IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 15508

Childhood Vaccinations and Demographic Transition: Long-Term Evidence from India

Arindam Nandi
Amit Summan
Thoại D. Ngô
David E. Bloom

AUGUST 2022

DISCUSSION PAPER SERIES

IZA DP No. 15508

Childhood Vaccinations and Demographic Transition: Long-Term Evidence from India

Arindam Nandi
The Population Council

Amit Summan
One Health Trust

Thoại D. Ngô
The Population Council

David E. Bloom
Harvard T.H. Chan School of Public Health and IZA

AUGUST 2022

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Childhood Vaccinations and Demographic Transition: Long-Term Evidence from India*

Childhood vaccines can increase population growth in the short term by improving the survival rates of young children. Over the long run, reductions in child mortality rates are associated with lower demand for children and fertility rates (known as "demographic transition"). Vaccines can potentially aid demographic transition by lowering child mortality and improving future health, schooling, and labor market outcomes of vaccinated mothers, but these long-term demographic benefits remain untested. In this study, we examine the demographic effects of India's national childhood vaccination program (the Universal Immunization Programme or UIP). We combine data on the district-wise rollout of UIP during 1985–1990 with fertility preference data of 625,000 adult women from the National Family Health Survey of India 2015–2016. We include women who were born five years before and after the rollout period (1980–1995) and were cohabiting with a partner at the time of the survey. We divide these 20-36-year-old women into two groups: those who were exposed to UIP at birth (treatment group) and those who were born before the program (control group). After controlling for individual- and household-level factors and age and district fixed effects, treatment group women are 2% less likely to have at least one child and want 2% fewer children in their lifetime as compared with the control group. The negative effect on at least one childbirth is larger for more educated and richer women, while the effect on the desired number of children is larger for uneducated and poorer women.

JEL Classification: I15, J13, J18, I10

Keywords: India, UIP, demographic transition, demand for fertility

Corresponding author:
David E. Bloom
Department of Global Health and Population
Harvard T. H. Chan School of Public Health
665 Huntington Avenue
Boston, Massachusetts 02115
USA
E-mail: dbloom@hsph.harvard.edu

* We thank Santosh Kumar for sharing the Universal Immunization Programme rollout data. This work was supported in part by the Value of Vaccination Research Network through a grant from the Bill & Melinda Gates Foundation [OPP1158136]. The content is solely the responsibility of the authors and does not necessarily reflect the views of the Value of Vaccination Research Network (or the foundation).

1. Introduction

Childhood immunization is one of the greatest accomplishments of modern medicine and public health. In 2000–2030, routine immunization is projected to prevent 69–97 million childhood deaths worldwide, of which 37–50 million lives are estimated to have been saved during 2000 to 2019 (Li et al., 2021; Toor et al., 2021). In low- and middle-income countries (LMICs), childhood vaccines are also projected to help avert $1.5 trillion in medical expenditure during 2011–2030, with an economic return greater than 50 times per dollar spent when measured in terms of willingness to pay (Sim et al., 2021; Watts et al., 2021).

Health interventions that reduce infant and child mortality—such as prenatal and postnatal care and vaccines—may have important implications for the demand for children and long-term population growth. Fewer deaths may increase the cohort size of children and increase the population growth rate in the short term, especially following medical or public health breakthroughs in infant survival such as the advent of new drugs (Alsan et al., 2021; Bhalotra and Venkataramani, 2011; Jayachandran et al., 2010; Keenan et al., 2018). However, child mortality and population fertility rates often move downward together over a longer time horizon (Bhalotra et al., 2022; Bloom et al., 2020; Doepke, 2005; Galor, 2012; Palloni and Rafalimanana, 1999; Soares, 2005). This phenomenon, known as demographic transition, has been observed for more than a century and is considered to be a major driver of economic growth in many countries. With lower fertility rates, the ratio of working-age populations to non-working-age populations increases, which in turn can aid sustained high levels of economic productivity (Bloom et al., 2003; Bloom and Canning, 2008; Bloom and Williamson, 1998). This so-called "demographic dividend" was behind the rapid growth of the East Asian miracle economies during the 1960s to 1990s and has been projected to benefit many African countries in the near future (Bloom et al., 2017; Bloom and Williamson, 1998).

Several contributing factors for demographic transition have been explored and debated (Galor, 2012, 2011). The first pathway is based on the physiological and psychological effect of the death of a child. Infant death and ceased breastfeeding can potentially trigger reproductive cycles and allow women to conceive again (Palloni and Rafalimanana, 1999). A related psychological factor is the "replacement effect," i.e., parents may want to replace a child who has died by having more children until the desired number of children are born (Nandi et al., 2018; Nobles et al., 2015). Improvements in child survival rates will therefore have an opposite effect on the demand for fertility: parents will have fewer children as they know that a child is likely to survive more than ever before, and the time between subsequent births will increase (Chowdhury et al., 1976; Doepke, 2005; Galor, 2012; Montgomery and Cohen, 1998; Palloni and Rafalimanana, 1999; Pritchett, 1994; Soares, 2005; Wolpin, 1997).

Empirical evidence on child survival–driven demographic transition is mixed (Galor, 2012). Ager et al. (2018), Bhalotra et al. (2022), and Canning et al. (2013) link child mortality (or mortality expectations) positively with fertility rates. In particular, Canning et al. (2013) use data from 46 LMICs to estimate that a 1% increase in child survival rate can reduce the number of children born by 0.6% at the individual level. At the community level, where a woman's fertility decision may also be affected by other women's fertility preference, a 1% increase in child survival rate is linked with 1.1% fewer births (Canning et al., 2013). In contrast, analysis using data from 19th century England and France show that reductions in child mortality rates substantially predated—and did not cause—reductions in fertility rates (Doepke, 2005; Galor, 2012; Murphy, 2015).

A review by Galor (2012) argues that other factors such as technological progress and rise in the demand for human capital, improved educational attainment, and higher income levels may instead be the main drivers of demographic transition. With industrialization and higher demand for skilled labor, parents may have fewer children and invest more resources in the human capital development of each child, which is conceptualized in the so-called child quantity-quality tradeoff theory (Becker and Lewis, 1973; Becker and Tomes, 1976). Improvements in schooling access and quality may accelerate this process by increasing the returns to schooling (Becker et al., 2010; Bleakley and Lange, 2009; Galor, 2012; Murphy, 2015; Murtin, 2013). Finally, rise in educational attainment, returns to education, and income may increase the opportunity cost of childbearing. As a result, women may reduce their demand for fertility and participate more in gainful economic activities (Aaronson et al., 2014; DeCicca and Krashinsky, 2022; Finlay, 2021; Galor, 2012; Galor and Weil, 2000).

Studies of whether health interventions can affect the demand for children and population growth are limited. Lucas (2013) estimates that the national malaria eradication program of Sri Lanka in the 1940s increased the annual probability of childbirth by 5.8 percentage points during the next three decades. Gooch (2017) estimates that at least 1.5% of the global population growth—and 14% in Africa—since 1900 can be attributed to measures that reduce the transmission of mosquito-borne diseases. Kuecken et al. (2021) use variations in cohort-level exposure to the World Health Organization's (WHO) malaria eradication program (known as the Roll Back Malaria Partnership, 1998) in 27 African countries to show that the program reduced the probability of childbirth by 0.4 percentage points. The program also increased schooling attainment by 0.4 years and the adult employment rate by 6 percentage points. Ager et al. (2018) use a difference-in-difference framework to find that a one standard deviation reduction in smallpox mortality due to the introduction of the smallpox vaccine reduced births by 1.16 per 1,000 population and 5.6 births per 1,000 women of age 15–45 years in early 19th century Sweden. Wilson (2015) finds that a package of prevention of mother-to-child transmission of HIV in the early 2000s in Zambia reduced pregnancy rates by 10%. Among yet unpublished studies, Bhalotra et al. (2022) link the 1937 introduction of antibiotics in the United States with delayed childbearing and fewer children born, and Wilde et al. (2019) and Bhattacharjee and Dasgupta (2019) associate malaria control efforts in Sub-Saharan Africa and India respectively with higher childbirth probability.

In this paper, we examine the long-term effect of India's national program for child vaccination, known as the Universal Immunization Programme (UIP), on future demand for children. We use data from the National Family Health Survey 2015–2016 (NFHS-4), a nationally representative survey covering 601,509 households in India, and combine them with retrospective data on the district-wise introduction of UIP during 1985–1990. We consider women who were born during 1985–1990 and compare the demand for children of those who were exposed to the program at birth (intervention group) with that of those who were born before the program reached their district and therefore were not exposed (control group). To control for time-invariant and time-varying factors that may be correlated with program implementation and study outcomes, we employ year (age) and district fixed-effects regression models. We also conduct robustness checks involving variations in study periods and a falsification test and explore heterogeneity in treatment effect.

Our study makes important contributions to the existing literature on the demographic effects of health interventions. Previous studies focused heavily on malaria control, with all but one study showing a positive effect on fertility demand. In comparison, the three drug and vaccine studies (including the prevention of mother-to-child transmission of HIV, which included antiretroviral drugs) all show reductions in the demand for children. To the best of our knowledge, Ager et al. (2018) is the only study to link vaccines with reduced fertility demand, examining smallpox vaccine introduction during the late 1700s and early 1800s in Sweden. No evidence is available from other countries or time periods, especially in LMICs where vaccines have saved millions of lives in the past few decades absent other public health measures such as access to clean water, sanitation, and primary healthcare. Fertility rates in LMICs have also been historically higher, with slower rates of demographic transition, as compared with high-income countries. India has experienced a reduction in total fertility rate (average number of children a woman has in her lifetime) from 4 in 1990 to a replacement level of 2 in 2021 (Pearce, 2021; World Bank, 2021). Understanding the possible role of UIP in accelerating demographic transition may provide important policy insights for other high-fertility LMICs such as the countries in sub-Saharan Africa. Finally, our study is also the first to examine the demographic effects of a comprehensive national child immunization program instead of a single vaccine or drug. The smallpox vaccine examined by Ager et al. (2018) was given to the entire Swedish population without age restrictions, which might have a different implication for mortality and subsequent demand for children than childhood vaccines, which are typically given within the first two years of life.

2. Universal Immunization Programme and the potential pathways of its demographic effects

India introduced the World Health Organization's Expanded Programme on Immunization in 1978 with vaccines for Bacillus Calmette-Guérin; polio (oral polio vaccine); diphtheria, pertussis, and tetanus (DPT); and typhoid-paratyphoid (Lahariya, 2014; Pradhan, 2010; Sokhey et al., 1989). Until the mid-1980s, vaccines were only distributed through government hospitals in urban areas and the coverage rates were very low (Lahariya, 2014). In 1985, the government introduced the Universal Immunization Programme on a rolling basis. In the first year, 31 districts were covered, and by 1990, the program had reached all districts of India. In addition to the previously mentioned vaccines, UIP also introduced the measles vaccine. The typhoid-paratyphoid vaccine was removed from the Expanded Programme on Immunization in 1981 and was not included in UIP. UIP also provided the maternal tetanus vaccine, which was introduced in 1983 (Lahariya, 2014). UIP targeted primarily children under the age of 1 year (Sokhey et al., 1989).

A few studies argue that the introduction of UIP may have been prioritized in districts with better health infrastructure before other districts (Anekwe and Kumar, 2012; Kumar, 2009; Lahariya, 2014). However, Summan et al. (2022) used village-level data from the 1991 census of India to show that the phasing across districts was not linked with many health infrastructure indicators such as the availability of a primary health center or subcenter, community health worker, and paved road, or demographic indicators such as population size or literacy rates. Figure 1 presents the phase-wise rollout of the program across districts during 1985–1990. Although UIP had a goal of covering 85% of eligible children by 1990, India's first National Family Health Survey 1992–1993 (NFHS-1) shows that the target was not achieved (International Institute for Population Sciences and ICF, 1995). Out of 12-23-month-old children represented in the NFHS-1 data, 30% did not receive any vaccines, while coverage rates among the remaining children ranged from 42% for the measles vaccine to 62% for the Bacillus Calmette-Guérin vaccine. The coverage rate of the DPT third dose—an indicator often used to measure the performance of national immunization programs—was 52%.

