Received: 29 April 2022 | Revised: 26 September 2023 | Accepted: 19 December 2023

DOI: 10.1002/hec.4798

RESEARCH ARTICLE

Health Economics WILEY

Health insurance and child mortality: Evidence from India

Anaka Aiyar[1] | **Naveen Sunder**[2]

[1]Department of Community Development and Applied Economics, University of Vermont, Burlington, Vermont, USA

[2]Department of Economics, Bentley University, Waltham, Massachusetts, USA

Correspondence
Naveen Sunder.
Email: nsunder@bentley.edu.

Funding information
University of Vermont

Abstract
Although less than a third of the population in developing countries is covered by health insurance, the number has been on the rise. Many countries have implemented national insurance policies in the past decade. However, there is limited evidence on their impact on child mortality in low- and middle-income contexts. Here we document the child mortality reducing effects of an at-scale national level health insurance policy in India. The Rashtriya Swasthya Bima Yojana (RSBY), was rolled out across India between 2008 and 2013. Leveraging the temporal and spatial variation in program implementation, we demonstrate that it lowered infant mortality by 6% and child under five mortality by 5%. The effects are largely concentrated among urban poor households. In terms of mechanisms, we find that the program effects seem to be driven by increased usage of reproductive health services by mothers. We also demonstrate a rise in usage of complementary health services that were were not covered under the policy (such as child immunizations), which suggests that RSBY had significant positive spillover effects on health care usage.

KEYWORDS
child mortality, health insurance, India, national family health survey, post natal care, vaccinations

JEL CLASSIFICATION
I1, I13, I3, N35

1 | INTRODUCTION

Despite significant reductions in infant mortality over the past 2 decades, the global IMR remains high at 29 deaths per 1000 live births. India, the context we study, accounts for roughly half of all infant deaths across the world. Evidence suggests that a large proportion of under-5 child mortality is due to preventable causes. Nearly 40% can be averted by improving access to child health services, while an additional 25% of these deaths can be avoided by increasing availability of reproductive health services. Although such health services are heavily subsidized (or sometimes available free of cost) in India, their utilization remains low—less than two-thirds of all new mothers use postnatal care, while around 62% of infants complete their recommended first-year vaccination schedule. The literature suggests that health care demand is highly price sensitive in developing countries, especially among the poor (Cohen & Dupas, 2010; Kremer & Glennerster, 2011). In India out-of-pocket (OOP) spending on doctors, transportation, diagnostics and, drugs are high and the burden is further exacerbated by indirect costs

[Correction added on 27 January 2024, after first online publication: The copyright line was changed.]

associated with health service use (like opportunity cost of time)—these high costs have a dampening effect on demand. This is illustrated by the fact that studies have found that policies that provide pecuniary (Joshi & Sivaram, 2014; Powell-Jackson et al., 2015) or non-pecuniary (Banerjee et al., 2010) benefits are effective in improving usage of health services, especially in India. It is in this context that we explore the effect of health insurance provision on child health.

In 2008, the government of India introduced a national-level health insurance policy called the Rashtriya Swasthya Bima Yojana (RSBY). Through the RSBY, poor households received health insurance coverage worth Rupees (INR) 30,000 (approximately, USD 1712, PPP) at an annual premium of INR 30 (USD 1.712, PPP) (Malani et al., 2021). The coverage was substantial as the minimum wage around the time of policy implementation (2009) was about INR 10,000. Additionally the RSBY required that there would be no co-pays or deductibles charged to beneficiaries by the insurance companies. Empaneled hospitals had to provide cashless services for RSBY beneficiaries.

The policy was implemented in a staggered manner across India, with more than 90% of the districts (640 in total) receiving RSBY by 2014. We leverage quasi-random temporal and spatial variation in policy rollout and find that the RSBY policy reduced child mortality by around 5%. We confirm the results using an event-study design and also demonstrate that our results are robust to using novel differences-in-differences estimation techniques that account for biases in two-way fixed effects (TWFE) specifications (De Chaisemartin & d'Haultfoeuille, 2020; Callaway & Sant'Anna, 2020; Sun & Abraham, 2020). These findings are in line with studies from countries such as Mexico, Taiwan, Thailand, and the United States, where health insurance policies targeted to the poor led to a 10%–20% reduction in child mortality among targeted groups (Cesur et al., 2017; Chou et al., 2014; Goodman-Bacon, 2018; Gruber et al., 2014). The effects are concentrated among urban poor families, who experience some of the largest declines in IMR in response to this policy.

We demonstrate that program availability and the timing of implementation were not correlated with socioeconomic or health characteristics of districts. We also rule out the possibility that the observed effects are driven by other related policies, such as the Janani Suraksha Yojana (JSY) and the National Rural Employment Guarantee Program. Our results are robust to a number of other checks, including conducting the analysis at the district-level. This addresses concerns that household (or individual) level unobserved factors could potentially impact selection into RSBY. We also show that, even though there are health benefits, households do not change fertility preferences in response to the RSBY.

Further, we probe the potential mechanisms driving these findings. In line with the literature, we find that an increase in usage of maternal health services is a key mediating factor (Aquino et al., 2009; Cesur et al., 2017; Chen & Jin, 2012; Chou et al., 2014; Conti & Ginja, 2023; Gruber et al., 2014). RSBY mothers were more likely to give birth in health facilities and in the presence of skilled medical professionals. This is indicative of the direct impact of RSBY on healthcare usage (since child delivery and neonatal services are covered under RSBY) (Daysal et al., 2015). We also find significant spillover effects of RSBY on usage of preventative healthcare services that were not directly covered by the policy, such as post-natal care and child vaccination. Mothers with RSBY access were 1.0% points more likely to use postnatal care (PNC) services and were more likely to have interacted with a doctor during those visits. Children in treatment regions were more likely to have completed their required immunization schedules for Diphtheria-Pertussis-Tetanus (DPT), polio and Bacille-Calmette-Guerin (BCG) vaccines in the first 12 months of life. Put together, these findings support the conclusion that RSBY led to increased usage of the formal healthcare system as a whole which in turn reduced infant mortality.

Our paper thus presents novel evidence that provision of health insurance can be one more health policy tool that can improve child health even in contexts where many health services are heavily subsidized.

2 | HEALTH SYSTEMS CONTEXT

2.1 | Organization of the Indian health system

India has a three tiered system of healthcare, and consists of a mixture of both public and private providers (Berman, 1998; Chokshi et al., 2016). The lowest tier comprises of sub-centres that deliver primary services, most common among them being basic reproductive and child health (RCH) services like (women's) check ups and immunizations. Primary health centers, the second tier, provide diagnostic and/or minimally invasive procedures like fixing broken bones, prescribing antibiotics for illnesses etc. For secondary and tertiary care, individuals visit larger hospitals which are typically located in larger urban centres like towns, which have sophisticated medical technology and access to specialists. Patients with complications during child birth, neonatal surgeries and for relatively advanced procedures like hysterectomies, dialysis, or appendectomies, access services at secondary hospitals. Tertiary hospitals are akin to super specialities which focus on the diagnosis and treatment of acute/rare health conditions. While (tax-financed) public hospitals provide services at highly subsidized prices, patients still needed to pay for some health services OOP prior to RSBY.

There is also a concurrent largely unregulated private health system which provides services at all the aforementioned tiers. Recent studies have shown that low quality care dominates smaller clinics and private practices providing care in poorer neighborhoods (Das et al., 2012). However, it is also important to note that there is a large degree of heterogeneity in the price and quality of privately supplied health care. Anecdotally, many individuals prefer to use private health care when they can afford it. Prior to the implementation of RSBY, less than six percent of India's population had any health insurance. Naturally, this implies that spending on private health services was entirely OOP.[1]

2.2 | The Rashtriya Swasthya Bima Yojana program

Concerned about the large OOP spending on health care and its impact on health equity, the Indian government implemented a novel insurance program called the RSBY in 2008. The goal of the program was to use insurance to cover health expenses that below-poverty line households were paying for OOP. Under the RSBY, households received coverage worth INR 30,000 every year (for upto a maximum of five members) on payment of an annual fee of INR 30. Based on purchasing power parity conversions, this translates to a coverage of around USD 1712 for an annual premium of USD 1.7. The coverage provided was not only substantial in terms of size (it amounted to about three times the minimum income guarantee in India at the time), but was also wide in scope and eligibility. RSBY provided coverage regardless of any pre-existing health conditions and included comprehensive coverage for both secondary and tertiary care services (Das & Leino, 2011; Malani et al., 2021; Palacios et al., 2011). Importantly for this study, RSBY also covered reproductive health services, neonatal care and family planning (Mozumdar et al., 2018). The policy also provided reimbursements for transportation expenses of up to a maximum of INR 1000 (60 USD, PPP) per year. When it was first implemented, households below the poverty line (BPL) across the country were eligible, but it was quickly extended to all low-income families across the country. Eventually RSBY provided coverage to nearly 170 million individuals (Malani et al., 2021).

Even though community based insurance programs and private insurance existed, the RSBY program was the first of its kind in many aspects.[2] It was the first nationally implemented program that was targeted to *all* poor and vulnerable households in the country. It mandated cashless services should be provided for beneficiaries and it covered allied costs like transportation and wage loss for attendants of patients. In the past, other insurance programs were primarily employment based and was restricted to a small section of the population that had formal sector employment. Less than six percent of the population had some health insurance prior to RSBY. Unlike other insurance programs, the RSBY allowed both private and public insurers to participate and required that both private and public hospitals be empaneled (Palacios et al., 2011; Virk & Atun, 2015). The latter would ensure that a greater number of hospitals would be available for beneficiaries to use. RSBY was primarily funded by the central (federal) government who paid 75% of the total premium (while the rest was paid for by the state government). Prices for medical procedures were set by the central government but states were allowed to change the rates based on their specific market conditions (Malani et al., 2021; Palacios et al., 2011).[3] The state governments were responsible for the roll-out of the program. Insurance companies were selected by the state government through a bidding process. The insurance company was expected to work with local government officials to identify and enroll eligible families.

