic treatment effects estimated by Callway and Sant'Anna (2021)'s estimator in the pre-treatment and post-treatment time periods. These are presented in Panels A (any disability), B (locomotor

[3] Available on request.

disability) and C (polio disability) of Figure 2 and show that declines in the incidence of these disabilities are evident well into the post-treatment period.[4] Second, we report tests from the Callway and Sant'Anna (2021) estimator that checks for parallel trends up to ten periods before treatment in the main results table (Table 2). In all cases, we cannot reject the null that pre-trends are absent (that is, the parallel trends assumption holds). Heterogeneity in these ATTs by gender, rural/urban status, caste and education status are reported in Table 3.

3.3. Saturated Fixed-Effects Specification

While Callway and Sant'Anna (2021)'s estimator provides the appropriate ATTs of the impact of OPV access on the incidence of disabilities, the method does not report coefficients on the regressors included as controls (the individual and households controls are listed in Table 1). In order to understand their impacts and also to evaluate whether the number of years of access to OPVs has differential impacts across districts, we estimate linear probability models that include the variables of interest as well as district and year of birth fixed-effects, along with their interactions. The basic formulation of these models is:

$$y_{ijt} = \beta_1\, Exp_{ijt} + \beta_2 No.of\ years_{ijt} + \beta_3\left(Exp_{ijt} \times No.of\ years_{ijt}\right) + \beta_4\, X_{ij} + \alpha_j + \theta_t + (\alpha_j \times \theta_t) + \vartheta_{it} \qquad (2)$$

Where subscripts are as defined above and $No.of\ years_{ijt}$ measures the number of years an individual's district had access to OPVs when she/he was born. The interaction of this variable with Exp_{ijt} reveals the differential impact of years of access among those who are exposed (for example, someone who is exposed at birth in a district that has had access for one year may experience a different effect as compared to someone who is exposed at birth in a district that has

[4] These graphs estimate different coefficients from DD with multiple time period models that include regressors as noted in Table 2, but look similar given their relative sizes in one figure.

had access for ten years). Individual, household and state-specific (time-invariant) regressors are in X_{ij} and the coefficients of interest is β_4. These results are reported in Appendix Table 2.

4. Data and Summary Statistics

Our study primarily uses three sources of data. The first is the National Sample Survey Organization (NSSO) data's disability modules from 2002 and 2018. NSSO had an earlier disability module in 1990, but these data do not include information on districts, our preferred unit of analysis for the spread of OPV vaccines, and thus cannot be used. The NSSO disability modules are the source of our outcome variables and the individual and household level controls. We consider three types of disabilities – any, locomotor, and polio-related disability – as indicator variables. Any disability includes locomotor (paralysis, deformity/loss of limb or dysfunction of joints/limbs), visual (no light perception, has perception but cannot count fingers even with spectacles up to a distance of one to three meter, and normally uses spectacles), hearing (profound, severe, and moderate), speech (cannot speak, speaks in single words, speaks unintelligibly, stammers, speaks with abnormal voice, any other speech defect), and mental (unnecessary and/or excessive worry and depression, repetitive behavior, changes of mood/mood swings, talking/laughing to self, and seeing visions). Causes of locomotor disability include cerebral palsy, polio, leprosy (cured/not cured), stroke, arthritis, cardio-respiratory disease, cancer, tuberculosis, burns/injuries, medical/surgical intervention, and old age. As noted above, polio is the largest cause of locomotor disability with 19.9% of those with the latter identifying this disease as the reason.

We note two qualifications here. First, up to 70% of individuals with polio may not exhibit symptoms (Ochmann and Roser 2017). Thus our estimates may be an undercount. This is however a conservative bias for us since if we did have an accurate (higher) count, our results would be even larger than they currently are. Second, general development of a district may reduce the incidence of polio by improving sanitation, the nutritional environment, and access to health care and infrastructure. We control for this in our preferred specification as timing of access to OPVs is a district specific variable, and because we include regressors for demographic and socio-economic characteristics in our repeated cross-section sample. Our alternate specification takes this into account by including district fixed-effects and the interaction of these district fixed-effects with time fixed-effects (to control for time-varying district unobservables).