The burden of vaccine-preventable diseases (VPD) in India before UIP introduction was presumably very high, but systematic data collection was lacking (Lahariya, 2014; Sokhey et al., 1989). For example, government data indicate that India had an estimated 320,000 cases of measles infections in 1980 (Lahariya, 2014). However, community- and hospital-based studies from the early 1980s indicate that almost 90% of Indian children under the age of 5 years were exposed to or infected with measles (Sokhey et al., 1989). Despite lower than target coverage of vaccines, UIP likely helped saved millions of children from VPD mortality and morbidity by the early 1990s through primary and secondary (community) protection. Furthermore, new evidence shows that a measles infection can substantially reduce innate immunity against other diseases for a period of 2–3 years (Mina et al., 2019, 2015; Vries et al., 2012; Vries and Swart, 2014). The measles vaccine under UIP may therefore have been cross-protective against many other childhood infectious diseases. Figure 2 presents the trends infant mortality rate (IMR), which is defined as the number of deaths before the age of one year per 1,000 live births, and its annual rate of change in India for two decades following the introduction of UIP in 1985. While IMR consistently reduced during this period, its annual rate of reduction remained stable at around 2.5% until the early 1990s, followed by a sharp increase to over 3% and beyond which may indicate the potential lifesaving effect of the UIP.

The long-term effect of UIP on the demand for children has a few potential pathways (Figure 3). Previous studies of the smallpox vaccine and antibiotics show that reductions in infant deaths following UIP could induce families to have fewer children (Ager et al., 2018; Bhalotra et al., 2022). Prospective parents may notice the increase in child survival rates in their community over time and decide to conceive fewer times than the parents of previous generations. A second potential pathway is through intergenerational transfer of health. Longitudinal studies in India and other countries have linked the measles and *Haemophilus influenzae* type b vaccines with 0.1–0.2 higher height and weight z-scores and a 9 percentage point lower likelihood of stunting during ages 7–15 years (Nandi et al., 2019b, 2019a; Upadhyay and Srivastava, 2017). Bogler et al. (2019) use data from 65 LMICs and associate the measles vaccine with 10% lower probability of being stunted or underweight among under-5 children. Anekwe and Kumar (2012) link UIP with 0.3–0.5 higher height-for-age and weight-for-age z-scores of under-4 Indian children. For women who were vaccinated under UIP in their own childhood (or received secondary protection through community-level immunity), these health benefits may continue through reproductive age and on to the next generation.

A large international literature links mother's height with higher birthweight, improved child anthropometric outcomes, and lower child mortality (Addo et al., 2013; Özaltin et al., 2010; Subramanian et al., 2009; Thomas et al., 1991). Maternal antibodies that are transferred *in utero* and through breastfeeding (e.g., for adult flu and maternal tetanus vaccines) may additionally reduce mortality and improve newborn health (Perrett and Nolan, 2017; Shakib et al., 2016).

In addition to improving child survival rates, UIP may reduce the demand for children through economic empowerment. Studies of the measles and *Haemophilus influenzae* type b vaccines in Ethiopia, India, South Africa, and Vietnam show 1.7–4.8 percentage points higher standardized test scores and 0.1–0.3 more schooling grades attained by vaccinated children as compared with unvaccinated children (Anekwe et al., 2015; Nandi et al., 2019a, 2019b). Similarly, full immunization has been linked with 0.5 standard deviations higher test scores in the Philippines (Bloom et al., 2012) and 6–12% gains in test scores in India (Arsenault et al., 2020). Another study of UIP linked exposure to the program in early life with 0.2–0.3 additional schooling grades gained at age 20–36 years (Nandi et al., 2020). Among women, the effect of UIP was even higher at 0.3–0.5 extra schooling grades. Internationally, a large body of evidence links higher female educational attainment with reduced demand for fertility (Currie and Moretti, 2003; Kim, 2010; McCrary and Royer, 2011; Sheikh and Loney, 2018).

Three studies estimate the potential long-term labor market benefits of receiving childhood vaccines. Atwood (2021) uses data on the rollout of the measles vaccine in the United States during the 1960s to show a 0.3% higher employment rate and 1.1% higher earnings in later life among individuals exposed to the vaccination program compared with those not exposed. Summan et al. (2022) finds that 21-26-year-old adults who were exposed to UIP in childhood have 14% higher wages and 3% higher monthly per capita consumption expenditure. Atwood and Pearlman, (2022) link the national measles vaccination program of 1973 in Mexico with 12% increase in earnings. These findings indicate that vaccination may improve schooling attainment and labor market outcomes of women, thereby increasing the opportunity cost of childbearing (Aaronson et al., 2014; DeCicca and Krashinsky, 2022; Finlay, 2021; Galor, 2012; Galor and Weil, 2000).

3. Data and descriptive statistics

Data on UIP rollout—which include the year of UIP implementation in each district—are from Indian government sources and are used in previously published studies (Anekwe and Kumar, 2012; Nandi et al., 2020; Summan et al., 2022). We combine these data at the district level with data from NFHS-4 (International Institute for Population Sciences, 2017). NFHS-4 is a nationally representative survey covering 601,509 households and 2.87 million individuals from all 640 districts of India. There were 353 districts in India during the implementation of UIP that were later divided into 640 districts by the 2011 census of India and more than 750 districts today. We gathered information on district boundary changes from secondary sources and successfully matched 621 NFHS-4 districts with the 353 UIP-era districts (Nandi et al., 2020). We exclude NFHS-3 data from the remaining 19 districts from our analysis.

NFHS-4 collected basic demographic information such as age, sex, marital status, and schooling attainment level for all household members. A separate questionnaire collected detailed health data, including sexual and reproductive health; female autonomy; and child health, nutrition, and vaccination, from 699,686 women of age 15–49 years. A third questionnaire collected data on marriage, family, and fertility preference from a 15% subsample of 15-54-year-old men. We use data from the women's questionnaire, which has information on the complete birth history of each woman and family planning.

Our main outcome variables of interest are (i) the binary indicator that a woman has at least one child and (ii) total fertility preference, i.e., the ideal number of children a woman reports that she wants in her lifetime. Number of ideal children ranges from 0 to 30 in the data, and we censor the distribution by top coding at 10 (99^{th} percentile).

Women who were born during the year of implementation of UIP in their home district or during later years are included in the treatment group (UIP exposed). Women who were born before the year of implementation of UIP in their home district are in the control group. However, considering the 15-49-year age range of women in the data, treatment and control groups could have many systematic differences that might affect outcome indicators. For example, background characteristics and fertility preferences and outcomes of adolescent women may differ substantially from those of women in their 40s. To reduce the heterogeneity between the treatment and control groups, we limit our analysis sample to women who were born during the 1985–1990 UIP implementation and in the five years before (1980–1984) and after (1991–1995) and who were cohabiting with a partner at the time of the survey. In additional robustness checks discussed later, we also consider shorter and longer time periods.

Table 1 presents summary statistics of our study sample. Among the 300,279 women of age 20-36- years in our study sample, 40% belong to the treatment group and 60% fall in the control group. The rates of having at least one child among women in the two groups were 87% and 96% respectively, and the ideal numbers of children wanted were 2.22 and 2.35. The differences were statistically significant at 1% for both outcomes. Differences in background characteristics of the treatment and control groups were statistically significant except for the indicator of Sikh religion. Treatment group women were younger, more educated, more likely to be daughters-in-law than wives of the household heads, and less likely to be from households in the top wealth quintile. Other differences such as membership of socioeconomically disadvantages groups or various religions, although statistically significant, were not meaningfully large.

4. Empirical analysis: Fixed-effects regression models

Although previous analysis using 1991 census data shows no significant associations between community-level health infrastructure and UIP rollout (Summan et al., 2022), unobserved program placement biases may affect our analysis. For example, program rollout may have been correlated with the pre-UIP burden of VPDs, infant and child mortality rates, or political factors that can affect the provision of public goods in India (Banerjee and Somanathan, 2007). In addition to initial systematic differences between the treatment and control groups due to these unobserved factors, differences may also emerge over time. For example, if districts that were prioritized into UIP also received more schooling or family planning inputs from the government later, it might bias least squares estimates of any negative effect of UIP on fertility demand. The true effect would be smaller in magnitude or closer to zero.

To mitigate these potential biases, we estimate an age and district fixed-effects (with interactions) linear regression model as follows:

$$Y_{id} = \alpha_0 + \alpha_1 UIP_{id} + \alpha_2 X_{id} + \alpha_3 Age_i + \alpha_4 District_d + \alpha_5 Age_i \times District_d + \epsilon_{id} \quad (1)$$

where Y_{id} denotes the outcome variable—binary indicator of at least one birth and the ideal number of children wanted, examined separately—of the i-th individual in the d-th district. Only

20-36-year-old women who cohabit with a partner are included in the regression. $UIP_{id} = 1$ if the i-th individual living in the d-th district was born during or after the year of UIP implementation in d. $UIP_{id} = 0$ for those who were born before the implementation of UIP in district d. Binary indicators of Age_i of the i-th individual are included to account for cohort-specific time-invariant factors (year of birth effects), while $District_d$ dummy variables account for location-specific factors. Time-varying factors that affect women in different districts differently over time are controlled for by including the interaction terms $Age_i \times District_d$. Note that the individual age and district fixed effects are absorbed by the interaction term, and the source of the variation in the model originates from different birth years for the same age (due to variations in the year of the survey). The error term of the model is ϵ_{id}. Standard errors are clustered at the age and district level.

The vector X_{id} is a set of individual and household characteristics of women. It includes an indicator of marital status (whether single), age in years at the first cohabitation with partner, and years of schooling completed by the woman. Including indicators of the woman's relationship to the household head (e.g., whether wife, daughter, or daughter-in-law of the head) captures intrahousehold bargaining and resource allocation. At the household level, the following variables are included in *X*: age, sex (whether female), and years of schooling completed by the household head; household size; location (whether rural); indicators of socioeconomic disadvantaged groups (defined by the Indian government as scheduled caste, scheduled tribe, and other backward classes); and religion (Muslim, Sikh, or Christian). Creating a composite index of ownership of durable assets, such as radio, TV, and car, and household living condition indicators, such as the availability of a toilet and electricity, measure the standard of living of a household (Filmer and Pritchett, 2001; Pollitt et al., 1993). We divide the asset index into five quintiles and include indicators of the top four quintiles in *X*.

Outmigration from the district of birth poses a potential challenge for our analysis. Patrilocal exogamy, i.e., a woman resides with her husband's family after getting married, characterizes marriages in India. Partner selection is heavily based on assortative mating, i.e., spouses have the same or highly similar caste, religion, and economic backgrounds and may also be from the same village or community (Banerjee et al., 2013; Dyson and Moore, 1983; Goli et al., 2013; Lin et al., 2020; Rammohan and Vu, 2018). NFHS-4 asked women if they had lived in the same location (village or city ward) since birth. Less than 10% of women in treatment and control groups reported living in the natal location (Table 1), which reflects the practice of exogamy. The survey did not collect data on the previous place of residence of women. However, the proportion of population migrating out of natal district in their lifetime has consistently remained around 15% over the past few decades in India (Office of the Registrar General and Census Commissioner, 2011). Considering that the treatment assignment is at the district level, marriage-related migration is unlikely to affect our results substantially. In any case, we account for migration by including a binary indicator (whether the woman lived in the same place since birth) in the covariate set *X*.

5. Results

5.1 Parallel trends test

A potential threat to the validity of our treatment-effect analysis comes from variations in secular pre-trends. For our findings to be valid, demand for fertility among women in UIP and non-UIP districts should follow similar time trends leading up to the introduction on UIP. Otherwise, different pre trends between the two groups may be contribute to any observed difference in outcomes after program introduction.

To test for parallel pre-trends in the context of the staggered rollout of the program, we consider each year of UIP implementation separately and include women from districts in which UIP was implemented in that year in the treatment group. Women from districts yet to receive the program at that time are included in the control group. This creates four sets of treatment and control groups (Summan et al., 2022): (1) 1985-1986 UIP districts (treatment) versus all other districts (control); (2) 1986-1987 UIP districts (treatment) versus all other districts except for 1985-1986 UIP districts (control); (iii) 1987-1988 UIP districts (treatment) versus all other districts except for 1985-1986 and 1986-1987 UIP districts (control); and (iv) 1988-1989 UIP districts (treatment) versus all other districts except for 1985-1986, 1986-1987, and 1987-1988 UIP districts (control). By 1989-1990 the last set of districts received the UIP, completing the implementation of the program across India.

We analyze pre-trends starting from 1975 through the year preceding UIP introduction. For the first treatment-control group pair, we analyze outcomes during 1975-1984, while for the second pair, during 1975-1985, and so on. Separately for each treatment and control group pair, we regress the demand for fertility outcome indicator on an indicator for the treatment group, identifiers for year of birth, interaction terms between year and the treatment indicator, and the covariate set X_{id}. Controlling for X and year of birth and district level factors, the treatment and birth year interaction indicates whether demand for fertility was different year-on-year between the treatment and control groups up to the introduction of UIP.

Estimated coefficients of the treatment and birth year interaction terms from the regressions of at least one childbirth and desired number of children are summarized in Figures 4 and 5 respectively. The coefficients are statistically indistinguishable from zero, implying that there were no differences in the pre-trends between the treatment and control groups leading up UIP introduction. For the analysis of desired number of children, and handful of coefficients are significant and positive, but they do not indicate any differential trend over time. Therefore, we argue that the parallel trends assumption is satisfied.