3 | LITERATURE REVIEW

3.1 | Health insurance and child health

Over the past few decades, developing countries have been expanding health system coverage in two different ways. The first comprises of different types of supply side interventions such as providing new and enhanced primary services, increasing access to doctors and improving rural outreach. These types of interventions have been successful in increasing access to preventative health services and reducing child mortality in a variety of developing country contexts such as Brazil, Nigeria, Turkey and Thailand (Aquino et al., 2009; Cesur et al., 2017; Gruber et al., 2014; Okeke, 2023). The second genre of policies focused on demand-side factors, an important component of which was the introduction of health insurance programs (other prominent examples include cash transfers and information campaigns). The goal of health insurance expansions have been to increase usage of health services by reducing OOP spending on health. Evaluations of health insurance policies implemented in China (Chen & Jin, 2012), Colombia (Camacho & Conover, 2013), Mexico (Conti & Ginja, 2023), Vietnam (Aiyar &

Venugopal, 2020), Nicaragua (Fitzpatrick & Thornton, 2019) and Taiwan (Chou et al., 2014) suggest that health insurance has largely been successful in increasing access to child health services. Studies have also found that access to health insurance has led to an increase in the usage of preventative health services among women. Our evaluation adds to this literature by (i) providing evidence of the effectiveness of an at-scale health insurance policy in reducing child mortality, and (2) providing further evidence that health insurance has a positive effect on the usage of health services, even those that might not be directly covered by the policy.

3.2 | Literature related to RSBY

Estimates suggest that nearly 41 million RSBY cards were issued by the end of 2016 (providing coverage to more than 170 million individuals). Despite the widespread implementation of the policy, it received criticism for its "*weaker than expected*" performance (Rajasekhar et al., 2011). This has been supported by studies examining the effects of RSBY, which have found low (or no) effect on OOP health spending (Azam, 2018; Das & Leino, 2011; Karan et al., 2017; Palacios et al., 2011; Ravi & Bergkvist, 2014). However, more recent evidence shows that the program increased access to inpatient services with no impact on inpatient expenditure (Sriram & Khan, 2020). We add to this literature by examining the effects of RSBY on child mortality, and the potential factors that mediate this effect. The paper most closely related to our analysis is Malani et al. (2021)—they conduct a randomized experiment (2013–2018) in two Indian districts (counties) in the state of Karnataka, where they provide different levels of subsidies and measured insurance uptake. They find that uptake of health insurance increases with the subsidy amount with highest uptake being when insurance is provided free of cost. They also find positive and significant peer effects in take-up (by leveraging across village difference in proportion of households offered insurance). However they find that insurance has limited effects on health outcomes.

Previous studies focused on evaluating take-up, utilization and spending of the program and do not detect any health improvements, partly due the lack of availability of child specific data but also due to the timing of their evaluations. A bulk of these analyses use data for only the early years of RSBY at which time the program had not been fully implemented across India (Azam, 2018; Das & Leino, 2011; Karan et al., 2017; Rajasekhar et al., 2011; Ravi & Bergkvist, 2014). This likely explains the null results documented in the past literature (which is compatible with the implementation challenges faced in the initial phase of implementation). We improve on this in three ways—(1) we use the latest available nationally representative health data for India, which contains information till 2019 to measure the impact of the program, (2) we examine relatively medium-run impacts of the policy as some of the districts in our sample would have been RSBY beneficiaries for around five years, and (3) some of the aforementioned studies use self-reported data on insurance coverage, which is likely to have selection bias arising from differences in who chooses to enroll for health insurance. We improve on this by using insurance availability at the district level as our independent variable of interest. This variable is created based on information from an administrative dataset, which is unlikely to be affected by individual or household level selection (we describe this in more detail in the next section).

4 | DATA

4.1 | Data on RSBY implementation

The data on RSBY implementation comes from a government of India database website. An earlier version of this data was used in Nandi et al. (2013). This website published cumulative updates on the implementation of RSBY by district and month till 2016. This included district level information on the number of people eligible for and enrolled in RSBY, number of hospitals empaneled, the insurance company responsible, the contact information of the government agency implementing the program at the local level, and the premiums. We accessed the website to retrieve district level program data between 2008 and 2016. The final dataset used in this analysis, that provides spatial and temporal variation in health insurance availability, includes information on the program start date in each district. This information has then been verified with program start date (for selected districts) available in Palacios et al. (2011) and Nandi et al. (2013).

Analysis of the program data reveals that even though RSBY was announced in 2008, less than seven percent of all districts across the country had implemented RSBY by the end of that year. However, by 2012 (left panel of Figure 1) 446 districts (out of 640 districts) across the country had implemented the program.[4] This suggests that even though the implementation of the policy was staggered, it was done in a relatively short period of time (considering the scale of the policy). In the right panel of Figure 1 we present a map with the program's start years in districts. The figure suggests that there is no observable spatial

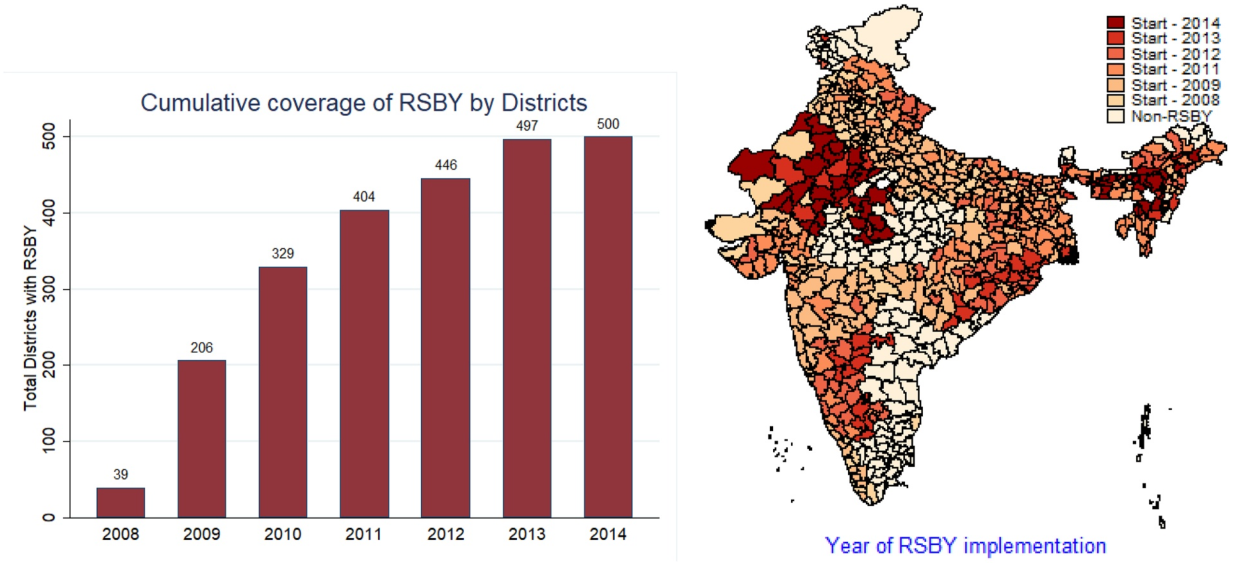

FIGURE 1 Implementation of RSBY. The figure and the map is based on government data pertaining to RSBY implementation across the country. The plot in the left panel provides the number of districts that implemented RSBY in each calendar year. The map in the right panel demonstrates the spatial and temporal pattern in implementation. RSBY, Rashtriya Swasthya Bima Yojana. [Colour figure can be viewed at wileyonlinelibrary.com]

pattern in the timing of RSBY implementation. Controlling for state fixed effects, Table B1 shows that implementation in a year does not depend on district-level socioeconomic and health indicators (intensity of night lights, sex ratio, literacy, population density, labor force participation, literacy rates, and the medical facilities). Thus we find no association between a socioeconomic characteristic and the propensity of the district to implement the policy in a particular year.[5]

In appendix Table B2, we summarize additional information on RSBY using a snapshot of the data set from May 2014. We restrict the sample to only districts with RSBY and for whom information is available. Enrollment rate, defined as the share of those enrolled among those eligible, ranges from 0 to 98% with a mean enrollment rate of 48%. As expected, enrollment rates were higher among districts that had implemented the program earlier.

4.2 | Child mortality and health-related outcomes

Data on health outcomes are from the National Family Health Survey (NFHS). We use data from the two latest surveys—round 4 (conducted in 2015–2016) and round 5 (conducted in 2019–2021). These are nationally representative cross-sectional surveys that collect information on demographic and health variables from women and children (under 5 years of age). The sample for each survey round is selected using a two-step procedure. First, enumeration areas are randomly sampled from the universe of enumeration areas in a district, and then households are randomly selected from the list of all households within an enumeration area. This survey is the Indian iteration of a data collection effort that is conducted globally, and is referred to as the Demographic and Health Survey (DHS).

We extract child mortality information from birth histories collected from the sample of reproductive-age women eligible for the NFHS interviews. The Birth Recode DHS recode files provides the key outcomes used in this analysis - whether a child died during the first month of birth (neo-natal mortality), during the first year after birth (infant mortality), within the first 2 years (under-2 mortality) or within the first 5 years (under-5 mortality). We restrict the sample of analysis to pregnancies that occurred between 2007 and 2016. Children born after the implementation of the policy in their district are considered to be part of the treatment group, and others are part of the control group.

4.3 | Other covariates

In our analysis we control for various child-level covariates including month and year of birth, gender of the child, birth order, and whether it is a single birth. Mother-level controls include mother's education, mother's age at birth, and mother's body mass index *Z* score. Household-level covariates in our analysis include the wealth index, and the household's urban residence status, caste, religion, access to piped water and access to private toilet facilities. These factors shape household's access to and usage of RSBY and the various outcomes analyzed. In Table B3, we provide summary statistics on the outcomes and control variables that are used in the analysis. Neo-natal Mortality, Infant mortality, Under-2 mortality and Under-5 Mortality are on average 20, 31, 33, and 35 per 1000 births in our sample. The average age of mothers at the time of child birth in our sample is 25 years, and a little more than one-third of them are illiterate. Of the households in the sample, 72% were Hindu, 22% live in urban areas, 40% belong to the scheduled caste and scheduled tribe community, and 44% had BPL cards. In column 3 and 5, we compare the means of the sample between children who had RSBY prior to birth versus children who did not have RSBY in the same district. Column 7 showcases the means of the sample of children whose districts never received RSBY. The key points of difference include that children born after RSBY are younger than those with no exposure to RSBY in the sample. This can be expected given the timing of the program in relationship to the timing of the survey.

5 | EMPIRICAL STRATEGY

5.1 | Difference-in-Differences

We leverage the quasi-random variation in the timing and availability of RSBY across districts in a difference-in-differences estimation strategy:

$$Y_{ibmd} = \beta * RSBY_{ibmd} + \pi_d + \phi_m + \phi_b + \sum_{k=1}^{K} \gamma_k * X_{id}^k + \sum_{j=1}^{J} \partial_j * W_{id}^j + \epsilon_{ibmd} \tag{1}$$

where Y_{ibmd} denotes the outcome of interest, for example, infant mortality, for child i born in birth year b in district d in month m. The coefficient of interest is β, which measures how RSBY availability shapes the outcomes of interest. We combine information on birth month/year of each child with the start date of the RSBY in a district to create the categorical treatment variable. $RSBY_{ibmd}$ takes a value of one if the child was born after RSBY started in their district and zero otherwise. Based on this definition, 51 percent of our sample children are classified as RSBY beneficiaries (Table B3). In the main sample, the control group consists of two sets of children, (1) those born before RSBY started in treatment districts and (2) those born in districts where RSBY was not available during the study period.