The second source of information we use is the National Family Health Surveys (NFHS) data which are the Demographic and Health Surveys (DHS) for India. There are four rounds that are currently publicly available (1992-1993, 1998-1999, 2005-2006 and 2015-2016) but again, the third round does not reveal district identities and thus are not used. The NFHS data are the source of information for the earliest year in which a district had access to the first dose of the OPV vaccine.[5] We gather these data by tracking responses to questions asked of mothers on the polio vaccination status of their last three children. In particular across the first, second and fourth NFHS surveys, the questionnaire asks (for children 0 – 5 years) "Please tell me if (NAME) (has) received…Polio vaccine, that is, drops in the mouth?" Mothers who respond "yes" are then asked the month and year in which the child received the first, second, third and fourth doses.[6] We track the year in which mothers report their child received the first dose, and then using information on mother's district of residence, we calculate the earliest year in which a particular district gained access to OPVs.[7] This procedure was implemented for the earliest

[5] District Level Household and Facility Survey (DLHS) data track the presence of cold-storage facilities which might be used to proxy for vaccine access. However, the NFHS data are widely considered to be more reliable in its immunization measures as compared to the DLHS.
[6] We thought about using the month information but the NSSO does not report an individual's month of birth.
[7] We use information on the second through fourth doses to calibrate that the year in which the first dose was received in a district is correct. That is, we know that the second dose cannot have been received in an earlier year to the first dose, the third cannot be before the first, and so on.

NFHS round from 1992-93 and then repeated for the remaining rounds. District boundaries have changed substantially over the time-period of our analysis because new states were carved out of old ones and because existing districts split into components. We thus created a detailed crosswalk that maps newly created districts to their parent district over the 1985 to 2018 time period. Districts were then matched homogenously over the time-span of our research.

The third source of data we use is the Family Planning Statistics (FPS) of India manuals that provide information on an annual basis for the polio campaign from 1988 to 2016 on performance measures related to OPV disbursement at the state-level including the percent of the target (number of children in thousands who were slated to receive the vaccine) that was completed. We create the sample for analysis by appending the NSSO rounds with disability data from 2002 and 2018 (a repeated cross-section), and then merging the NFHS information on earliest year of access on the basis of districts. Data from the FPS are consequently merged on the basis of state identifiers, which also had to be carefully tracked given changes in state boundaries over these years.

Table 1 presents weighted summary statistics for the variables we use. Panel A denotes estimates for the outcome variables in the full sample while Panel B shows estimates for the outcomes at baseline (1985). As noted above, we begin our analysis from 1985 onwards as this is the year from which the immunization campaign began to extend to all regions of India and was no longer concentrated in urban settings. Statistics in Panel A reveal that 2.5% of the sample had any disabilities, 1.4% had a locomotor disability, and 0.4% had a polio-related disability. Considering conditional means increases these estimates. The proportion with any disability in the overall sample has a mean of 12%, while the proportion of those with locomotor disabilities among those with any disability is 51.9%. As above, proportion with polio disability among those with locomotor disabilities is 19.9%. Panel B statistics indicate that incidence of these disabilities was about three times as high in the baseline year of 1985.

Since we restrict the analysis to those born in 1985 or after, the individual characteristics in Panel C reveal that the mean age is 15.6 years (average year of birth is 2000) of which 46.8% are female.[8] About 4.1% of the respondents had parents who are related, and close to 21.0% percent of the sample is illiterate while only 7.8% has completed graduate school or above. The proportion that is married is 46.4%. In terms of exposure, 83.0% of the sample is born in the same year or after her/his district gains access to OPVs, and the average number of years of exposure an individual has at the time of birth is close to ten years.

Panel D shows estimates for the household-level variables including caste status, household size, land area owned, monthly per capita expenditure, and whether the household is classified as rural. In these data, 73.7% of the households are low-caste and 70.2% are rural.[9] Finally, Panel E indicates that the mean year of OPV availability at the district-level is 1991, and Panel F reports that the mean percent of the state-level targets completed is 92.7%.

5. Results

5.1. Naïve Specification

Results from the naïve specification in equation (1) are reported in Appendix Table 1 (with and without controls) and show that the treatment indicator ("Exposed") is uniformly insignificant across all columns. At the bottom of this table, results from the Goldring (2019) and Goodman-Bacon (2021) decomposition reveal that close to 69.9% of the comparisons are of

[8] An advantage of this relatively younger age-group is that we are more confident that their current district of residence is also likely their district of birth. Also as noted in Munshi and Rosenzweig (2009), permanent migration rates in India are relatively low.

[9] The 2002 NSSO disability module does not contain information on religion. We thus consider caste-status instead as this variable is available in both the 2002 and 2018 NSSO rounds.

the "forbidden" type where earlier treated units are used as controls for later treated ones. Given this, we focus our discussion on results from our preferred specification.

5.2. Preferred Specification: Difference-in-Differences with Multiple Time Period Models

Group-time aggregate ATT estimates from DD with multiple time period models using Callway and Sant'Anna (2021)'s procedure on weighted sample data along with standard errors clustered at the district-level are presented in Table 2, along with reports on chi-squared statistics and the corresponding *p*-values from tests for the absence of pre-trends in the ten periods before treatment.[10] The odd numbered columns in this table report results when models include no right hand side regressors (controls); the even numbered columns report results with controls. In each case the control group is those who were never treated and not yet treated. Following Bellemare and Wichman (2020) and Prem et al. (2021), we report the percentage change in the outcomes as per a hyperbolic sine transformation of $e^{\widehat{\beta}} - 1$.