5.2 Regression Results

Table 2 presents the main set of results. Controlling for background characteristics and age and district fixed effects, women who were exposed to UIP at birth have 2 percentage points (pp) lower likelihood of having at least one child and 0.05 fewer ideal number of children than women who were born before UIP was implemented in their residence district (both significant at 1%). Compared with the control group, both effect sizes are equivalent to a 2% reduction.

5.3 Robustness checks

We test the robustness of our results in four ways. First, we examine whether the selection of study period affects our findings. We repeat our regression analysis (equation 1) for two additional study samples that include (i) only women who were born during 1985–1990 (25-31-year-old women in NFHS-4) and (ii) all 18-49-year-old women surveyed in NFHS-4. The results, presented in Tables 3 and 4 respectively, are similar to those of the original model. In the 25-31-year-old sample, treatment group women have 2 pp lower likelihood of having at least one child and 0.04 fewer desired number of children. In the 18-49-year-old sample, the corresponding estimates are 3 pp lower likelihood of having at least one child and 0.06 fewer desired number of children respectively.

Second, in our main results we consider only those who report cohabiting with a husband or partner, which constitutes 80% of women with fertility data in NFHS-4 because childbearing out of wedlock is virtually nonexistent in India (Chakravorty et al., 2021). However, understanding the potential effect of UIP on fertility preference (ideal number of children) on both married and unmarried women is important. We repeat our analysis by including the additional sample of unmarried women (see Table 5). Across the three subsamples (age groups), treatment group women have 2–3 pp lower likelihood of at least one childbirth and 0.4–0.5 fewer desired number of children.

Third, we estimate another set of regression models by excluding the years of schooling completed by the woman from the set of explanatory variables *X*. Childhood vaccinations could affect schooling attainment. Previous studies show consistent improvements in schooling attainment by 0.2–0.3 years across several LMICs in vaccinated children over the life course (Anekwe et al., 2015; Nandi et al., 2020, 2019a, 2019b). The results remain robust to the exclusion of schooling attainment (Table 5), with 2–3 pp lower likelihood of at least one childbirth and 0.4–0.6 fewer desired number of children in the treatment group than in the control group.

Finally, we conduct a falsification test to examine the validity of our findings. NFHS-4 asked women about their fertility preference, i.e., whether they would like to have more children in the future, or if they were sterilized (respondent or partner) or declared infecund. Assuming that infecundity is exogenously determined (Agüero and Marks, 2011), as opposed to sterilization, which may be a decision based on past childbearing, UIP should have no or minimal effect on the likelihood of childbearing or desired number of children of women who know that they are infecund. We estimate our regression analysis separately for infecund women (5% of all women) and find that indeed no statistically significant effects of UIP are evident across the three age groups (Table 5).

5.4 Heterogeneity in treatment effect across subgroups

The effect of UIP on the demand for children may vary across populations. We examine treatment effect heterogeneity among the following subpopulations: women from rural and urban areas, those belonging to a socioeconomically privileged caste group (general caste), and disadvantaged caste groups known officially as scheduled caste (SC) or scheduled tribe (ST) and other backward classes (OBC). We also analyze treatment effect among women with no schooling and among those with 1–9 years of schooling and at least 10 years of schooling. Finally, we consider two subsamples of women belonging to the bottom two and top two wealth index quintiles. Table 6 presents the results.

The effect of UIP is negative and statistically significant in all subsamples except for a few cases. The effect on at least one childbirth is similar in magnitude across location and among caste groups. The effect is stronger among women (3–5 pp reduction) with at least 10 years of schooling as compared with those with no schooling (2–3 pp) and among women in the top two wealth quintiles (2–3 pp) as compared with those in the bottom two quintiles (1–2 pp).

For the desired number of children, the negative effect of UIP is similar in rural and urban areas, but stronger for the general caste group (0.6–0.7 fewer children) than for SC, ST, or OBC groups (0.3–0.5 fewer children). The negative effect is also larger among women with no schooling (0.7 fewer children) as compared with women with 1–9 or at least 10 years of schooling (0.3–0.5 fewer children). Similarly, the effect size is larger among women in the bottom two wealth quintiles (0.5–0.8 fewer children) than in the top two wealth quintiles (0.3–0.4 fewer children).

6. Discussion and conclusion

India has achieved replacement level of fertility (2.1 children born per woman) in 2021 (Pearce, 2021; World Bank, 2021). We use nationally representative data to employ age and district fixed-effects regression and link childhood vaccinations under UIP with a 2% reduction in childbirth probability and the number of children desired by women in the long term. The findings indicate that UIP may have helped aid the recent demographic transition in India.

Our findings are consistent with previous studies of vaccines or drugs and the demand for fertility. Ager et al. (2018) estimate the smallpox vaccination program in Sweden during the end of 18th century and the beginning of the 19th century reduced the crude birth rate by 0.02 and general fertility rate by 0.1. However, the authors show that this coincided with a 0.3–0.5 reduction in infant mortality rates (deaths per 1,000 live births) and therefore there was no long-term impact on population growth. Similarly, Bhalotra et al. (2022) estimate that every year of exposure to the newly introduced sulfa drugs in the United States during the 1930s was associated with 0.013 fewer births, which is equivalent to 15% fewer births for the average 18-40-year-old woman. Among women who had completed their fertility (40-50-year-olds), sulfa drugs and related reductions in child mortality were linked with 5.7% fewer childbirths. In comparison with individual vaccines or drugs, we find that comprehensive national child immunization programs such as UIP can also reduce the demand for children.

Our results can also be indirectly validated based on previous literature on the relationship between female education and fertility demand. Using data from the 1980s and 1990s, Dreze and Murthi (2001) and Murthi et al. (1995) link female literacy rates with a 2–3% reduction in the total fertility rate in India. More recent evidence from LMICs such as Ethiopia, Zimbabwe, Uganda, Nigeria, and China show that one extra year of female education is associated with a 2–7% reduction in childbirth probability or the number of children born (Agüero and Ramachandran, 2020; Chen and Guo, 2022; Chicoine, 2021; Duflo et al., 2015; McCrary and Royer, 2011; Osili and Long, 2008; Zenebe Gebre, 2020). Considering that the previous study associated UIP with 0.3–0.5 extra years of schooling among adult women in India (Nandi et al., 2020), our reduced-form effects of UIP on demand for fertility and desired fertility are consistent with this body of evidence.

Understanding the implications of the negative effect of UIP on demand for fertility is important. Improvements in child survival rates may induce parents to have fewer children (Chowdhury et al., 1976; Doepke, 2005; Galor, 2012; Montgomery and Cohen, 1998; Palloni and Rafalimanana, 1999; Pritchett, 1994; Soares, 2005; Wolpin, 1997). However, such changes may be slow as parents of successive cohorts or generations notice the reductions in child mortality rates in their community and respond accordingly. In our shortest-duration model, we compare treatment and control groups over a five-year period (1985–1990), which may not be adequate for large changes in parental preferences. Instead, rise in female schooling attainment may be the main contributing factor to reduced demand for children by increasing the opportunity cost of childbearing. In models with longer time horizons, reductions in child mortality may also play a role (Ager et al., 2018; Bhalotra et al., 2022).

In additional analysis, we find no statistically significant effect of UIP on women's use of spacing contraceptives (whether currently using a modern method such as condom, pill, or intrauterine device) but a negative effect on sterilization rates. Contraceptive use patterns in India are uniquely different from the rest of the world. An estimated 37% of adult women of reproductive age are sterilized in India, and in rural areas of states such as Andhra Pradesh and Telangana, the rates are as high as 70% (Bansal et al., 2022; International Institute for Population Sciences, 2021; Singh et al., 2021). Sterilization rates are higher among older women and those from poor or uneducated backgrounds, and concerns about potentially forced sterilizations persist (Singh et al., 2021; Wynne et al., 2014). It is possible that unobserved cohort-level factors related to local sterilization policies are driving the perceived negative effect of UIP.

We also examine if the negative effect of UIP on the demand for children is mediated through birth spacing. For women who had at least one child during the 5 years preceding the survey (since January 1, 2011) and wanted to have more children, NFHS-4 collected information on the desired wait time before the next birth. The response to this question ranged from less than 1 year to 6 years or more. We regress the desired wait time on UIP exposure using the age and district fixed-effects model in equation (1). We find that the desired wait time is 0.11–0.18 years longer among the treatment group women as compared with the control group (Table 5).

Rise in female education and birth spacing linked with UIP may have additional long-term implications for fertility demand. In India and other LMICs, mother's education level has been linked with lower child mortality rates and improved child vaccination, nutrition, and growth outcomes (Forshaw et al., 2017; Mensch et al., 2019; Paul et al., 2022; Vikram and Vanneman, 2020). Molitoris et al. (2019) show that probability of death before the age of 1 year reduces substantially from 15% to less than 6% when a child is born with a gap of 36 months or more from their elder sibling as compared with a 12-month gap. Other studies show similar negative effects of inadequate birth spacing on child mortality rates and health outcomes (Bhalotra and van Soest, 2008; Dewey and Cohen, 2007; Kozuki et al., 2013; Rutstein, 2005). By increasing maternal education levels and birth spacing, UIP may therefore help improve child survival and health outcomes, reducing demand for fertility further.

Our analysis has some limitations. Due to lack of retrospective data on vaccine receipt, we are unable to estimate the treatment on the treated (those who received the vaccine) effect of UIP. Instead, our estimates represent intent-to-treat (i.e., providing access to vaccines without knowing who actually received it) which may be a lower bound of the true effect of UIP. Coverage rates of different vaccines after the introduction of UIP, based on the NFHS-1 survey of 1992–1993, ranged from 42% to 62% (International Institute for Population Sciences and ICF, 1995). Near universal coverage might have had a larger negative effect on future demand for fertility. Also, our analysis implicitly captures potential secondary immunity conferred by vaccinated individuals to those who were unvaccinated. Vaccine receipt information would have allowed us to precisely estimate these spillover effects.

Although we use a rigorous model specification accounting for several potentially confounding factors and age and district fixed effects, unobserved factors may affect our findings. For example, parents may selectively allocate human capital development resources among children based on indicators that are unobserved in our data such as birth order or birth weight. If girls who were vaccinated by their parents also received more schooling or healthcare resources as compared with their siblings, it may bias the positive effect of UIP on schooling and subsequent negative effect on fertility upward.

Finally, women's age in NFHS-4 is reported in years and not months, which may create some measurement error. Women who were born during the year preceding the introduction of UIP in a district may have received some vaccines during the remaining months of the first year of life.

This would potentially bias our results downward, and the true negative effect of UIP on fertility demand may be larger.

Despite these limitations, our analysis shows that childhood vaccines can reduce the demand for children, increase birth spacing, and aid demographic transition in high–initial fertility and low-resource settings such as India. Subject to external validity, these findings may provide important policy lessons for countries experiencing high fertility rates today. For example, in 2019, countries in sub-Saharan Africa had a total fertility rate of 4.6 and a 59% full immunization rate of children (Fenta et al., 2021; World Bank, 2021). The ongoing COVID-19 pandemic has further worsened child immunization rates across the world, with a 9% reduction in DPT3 completion rate in the WHO Africa region (Shet et al., 2022). Universal coverage of childhood vaccines may help sub-Saharan Africa reach replacement fertility levels sooner than expected.

Conflict of interest

DB has previously received research support or personal fees from GlaxoSmithKline plc, Merck, Pfizer, and Sanofi-Pasteur related generally to value-of-vaccination research, but not for this study. All other authors declare no conflict of interest.

References

Aaronson, D., Lange, F., Mazumder, B., 2014. Fertility Transitions along the Extensive and Intensive Margins. American Economic Review 104, 3701–3724. https://doi.org/10.1257/aer.104.11.3701

Addo, O.Y., Stein, A.D., Fall, C.H., Gigante, D.P., Guntupalli, A.M., Horta, B.L., Kuzawa, C.W., Lee, N., Norris, S.A., Prabhakaran, P., Richter, L.M., Sachdev, H.S., Martorell, R., 2013. Maternal Height and Child Growth Patterns. J Pediatr 163, 549-554.e1. https://doi.org/10.1016/j.jpeds.2013.02.002

Ager, P., Worm Hansen, C., Sandholt Jensen, P., 2018. Fertility and Early-Life Mortality: Evidence from Smallpox Vaccination in Sweden. Journal of the European Economic Association 16, 487–521. https://doi.org/10.1093/jeea/jvx014

Agüero, J.M., Marks, M.S., 2011. Motherhood and Female Labor Supply in the Developing World: Evidence from Infertility Shocks. Journal of Human Resources 46, 800–826.