In Equation (1), π_d represents district fixed effects that account for time-invariant factors within the district, ϕ_m are birth-month fixed effects, ϕ_b are birth-year fixed effects. X_{id} refers to the child-level controls and W_{id}^j is the vector of household-level and mother-level controls. All final regressions include the full set of controls and standard errors are clustered at the district level.[6]

5.2 | Event study analysis

As a next step, we estimate an event-study model that takes the following form:

$$\begin{aligned} Y_{ibd} = {} & \sum_{\tau \neq -1} \beta_\tau * 1.\left(t - T_d^* = \tau\right) + \pi_d + \varnothing_y + \varnothing_m \\ & + \sum_{k=1}^{k} \gamma_k^j * X_{ibd}^k + \sum_{j=1}^{j} \partial_j^1 * W_{bd}^j + \varepsilon_{ibd} \end{aligned} \tag{2}$$

Here, T_d^* represents the year of RSBY implementation in district d. In Equation (2) the coefficients on the event year dummies $1.\left(t - T_d^* = \tau\right)$ takes a value of one in the year which is τ years away from T_d^* τ ranges from −3 to +3 years with zero representing the year when the policy starts. Coefficients from the event year dummies capture the effects of the exposure of RSBY on child health outcomes (Y_{ibd}) in different time periods relative to a reference period. We select the reference year as the year prior to the start of the program ($\tau = -1$). Here too, we identify RSBY effects by examining within-district changes in child mortality that correspond to the year of RSBY implementation. This approach offers two advantages: first, since the program was implemented in a staggered manner, there is no particular year/month when all districts received RSBY. Therefore, disaggregating effects relative to the period of implementation in each unit reduces the possibility of other contemporaneous shocks driving our findings (as compared to a situation where all units are treated in the same time period). This also allows for the effect to change non-monotonically over time. Second, it enables us to test the identification assumption of whether treated and control districts would have trended similarly in absence of the program.

5.3 | Accounting for bias in TWFE models

The coefficient of interest (β) in Equation (1) is a weighted sum of the average treatment effects (ATEs) in each group and period, where group refers to a set of units that are treated in a given time period. Goodman-Bacon (2021) demonstrates that these weights, which are proportional to group sizes and the variance of the treatment, can be negative and cause bias in the estimates of two way fixed effect models. To assuage concerns that this bias may be driving our findings, we present as robustness checks results based on estimators that account for such bias. Below, we discuss these estimators briefly.

De Chaisemartin and d'Haultfoeuille (2020) propose an estimator that is valid under conditions of heterogeneous treatment effects. In this case the treatment effect is estimated based on comparisons between units that change their treatment status between two consecutive time periods (e.g., t-1 and t) and those whose treatment status does not change between those time periods. The ATE is then equal to the average of all of these comparisons across all possible consecutive time periods and for all possible values of the treatment (which in our case is binary). In our analysis, we use this to (1) assess pre-trends, and (2) estimate an overall treatment effect of RSBY.

Callaway and Sant'Anna (2020) propose an estimator that allows for arbitrary treatment effect heterogeneity and dynamic effects in a difference-in-differences design. This estimator creates the causal parameter of interest based on a number of two-by-two comparisons, but excludes the bad comparisons discussed in Goodman-Bacon (2021) This method provides estimates for the ATE on the treated (ATT) for each group (units treated in the same calendar time) in each time period. We present the aggregate treatment effects for each group separately. Sun and Abraham (2020) provide an estimator that accounts for staggered policy roll-out and heterogeneous treatment effects across units in an event-study design. They demonstrate that heterogeneity in treatment effect leads to the violation of the strict exogeneity assumption, which in turn implies that the coefficients on lead and lag indicators (like in Equation 2) will be contaminated with information from other leads and lags. As a result, many conventional tests employed in diff-in-diff designs, such as testing the joint significance on the pre-treatment leads, may yield false negatives/positives. We implement this estimator (using the never treated districts as the comparison group).

6 | RESULTS

6.1 | Main results

Table 1 presents estimates of the effect of RSBY on child mortality using Equation (1). Results in column 1 suggest that neonatal mortality (NNM) falls by 1.23 for every 1000 births, but the effect is not statistically significant. However, infant mortality rate (IM) drops by around 1.98 deaths for every 1000 births after RSBY implementation—this represents a reduction in infant mortality by around 6% from its mean value. Similarly, under-2 mortality (U2M) falls by 1.94 per 1000 births (Table 1, column

TABLE 1 Effect of Rashtriya Swasthya Bima Yojana on child mortality (per 1000 births).

	(1) Neo-natal mortality	(2) Infant mortality	(3) Under-2 mortality	(4) Under-5 mortality
Born after RSBY	−1.229	−1.978***	−1.943***	−2.162***
	(0.57)	(0.685)	(0.716)	(0.766)
R-squared	0.01	0.02	0.02	0.02
N	929,968	929,968	929,968	929,968
Mean	19.94	30.65	32.81	35.53

Note: This table reports the results from estimating the effect of RSBY on child mortality using Equation (1). The data comes from rounds 4 and 5 of the NFHS survey, and all regressions include district fixed effects, year fixed effects, along with the full set of controls. Mortality is calculated as a recorded death (=1) or not (=0). If a child died within 30 days of birth, it is considered as a Neo Natal death (NNM). If the child died within the first 365 days of birth, it is considered as an infant death (IM). If a child died within 730 days of birth, it is considered as a death by age 2 (U2M). If a children died by age 5, it is considered an under 5 mortality (U5M). Mortality per 1000 births has been calculated by multiplying each indicator by 1000. *RSBY*, that takes a value of one for children born after RSBY implementation in their district and zero otherwise. This variable always takes a value of zero for children in never-RSBY districts. The sample includes all births reported by the women after 2007. Standard errors are clustered at the district level. * Significant at 10 percent. ** Significant at 5 percent. *** Significant at 1 percent.

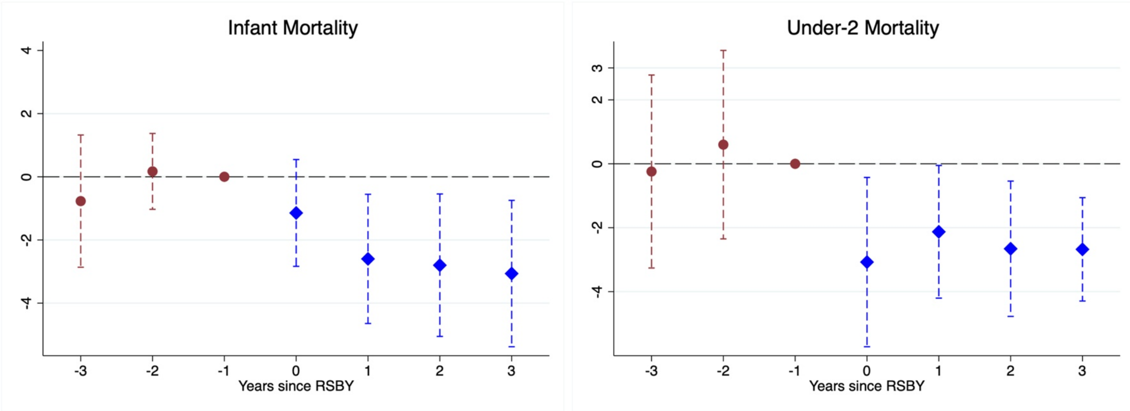

FIGURE 2 Event study analysis. The data comes from the National Family Health Survey 4 and 5 surveys, and all regressions include district and year fixed effects, along with the full set of controls specified earlier. Mortality is calculated as a recorded death (=1) or not (=0). If a child died within 30 days of birth, it is considered as a Neo Natal death. If the child died within the first 365 days of birth, it is considered as an infant death. If a child died within 730 days of birth, it is considered as a death by age 2. Mortality per 1000 births can be calculated by multiplying the mean values by 1000. Standard errors are clustered at the district level. [Colour figure can be viewed at wileyonlinelibrary.com]

3), an effect of roughly 5.3% relative to the mean. Under-five mortality decreases by 2.16 births per 1000, which is a 5.4% reduction relative to the mean value. Based on information we have on enrollment rates, we see that the average RSBY enrollment in a district was around 48%. This implies that if the program had enrolled all eligible households, our estimate would plausibly have been almost twice as large. This which would imply reductions in IM and U2M of around 10%–11%.[7]

These findings provide further evidence on the health improving effects of insurance provision and are in line with the literature that estimates the impacts of similar programs in other contexts. Gruber et al. (2014) find a 13%–30% reduction in child mortality in Thailand in response to a introduction of a health insurance policy, while Chou et al. (2014) document an around 20% decline in child mortality after the introduction of national health insurance program in Taiwan. Goodman-Bacon (2018) finds similar reductions in child mortality in the United States following the introduction of Medicaid, while Conti and Ginja (2023) find a 10% fall in child mortality when families get access to health insurance (*Seguro Popular*) in Mexico. Cesur et al. (2017) find that a single player health program in Turkey reduces infant mortality by 23%. Thus, our results are on the lower end of global evidence of the infant mortality reduction impacts of health insurance.

To allow for dynamic treatment effects, we use the event-study model outlined in Equation (2). In this specification, we consider the year in which RSBY was implemented in a district to be time zero ($t = 0$). The graphs in Figure 2 plot the RSBY coefficients over different time periods with the base period as the year prior to the implementation of the program (-1). Starting in period $t = 1$, the coefficients become negative and are largely statistically significant. This further corroborates our main findings. We also reject the hypothesis that the average of the coefficients in the pre- and post-RSBY period are equal (p-value = 0.001). Additionally, we assess the parallel assumption—the plots in Figure 2 suggest that the coefficients for the cohorts born prior to RSBY implementation ($t = -2$ and $t = -3$) are statistically insignificant, implying that there were no significant differences in the child mortality patterns between RSBY and non-RSBY districts in the pre-policy period. We are also cannot reject the null that all the pre-treatment coefficients are equal to zero (p-value = 0.52). This suggests that the parallel trends assumption holds.