The ATT coefficient in column (1) indicates that the incidence of any disability decreased by 1.2% on average in the years after a district had access to OPVs in the baseline model that excludes all regressors. Given the mean of any disability in the earliest year of birth in the sample (baseline of 1985), this is a 18.2% decline. The corresponding models for locomotor and polio disability in columns (3) and (5) respectively, have the expected negative signs but are insignificant. The statistics reported on tests for absence of pre-trends in the decade before a district gains access to the OPV cannot reject the null that pre-trends are absent.

We next consider results from models that include regressors. The coefficient in column (2) for any disability translates into a 61.4% decline on average after the district gains access to

[10] We chose the previous ten time periods before treatment to be consistent with the graphs presented in Figure 2. In most cases, researchers test for absence of pre-trends in significantly fewer time periods before treatment. For instance, Prem et al. (2021) considers three year before treatment.

OPVs. This is a more than nine-fold decline in the incidence of any disabilities relative to the baseline mean.[11] Considering locomotor disabilities next, the coefficient tin column (4) indicates that with district access to OPVs, there was an average 57.3% decline in the incidence of this type of disability. The corresponding decline for polio disability is 55.9% on average. As in the case of models without regressors, test statistics for pre-trends cannot reject their absence (confirmed in Figure 2). These results in Table 2 underline that the arrival of OPVs brought substantial benefits to populations in districts that gained access.

We test for heterogeneity in the incidence of polio-related disability by considering sub-samples of the data by gender, rural/urban status, caste status and by literacy level. These ATT results from Callway and Sant'Anna (2021)'s procedure disaggregated by average ATT in the pre- and post-treatment time periods are reported in Table 3. Although the ATTs after treatment are negative by gender status, these are insignificant. The coefficients are also measured with insignificance when it comes to sector differentials. In the case of caste, the average ATTs reveal a significant increase for low-caste groups suggesting some inequity in access, while for upper-caste individuals, there is a decline in the size of the (positive) ATT estimate from pre- to post-time periods. While the magnitude of the ATT shows a decline for those who are illiterate, the ATTs are not significant. The estimates in column (8) show that the literate group had a negative and significant ATT in the pre-treatment time period that became more marked (more negative in magnitude) as their district gained access.

5.3. Saturated Fixed-Effects Specification

We end this section by discussing results from equation (2) that considers whether an individual was born in the same year or after the district gains access to OPV ("Exposed") and

[11] As we note above, this outcome may reflect access to other vaccines beyond OPVs alone and may thus overestimate effects of OPV access.

the number of years the district had access to the vaccine in the year in which an individual is born ("No. of years"). These results are reported in Appendix Table 2 for the three outcomes we consider. In each case, being exposed to OPVs reduces the probability of disability. Focusing on column (1) first, the likelihood of any disability declines by 9 percentage points. Correspondingly, the likelihood of locomotor and polio disability declines by 6.2 percentage points and 2.1 percentage points in columns (5) and (9), respectively. Columns (2), (6) and (10) are conditional on years of exposure alone. For polio, the coefficient in column (10) indicates that an additional year of exposure reduces the likelihood of contracting this disease by 1.1%.

When exposure and years of exposure are jointly estimated in the same model (columns (3), (7) and (11)), it is years of exposure that retains its significance and sign. The interaction of exposure and years of exposure captures the additional effect of the years variable on those who were exposed. The negative sign on this interaction term in columns (4), (8) and (12) suggest that there is an amplified impact of years of exposure on those who were exposed. However, in no case is this interaction term measured significantly.

Considering the other regressors in these models, older individuals report lower incidence of disabilities as do females (mainly for any and locomotor disability). Having parents who were blood related increases the incidence of any disabilities while higher levels of education (the excluded category is that the individual is illiterate) and marriage have a mostly negative impact across all columns. Low-caste individuals report higher likelihoods of locomotor and polio disabilities, while household size has a positive effect mainly for polio. There is less of a clear pattern when it comes to land owned while rural households are more likely to report higher incidence as compared to urban households. Finally, districts where higher proportions of state-level targets were met experience negative impacts on disability across most columns.

6. Conclusions and Policy Implications

We demonstrate causally that access to OPVs for children in the 0-5 years age-group across the districts of India from 1985 to 2018 brought significant beneficial impacts on disability. Our preferred specification, DD with multiple time period models that control for time-invariant individual and household demographic and SES characteristics, estimates ATTs that indicate that the incidence of any disability declined by 61.4%, of locomotor disability declined by 57.3%, and of polio-related disability decreased by 55.9%. Heterogeneity tests reveal that access to OPVs reduced disability incidence for most gender, rural/urban, and literacy groups, except for those who identified as low-caste. We test for pre-trends and present results from alternate models as robustness checks for the results from our preferred specification.