Agüero, J.M., Ramachandran, M., 2020. The Intergenerational Transmission of Schooling among the Education-Rationed. J. Human Resources 55, 504–538. https://doi.org/10.3368/jhr.55.2.0816.8143R

Alsan, M., Atella, V., Bhattacharya, J., Conti, V., Mejía-Guevara, I., Miller, G., 2021. Technological Progress and Health Convergence: The Case of Penicillin in Postwar Italy. Demography 58, 1473–1498. https://doi.org/10.1215/00703370-9368970

Anekwe, T.D., Kumar, S., 2012. The effect of a vaccination program on child anthropometry: evidence from India's Universal Immunization Program. J Public Health (Oxf) 34, 489–497. https://doi.org/10.1093/pubmed/fds032

Anekwe, T.D., Newell, M.-L., Tanser, F., Pillay, D., Bärnighausen, T., 2015. The causal effect of childhood measles vaccination on educational attainment: A mother fixed-effects study in rural South Africa. Vaccine 33, 5020–5026. https://doi.org/10.1016/j.vaccine.2015.04.072

Arsenault, C., Harper, S., Nandi, A., 2020. Effect of vaccination on children's learning achievements: findings from the India Human Development Survey. J Epidemiol Community Health. https://doi.org/10.1136/jech-2019-213483

Atwood, A., 2021. The Long-Term Effects of Measles Vaccination on Earnings and Employment. American Economic Journal: Economic Policy. https://doi.org/10.1257/pol.20190509

Atwood, A., Pearlman, S., 2022. Measles, Mexico and Labor Markets. NBER Summer Institute Working Paper 66.

Banerjee, A., Duflo, E., Ghatak, M., Lafortune, J., 2013. Marry for What? Caste and Mate Selection in Modern India. American Economic Journal: Microeconomics 5, 33–72. https://doi.org/10.1257/mic.5.2.33

Banerjee, A.V., Somanathan, R., 2007. The political economy of public goods: Some evidence from India. Journal of Development Economics 82, 287–314. https://doi.org/10.1016/j.jdeveco.2006.04.005

Bansal, A., Dwivedi, L.K., Ali, B., 2022. The trends of female sterilization in India: an age period cohort analysis approach. BMC Women's Health 22, 272. https://doi.org/10.1186/s12905-022-01857-0

Becker, G.S., Lewis, H.G., 1973. On the Interaction between the Quantity and Quality of Children. Journal of Political Economy 81, S279-88.

Becker, G.S., Tomes, N., 1976. Child Endowments and the Quantity and Quality of Children. The Journal of Political Economy 84, S143–S162.
Becker, S.O., Cinnirella, F., Woessmann, L., 2010. The trade-off between fertility and education: evidence from before the demographic transition. J Econ Growth 15, 177–204. https://doi.org/10.1007/s10887-010-9054-x
Bhalotra, S., van Soest, A., 2008. Birth-spacing, fertility and neonatal mortality in India: Dynamics, frailty, and fecundity. Journal of Econometrics 143, 274–290.
Bhalotra, S., Venkataramani, A., Walther, S., 2022. Fertility and Labor Market Responses to Reductions in Mortality.
Bhalotra, S.R., Venkataramani, A., 2011. The Captain of the Men of Death and His Shadow: Long-Run Impacts of Early Life Pneumonia Exposure (SSRN Scholarly Paper No. ID 1951332). Social Science Research Network, Rochester, NY.
Bhattacharjee, S., Dasgupta, A., 2019. Disease eradication, infant mortality and fertility response: Evidence from malaria eradication in India (Working Paper No. 22). Ashoka University, Department of Economics.
Bleakley, H., Lange, F., 2009. Chronic Disease Burden and the Interaction of Education, Fertility, and Growth. Rev Econ Stat 91, 52–65. https://doi.org/10.1162/rest.91.1.52
Bloom, D.E., Canning, D., 2008. Global Demographic Change: Dimensions and Economic Significance. Population and Development Review 34, 17–51.
Bloom, D.E., Canning, D., Sevilla, J., 2003. The Demographic Dividend: A New Perspective on the Economic Consequences of Population Change, 1st ed. RAND Corporation.
Bloom, D.E., Canning, D., Shenoy, E.S., 2012. The effect of vaccination on children's physical and cognitive development in the Philippines. Applied Economics 44, 2777–2783. https://doi.org/10.1080/00036846.2011.566203
Bloom, D.E., Kuhn, M., Prettner, K., 2020. The contribution of female health to economic development. The Economic Journal 130, 1650–1677. https://doi.org/10.1093/ej/ueaa061
Bloom, D.E., Kuhn, M., Prettner, K., 2017. Africa's Prospects for Enjoying a Demographic Dividend. Journal of Demographic Economics 83, 63–76. https://doi.org/10.1017/dem.2016.19
Bloom, D.E., Williamson, J.G., 1998. Demographic Transitions and Economic Miracles in Emerging Asia. The World Bank Economic Review 12, 419–455.
Bogler, L., Jantos, N., Bärnighausen, T., Vollmer, S., 2019. Estimating the effect of measles vaccination on child growth using 191 DHS from 65 low- and middle-income countries. Vaccine 37, 5073–5088. https://doi.org/10.1016/j.vaccine.2019.06.054
Canning, D., Günther, I., Linnemayr, S., Bloom, D., 2013. Fertility choice, mortality expectations, and interdependent preferences—An empirical analysis. European Economic Review 63, 273–289. https://doi.org/10.1016/j.euroecorev.2013.07.005
Chakravorty, S., Goli, S., James, K.S., 2021. Family Demography in India: Emerging Patterns and Its Challenges. SAGE Open 11, 21582440211008176. https://doi.org/10.1177/21582440211008178
Chen, J., Guo, J., 2022. The effect of female education on fertility: Evidence from China's compulsory schooling reform. Economics of Education Review 88, 102257. https://doi.org/10.1016/j.econedurev.2022.102257
Chicoine, L., 2021. Free Primary Education, Fertility, and Women's Access to the Labor Market: Evidence from Ethiopia. The World Bank Economic Review 35, 480–498. https://doi.org/10.1093/wber/lhz042

Chowdhury, A.K.M.A., Khan, A.R., Chen, L.C., 1976. The Effect of Child Mortality Experience on Subsequent Fertility: in Pakistan and Bangladesh. Population Studies 30, 249–261. https://doi.org/10.2307/2173608
Currie, J., Moretti, E., 2003. Mother's Education and the Intergenerational Transmission of Human Capital: Evidence from College Openings*. The Quarterly Journal of Economics 118, 1495–1532. https://doi.org/10.1162/003355303322552856
DeCicca, P., Krashinsky, H., 2022. The effect of education on overall fertility. J Popul Econ. https://doi.org/10.1007/s00148-022-00897-y
Dewey, K.G., Cohen, R.J., 2007. Does birth spacing affect maternal or child nutritional status? A systematic literature review. Maternal & Child Nutrition 3, 151–173.
Doepke, M., 2005. Child mortality and fertility decline: Does the Barro-Becker model fit the facts? J Popul Econ 18, 337–366. https://doi.org/10.1007/s00148-004-0208-z
Dreze, J., Murthi, M., 2001. Fertility, Education, and Development: Evidence from India. Population and Development Review 27, 33–63.
Duflo, E., Dupas, P., Kremer, M., 2015. Education, HIV, and Early Fertility: Experimental Evidence from Kenya. American Economic Review 105, 2757–2797. https://doi.org/10.1257/aer.20121607
Dyson, T., Moore, M., 1983. On Kinship Structure, Female Autonomy, and Demographic Behavior in India. Population and Development Review 9, 35–60.
Fenta, S.M., Biresaw, H.B., Fentaw, K.D., Gebremichael, S.G., 2021. Determinants of full childhood immunization among children aged 12–23 months in sub-Saharan Africa: a multilevel analysis using Demographic and Health Survey Data. Tropical Medicine and Health 49, 29. https://doi.org/10.1186/s41182-021-00319-x
Filmer, D., Pritchett, L.H., 2001. Estimating wealth effects without expenditure data-or-tears: An application to educational enrollments in States of India. Demography 38, 115–132.
Finlay, J.E., 2021. Women's reproductive health and economic activity: A narrative review. World Development 139, 105313. https://doi.org/10.1016/j.worlddev.2020.105313
Forshaw, J., Gerver, S.M., Gill, M., Cooper, E., Manikam, L., Ward, H., 2017. The global effect of maternal education on complete childhood vaccination: a systematic review and meta-analysis. BMC Infectious Diseases 17, 801. https://doi.org/10.1186/s12879-017-2890-y
Galor, O., 2012. The demographic transition: causes and consequences. Cliometrica 6, 1–28. https://doi.org/10.1007/s11698-011-0062-7
Galor, O., 2011. Unified Growth Theory. Princeton University Press, Princeton NJ.
Galor, O., Weil, D.N., 2000. Population, Technology, and Growth: From Malthusian Stagnation to the Demographic Transition and Beyond. American Economic Review 90, 806–828. https://doi.org/10.1257/aer.90.4.806
Goli, S., Singh, D., Sekher, T.V., 2013. Exploring the Myth of Mixed Marriages in India: Evidence from a Nation-wide Survey. Journal of Comparative Family Studies 44, 193–206.
Gooch, E., 2017. The impact of reduced incidence of malaria and other mosquito-borne diseases on global population. Journal of Development Economics 124, 214–228. https://doi.org/10.1016/j.jdeveco.2016.10.003
International Institute for Population Sciences, 2021. National Family Health Survey (NFHS-5) 2019-2020 [WWW Document]. URL http://rchiips.org/nfhs/factsheet_NFHS-5.shtml
International Institute for Population Sciences, 2017. National Family Health Survey (NFHS-4) 2015-2016: India. IIPS, Mumbai.

International Institute for Population Sciences, ICF, 1995. National Family Health Survey (NFHS-1) 1992-1993: India. IIPS, Bombay.
Jayachandran, S., Lleras-Muney, A., Smith, K.V., 2010. Modern Medicine and the Twentieth Century Decline in Mortality: Evidence on the Impact of Sulfa Drugs. American Economic Journal: Applied Economics 2, 118–146. https://doi.org/10.1257/app.2.2.118
Keenan, J.D., Bailey, R.L., West, S.K., Arzika, A.M., Hart, J., Weaver, J., Kalua, K., Mrango, Z., Ray, K.J., Cook, C., Lebas, E., O'Brien, K.S., Emerson, P.M., Porco, T.C., Lietman, T.M., 2018. Azithromycin to Reduce Childhood Mortality in Sub-Saharan Africa. New England Journal of Medicine 378, 1583–1592. https://doi.org/10.1056/NEJMoa1715474
Kim, J., 2010. Women's Education and Fertility: An Analysis of the Relationship between Education and Birth Spacing in Indonesia. Economic Development and Cultural Change 58, 739–774. https://doi.org/10.1086/649638
Kozuki, N., Lee, A.C., Silveira, M.F., Victora, C.G., Adair, L., Humphrey, J., Ntozini, R., Black, R.E., Katz, J., 2013. The associations of birth intervals with small-for-gestational-age, preterm, and neonatal and infant mortality: a meta-analysis. BMC Public Health 13, S3.
Kuecken, M., Thuilliez, J., Valfort, M.-A., 2021. Disease and Human Capital Accumulation: Evidence from the Roll Back Malaria Partnership in Africa. The Economic Journal 131, 2171–2202. https://doi.org/10.1093/ej/ueaa134
Kumar, S., 2009. Childhood Immunization, Mortality and Human Capital Accumulation: Micro-Evidence from India (MPRA Paper). University Library of Munich, Germany.
Lahariya, C., 2014. A brief history of vaccines & vaccination in India. Indian Journal of Medical Research 139, 491–511.
Li, Xiang, Mukandavire, C., Cucunubá, Z.M., Londono, S.E., Abbas, K., Clapham, H.E., Jit, M., Johnson, H.L., Papadopoulos, T., Vynnycky, E., Brisson, M., Carter, E.D., Clark, A., Villiers, M.J. de, Eilertson, K., Ferrari, M.J., Gamkrelidze, I., Gaythorpe, K.A.M., Grassly, N.C., Hallett, T.B., Hinsley, W., Jackson, M.L., Jean, K., Karachaliou, A., Klepac, P., Lessler, J., Li, Xi, Moore, S.M., Nayagam, S., Nguyen, D.M., Razavi, H., Razavi-Shearer, D., Resch, S., Sanderson, C., Sweet, S., Sy, S., Tam, Y., Tanvir, H., Tran, Q.M., Trotter, C.L., Truelove, S., Zandvoort, K. van, Verguet, S., Walker, N., Winter, A., Woodruff, K., Ferguson, N.M., Garske, T., 2021. Estimating the health impact of vaccination against ten pathogens in 98 low-income and middle-income countries from 2000 to 2030: a modelling study. The Lancet 397, 398–408. https://doi.org/10.1016/S0140-6736(20)32657-X
Lin, Z., Desai, S., Chen, F., 2020. The Emergence of Educational Hypogamy in India. Demography 57, 1215–1240. https://doi.org/10.1007/s13524-020-00888-2
Lucas, A.M., 2013. The Impact of Malaria Eradication on Fertility. Economic Development and Cultural Change 61, 607–631. https://doi.org/10.1086/669261
McCrary, J., Royer, H., 2011. The Effect of Female Education on Fertility and Infant Health: Evidence from School Entry Policies Using Exact Date of Birth. Am Econ Rev 101, 158–195. https://doi.org/10.1257/aer.101.1.158
Mensch, B.S., Chuang, E.K., Melnikas, A.J., Psaki, S.R., 2019. Evidence for causal links between education and maternal and child health: systematic review. Trop Med Int Health 24, 504–522. https://doi.org/10.1111/tmi.13218
Mina, M.J., Kula, T., Leng, Y., Li, M., Vries, R.D. de, Knip, M., Siljander, H., Rewers, M., Choy, D.F., Wilson, M.S., Larman, H.B., Nelson, A.N., Griffin, D.E., Swart, R.L. de, Elledge, S.J., 2019. Measles virus infection diminishes preexisting antibodies that offer