We further examine the parallel trends assumption underlying our diff-in-diff strategy using child mortality information in the decade before RSBY implementation. We conduct this check using information from another household survey—three rounds of the nationally representative District Level Health Surveys (DLHS), which were conducted in 1999, 2004 and 2007 respectively. These surveys provide information on the evolution of child mortality in the pre-RSBY period (1998–2007). In Figure 3, we plot the coefficient of the RSBY status using DLHS data (rounds 1, 2 and 3). The figure compares child mortality in RSBY and non-RSBY districts—it clearly demonstrates that there was limited and statistically insignificant difference in IM and U2M across RSBY and non-RSBY districts in the pre-policy period. This suggests that parallel trends likely held in this context.

Finally, we present results using novel diff-in-diff estimators. We start with a plot based on the methodology outlined in De Chaisemartin and d'Haultfoeuille (2020) (Figure 4, top left) - here we present estimates for the pre-trend and an overall treatment effect. The figure indicates that there are no statistically significant pre-trends (all these coefficients are in fact positive in value), while the treatment effects appear after the implementation of RSBY. Further, Figure 4 (top right) presents the

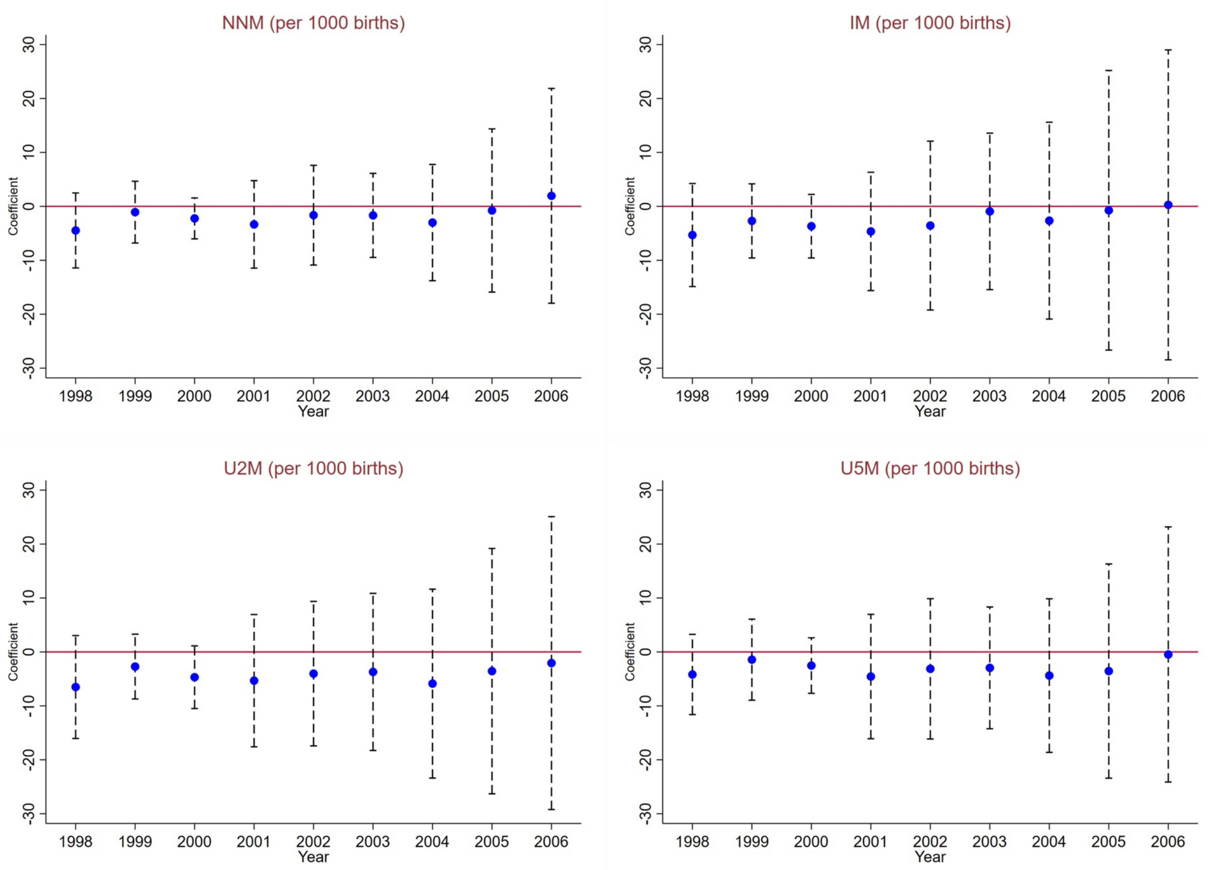

FIGURE 3 Differences between RSBY and Non-RSBY districts in pre-policy period. The data comes from rounds 1, 2 and 3 of the DLHS survey, and all regressions include district and year fixed effects. Mortality is calculated as a recorded death (=1) or not (=0). If a child died within 30 days of birth, it is considered as a Neo Natal (NNM) death. If the child died within the first 365 days of birth, it is considered as an infant death (IM). If a child died within 730 days of birth, it is considered as a death by age 2 (U2M). If the child dies by age five, it is considered as a under 5 death (U5M). Mortality per 1000 births can be calculated by multiplying values by 1000. The coefficient for the RSBY effect and the associated 95 percent confidence intervals are shown. Standard errors are clustered at the district level. RSBY, Rashtriya Swasthya Bima Yojana. [Colour figure can be viewed at wileyonlinelibrary.com]

groupwise estimates of the treatment effect based on Callaway and Sant'Anna (2020). The groupwise estimates suggest that the treated units demonstrate large and statistically significant reductions in mortality due to RSBY. The findings are similar when we use the methodology described in Sun and Abraham (2020)—the results are presented in the bottom panel of Figure 4 and also demonstrate that there were no significant pre-trends and that the implementation of the policy led to significant declines in infant mortality. Note that in the results based on Sun and Abraham (2020), the control group consists of observations in districts that never received RSBY. Put together, the estimates from these different methodologies suggest that our findings are robust to accounting for the biases in the TWFE models.

6.2 | Robustness checks

Additional robustness checks in this section confirm that our results are not impacted by policy rules that impacted program allocation, or other non-random household behaviors. We begin by exploring whether unobserved factors might impact selection into RSBY. First, we drop states with lower coverage from the sample to control for potential institutional selection that determines whether a person is covered or not. As seen in Panel A, dropping states with low or no coverage does not change the outcome and the main results and interpretations are robust to their exclusion. Second, we aggregate the data to the district-level. The results from this analysis are presented in Panel B of Table 2, and indicate that our main findings are robust to this level of aggregation. This check addresses the concern that there maybe unobserved household behaviors that impact program outcomes when running the analysis at the individual level. Further, we address the possibility that any non-RSBY districts

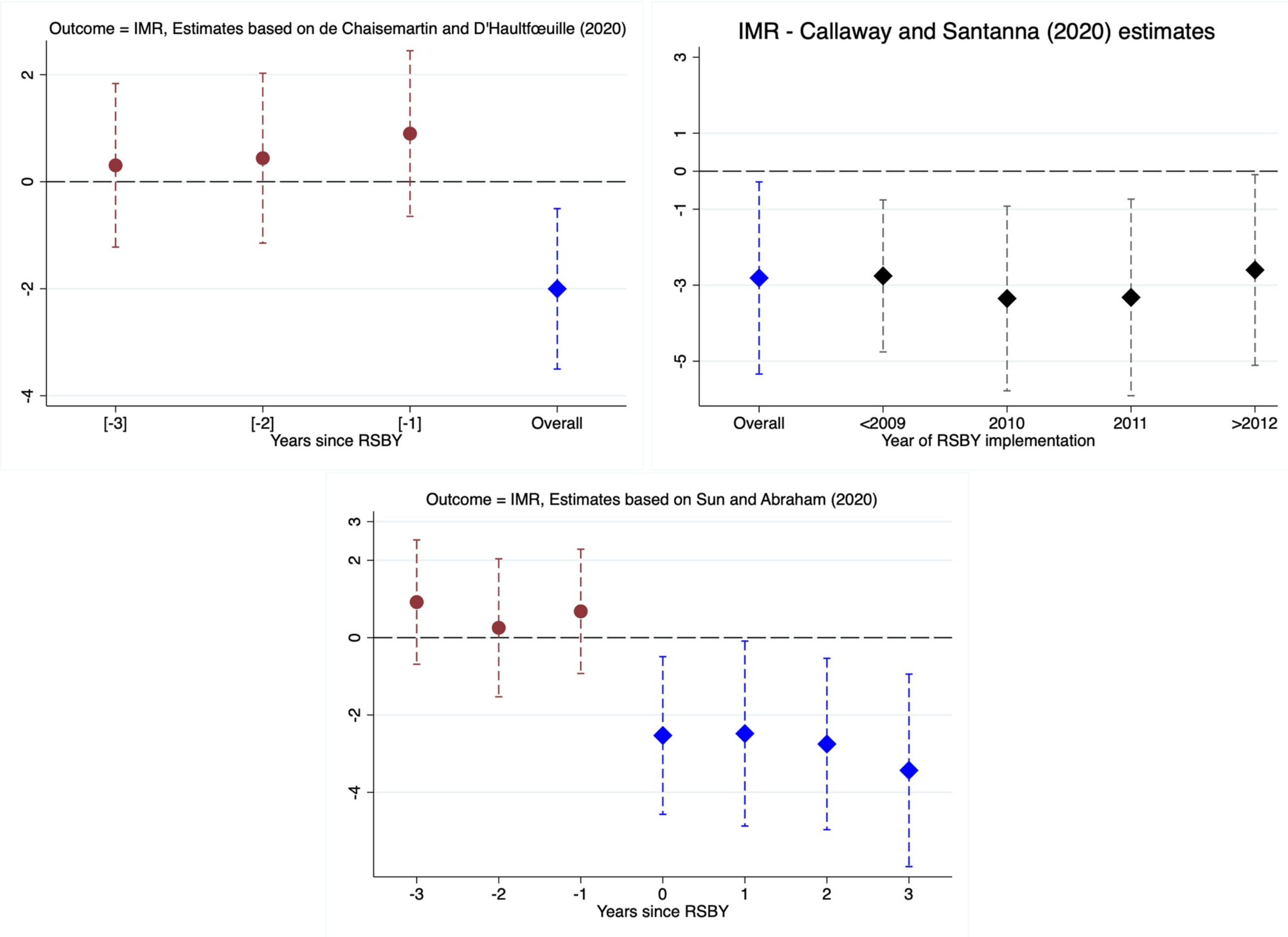

FIGURE 4 Estimate of RSBY impacts based on alternative estimators. In the top left graph, the estimates are based on the methodology described in De Chaisemartin and d'Haultfoeuille (2020)—in particular, we plot the DID_M and DID_M^{PT} estimates that are discussed in their paper. The right panel on top shows the group-wise coefficients discussed in Callaway and Sant'Anna (2020), while the bottom panel presents results based on the methodology described in Sun and Abraham (2020). In the estimations based on Sun and Abraham (2020) we use the never-RSBY group as the control group. Confidence intervals are at the 95 percent level. [Colour figure can be viewed at wileyonlinelibrary.com]

might be driving our findings. To assuage this concern, we drop never-RSBY districts from our analysis (these are districts that never received the RSBY policy in the study period). In panel C, the causal effect of RSBY is identified using within–district (temporal) variation in treatment exposure among the sample of RSBY districts. The results show that the magnitudes of the effects are significantly larger than the ones observed in Table 1 and remain negative and statistically significant.