The socio-economic benefits of WPV eradication in India have been substantial, and this achievement is one of the less appreciated public health success stories of the twenty-first century. Estimates in Nandi et al. (2016) using 1982 - 2012 data suggest that the economic gain (using a value of statistical life yardstick that takes productivity gains and disability-adjusted life years into account) was USD 1.7 trillion (2022 USD 2.1 trillion) – a major contribution to economic growth. This success fuels optimism that other diseases such as dengue, tuberculosis, typhoid, or malaria that is holoendemic in India, and which also impose significant health and economic costs, may be brought under control through concerted efforts. Policy recommendations include using the framework of the successful polio eradication programs that extended outreach of OPVs coupled with attention on improving sanitation, nutrition, and educational interventions to raise literacy and awareness to try to replicate achievements in these other disease domains as well.

References

Bagcchi, S. 2019. "Surviving polio with disabilities." *The Lancet Infectious Diseases*, 19(3), p251.

Bellemare, M. and C. Wichman. 2020. "Elasticities and the inverse hyperbolic sine transformation." *Oxford Bulletin of Economics and Statistics*, 82, 50-61.

Callway B. and P. Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics*, 225, 200-230.

Goldring, T. 2019. *ddtiming: Stata module to perform a Goodman-Bacon decomposition of difference-in-differences estimation.* https://tgoldring.com/projects/ddtiming.

Goodman-Bacon, A. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225, 254-277.

Government of India. 2016. "India - persons aged 60 plus survey: NSS 42nd round schedule 27 (1986-87)." Ministry of Statistics and Program Implementation, National Sample Survey Organization.

Hajizadeh, M. 2018. "Socioeconomic inequalities in child vaccination in low/middle-income countries." *Journal of Epidemiology and Community Health*, 72(8), 719-725.

John, T. 1981. "The costs and benefits of immunization in India." *Indian Pediatrics*, 18, 513-516.

John, T. and V. Vashishtha. 2013. "Eradicating poliomyelitis: India's journey from hyperendemic to polio-free status." *Indian Journal of Medical Research*, 137, 881-894.

Munshi, K. and M. Rosenzweig. 2009. "Why is mobility in India so low? Social insurance, inequality, and growth." National Bureau of Economic Research, Working Paper w14850.

Nandi, A., D. Barter, S. Prinja, and T. John. 2016. "The estimated health and economic benefits of three decades of polio elimination efforts in India." *Indian Pediatrics*, 53(1), S7-S13.

Ochmann, S. and M. Roser. 2017. "Polio". *Published online at OurWorldInData.org.* Retrieved from: 'https://ourworldindata.org/polio' [Online Resource]

Pande, R. and A. Yazbek. 2003. "What's in a country average? Wealth, gender, and regional inequalities in immunization in India." *Social Science and Medicine*, 57, 2075-2088.

Prem, M., M. Purroy, and J. Vargas. 2021. "Landmines: The local effects of demining." Working Paper. https://ssrn.com/abstract=3924929.

Shiri, S., I. Gartsman, Z. Meiner, and I. Schwartz. 2015. “Long-standing poliomyelitis and psychological health.” *Disability and Rehabilitation*, 37(34), 2233-2237.