protection from other pathogens. Science 366, 599–606. https://doi.org/10.1126/science.aay6485
Mina, M.J., Metcalf, C.J.E., de Swart, R.L., Osterhaus, A.D.M.E., Grenfell, B.T., 2015. Long-term measles-induced immunomodulation increases overall childhood infectious disease mortality. Science 348, 694–699. https://doi.org/10.1126/science.aaa3662
Molitoris, J., Barclay, K., Kolk, M., 2019. When and Where Birth Spacing Matters for Child Survival: An International Comparison Using the DHS. Demography 56, 1349–1370. https://doi.org/10.1007/s13524-019-00798-y
Montgomery, M., Cohen, B., 1998. From death to birth: mortality decline and reproductive change. National Academy Press, Washington DC, National Academy Press, Washington DC.
Murphy, T.E., 2015. Old habits die hard (sometimes). J Econ Growth 20, 177–222. https://doi.org/10.1007/s10887-015-9111-6
Murthi, M., Guio, A.-C., Drèze, J., 1995. Mortality, Fertility, and Gender Bias in India: A District-Level Analysis. Population and Development Review 21, 745–782. https://doi.org/10.2307/2137773
Murtin, F., 2013. Long-Term Determinants of the Demographic Transition, 1870–2000. The Review of Economics and Statistics 95, 617–631.
Nandi, A., Deolalikar, A.B., Bloom, D.E., Laxminarayan, R., 2019a. Haemophilus influenzae type b vaccination and anthropometric, cognitive, and schooling outcomes among Indian children. Annals of the New York Academy of Sciences 1449, 70–82. https://doi.org/10.1111/nyas.14127
Nandi, A., Kumar, S., Shet, A., Bloom, D.E., Laxminarayan, R., 2020. Childhood vaccinations and adult schooling attainment: Long-term evidence from India's Universal Immunization Programme. Social Science & Medicine 250, 112885. https://doi.org/10.1016/j.socscimed.2020.112885
Nandi, A., Mazumdar, S., Behrman, J.R., 2018. The effect of natural disaster on fertility, birth spacing, and child sex ratio: evidence from a major earthquake in India. J Popul Econ 31, 267–293. https://doi.org/10.1007/s00148-017-0659-7
Nandi, A., Shet, A., Behrman, J.R., Black, M.M., Bloom, D.E., Laxminarayan, R., 2019b. Anthropometric, cognitive, and schooling benefits of measles vaccination: Longitudinal cohort analysis in Ethiopia, India, and Vietnam. Vaccine 37, 4336–4343. https://doi.org/10.1016/j.vaccine.2019.06.025
Nobles, J., Frankenberg, E., Thomas, D., 2015. The effects of mortality on fertility: population dynamics after a natural disaster. Demography 52, 15–38.
Office of the Registrar General and Census Commissioner, 2011. Census of India 2011 [WWW Document]. Government of India. URL http://censusindia.gov.in/2011-Common/CensusData2011.html (accessed 4.1.19).
Osili, U.O., Long, B.T., 2008. Does female schooling reduce fertility? Evidence from Nigeria. Journal of Development Economics 87, 57–75. https://doi.org/10.1016/j.jdeveco.2007.10.003
Özaltin, E., Hill, K., Subramanian, S.V., 2010. Association of Maternal Stature With Offspring Mortality, Underweight, and Stunting in Low- to Middle-Income Countries. JAMA 303, 1507–1516. https://doi.org/10.1001/jama.2010.450
Palloni, A., Rafalimanana, H., 1999. The Effects of Infant Mortality on Fertility Revisited: New Evidence from Latin America. Demography 36, 41–58. https://doi.org/10.2307/2648133

Paul, Sohini, Paul, Sourabh, Gupta, A.K., James, K.S., 2022. Maternal education, health care system and child health: Evidence from India. Social Science & Medicine 296, 114740. https://doi.org/10.1016/j.socscimed.2022.114740
Pearce, 2021. India defuses its population bomb: Fertility falls to two children per woman. Science.
Perrett, K.P., Nolan, T.M., 2017. Immunization During Pregnancy: Impact on the Infant. Pediatr Drugs 19, 313–324. https://doi.org/10.1007/s40272-017-0231-7
Pollitt, E., Gorman, K.S., Engle, P.L., Martorell, R., Rivera, J., 1993. Early supplementary feeding and cognition: effects over two decades. Monographs of the Society for Research in Child Development 58, 1–99; discussion 111-8.
Pradhan, S.K., 2010. Time to revamp the universal immunization program in India. Indian Journal of Public Health 54, 71. https://doi.org/10.4103/0019-557X.73273
Pritchett, L.H., 1994. Desired Fertility and the Impact of Population Policies. Population and Development Review 20, 1–55. https://doi.org/10.2307/2137629
Rammohan, A., Vu, P., 2018. Gender Inequality in Education and Kinship Norms in India. Feminist Economics 24, 142–167. https://doi.org/10.1080/13545701.2017.1364399
Rutstein, S.O., 2005. Effects of preceding birth intervals on neonatal, infant and under-five years mortality and nutritional status in developing countries: evidence from the demographic and health surveys. International Journal of Gynecology & Obstetrics 89, S7–S24.
Shakib, J.H., Korgenski, K., Presson, A.P., Sheng, X., Varner, M.W., Pavia, A.T., Byington, C.L., 2016. Influenza in Infants Born to Women Vaccinated During Pregnancy. Pediatrics 137, e20152360. https://doi.org/10.1542/peds.2015-2360
Sheikh, S.M., Loney, T., 2018. Is Educating Girls the Best Investment for South Asia? Association Between Female Education and Fertility Choices in South Asia: A Systematic Review of the Literature. Frontiers in Public Health 6.
Shet, A., Carr, K., Danovaro-Holliday, M.C., Sodha, S.V., Prosperi, C., Wunderlich, J., Wonodi, C., Reynolds, H.W., Mirza, I., Gacic-Dobo, M., O'Brien, K.L., Lindstrand, A., 2022. Impact of the SARS-CoV-2 pandemic on routine immunisation services: evidence of disruption and recovery from 170 countries and territories. The Lancet Global Health 10, e186–e194. https://doi.org/10.1016/S2214-109X(21)00512-X
Sim, S.Y., Watts, E., Constenla, D., Huang, S., Brenzel, L., Patenaude, B.N., 2021. Costs of Immunization Programs for 10 Vaccines in 94 Low- and Middle-Income Countries From 2011 to 2030. Value in Health 24, 70–77. https://doi.org/10.1016/j.jval.2020.07.010
Singh, Pragya, Singh, K.K., Singh, Pooja, 2021. Factors explaining the dominion status of female sterilization in India over the past two decades (1992-2016): A multilevel study. PLoS One 16, e0246530. https://doi.org/10.1371/journal.pone.0246530
Soares, R.R., 2005. Mortality Reductions, Educational Attainment, and Fertility Choice. American Economic Review 95, 580–601. https://doi.org/10.1257/0002828054201486
Sokhey, J., Kim-Farley, R.J., Bhargava, I., 1989. The expanded programme on immunization: a decade of progress in India. Annals of Tropical Paediatrics 9, 24–29. https://doi.org/10.1080/02724936.1989.11748590
Subramanian, S.V., Ackerson, L.K., Smith, G.D., John, N.A., 2009. Association of Maternal Height With Child Mortality, Anthropometric Failure, and Anemia in India. JAMA 301, 1691–1701. https://doi.org/10.1001/jama.2009.548

Summan, A., Nandi, A., Bloom, D.E., 2022. A Shot at Economic Prosperity: Long-term Effects of India's Childhood Immunization Program on Earnings and Consumption Expenditure. Working Paper Series. https://doi.org/10.3386/w30173
Thomas, D., Strauss, J., Henriques, M.-H., 1991. How Does Mother's Education Affect Child Height? The Journal of Human Resources 26, 183–211. https://doi.org/10.2307/145920
Toor, J., Echeverria-Londono, S., Li, Xiang, Abbas, K., Carter, E.D., Clapham, H.E., Clark, A., de Villiers, M.J., Eilertson, K., Ferrari, M., Gamkrelidze, I., Hallett, T.B., Hinsley, W.R., Hogan, D., Huber, J.H., Jackson, M.L., Jean, K., Jit, M., Karachaliou, A., Klepac, P., Kraay, A., Lessler, J., Li, Xi, Lopman, B.A., Mengistu, T., Metcalf, C.J.E., Moore, S.M., Nayagam, S., Papadopoulos, T., Perkins, T.A., Portnoy, A., Razavi, H., Razavi-Shearer, D., Resch, S., Sanderson, C., Sweet, S., Tam, Y., Tanvir, H., Tran Minh, Q., Trotter, C.L., Truelove, S.A., Vynnycky, E., Walker, N., Winter, A., Woodruff, K., Ferguson, N.M., Gaythorpe, K.A., 2021. Lives saved with vaccination for 10 pathogens across 112 countries in a pre-COVID-19 world. eLife 10, e67635. https://doi.org/10.7554/eLife.67635
Upadhyay, A.K., Srivastava, S., 2017. Association between Haemophilus influenza type B (Hib) vaccination and child anthropometric outcomes in Andhra Pradesh (India): Evidence from the Young Lives Study. J Public Health 25, 581–589. https://doi.org/10.1007/s10389-017-0824-1
Vikram, K., Vanneman, R., 2020. Maternal Education and the Multidimensionality of Child Health Outcomes in India. J Biosoc Sci 52, 57–77. https://doi.org/10.1017/S0021932019000245
Vries, R.D. de, McQuaid, S., Amerongen, G. van, Yüksel, S., Verburgh, R.J., Osterhaus, A.D.M.E., Duprex, W.P., Swart, R.L. de, 2012. Measles Immune Suppression: Lessons from the Macaque Model. PLOS Pathogens 8, e1002885. https://doi.org/10.1371/journal.ppat.1002885
Vries, R.D. de, Swart, R.L. de, 2014. Measles Immune Suppression: Functional Impairment or Numbers Game? PLOS Pathogens 10, e1004482. https://doi.org/10.1371/journal.ppat.1004482
Watts, E., Sim, S.Y., Constenla, D., Sriudomporn, S., Brenzel, L., Patenaude, B., 2021. Economic Benefits of Immunization for 10 Pathogens in 94 Low- and Middle-Income Countries From 2011 to 2030 Using Cost-of-Illness and Value-of-Statistical-Life Approaches. Value in Health 24, 78–85. https://doi.org/10.1016/j.jval.2020.07.009
Wilde, J., Apouey, B., Coleman, J., Picone, G., 2019. c. https://doi.org/10.2139/ssrn.3452844
Wilson, N., 2015. Child mortality risk and fertility: Evidence from prevention of mother-to-child transmission of HIV. Journal of Development Economics 116, 74–88. https://doi.org/10.1016/j.jdeveco.2015.01.007
Wolpin, K.I., 1997. Chapter 10 Determinants and consequences of the mortality and health of infants and children, in: Handbook of Population and Family Economics. Elsevier, pp. 483–557. https://doi.org/10.1016/S1574-003X(97)80027-X
World Bank, 2021. DataBank | The World Bank [WWW Document]. URL https://databank.worldbank.org/home.aspx (accessed 9.23.21).
Wynne, Z., Barpanda, S., Masih, M., 2014. Mistreatment and Coercion: Unethical Sterilization in India. HRLN, Human Rights Law Network.
Zenebe Gebre, T., 2020. Free Primary Education, Timing of Fertility, and Total Fertility. The World Bank Economic Review 34, 730–748. https://doi.org/10.1093/wber/lhz003