In our preferred specification we use a number of household and individual level controls in addition to district and birth year fixed effects. Since the covariates have been chosen using researcher discretion, it could be the case that the covariates could be shaping our findings. As a robustness check, we use methods described in Chernozhukov et al. (2015) and Belloni et al. (2014) to implement the least absolute shrinkage and selection (LASSO) procedure to select the covariates (enables in estimating a sparse version of a high-dimensional specification). In other words, this procedure provides an algorithm to select the covariates to be included in the estimation from the full set of covariates, thus removing researcher discretion from the process. When using LASSO procedures (Table 2, Panel D), our estimates retain both sign and significance. In Panel E, we add district-specific time trends to the main specification—these control for within-district linear changes across time. We find that the results remain robust to adding these controls to our main specification. Since our main analysis uses both rounds 4 and 5 of the NFHS survey, in panels F and G of Table 2 we present results using these datasets separately—we find that the results are qualitatively similar when using one dataset at a time (RSBY has a statistically significant negative effect on mortality), but the effects are slightly higher in magnitude in the more recent dataset.

The RSBY impacts we estimate would be biased if there were any concurrent policy initiatives that (1) had an effect on child mortality, and (2) had the same implementation pattern (both spatially and temporally) as the RSBY. To the best of our

TABLE 2 Robustness: Effect of Rashtriya Swasthya Bima Yojana on child mortality.

	(1) NNM	(2) IM	(3) U2M	(4) U5M
Panel A—Dropping states with low coverage				
Born after RSBY (=1)	−0.845	−2.255***	−2.511***	−3.229***
	(0.662)	(0.830)	(0.866)	(0.912)
N	838,029	838,029	838,029	838,029
*r*2	0.01	0.02	0.02	0.02
Panel B—District level regressions (data collapsed to district-year level)				
Born after RSBY (=1)	−0.856	−2.251***	−2.509***	−3.229***
	(0.663)	(0.830)	(0.865)	(0.912)
N	5331	5331	5331	5331
*r*2	0.38	0.45	0.46	0.49
Panel C—Only including Ever-RSBY in the estimation sample				
Born after RSBY	−0.696	−1.857**	−1.905**	−2.602***
	(0.628)	(0.790)	(0.830)	(0.882)
N	332,289	332,289	332,289	332,289
*r*2	0.02	0.02	0.02	0.02
Panel D—Using lasso to select controls				
Born after RSBY	−1.175**	−1.886***	−1.850***	−2.070***
	(0.528)	(0.653)	(0.676)	(0.704)
N	929,968	929,968	929,968	929,968
Panel E—Including district time trends in the specification				
Born after RSBY	−1.303**	−2.086***	−2.064***	−2.272***
	(0.573)	(0.686)	(0.718)	(0.767)
N	929,968	929,968	929,968	929,968
*r*2	0.02	0.02	0.02	0.02
Panel F—Using only data from NFHS round 5 (2019–2020)				
Born after RSBY	−1.699**	−2.736***	−2.749***	−3.005***
	(0.735)	(0.867)	(0.898)	(0.933)
N	511,788	511,788	511,788	511,788
*r*2	0.01	0.02	0.02	0.02
Panel G—Using only data from NFHS round 4 (2015–2016)				
Born after RSBY	−0.825	−1.227**	−1.332***	−1.424**
	(0.867)	(0.547)	(0.53)	(0.72)
N	418,180	418,180	418,180	418,180
*r*2	0.02	0.02	0.02	0.02

Note: This table reports the results from estimating the effect of RSBY on child mortality. The data comes from rounds 4 and 5 of the NFHS survey, and all regressions include district fixed effects, year fixed effects, along with the full set of controls. Mortality is calculated as a recorded death (=1) or not(=0). If a child died within 30 days of birth, it is considered as a Neo Natal death (NNM). If the child died within the first 365 days of birth, it is considered as an infant death (IM). If a child died within 730 days of birth, it is considered as a death by age 2 (U2M). If a children died by age 5, it is considered an under 5 mortality (U5M). Mortality per 1000 births has been calculated by multiplying each indicator by 1000. *RSBY*, that takes a value of one for children born after RSBY implementation in their district and zero otherwise. This variable always takes a value of zero for children in never-RSBY districts. The sample includes all births reported by women between 2008 and 2016. Standard errors are clustered at the district level. * Significant at 10 percent. **Significant at 5 percent. *** Significant at 1 percent.

knowledge, there is no other national (or sub-national) policy implemented in India in the time period of this study (2008–2016) that satisfies both those criteria. However, there is a maternal and child health policy called Janani Suraksha Yojana (JSY) that was implemented before RSBY that might be of potential interest here. Beginning in 2005, JSY offered cash (INR 600–3000) to women who gave birth to children in government hospitals. This program was aimed toward reducing home births and increasing the rate of deliveries in government hospitals. Previous studies have shown that the JSY did not decrease mortality but did increase births in hospitals (Joshi & Sivaram, 2014; Powell-Jackson et al., 2015). By the time the RSBY had been implemented, the JSY was available across all districts, thus there were no significant differences between the JSY availability in treated and control districts. Using other data we verify that JSY coverage is almost universal across across the country in the post-2009 period[8]

Information on child mortality/survival is based on the memory (recall) of mothers. This could create measurement error, especially for births/deaths that occurred too far in the past. This measurement error is unlikely to cause the effects we find because (1) such a bias would attenuate the coefficient, thus biasing us against finding an effect, and (2) measurement error of this type is also unlikely to be systematically related to policy exposure/implementation. In the Table B4, we show that fertility within a birth-month-cluster is at worst decreasing after the RSBY is introduced. This implies that gains from insurance are coming from deaths falling faster than births decreasing. This rules out any concerns that the program reduced child mortality through a positive fertility effect.

6.3 | Heterogeneity in RSBY effects

In Figure 5 we explore additional dimensions of heterogeneity. We find that girls benefit significantly more than boys. Past studies have documented intra-household differences in allocations of health inputs, especially among income constrained households, explain lower health outcomes for such groups (Aiyar, 2021). In this evaluation, we find that health insurance coverage health benefits these groups by more. This result is not consistent with Dupas and Jain (2021) who find that adult women use less health services relative to men after they receive the Bhamashah Swasthya Bima Yojana in Rajastjan. Shaikh et al. (2018) also find similar gendered effects of health insurance program among adults in the Rajiv Aarogyasri Community Health Insurance Scheme in Andhra Pradesh. We propose that the reason the effects might be larger for girls than for boys is because the marginal effects of additional health inputs is higher for girls (since they have less health to begin with). Thus, access to insurance leads to a larger improvement for girls in our sample, compared to boys.

Our results also indicate that urban children gained more from RSBY policy, suggesting that supply-side factors like access to healthcare services also play an important role in determining the efficacy of such demand side interventions. In urban areas in

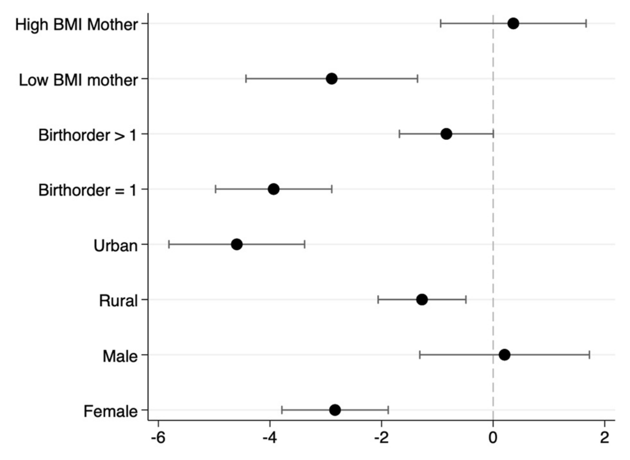

FIGURE 5 Effect of RSBY on different sub-groups. This table reports the results from estimating the effect of RSBY on infant mortality. Each coefficient comes from a separate regression where we run the specification described in Equation (1) for a different sub-sample of the data. The data comes from the rounds 4 and 5 of the National Family Health Survey survey, and all regressions include district fixed effects, along with the full set of controls. The coefficient for the RSBY effect and the associated 95 percent confidence intervals are shown. *RSBY*, that takes a value of one if the child was born after RSBY implementation in their district and zero otherwise. This variable always takes a value of zero for children in never-RSBY districts. Standard errors are clustered at the district level. RSBY, Rashtriya Swasthya Bima Yojana.

India, more health facilities and better roads/transportation infrastructure reduce the cost of accessing health services. Thus our results are in line with the literature that high elasticity of demand for health care due to allied (transportation) and non-pecuniary (distance to health services) costs reduce effectiveness of health care programs (Kremer & Glennerster, 2011). Thus health interventions need to consider both demand and supply side effects when evaluating the relative costs and benefits of policies.

6.4 | Mechanisms

We explore if the program changed the use of maternal and child health inputs, that might have plausibly led to the reduction in infant mortality observed in our findings.

We start by looking at the effect of health insurance provision on the probability of giving birth in a formal health facility. Studies in other contexts have shown that giving birth in a hospital and in the presence of skilled birth attendants have a positive effect on child health outcomes (Daysal et al., 2015; Lorentzon & Pettersson-Lidbom, 2021) - this effect is especially important in the Indian context as around one in five pregnant women still give birth at home.[9] We find that RSBY had a positive impact on the rate of hospital births (column 1 in Table 3). We observe an increase in the probability of giving birth in government hospitals (Column 3), but not in private hospitals (Column 2).[10]

We also observe an increase in the probability of child birth in the presence of a trained health professional, like a doctor (column 4), and the likelihood of C-sections following RSBY implementation (Column 5).