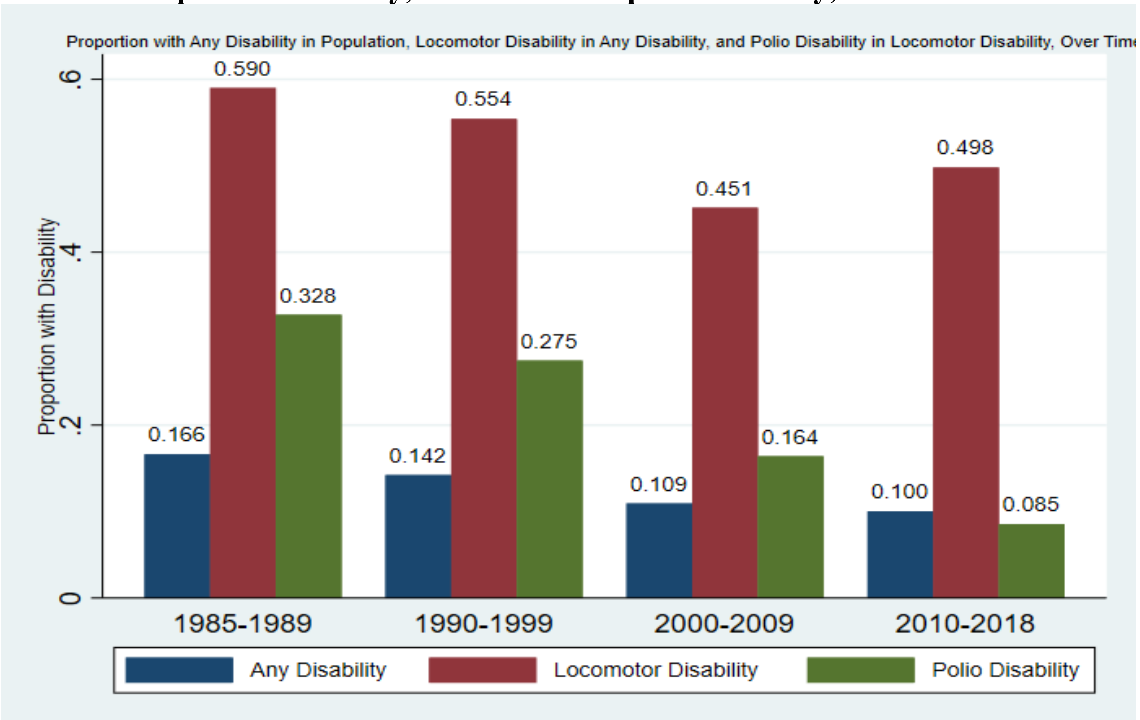
Shrivastwa, N., B. Gillespie, G. Kolenic, et al. 2015. “Predictors of vaccination in India for children aged 12-36 months.” *American Journal of Preventive Medicine*, 49(6), S435-S444.

Stafford, W. and R. Gurney. 1951. “Respiratory failure in poliomyelitis: A simple method for its recognition and control.” *Annals of Internal Medicine*, 34(1), 203-211.

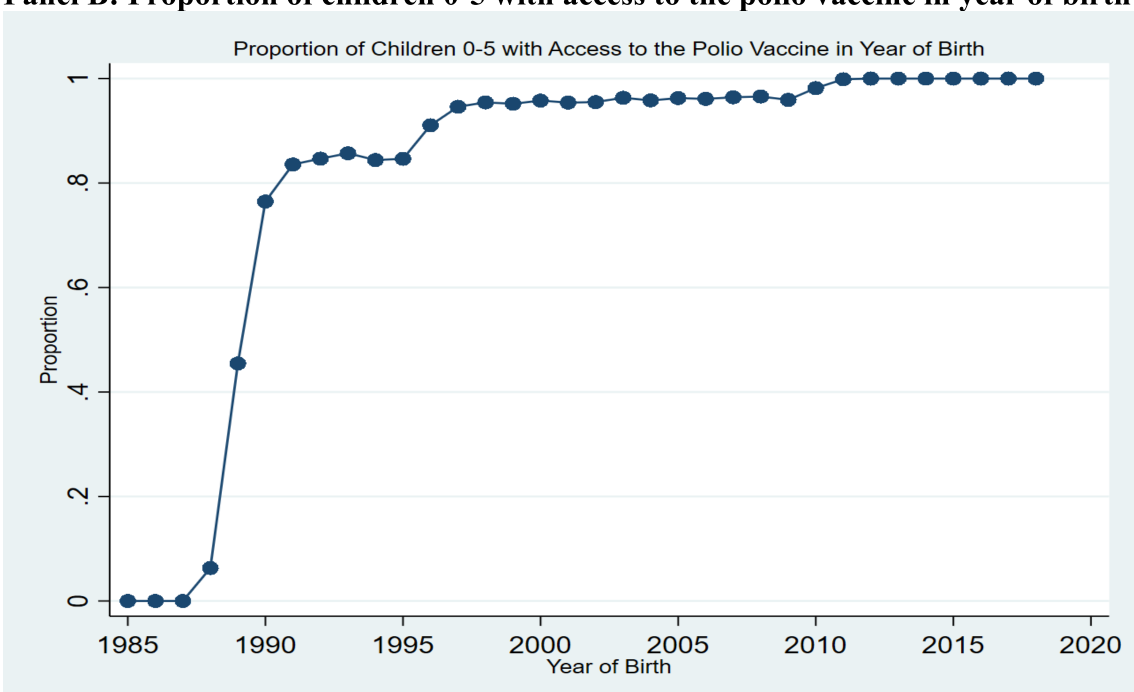
World Bank. 2013. “Official exchange rate (LCU per US$, period average) – India 1960-2013.” *World Development Indicators*, The World Bank Group, https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=IN. Accessed February 7, 2022.