Table 1: Summary statistics of the study sample

	Intervention group (UIP exposure)	**Control group (no exposure)**	**Difference (intervention – control)**
Had at least one child	0.87 (0.34)	0.96 (0.2)	-0.09**
Ideal number of children wanted	2.22 (0.82)	2.35 (0.99)	-0.13**
Age	23.77 (2.38)	31.29 (3.16)	-7.52**
Whether single	0 (0.06)	0 (0.05)	0.00**
Age at first cohabitation	18.36 (3.07)	18.72 (4.21)	-0.36**
Years of schooling	7.23 (4.87)	6.16 (5.23)	1.07**
Relationship to household head:			
Self	0.02 (0.15)	0.04 (0.2)	-0.02**
Wife	0.4 (0.49)	0.64 (0.48)	-0.24**
Child	0.07 (0.25)	0.03 (0.18)	0.04**
Daughter-in-law	0.46 (0.5)	0.25 (0.43)	0.21**
Grandchild	0 (0.07)	0 (0.03)	0.00**
Did not migrate	0.06 (0.24)	0.07 (0.25)	-0.01**
Household characteristics:			
Age of household head	44.83 (15.87)	44.46 (13.65)	0.37**
Female household head	0.12 (0.32)	0.1 (0.3)	0.02**
Head's schooling years	5.7 (6.02)	6.53 (5.98)	-0.83**
Household size	6.06 (2.9)	5.84 (2.66)	0.22**
Rural	0.76 (0.43)	0.71 (0.46)	0.05**
Scheduled caste	0.19 (0.4)	0.18 (0.38)	0.01**
Scheduled tribe	0.18 (0.38)	0.17 (0.38)	0.01**
Other backward classes	0.4 (0.49)	0.39 (0.49)	0.01**
Muslim	0.14 (0.35)	0.13 (0.33)	0.01**
Christian	0.06 (0.24)	0.07 (0.25)	-0.01**
Sikh	0.02 (0.14)	0.02 (0.14)	0.00
Household standard of living:			
Wealth quintile 2	0.21 (0.41)	0.19 (0.39)	0.02**
Wealth quintile 3	0.22 (0.41)	0.2 (0.4)	0.02**
Wealth quintile 4	0.2 (0.4)	0.21 (0.41)	-0.01**
Wealth quintile 5	0.17 (0.38)	0.22 (0.41)	-0.05**
Sample size	120,116	180,163	

Note: Data are from the National Family Health Survey of India 2015–2016. Sample includes women born during 1980–1995 (20–36 years of age) in India. Mean values are shown with standard errors in the parenthesis. Last column shows the difference in group means. *P < 0.05, **P < 0.01.

Table 2: Age and district fixed-effects linear regression of fertility outcomes of 20-36-year-old women in India

	At least one child born	**Ideal number of children wanted**
UIP exposure	-0.02 (-0.02, -0.01)**	-0.05 (-0.07, -0.03)**
Whether single	-0.09 (-0.12, -0.07)**	-0.04 (-0.1, 0.03)
Age at first cohabitation	-0.01 (-0.01, -0.01)**	-0.02 (-0.02, -0.02)**
Years of schooling	0 (0, 0)*	-0.01 (-0.02, -0.01)**
Relationship to household head:		
Self	0.1 (0.09, 0.11)**	0.17 (0.15, 0.2)**
Wife	0.1 (0.09, 0.1)**	0.18 (0.16, 0.2)**
Child	0.04 (0.03, 0.05)**	0.07 (0.05, 0.09)**
Daughter-in-law	0.05 (0.04, 0.06)**	0.11 (0.09, 0.12)**
Grandchild	-0.06 (-0.09, -0.03)**	0 (-0.06, 0.06)
Did not migrate	-0.02 (-0.02, -0.01)**	-0.02 (-0.04, 0)
Household characteristics:		
Age of household head	0 (0, 0)**	0 (0, 0)**
Female household head	0.01 (0.01, 0.02)**	0.01 (0, 0.03)*
Head's schooling years	0 (0, 0)	0 (0, 0)**
Household size	0.02 (0.01, 0.02)**	0.03 (0.03, 0.04)**
Rural	0 (0, 0)	0.02 (0.02, 0.03)**
Scheduled caste	0 (-0.01, 0)**	0.08 (0.07, 0.09)**
Scheduled tribe	-0.01 (-0.01, -0.01)**	0.13 (0.11, 0.14)**
Other backward classes	0 (0, 0)	0.04 (0.03, 0.04)**
Muslim	0 (-0.01, 0)*	0.39 (0.37, 0.4)**
Christian	0 (0, 0.01)	0.18 (0.15, 0.21)**
Sikh	0.01 (0, 0.02)**	-0.04 (-0.06, -0.02)**
Wealth quintile 2	0 (0, 0)	-0.11 (-0.12, -0.1)**
Wealth quintile 3	0 (-0.01, 0)*	-0.2 (-0.21, -0.19)**
Wealth quintile 4	-0.01 (-0.01, 0)**	-0.25 (-0.27, -0.24)**
Wealth quintile 5	-0.02 (-0.02, -0.01)**	-0.28 (-0.29, -0.26)**
Constant term	1.04 (1.03, 1.06)**	2.49 (2.45, 2.53)**
Sample size	299,608	298,318
p-value of F-test	0	0

Note: Data are from the National Family Health Survey of India 2015–2016. Sample includes women born during 1980–1995 (20–36 years of age) in India. All models included age (years) and district fixed effects. Standard errors were clustered at the age and district level. 95% confidence intervals are presented in parenthesis. *P < 0.05, **P < 0.01.

Table 3: Age and district fixed-effects linear regression of fertility outcomes of 25-31-year-old women in India

	At least one child born	**Ideal number of children wanted**
UIP exposure	-0.02 (-0.03, -0.01)**	-0.04 (-0.06, -0.02)**
Whether single	-0.07 (-0.1, -0.03)**	-0.07 (-0.17, 0.03)
Age at first cohabitation	-0.02 (-0.02, -0.02)**	-0.01 (-0.02, -0.01)**
Years of schooling	0 (0, 0)	-0.01 (-0.02, -0.01)**
Relationship to household head:		
Self	0.13 (0.11, 0.14)**	0.2 (0.16, 0.24)**
Wife	0.12 (0.11, 0.13)**	0.2 (0.17, 0.22)**
Child	0.04 (0.03, 0.06)**	0.08 (0.05, 0.11)**
Daughter-in-law	0.06 (0.05, 0.07)**	0.12 (0.09, 0.14)**
Grandchild	-0.05 (-0.1, 0)	0.05 (-0.05, 0.14)
Did not migrate	-0.01 (-0.02, 0)**	-0.03 (-0.05, 0)
Household characteristics:		
Age of household head	0 (0, 0)	0 (0, 0)**
Female household head	0.02 (0.01, 0.02)**	0.01 (0, 0.03)
Head's schooling years	0 (0, 0)	0 (0, 0)**
Household size	0.02 (0.02, 0.02)**	0.03 (0.03, 0.04)**
Rural	0.01 (0, 0.01)**	0.03 (0.01, 0.04)**
Scheduled caste	-0.01 (-0.01, 0)**	0.08 (0.06, 0.09)**
Scheduled tribe	-0.01 (-0.02, -0.01)**	0.12 (0.1, 0.14)**
Other backward classes	0 (0, 0)	0.02 (0.01, 0.04)**
Muslim	-0.01 (-0.01, 0)**	0.37 (0.35, 0.39)**
Christian	0.01 (0, 0.02)	0.21 (0.17, 0.25)**
Sikh	0.02 (0, 0.03)	-0.04 (-0.07, -0.01)**
Wealth quintile 2	0 (0, 0)	-0.11 (-0.12, -0.09)**
Wealth quintile 3	0 (-0.01, 0)	-0.2 (-0.21, -0.18)**
Wealth quintile 4	0 (-0.01, 0)	-0.24 (-0.26, -0.23)**
Wealth quintile 5	-0.02 (-0.03, -0.01)**	-0.27 (-0.29, -0.24)**
Constant term	1.11 (1.09, 1.13)**	2.44 (2.38, 2.49)**
Sample size	137,929	137,355
p-value of F-test	0	0

Note: Data are from the National Family Health Survey of India 2015–2016. Sample includes women born during 1985–1990 (25–31 years of age) in India. All models included age (years) and district fixed effects. Standard errors were clustered at the age and district level. 95% confidence intervals are presented in parenthesis. *P < 0.05, **P < 0.01.

Table 4: Age and district fixed-effects linear regression of fertility outcomes of 18-49-year-old women in India

	At least one child born	**Ideal number of children wanted**
UIP exposure	-0.03 (-0.03, -0.02)**	-0.06 (-0.08, -0.04)**
Whether single	-0.08 (-0.09, -0.06)**	-0.01 (-0.07, 0.04)
Age at first cohabitation	-0.01 (-0.01, -0.01)**	-0.02 (-0.02, -0.02)**
Years of schooling	0 (0, 0)	-0.02 (-0.02, -0.01)**
Relationship to household head:		
Self	0.11 (0.1, 0.11)**	0.21 (0.19, 0.24)**
Wife	0.11 (0.1, 0.12)**	0.23 (0.21, 0.24)**
Child	0.04 (0.03, 0.05)**	0.09 (0.07, 0.11)**
Daughter-in-law	0.06 (0.05, 0.06)**	0.13 (0.12, 0.15)**
Grandchild	-0.06 (-0.09, -0.03)**	0.03 (-0.02, 0.09)
Did not migrate	-0.01 (-0.02, -0.01)**	-0.02 (-0.03, 0)*
Household characteristics:		
Age of household head	0 (0, 0)**	0 (0, 0)**
Female household head	0.02 (0.02, 0.02)**	0.02 (0.01, 0.03)**
Head's schooling years	0 (0, 0)**	0 (0, 0)**
Household size	0.02 (0.02, 0.02)**	0.05 (0.05, 0.05)**
Rural	0 (0, 0)	0.03 (0.02, 0.04)**
Scheduled caste	-0.01 (-0.01, -0.01)**	0.09 (0.08, 0.1)**
Scheduled tribe	-0.01 (-0.01, -0.01)**	0.15 (0.14, 0.16)**
Other backward classes	0 (-0.01, 0)**	0.04 (0.04, 0.05)**
Muslim	-0.01 (-0.01, -0.01)**	0.42 (0.4, 0.43)**
Christian	0 (0, 0.01)	0.19 (0.16, 0.21)**
Sikh	0.01 (0.01, 0.02)**	-0.04 (-0.06, -0.02)**
Wealth quintile 2	0 (-0.01, 0)**	-0.11 (-0.12, -0.1)**
Wealth quintile 3	-0.01 (-0.01, -0.01)**	-0.21 (-0.22, -0.2)**
Wealth quintile 4	-0.02 (-0.02, -0.01)**	-0.27 (-0.28, -0.26)**
Wealth quintile 5	-0.02 (-0.03, -0.02)**	-0.3 (-0.32, -0.29)**
Constant term	1.03 (1.02, 1.04)**	2.51 (2.47, 2.54)**
Sample size	484,369	481,676
p-value of F-test	0	0

Note: Data are from the National Family Health Survey of India 2015–2016. Sample includes all 18–49-year-old women. All models included age (years) and district fixed effects. Standard errors were clustered at the age and district level. 95% confidence intervals are presented in parenthesis. *P < 0.05, **P < 0.01.