We also find that mothers in RSBY regions are 1.0% points (p.p.) more likely to go for a post-natal checkup (PNC) visit (Table 4, column 1). These check-ups are critical for the health of both the woman and the child, as they help identify risk factors and address them in a timely manner. Another important aspect of these PNC visits is that mothers are provided vital

TABLE 3 Effect of Rashtriya Swasthya Bima Yojana on deliveries.

	(1)	(2)	(3)	(4)	(5)
	At hospital	**Pvt hosp**	**Govt hosp**	**Delivered by doc**	**C-section**
Born after RSBY	0.046***	0.001	0.046***	0.036***	0.017***
	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)
R^2	0.23	0.26	0.14	0.20	0.18
N	343,798	343,798	343,798	343,798	343,798
Mean	0.85	0.21	0.64	0.85	0.24

Note: The data comes from the NFHS 4 and NFHS 5 surveys, and all (linear probability model) regressions include district fixed effects, along with the full set of controls. The outcome variables take the value = 1 if the the category described in the column is true, else it is 0. The sample excludes children who are not alive as the NFHS does not collect information on health use once it records a death. Sample sizes are smaller since outcomes are collected for the three most recent births after 2010 in NFHS 4 and after 2014 in NFHS-5. Standard errors are clustered at the district level. * Significant at 10 percent. ** Significant at 5 percent. *** Significant at 1 percent.

TABLE 4 Effect of Rashtriya Swasthya Bima Yojana (RSBY) on post natal care.

	(1)	(2)
	Any PNC	**Met a doctor**
Born after RSBY	0.010*	0.003
	(0.006)	(0.005)
R^2	0.11	0.10
N	238,571	238,571
Mean	0.35	0.31

Note: The data comes from the NFHS 4 and NFHS 5 surveys, and all (linear probability model) regressions include district fixed effects, along with the full set of controls. The outcome variables take the value = 1 if the the category described in the column is true, else it is 0. The sample excludes children who are not alive as the NFHS does not collect information on health use once it records a death. Sample sizes are smaller since outcomes are collected for the three most recent births after 2010 in NFHS 4 and after 2014 in NFHS-5. Standard errors are clustered at the district level. * Significant at 10 percent. ** Significant at 5 percent. *** Significant at 1 percent.

TABLE 5 Effect of Rashtriya Swasthya Bima Yojana on vaccination outcomes.

	(1) BCG	(2) DPT_all	(3) Polio_All
Born after RSBY	0.021***	0.019***	0.020***
	(0.007)	(0.006)	(0.005)
R^2	0.55	0.42	0.38
N	877,368	877,368	877,368
Mean	0.26	0.20	0.18

Note: The data comes from the NFHS 4 and NFHS 5 survey, and all (linear probability model) regressions include district fixed effects, along with the full set of controls. The outcome variables take the value = 1 if the the category described in the column is true, else it is 0. *RSBY*, that takes a value of one if the child was born after RSBY implementation in their district and zero otherwise. Standard errors are clustered at the district level. The sample excludes children who are not alive as the NFHS does not collect information on health use once it records a death. * Significant at 10 percent. ** Significant at 5 percent. *** Significant at 1 percent.

information pertaining to their child's health, for example, information on when, where and how to get their children immunized. The results in Table 5 show that RSBY led to large and significant effects on immunization rates. There is a 2 p.p. increase in the probability of completing the vaccinations for BCG, a 1.9 p.p. increase in completing DPT, and a 2.1 p.p. increase in the completion of the polio vaccines. These are administered in the first year of a child's birth. When viewed in conjunction with the enhanced PNC usage, our results support the hypothesis that at least a part of the effect that RSBY on infant mortality was driven by an increase in the usage of health services. The effect of RSBY on vaccination is especially critical because vaccination-related costs were not directly included for reimbursement under RSBY - which suggests that RSBY led to an increase in usage of complementary post-natal services. We cautiously interpret this as a spillover effect (on health services not covered directly covered by RSBY).

In summary, in this study, we show that implementation of a health insurance policy (RSBY) leads to robust reductions in child mortality among children exposed. We provide evidence that the program increases access to health services, which we propose drives our main results on mortality reduction. A natural follow-up question to ask would be - what might drive the increase in health care use that this study documents? One possible explanation is an increase in demand for healthcare services in response to a drop in it's effective price to consumers, while another is that financial incentives provided by the RSBY (to providers) stimulates hospitals to supply *more* healthcare. Unfortunately in this analysis we are unable to comment on the relative importance of the two in driving the observed effects. In Appendix A we provide some information related to reimbursement rates under RSBY and how it compares to OOP spending on similar services (here we focus on RCH services). We think this is an important area for further investigation as it will have implications for measuring cost-effectiveness of health insurance as a tool for improving health care access versus the cost-effectiveness of other types of supply side health interventions.

7 | CONCLUSION

In the recent past, many developing countries have implemented health insurance policies. The evidence suggests that they have a positive effect on usage of health care, but their impact on health (especially child health) in these contexts is mixed. While in countries like Thailand, Taiwan, Mexico and the US, health insurance has been found to reduce child mortality (Chou et al., 2014; Conti & Ginja, 2023; Currie & Gruber, 1996; Goodman-Bacon, 2018; Gruber et al., 2014), studies from China and Cost-Rica have found null effects (Camacho & Conover, 2013; Chen & Jin, 2012). Using a DID (and event-study) approach that leverages the spatial and temporal variation in implementation of a national-level health insurance program (RSBY) in India, we add causal evidence in favor of the health improving impacts of health insurance. This policy provided poor households USD 1712 (ppp) worth of health coverage at an annual fee of USD 1.71.

Specifically, we show that this national level health insurance program reduces child mortality by 2 per 1000 annually in India. These estimates imply that health insurance coverage leads to an annual reduction in infant mortality by 6% and under-five child mortality by 5%. While neo-natal mortality is also reducing, this effect is not statistically significant. Overall, our estimated effects likely understate the true causal effects since these are intent to treat estimates and the average enrollment in the program was around 50% during the evaluation period. Hence, it is likely that the true effect was around twice the size.

Children from urban areas and those who are relatively poorer are most likely to benefit from the program. This suggests that the key mechanism driving this change might be the availability of health services, which are more abundant in urban areas.

In terms of mechanisms, we demonstrate that access to health insurance increased hospital births, and the probability that women were attended to by a skilled professional during child birth. Demand for pre-birth and post-birth reproductive health services also increased in RSBY regions. Women report accessing more pre-birth health services, and the rates of Cesarean sections also increased. Mothers were 1.0% points more likely to visit doctors in the first month post childbirth. We hypothesize that access to doctors during this visit was likely a driver of the increase in vaccination rates among beneficiary cohorts - this is potentially due to doctors providing information regarding these services. This suggests that the effect of health insurance extends to increased demand for critical and life-saving preventative services that may not be covered by the insurance itself.

In summary, this study provides causal evidence on the effect of RSBY on child health, and in doing so demonstrates the benefit of a health insurance policy in a developing country context, India. The evaluation suggests that health insurance can close some of the gap related to access to health care services. However, it is also important to emphasize that bolstering the supply side in health care is also a key channel to improving health. Health insurance policy without concurrent reforms in the supply side of health systems present a missed opportunity for ensuring long term health improvements are sustained.

ACKNOWLEDGMENTS

We would like to thank Manoj Mohanan and two anonymous reviewers for their developmental inputs during the review process. We would also like to thank Marcella Aslan, Averi Chakrabarti, Jessica Cohen, Laura Dague, Anne Fitzpatrick, Mindy Marks, Edward Okeke, and Mircea Trandafir for their valuable inputs on previous drafts. Finally, we thank seminar participants at the Dyson seminar at Cornell University, Eastern Economic Association 2020, University of Nevada–Reno and the 2nd Asian Workshop for Health Economics for their valuable inputs. All remaining errors are our own.

CONFLICT OF INTEREST STATEMENT

We have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

The authors use publicly available datasets along with data that the authors procured from some government of India websites. Details on these are available from the authors on request.

ENDNOTES

[1] In fact, at that time most other insurance programs only offered reimbursements to patients after they submitted hospital bills paid for out-of-pocket. There were no cashless payment options where the insurance company would pay the hospital directly prior to RSBY.

[2] Prior to RSBY, private insurance in India covered only secondary and tertiary services and worked on a reimbursement model. Community based health insurance programs had different coverage limits, premiums and enrollment clauses but were limited in scope because they required group networks (Devadasan et al., 2004). Even successful programs (like the Yeshaswini) that increased access to tertiary care and reduced out-of-pocket spending were criticized because only well off families were using benefits from this insurance program (Aggarwal, 2010). Using an RCT that randomized bundling of health insurance with micro-finance, Banerjee et al. (2014) found that there was a larger resistance to healthy insurance take up even among the less healthy. This suggests that even though community based insurance existed during this time of this evaluation, it was not as successful as the RSBY in increasing both coverage and utilization of services. These programs only empaneled private providers (Devadasan et al., 2004).

[3] In Appendix A, we provide a brief discussion on the program's reimbursement rates for reproductive and child health medical procedures.

[4] In Appendix B, we provide more details on the policy allocation rules and why we think this spatial and temporal rollout is random.

[5] The only covariate that is consistently significant is whether the state government was aligned with the central government in the later years. This is plausible because 2014 was an election year and it is possible that election concerns drove implementation zeal across states. Nandi et al. (2013) find that implementation in years prior to 2013 was correlated with non-alignment with the central government.

[6] An important caveat to the analysis is that while child level information on deaths and births vary by month and year, variation in household-level and mother-level indicators is cross-sectional. There is no month-by-year variation in insurance status as the NFHS surveys collect information for this indicator only during the household survey month and not with birth recall information. Thus, we are not able to get to the treatment on treated effects by using an instrument such as enrollment share in RSBY in a month and year. All estimates are to be interpreted as (intent to treat) ITT effects.

[7] Post 2007, there was just one DLHS survey that was conducted in 2011–2012. We did not use this survey in the pre-trend analysis as the program had already started during survey implementation and the surveys covered only 17 out of 29 states. There are no other DLHS after 2011. The NFHS

4 is the only survey that produced district level estimates when it was released in 2018. In 2022, we re-ran the analysis using the NFHS 5 and found that our results still hold. Results are discussed in the robustness check section of the paper.

[8] Another major national policy implemented around this period was the National Rural Employment Guarantee Act (NREGA). This policy provided 100 days of employment annually to all rural households and could have potentially led to improvements in many socioeconomic outcomes, including child mortality. But, NREGA was implemented between 2006 and 2008, and was universally available before the bulk of RSBY policy rolled out (starting in 2012). Additionally, the implementation pattern of NREGA (which was based on a set of rules) differed from that of RSBY, thus making it even more unlikely that the effects could be driven by NREGA (Zimmermann, 2023).