Figure 1: Trends in disability proportions and children 0-5 with polio vaccine access

Panel A: Proportion with any, locomotor and polio disability, over time



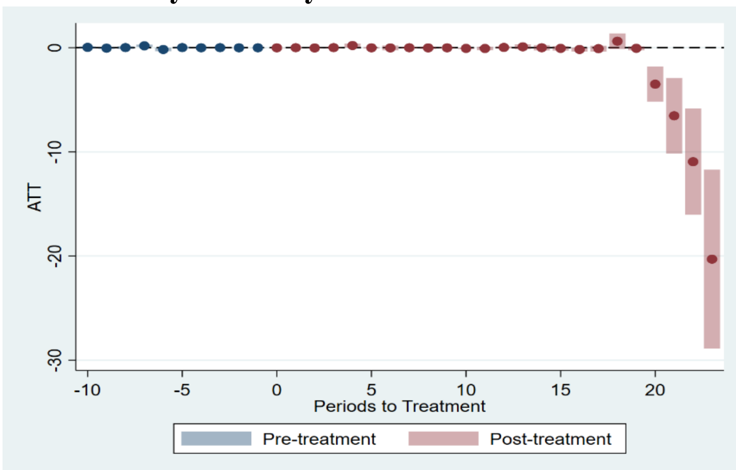
Panel B: Proportion of children 0-5 with access to the polio vaccine in year of birth



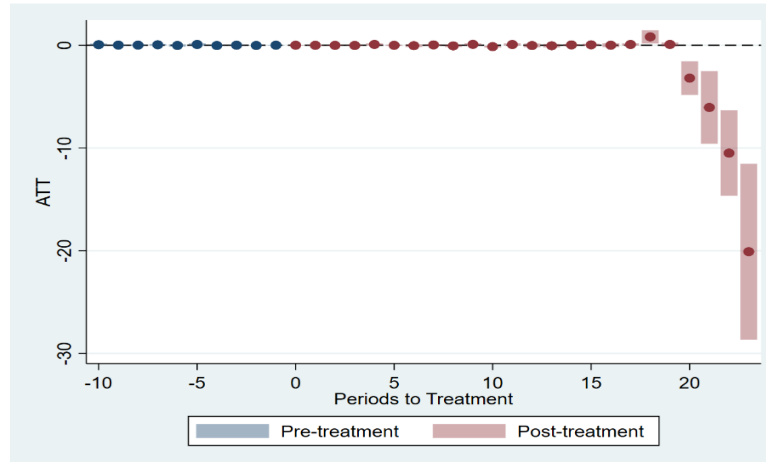
Notes: Authors' calculations using NSS and NFHS data. Sample includes repeated cross-sections of 118,659 individuals in 82,794 households across 1129 districts whose year of birth is 1985 or after in NSS rounds 2002 and 2018 (500 districts across 34 states in 2002, and 629 districts across 30 states in 2018). Figures report weighted statistics.

Figure 2: ATT estimates for any, locomotor and polio disability pre- and post-treatment

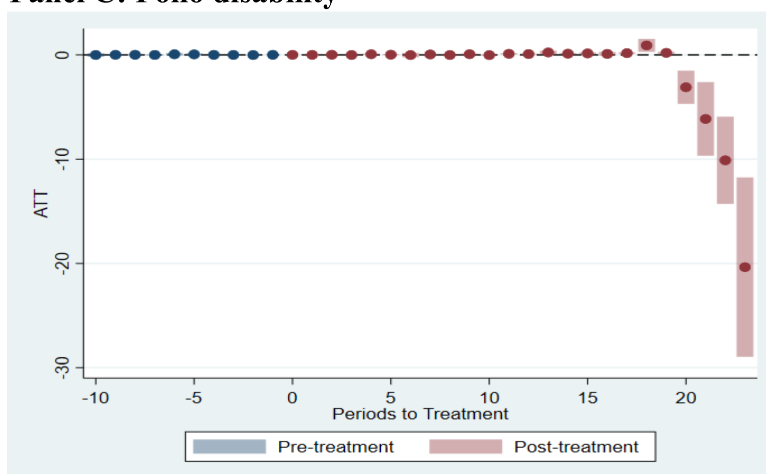
Panel A: Any disability



Panel B: Locomotor disability



Panel C: Polio disability



Notes: Authors' calculations using NSS and NFHS data. Sample includes repeated cross-sections of 118,659 individuals in 82,794 households across 1129 districts whose year of birth is 1985 or after in NSS rounds 2002 and 2018 (500 districts across 34 states in 2002, and 629 districts across 30 states in 2018). Models include all controls in Table 1. Control group includes those who were never treated and not yet treated (see Callway and Sant'Anna (2021) for details).