Table 5: Robustness checks

	20-36-year-old women		25-31-year-old women		18-49-year-old women	
	Coeff. of UIP exposure	**Sample size**	**Coeff. of UIP exposure**	**Sample size**	**Coeff. of UIP exposure**	**Sample size**
At least one child born:						
Married/cohabiting women	-0.02 (-0.02, -0.01)**	299,608	-0.02 (-0.03, -0.01)**	137,929	-0.03 (-0.03, -0.02)**	484,369
Married and unmarried women	-0.01 (-0.02, 0)**	369,497	-0.01 (-0.02, 0)*	155,952	-0.02 (-0.02, 0)**	610,563
Without controlling for schooling	-0.03 (-0.03, -0.02)**	300,279	-0.02 (-0.02, -0.01)**	138,228	-0.03 (-0.03, -0.01)**	485,425
Infecund women (self-reported)	0 (-0.04, 0.05)	10,566	0 (-0.05, 0.05)	4,441	-0.01 (-0.06, 0.04)	26,896
Ideal number of children wanted:						
Married/cohabiting women	-0.05 (-0.07, -0.03)**	298,318	-0.04 (-0.06, -0.02)**	137,355	-0.06 (-0.08, -0.04)**	481,676
Married and unmarried women	-0.04 (-0.06, -0.02)**	367,354	-0.04 (-0.06, -0.02)**	155,118	-0.05 (-0.07, -0.03)**	606,268
Without controlling for schooling	-0.05 (-0.07, -0.03)**	298,986	-0.04 (-0.06, -0.02)**	137,654	-0.06 (-0.08, -0.03)**	482,719
Infecund women (self-reported)	-0.03 (-0.16, 0.11)	10,515	-0.01 (-0.15, 0.13)	4,420	-0.04 (-0.18, 0.09)	26,669
Desired wait time (years) for next birth	0.14 (0.07, 0.21)**	93,647	0.11 (0.03, 0.18)**	39,927	0.18 (0.1, 0.27)**	62,629

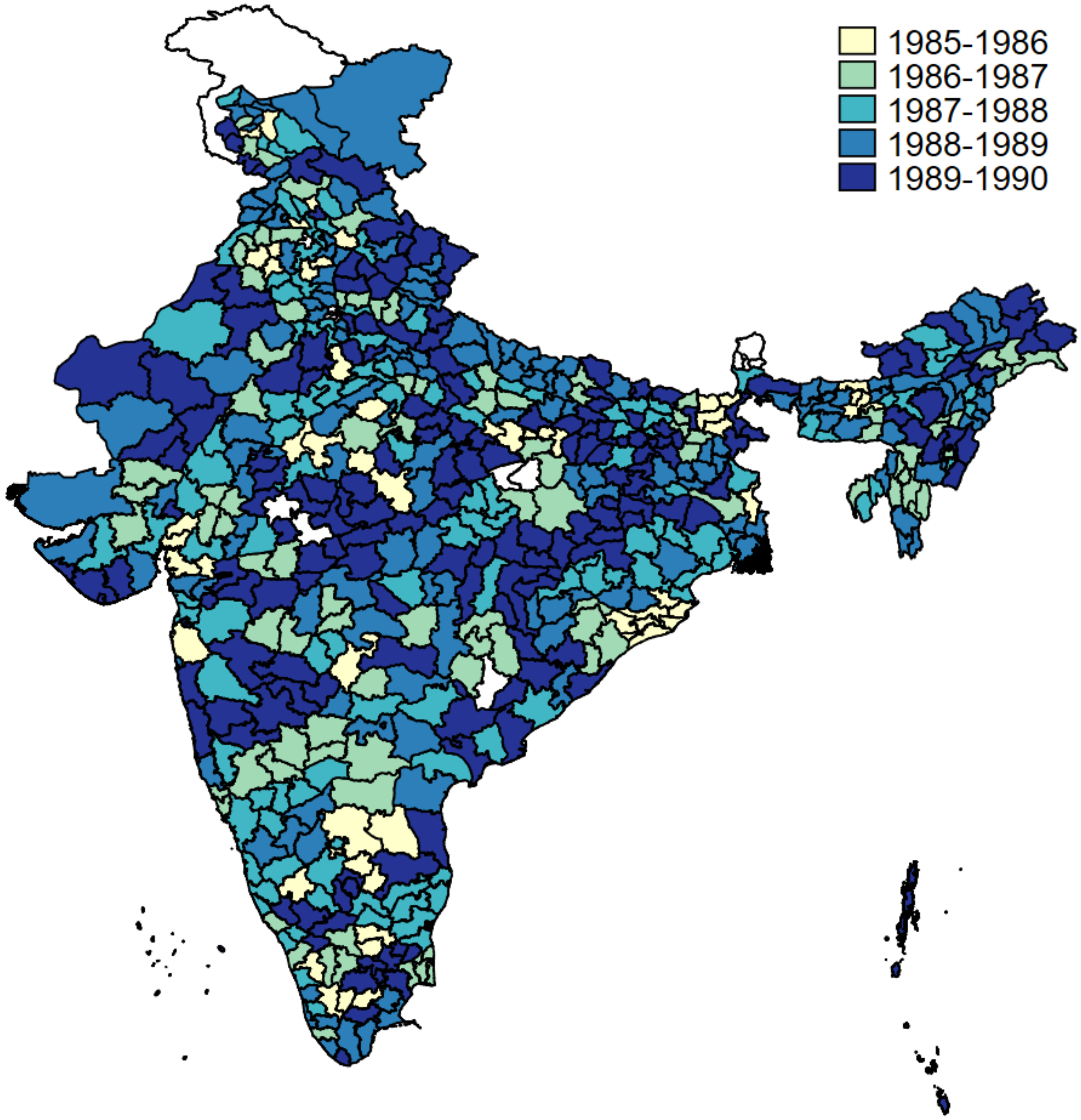
Note: Data are from the National Family Health Survey of India 2015–2016. Only the coefficient of UIP exposure (whether born when or after UIP was implemented in the district) from each regression is presented. The covariates of the models were age in years; squared age; marital status; years of schooling; migration status; indicators of relationship to household head; location, caste groups, religion, household size, age, sex, and schooling years of household head; and wealth quintiles, as applicable. All models included age and district fixed effects. Standard errors were clustered at the age and district level. 95% confidence intervals are presented in parenthesis. *P < 0.05, **P < 0.01.

Table 6: Heterogeneity in treatment effect

	20-36-year-old women		25-31-year-old women		18-49-year-old women	
	Coeff. of UIP exposure	**Sample size**	**Coeff. of UIP exposure**	**Sample size**	**Coeff. of UIP exposure**	**Sample size**
At least one child born:						
Rural	-0.02 (-0.02, -0.01)**	218,225	-0.02 (-0.02, -0.01)**	99,755	-0.03 (-0.03, -0.01)**	348,903
Urban	-0.03 (-0.04, -0.01)**	81,383	-0.03 (-0.04, -0.01)**	38,174	-0.03 (-0.04, -0.01)**	135,466
General caste	-0.02 (-0.03, 0)*	59,044	-0.03 (-0.04, -0.01)**	27,318	-0.03 (-0.05, -0.01)**	99,055
SC or ST	-0.02 (-0.03, 0)**	108,780	-0.02 (-0.03, 0)**	50,348	-0.03 (-0.03, -0.01)**	173,181
OBC	-0.02 (-0.02, 0)**	118,221	-0.02 (-0.03, 0)**	53,952	-0.02 (-0.03, -0.01)**	190,236
Women with no schooling	-0.02 (-0.03, 0)**	82,003	-0.02 (-0.03, 0)**	37,055	-0.03 (-0.04, -0.01)**	164,691
Women with 1–9 years of schooling	-0.01 (-0.01, 0)	123,238	-0.01 (-0.02, 0)**	56,722	-0.02 (-0.03, -0.01)**	187,532
Women with >=10 years of schooling	-0.03 (-0.04, -0.02)**	94,367	-0.05 (-0.06, -0.02)**	44,152	-0.04 (-0.05, -0.02)**	132,146
Wealth quintiles 1 and 2	-0.01 (-0.01, 0)	115,576	-0.01 (-0.01, 0)	52,434	-0.02 (-0.03, 0)**	182,300
Wealth quintiles 4 and 5	-0.03 (-0.03, -0.01)**	122,250	-0.04 (-0.05, -0.02)**	57,337	-0.03 (-0.04, -0.01)**	203,508
Ideal number of children wanted:						
Rural	-0.05 (-0.07, -0.02)**	217,206	-0.04 (-0.06, -0.01)**	99,302	-0.06 (-0.08, -0.03)**	346,812
Urban	-0.05 (-0.08, -0.01)**	81,112	-0.04 (-0.08, 0)*	38,053	-0.06 (-0.09, -0.01)**	134,864
General caste	-0.07 (-0.1, -0.02)**	58,907	-0.06 (-0.1, -0.01)**	27,260	-0.07 (-0.11, -0.02)**	98,707
SC or ST	-0.05 (-0.08, 0)*	108,089	-0.04 (-0.08, 0)	50,030	-0.05 (-0.09, -0.01)**	171,857
OBC	-0.05 (-0.07, -0.01)**	117,829	-0.03 (-0.06, 0)	53,785	-0.05 (-0.08, -0.02)**	189,341
Women with no schooling	-0.07 (-0.12, -0.01)**	81,516	-0.07 (-0.12, -0.01)*	36,849	-0.07 (-0.12, -0.02)**	163,356
Women with 1–9 years of schooling	-0.05 (-0.07, -0.01)**	122,687	-0.03 (-0.06, 0)	56,473	-0.05 (-0.08, -0.01)**	186,539
Women with >=10 years of schooling	-0.04 (-0.07, -0.01)**	94,115	-0.04 (-0.06, 0)*	44,033	-0.05 (-0.07, -0.01)**	131,781
Wealth quintiles 1 and 2	-0.07 (-0.1, -0.02)**	114,901	-0.05 (-0.09, -0.01)*	52,118	-0.08 (-0.11, -0.03)**	180,956
Wealth quintiles 4 and 5	-0.04 (-0.06, -0.01)**	121,926	-0.03 (-0.05, 0)*	57,196	-0.04 (-0.06, -0.01)**	202,792

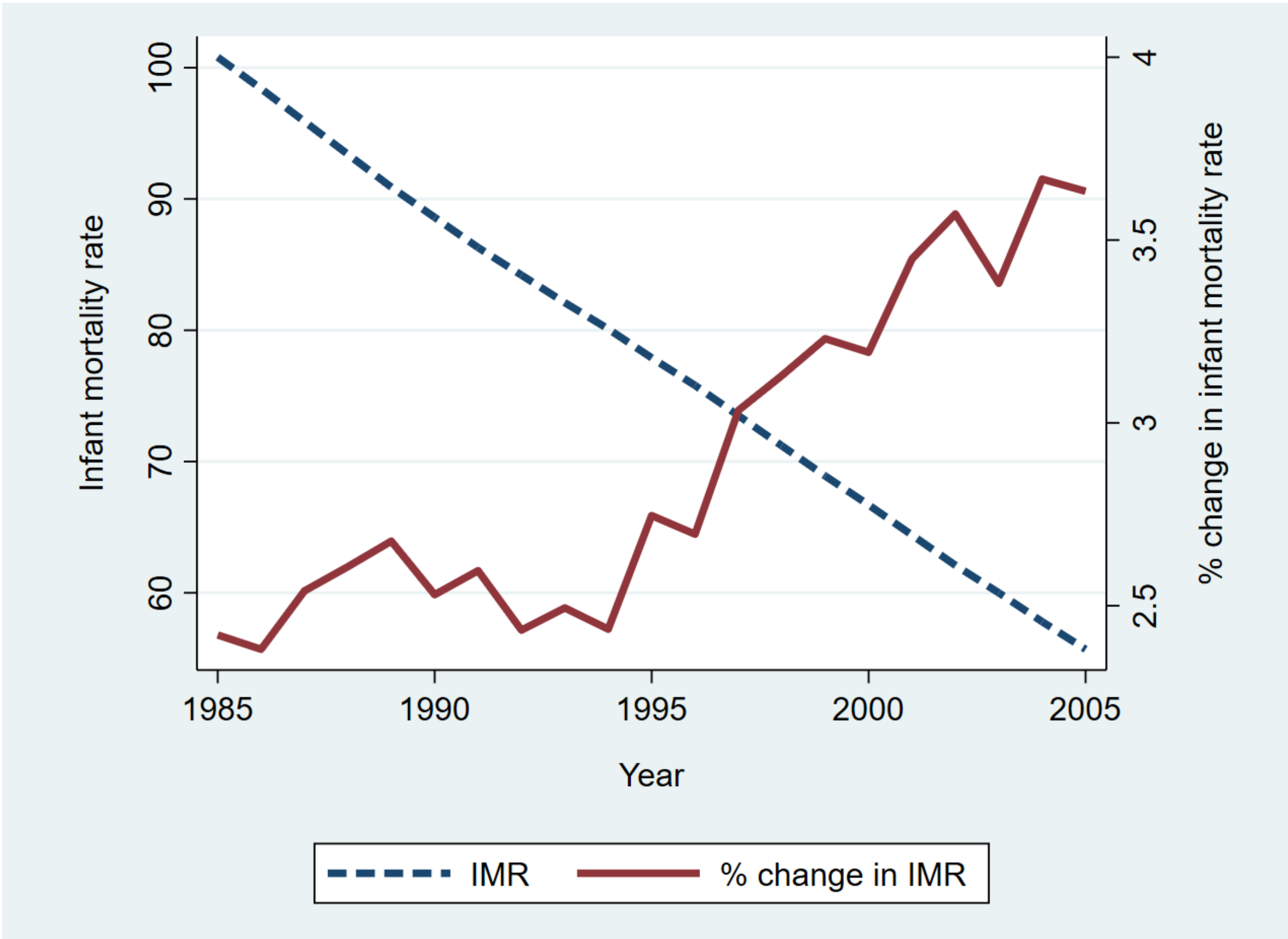
Note: Data are from the National Family Health Survey of India 2015–2016. Only the coefficient of UIP exposure (whether born when or after the UIP was implemented in the district) from each regression is presented. All models included age and district fixed effects. Standard errors were clustered at the age and district level. 95% confidence intervals are presented in parenthesis. *P < 0.05, **P < 0.01.