[9] We would like to note that the NFHS data only provides information on these (mechanism related) outcomes for a maximum of three births that have taken place in the 5 years preceding the survey date. IN the NFHS 4, data is available for birth after 2011 and in NFHS 5, data is available for births after 2014. Thus, the mechanisms analysis is based on a sub-sample of the dataset used in the full analysis.

[10] In Table B5 we present results for the rural and urban samples separately. We observe an increase in the probability of giving birth in a hospital in both urban and rural areas. In both urban and rural areas, this increase is driven by increases in the probability of births in government hospitals, while there is no statistically significant effect on the usage of private healthcare facilities.

[11] Note that this analysis is based on the sub-sample of our data for whom information is not missing for the corresponding variables. This is only a small proportion of our dataset and the results should be interpreted with caution. We also conduct a regression analysis using the main empirical specification—we find no statistical differences in health spending between births covered by RSBY and those that were not. This is consistent with other evidence published on the lack of effects of the RSBY on reducing health spending (Azam, 2018; Karan et al., 2017). Results available from the authors on request.

[12] Since this information is limited and available only for a few states, we exercise caution in interpreting these numbers, and is the reason why we have not used it in any type of regression analysis.

REFERENCES

Aggarwal, A. (2010). Impact evaluation of India's 'yeshasvini'community-based health insurance programme. *Health Economics*, *19*(S1), 5–35. https://doi.org/10.1002/hec.1605

Aiyar, A. (2021). Unintended spillovers of targeted health insurance on intra-household resource allocations. *Journal of Development Studies*, *57*(3), 502–518. https://doi.org/10.1080/00220388.2020.1806243

Aiyar, A., & Venugopal, S. (2020). Addressing the ethical challenge of market inclusion in base-of-the-pyramid markets: A macromarketing approach. *Journal of Business Ethics*, *164*(2), 243–260. https://doi.org/10.1007/s10551-019-04275-9

Aquino, R., De Oliveira, N. F., & Barreto, M. L. (2009). Impact of the family health program on infant mortality in brazilian municipalities. *American Journal of Public Health*, *99*(1), 87–93. https://doi.org/10.2105/ajph.2007.127480

Azam, M. (2018). Does social health insurance reduce financial burden? Panel data evidence from India. *World Development*, *102*, 1–17. https://doi.org/10.1016/j.worlddev.2017.09.007

Banerjee, A., Duflo, E., & Hornbeck, R. (2014). Bundling health insurance and microfinance in India: There cannot be adverse selection if there is no demand. *The American Economic Review*, *104*(5), 291–297. https://doi.org/10.1257/aer.104.5.291

Banerjee, A. V., Banerji, R., Duflo, E., Glennerster, R., & Khemani, S. (2010). Pitfalls of participatory programs: Evidence from a randomized evaluation in education in India. *American Economic Journal: Economic Policy*, *2*(1), 1–30. https://doi.org/10.1257/pol.2.1.1

Belloni, A., Chernozhukov, V., & Hansen, C. (2014). Inference on treatment effects after selection among high-dimensional controls. *The Review of Economic Studies*, *81*(2), 608–650. https://doi.org/10.1093/restud/rdt044

Berman, P. A. (1998). Rethinking health care systems: Private health care provision in India. *World Development*, *26*(8), 1463–1479. https://doi.org/10.1016/s0305-750x(98)00059-x

Callaway, B., & Sant'Anna, P. H. (2020). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Camacho, A., & Conover, E. (2013). Effects of subsidized health insurance on newborn health in a developing country. *Economic Development and Cultural Change*, *61*(3), 633–658. https://doi.org/10.1086/669263

Cesur, R., Güneş, P. M., Tekin, E., & Ulker, A. (2017). The value of socialized medicine: The impact of universal primary healthcare provision on mortality rates in Turkey. *Journal of Public Economics*, *150*, 75–93. https://doi.org/10.1016/j.jpubeco.2017.03.007

Chen, Y., & Jin, G. Z. (2012). Does health insurance coverage lead to better health and educational outcomes? Evidence from rural China. *Journal of Health Economics*, *31*(1), 1–14. https://doi.org/10.1016/j.jhealeco.2011.11.001

Chernozhukov, V., Hansen, C., & Spindler, M. (2015). Post-selection and post-regularization inference in linear models with many controls and instruments. *The American Economic Review*, *105*(5), 486–490. https://doi.org/10.1257/aer.p20151022

Chokshi, M., Patil, B., Khanna, R., Neogi, S. B., Sharma, J., Paul, V., & Zodpey, S. (2016). Health systems in India. *Journal of Perinatology*, *36*(3), S9–S12. https://doi.org/10.1038/jp.2016.184

Chou, S.-Y., Grossman, M., & Liu, J.-T. (2014). The impact of national health insurance on birth outcomes: A natural experiment in taiwan. *Journal of Development Economics*, *111*, 75–91. https://doi.org/10.1016/j.jdeveco.2014.08.004

Cohen, J., & Dupas, P. (2010). Free distribution or cost-sharing? Evidence from a randomized malaria prevention experiment. *Quarterly Journal of Economics*, *125*, 1–45. https://doi.org/10.1162/qjec.2010.125.1.1

Conti, G., & Ginja, R. (2023). Who benefits from free health insurance? Evidence from Mexico. *Journal of Human Resources*, *58*(1), 146–182.

Currie, J., & Gruber, J. (1996). Health insurance eligibility, utilization of medical care, and child health. *Quarterly Journal of Economics*, *111*(2), 431–466. https://doi.org/10.2307/2946684

Das, J., Holla, A., Das, V., Mohanan, M., Tabak, D., & Chan, B. (2012). In urban and rural India, a standardized patient study showed low levels of provider training and huge quality gaps. *Health Affairs*, *31*(12), 2774–2784. https://doi.org/10.1377/hlthaff.2011.1356

Das, J., & Leino, J. (2011). Evaluating the rsby: Lessons from an experimental information campaign. *Economic and Political Weekly*, 85–93.

Daysal, N. M., Trandafir, M., & Van Ewijk, R. (2015). Saving lives at birth: The impact of home births on infant outcomes. *American Economic Journal: Applied Economics*, *7*(3), 28–50. https://doi.org/10.1257/app.20120359

De Chaisemartin, C., & d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *The American Economic Review*, *110*(9), 2964–2996. https://doi.org/10.1257/aer.20181169

Devadasan, N., Ranson, K., Van Damme, W., & Criel, B. (2004). Community health insurance in India: An overview. *Economic and Political Weekly*, 3179–3183.

Devadasan, N., Seshadri, T., Trivedi, M., & Criel, B. (2013). Promoting universal financial protection: Evidence from the rashtriya swasthya bima yojana (rsby) in Gujarat, India. *Health Research Policy and Systems*, *11*(1), 1–8. https://doi.org/10.1186/1478-4505-11-29

Dupas, P., & Jain, R. (2021). Women left behind: Gender disparities in utilization of government health insurance in India. Technical report, Working Paper.

Fan, V. Y., Karan, A., & Mahal, A. (2012). State health insurance and out-of-pocket health expenditures in Andhra Pradesh, India. *International Journal of Health Care Finance and Economics*, *12*(3), 189–215. https://doi.org/10.1007/s10754-012-9110-5

Fitzpatrick, A., & Thornton, R. (2019). The effects of health insurance within families: Experimental evidence from Nicaragua. *The World Bank Economic Review*, *33*(3), 736–749. https://doi.org/10.1093/wber/lhx012

Goodman-Bacon, A. (2018). Public insurance and mortality: Evidence from medicaid implementation. *Journal of Political Economy*, *126*(1), 216–262. https://doi.org/10.1086/695528

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

Gruber, J., Hendren, N., & Townsend, R. M. (2014). The great equalizer: Health care access and infant mortality in Thailand. *American Economic Journal: Applied Economics*, *6*(1), 91–107. https://doi.org/10.1257/app.6.1.91

Hou, X., & Palacios, R. (2011). Hospitalization patterns in rsby: Preliminary evidence from the mis. In *India's health insurance scheme for the poor: Evidence from the early experience of the Rashtriya Swasthya Bima Yojana* (pp. 117–152). Centre for Policy Research.

Joshi, S., & Sivaram, A. (2014). Does it pay to deliver? An evaluation of India's safe motherhood program. *World Development*, *64*, 434–447. https://doi.org/10.1016/j.worlddev.2014.06.004

Karan, A., Selvaraj, S., & Mahal, A. (2014). Moving to universal coverage? Trends in the burden of out-of-pocket payments for health care across social groups in India, 1999–2000 to 2011–12. *PLoS One*, *9*(8), e105162. https://doi.org/10.1371/journal.pone.0105162

Karan, A., Yip, W., & Mahal, A. (2017). Extending health insurance to the poor in India: An impact evaluation of rashtriya swasthya bima yojana on out of pocket spending for healthcare. *Social Science and Medicine*, *181*, 83–92. https://doi.org/10.1016/j.socscimed.2017.03.053

Kremer, M., & Glennerster, R. (2011). Improving health in developing countries: Evidence from randomized evaluations. In *Handbook of health economics* (Vol. 2, pp. 201–315). Elsevier.

Lorentzon, L., & Pettersson-Lidbom, P. (2021). *Midwives and maternal mortality evidence from a midwifery policy experiment in 19th-century Sweden*. Journal of the European Economic Association.

Malani, A., Holtzman, P., Imai, K., Kinnan, C., Miller, M., Swaminathan, S., Voena, A., Woda, B., & Conti, G. (2021). *Effect of health insurance in India: A randomized controlled trial*. Technical report. National Bureau of Economic Research.

Mozumdar, A., Aruldas, K., Jain, A., & Reichenbach, L. (2018). Understanding the use of India's national health insurance scheme for family planning and reproductive health services in uttar pradesh. *The International Journal of Health Planning and Management*, *33*(4), 823–835. https://doi.org/10.1002/hpm.2531

Nandi, A., Ashok, A., & Laxminarayan, R. (2013). The socioeconomic and institutional determinants of participation in India's health insurance scheme for the poor. *PLoS One*, *8*(6), e66296. https://doi.org/10.1371/journal.pone.0066296

Okeke, E. N. (2023). When a doctor falls from the sky: The impact of easing doctor supply constraints on mortality. *The American Economic Review*, *113*(3), 585–627. https://doi.org/10.1257/aer.20210701

Palacios, R. J., Das, J., & Sun, W. (2011). *India's health insurance scheme for the poor: Evidence from the early experience of the Rashtriya Swasthya Bima Yojana*. Centre for Policy Research.