Table 1: Summary statistics for the repeated cross-section sample

Variable	Mean	Standard Deviation	Observations
Panel A: Outcomes:			
Indicator for any disability	0.025	0.156	118,659
Indicator for locomotor disability	0.014	0.119	118,659
Indicator for polio disability	0.004	0.063	118,659
Proportion with any disability in full sample	0.120	0.034	118,659
Proportion with locomotor dis. among those with any dis.	0.519	0.069	118,659
Proportion with polio dis. among those with loco. dis.	0.199	0.093	118,659
Panel B: Outcomes at baseline (1985):			
Indicator for any disability	0.066	0.248	2,949
Indicator for locomotor disability	0.042	0.200	2,949
Indicator for polio disability	0.012	0.109	2,949
Panel C: Controls: Individual specific			
Age in year	15.633	9.172	118,659
Female	0.468	0.499	118,659
Parents are blood related	0.041	0.198	85,726
Illiterate/informal education	0.209	0.407	85,730
Completed primary or middle school	0.483	0.500	85,730
Completed secondary or higher secondary	0.230	0.421	85,730
Completed graduate or above	0.078	0.268	85,730
Married	0.464	0.844	118,654
Year of birth	2000	9.210	118,659
Exposed	0.830	0.376	118,300
Number of years of exposure	9.905	10.125	118,300
Panel D: Controls: Household specific			
Low-caste household	0.737	0.441	82,794
Household size	5.424	2.389	82,794
Household land area in hectares	0.083	0.672	82,783
Household average monthly consumption expenditure	20.486	17.305	82,793
Rural household	0.702	0.457	82,794
Panel E: Control: District specific			
Year first dose of OPV became available in district	1991	5.566	1129
Panel F: Control: State specific			
Median percent completed of state-level targets under polio campaign 1988-2016	92.667	9.008	64

Notes: Table presents weighted statistics. Sample includes repeated cross-sections of 118,659 individuals in 82,794 households across 1129 districts whose year of birth is 1985 or after in NSS rounds 2002 and 2018 (500 districts across 34 states in 2002, and 629 districts across 30 states in 2018). Estimates in Panels A, B and C are at the individual level. Estimates in Panel D are at the household level, in Panel E are at the district-level, and in Panel F are at the state-level.

Table 2: ATT from difference-in-difference with multiple time periods models of OPV availability on types of disabilities

	Any disability		Locomotor disability		Polio disability	
	No controls	With controls	No controls	With controls	No controls	With controls
	(1)	(2)	(3)	(4)	(5)	(6)
Average treatment effect on the treated (ATT)	-0.012**	-0.951***	-0.004	-0.851***	-0.000	-0.819***
	(0.005)	(0.260)	(0.003)	(0.256)	(0.002)	(0.258)
Absence of pre-trends in ten periods before treatment:						
χ^2 (10)	7.870	13.420	5.280	11.520	10.300	7.650
Prob > χ^2 (10)	[0.642]	[0.201]	[0.871]	[0.319]	[0.415]	[0.663]
Mean of the dependent variable at baseline (1985)	0.066		0.042		0.012	
Observations	118,659	80,608	118,659	80,608	118,659	80,608

Notes: Sample includes repeated cross-sections of 118,659 individuals in 82,794 households across 1129 districts whose year of birth is 1985 or after in NSS rounds 2002 and 2018 (500 districts across 34 states in 2002, and 629 districts across 30 states in 2018). Table presents weighted statistics with standard errors clustered at the district-level. Models include all controls in Table 1. In these difference-in-difference with multiple time periods models the outcome model is least squares, the treatment model is inverse probability, and the control group is those who were never treated and not yet treated (see Callway and Sant'Anna (2021) for details). *p*-values in square brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 3: ATT from difference-in-difference with multiple time periods models of OPV availability on polio disability

Variables	Women (1)	Men (2)	Rural (3)	Urban (4)	Low caste (5)	Upper caste (6)	Illiterate (7)	Literate (8)
Pre-period average ATT	0.074	0.071	-0.056	0.029	0.168***	0.126*	2.240	-0.104**
	(0.108)	(0.079)	(0.043)	(0.086)	(0.045)	(0.066)	(1.530)	(0.043)
Post-period average ATT	-0.092	-0.052	0.048	0.159	1.014***	0.060	0.377	-0.808***
	(0.461)	(0.037)	(0.085)	(0.132)	(0.190)	(0.039)	(0.793)	(0.215)
Includes all controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	35,168	40,275	48,674	16,921	61,504	17,409	18,954	56,558

Notes: Sample includes repeated cross-sections of 118,659 individuals in 82,794 households across 1129 districts whose year of birth is 1985 or after in NSS rounds 2002 and 2018 (500 districts across 34 states in 2002, and 629 districts across 30 states in 2018). Table presents weighted statistics with standard errors clustered at the district-level. Models include all controls in Table 1. In these difference-in-difference with multiple time periods models the outcome model is least squares, the treatment model is inverse probability, and the control group is those who were never treated and not yet treated (see Callway and Sant'Anna (2021) for details). *p*-values in square brackets. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

APPENDIX

Appendix Table 1: Two-way fixed-effects model results of OPV availability on types of disabilities