Figure 1: District-wise rollout of the Universal Immunization Programme



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

Figure 2: Infant mortality rate and its annual rate of change in India, 1985-2005



Note: Data are from the World Bank. Infant mortality rate (IMR) is defined as the number of deaths per 1,000 live births before reaching the age of one year. Change is the percentage reduction in IMR from the previous year.

Figure 3: Potential pathways of the effect of childhood vaccines on the demand for children

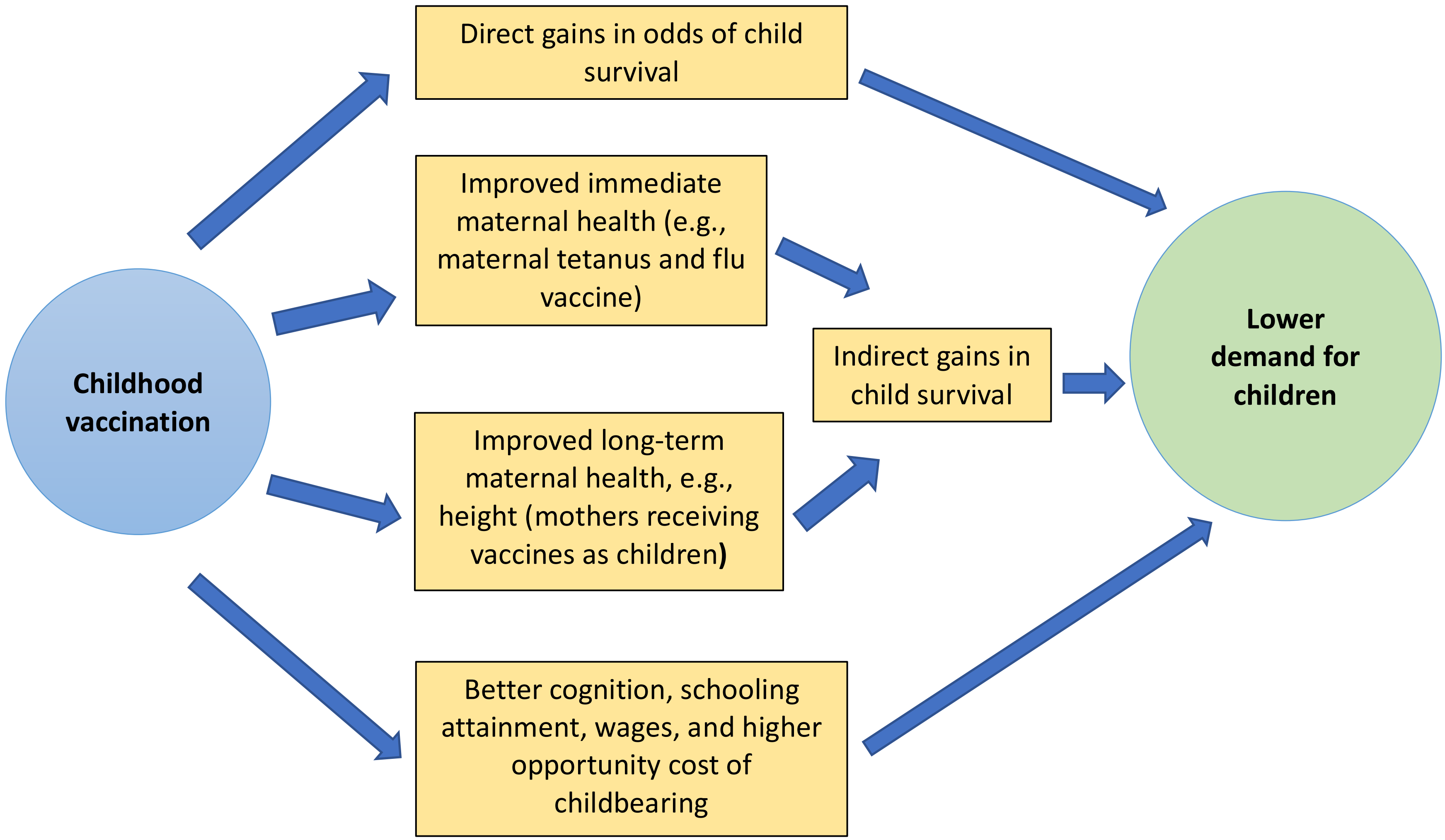
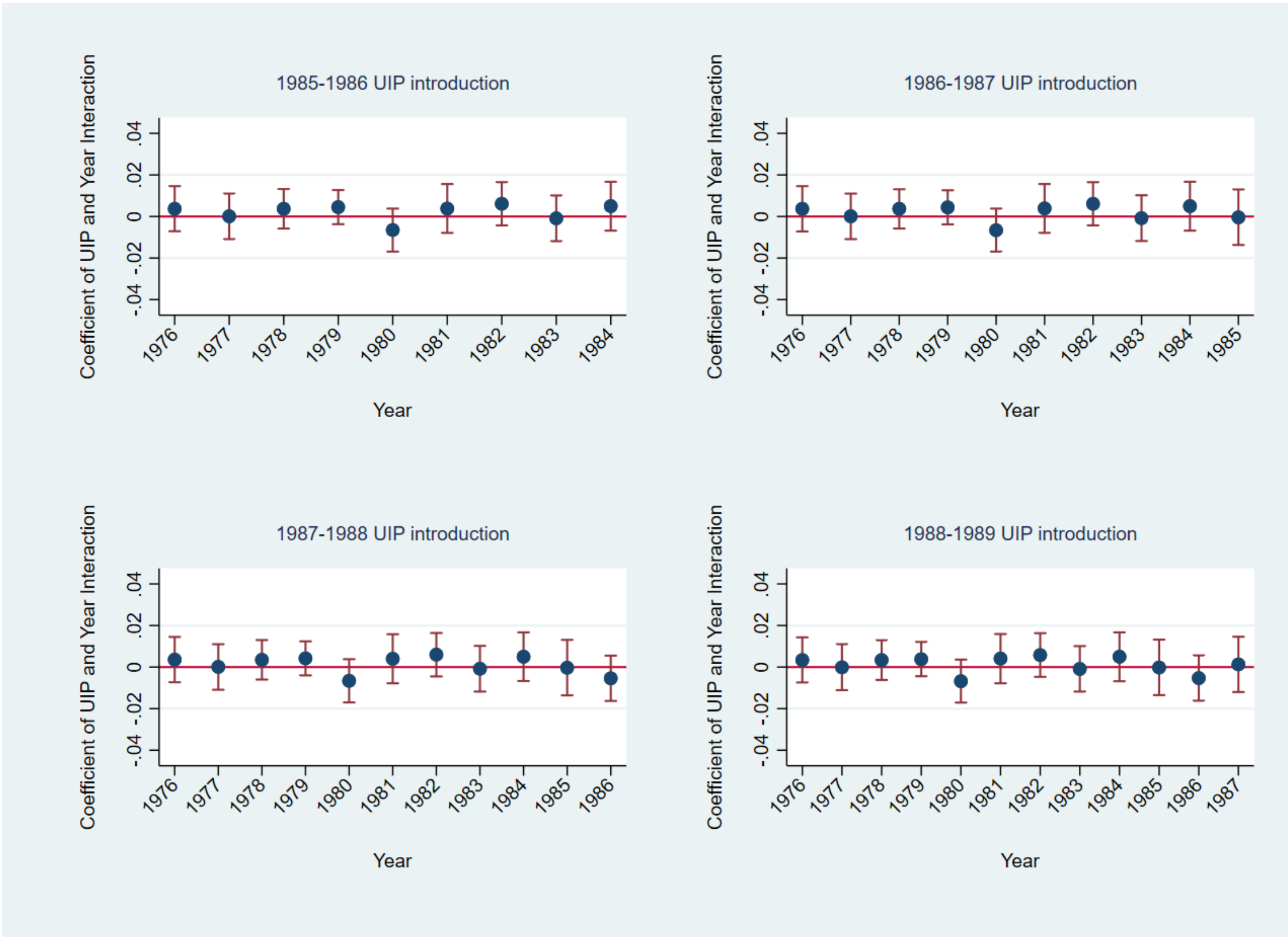
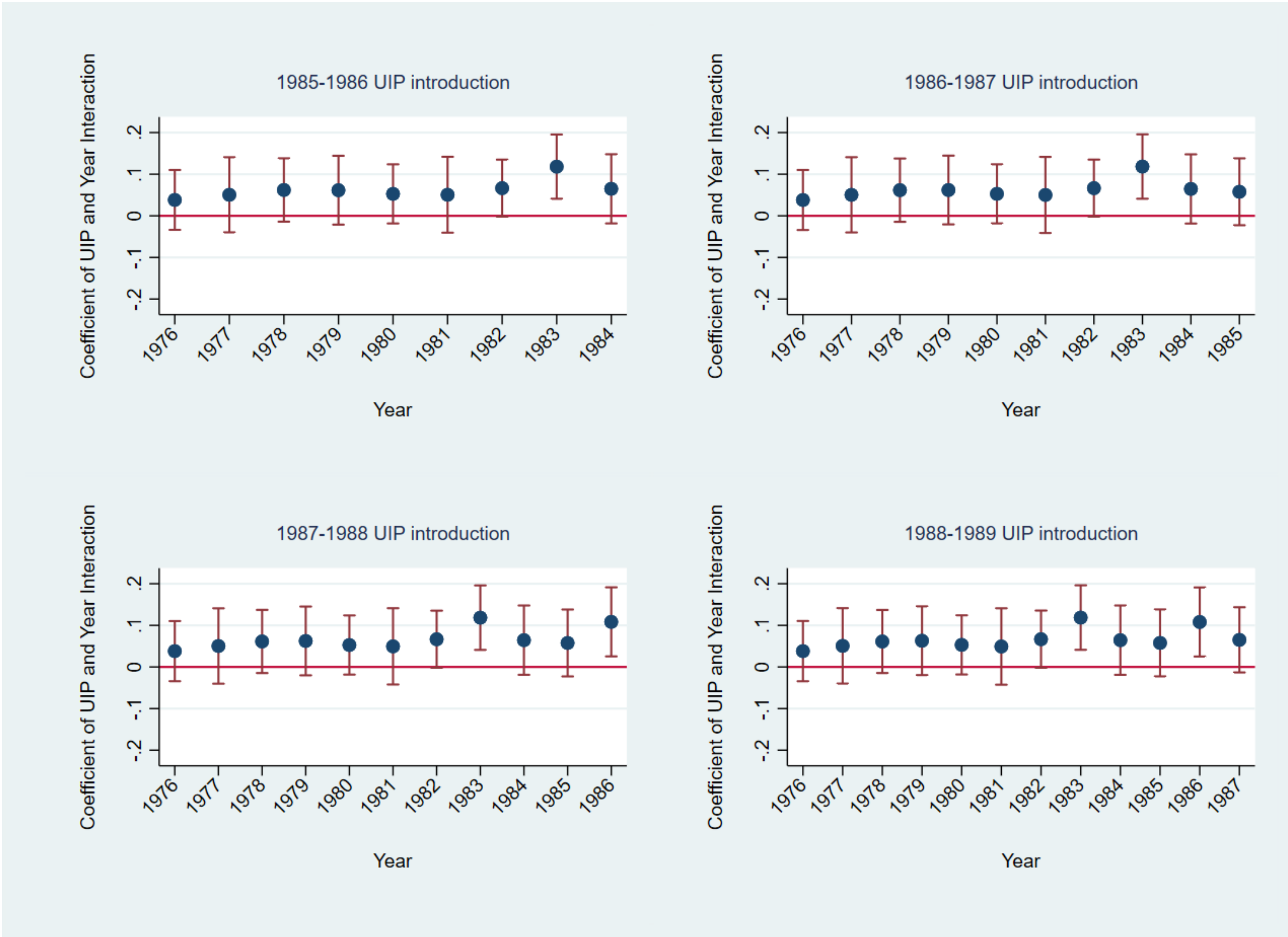


Figure 4: Coefficient of interaction between UIP district indicator and birth year in regression of at least one childbirth



Note: Data are from the National Family Health Survey of India 2015–2016. Coefficients of the interaction between treatment district and birth year along with 95% confidence intervals from each regression are shown.

Figure 5: Coefficient of interaction between UIP district indicator and birth year in regression of desired number of children



Note: Data are from the National Family Health Survey of India 2015–2016. Coefficients of the interaction between treatment district and birth year along with 95% confidence intervals from each regression are shown.