	Any disability		Locomotor disability		Polio disability	
	No controls	With controls	No controls	With controls	No controls	With controls
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Exposed	-0.007	-0.002	-0.003	-0.001	-0.002	-0.001
	(0.005)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Observations	118,300	84,799	118,300	84,799	118,300	84,799
R-squared	0.023	0.566	0.017	0.373	0.010	0.131

Goodman-Bacon decomposition

Earlier treated (T) vs. later treated (C)	0.276
Later treated (T) vs. earlier treated (C)	0.699
Treated (T) vs. never treated (C)	0.021
Treated (T) vs. already treated (C)	0.004

T=treatment; C=Control/comparison

Notes: Sample includes repeated cross-sections of 118,659 individuals in 82,794 households across 1129 districts whose year of birth is 1985 or after in NSS rounds 2002 and 2018 (500 districts across 34 states in 2002, and 629 districts across 30 states in 2018). Table presents weighted statistics with standard errors clustered at the district-level. Controls include those listed in Table 1. Models include district fixed-effects and year fixed-effects. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Appendix Table 2: Saturated fixed-effects model results of OPV availability on types of disabilities

	Any disability				Locomotor disability				Polio disability			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposed	-0.090***		0.006**	0.004	-0.062***		-0.002	-0.003	-0.021***		-0.003	-0.004*
	(0.005)		(0.003)	(0.003)	(0.004)		(0.003)	(0.003)	(0.003)		(0.002)	(0.002)
No. of years		-0.061***	-0.061***	-0.059***		-0.038***	-0.038***	-0.037***		-0.011***	-0.011***	-0.011***
		(0.000)	(0.000)	(0.001)		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Exposed*				-0.002				-0.001				-0.000
No. of years				(0.001)				(0.001)				(0.001)
Age	-0.037***	-0.057***	-0.057***	-0.057***	-0.024***	-0.037***	-0.037***	-0.037***	-0.008***	-0.011***	-0.011***	-0.011***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Female	-0.004***	-0.005***	-0.005***	-0.005***	-0.002**	-0.002***	-0.002***	-0.002***	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Parents are blood	0.025***	0.012***	0.012***	0.012***	0.011***	0.003	0.003	0.003	0.001	-0.001	-0.001	-0.001
related	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Completed prim/	-0.047***	-0.040***	-0.040***	-0.040***	-0.009***	-0.004***	-0.004***	-0.004***	0.004***	0.005***	0.005***	0.005***
middle school	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Completed secon.	-0.065***	-0.057***	-0.058***	-0.058***	-0.015***	-0.010***	-0.010***	-0.010***	0.003**	0.004***	0.004***	0.004***
higher secondary	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Completed grad/	-0.085***	-0.063***	-0.064***	-0.064***	-0.026***	-0.013***	-0.013***	-0.013***	-0.002	0.002*	0.002*	0.002*
above	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.027***	-0.018***	-0.018***	-0.018***	-0.012***	-0.007***	-0.007***	-0.007***	-0.006***	-0.004***	-0.004***	-0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Low-caste	-0.001	-0.000	-0.000	-0.000	0.001	0.002*	0.002*	0.002*	0.002**	0.002***	0.002***	0.002***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household size	0.000	-0.001***	-0.001***	-0.001***	0.001**	0.000	0.000	0.000	0.001***	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land owned in	0.054***	-0.000	-0.000	-0.000	0.034***	0.000	0.000	0.000	0.012***	0.002	0.002	0.002
hectares	(0.011)	(0.000)	(0.000)	(0.000)	(0.008)	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Monthly per	0.000***	0.000	0.000	0.000	0.000***	0.000	0.000	0.000	0.000***	0.000*	0.000*	0.000*
capita exp	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural	0.009***	0.003***	0.003***	0.003***	0.007***	0.003***	0.003***	0.003***	0.003***	0.002**	0.002**	0.002**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Median percent	0.032***	-0.009***	-0.009***	-0.009***	0.006	-0.020***	-0.020***	-0.020***	0.002	-0.006*	-0.006*	-0.006*
target completed	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.004)	(0.004)	(0.004)

Observations	84,736	84,736	84,736	84,736	84,736	84,736	84,736	84,736	84,736	84,736	84,736	84,736
R-squared	0.453	0.580	0.580	0.580	0.310	0.393	0.393	0.394	0.134	0.161	0.161	0.161

Notes: Sample includes repeated cross-sections of 118,659 individuals in 82,794 households across 1129 districts whose year of birth is 1985 or after in NSS rounds 2002 and 2018 (500 districts across 34 states in 2002, and 629 districts across 30 states in 2018). Table presents weighted statistics with standard errors clustered at the district-level. Models include a constant term, district fixed-effects, year fixed-effects, and their interactions. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.