Powell-Jackson, T., Mazumdar, S., & Mills, A. (2015). Financial incentives in health: New evidence from India's janani suraksha yojana. *Journal of Health Economics*, *43*, 154–169. https://doi.org/10.1016/j.jhealeco.2015.07.001

Rajasekhar, D., Berg, E., Ghatak, M., Manjula, R., & Roy, S. (2011). Implementing health insurance: The rollout of rashtriya swasthya bima yojana in Karnataka. *Economic and Political Weekly*, 56–63.

Ravi, S., & Bergkvist, S. (2014). *Are publicly financed health insurance schemes working in India*. (Vol. 11, pp. 157–185). Sage Publications. https://www.ncaer.org/wp-content/uploads/2022/09/1462175170India-Policy-Forum-2014-15-1.pdf#page=180

Shaikh, M., Peters, S. A., Woodward, M., Norton, R., & Jha, V. (2018). Sex differences in utilisation of hospital care in a state-sponsored health insurance programme providing access to free services in south India. *BMJ Global Health*, *3*(3), e000859. https://doi.org/10.1136/bmjgh-2018-000859

Sriram, S., & Khan, M. M. (2020). Effect of health insurance program for the poor on out-of-pocket inpatient care cost in India: Evidence from a nationally representative cross-sectional survey. *BMC Health Services Research*, *20*(1), 1–21. https://doi.org/10.1186/s12913-020-05692-7

Sun, L., & Abraham, S. (2020). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

Virk, A., & Atun, R. (2015). Towards universal health coverage in India: A historical examination of the genesis of rashtriya swasthya bima yojana–the health insurance scheme for low-income groups. *Public Health*, *129*(6), 810–817. https://doi.org/10.1016/j.puhe.2015.02.002

Zimmermann, L. (2023). *Why guarantee employment? Evidence from a large indian public-works program*. Economic Development and Cultural Change.

How to cite this article: Aiyar, A., & Sunder, N. (2024). Health insurance and child mortality: Evidence from India. *Health Economics*, *33*(5), 870–893. https://doi.org/10.1002/hec.4798

APPENDIX A: RSBY AND PRICES OF RCH PROCEDURES

In this section, we discuss the prices of RCH care services in the period around the implementation of RSBY.

Prior to the RSBY, there was no systematically documented and publicly available sources of the average cost of an RCH medical procedure in India. In public hospitals, who provided health services at highly subsidized prices, patients were not likely to know the total cost of their procedure but would be able to recall OOP spending on services. Research on the topic uncovered that these OOP payments included purchasing medicines when they were not available in the public pharmacy or OOP payments for getting ahead of long wait queues during the visit (Devadasan et al., 2013; Fan et al., 2012; Hou & Palacios, 2011; Karan et al., 2014). Private healthcare facilities provided an alternative, but was not affordable for most individuals. Prior to RSBY, less than six percent of India's population had any health insurance. All charges for private care were paid for OOP. Here too there was no information is available on prices charged by private providers for RCH related medical procedures.

Using the NFHS 4 and 5 datasets, we explore the costs of births, one type of medical procedure, at different types of facilities during our study time frame (2011–2016) to further illustrate the affordability issue. In Table A1, we compare the mean (reported) costs of deliveries for mothers with and without access to RSBY by institution type. There are a few notable observations—(1) the cost of giving birth at public facilities is subsidized but non-zero, and (2) the average cost of giving birth in private facilities is almost 13 times the corresponding cost in government facilities (in the non-RSBY regions) and it falls to around 10 times in RSBY regions.[11]

TABLE A1 Out-of-pocket spending on deliveries (in insurance coverage worth Rupees (INR)).

	(1) Did not have RSBY at birth mean (SD)	(2) Had RSBY at birth mean (SD)
Birth at private hospitals	18,088.98 (16,913.65)	17,387 (15,751.76)
	$N = 2402$	$N = 10,880$
Birth at public hospitals	1405.392 (4102.00)	1771.278 (4818.71)
	$N = 11,652$	$N = 29,364$

Note: Data here is the raw means summary obtained from the NFHS 4 and NFHS 5. The total sample size is smaller than the main regression analysis because only information on the most recent deliveries are collected.

After RSBY was implemented, a few state governments made their recommended "*RSBY package rates*" available in the public domain. The program designers believed that making the package rate publicly available would help cap out the total reimbursements to providers. This was essential for containing moral hazard on behalf of service providers. It was also meant to increase price transparency of health services provided. Table A2 provides an summary of the rates for some reproductive health procedures that were covered across states for which information was available. One can see that these rates varied by state.

TABLE A2 Prices of health care.

(1) Procedures	(2) State (Year)	(3) Cost
Caesarean delivery	Chattisgarh (2017)	18,500
	Himachal Pradesh (2012)	4500
	Karnataka (2023)	12,000 (G)
		15,000 (*p*)
	Manipur (2013)	11,500
	Punjab (2023)	15,180
Medical management of eclampsia with complications post delivery without ventilatory support	Chattisgarh (2017)	20,000
	Karnataka (2023)	6750 (G)
		9000 (*p*)
	Kerala (2023)	11,000
	Punjab (2023)	11,500
	Jaipur (unknown)	8280
Normal/Vacuum/forceps/Breech delivery with episiotomy including perineal tear if any	Chattisgarh (2017)	10,000
	Himachal Pradesh (2012)	2500
	Karnataka (2023)	9750 (G)
		13,000 (*p*)
	Kerala (2023)	7000
	Manipur (2013)	5000
	Jaipur (unknown)	8280
Shirodhkar stitch	Chattisgarh (2017)	5000
	Himachal Pradesh (2012)	2500
	Karnataka (2023)	3000 (G)
		4000 (*p*)
	Manipur (2013)	2500
	Jaipur (unknown)	3333
ANC I-: Consultation, medicine, vaccines, complete investigation	Chattisgarh (2017)	3000
ANC II-: Consultation, ultrasonography	Chattisgarh (2017)	2000
ANC III-: CBC, blood sugar, urine albumin and sugar 2 consultations	Chattisgarh (2017)	1000

Note: In Column 1, the names of services are matched across state documents, In column 2, the state refers to the reference state in which data is available and the year refers to the year for which this data is available online, In column 2, are the nominal prices as presented by the government on their documents, In column 3, G = govt provider reimbursement rate, P = Private provider reimbursement rate, not mentioned when both rates are the same. Information in this table is based on data collected from the Internet in July 2023 from a Google search on state wise package rates for the RSBY. More detailed information will be available on the author's website.

Based on Tables A1 and A2, we can also speculate that (1) for private providers, the reimbursements were lower than the average amount that mothers would spend OOP (INR 17,000–18,000), (2) the reimbursement rates were more generous than average OOP spending by patients in the public health facilities (INR 1400 to 1700).[12]

APPENDIX B: POLICY RULES OF THE RSBY

B1 | RSBY implementation

The implementation of the program took place between 2008 and 2012. During this time, whether the RSBY was made available in a district (or not) was determined by the involvement of the local government and the insurance company in administering the program. Anecdotal evidence and public work suggests that the central government did not provide strict norms on how to implement RSBY. For example, though the Ministry of Labor was the main funding agency of RSBY at the central government, state governments had the freedom to choose which of their departments would implement the policy. Most of the states delegated this to the Department of Labor, but some states delegated it to the Department of Health.

Private and public insurance companies were allowed to participate in the program (Virk & Atun, 2015). Insurance companies were selected through a bidding process set up by each state government. They were expected to enroll families and provide them with the identification cards (Palacios et al., 2011). Enrollment into RSBY was meant to occur annually and insurance companies contracted third party administrators to work with local panchayat members to implement the program on the ground. Thus, district level implementation depended on the ability of the local government and the insurance company to coordinate amongst each other rather than the health needs of the district or the areas in which it was implemented. Thus, the program implementation and its availability were correlated with political will rather than discussions around complementary programs or health needs.

These results are confirmed in Table B1, where we show that district level factors do not predict the availability of the program within and across states. The non-systematic nature of the roll of the program provides us the opportunity to utilize a quasi-experimental framework to measure the program's impacts. There are a few states with notably lower number of RSBY districts as compared to other states—Andhra Pradesh, Jammu & Kashmir, Madhya Pradesh, North-eastern states and Tamil Nadu. With regards to never treated districts, Tamil Nadu and Andhra Pradesh implemented their own version of a health insurance program and were not reliant on the central government policy. There is no information in the literature on why Jammu and Kashmir did not receive the program or why certain districts in Madhya Pradesh don't have the program. Empirically, dropping states that had a higher proportion of never-RSBY districts (Andhra Pradesh, Jammu & Kashmir, Madhya Pradesh, and Tamil Nadu) from our data does not impact our findings—the effect of RSBY on the various mortality outcomes. We also conduct the same analysis after excluding all never treated districts across the country and demonstrate that our results are not sensitive to this change as well. These results are presented in Table 2, panels A and C.

B2 | Process of selecting hospitals

On the hospital side, insurance companies were expected to enroll both public and private health care providers. Hospitals were mandated to provide cashless services to RSBY beneficiaries and use biometric software to track program and service use. Any additional fees beyond the RSBY approved amount was to be absorbed by the hospital and not passed on to the patient. In practice, the author working on the field uncovered that individuals did complain that there were asked to pay OOP when they tried to use their RSBY identification card at private hospitals. For public providers, the state governments were required to set up a *Health Committee* at each major hospital empaneled by the insurance company. This committee could use funds received (through the insurance companies) to cover any immediate hospital expenses or to pay service providers bonuses for medical procedures conducted under RSBY. The goal was to channel some of the RSBY funds to discretionary money that could be invested in improving quality of services provided through the public sector.

In Table B2 we summarize information from a dataset obtained in 2014 on details on the program's implementation. We can see that on average, in districts with RSBY in 2014, there was at least one hospital empaneled for 1000 enrolled with a maximum of 90 hospitals per 1000 enrolled. Around 48 percent of the hospitals enrolled in RSBY within a district were private, with some districts having no private hospitals empaneled and (very) few districts with only private hospitals empaneled. Using total government disbursements as of May 2014, we calculate two indicators - spending per-capita enrolled and spending on hospitals per-capita. The maximum amount spent under RSBY (based on these utilization rates) is around INR 26,461 per person. This is approximately equal to the maximum potential coverage under the policy. Among those enrolled, program spending was around INR 171.25 (USD 2.5), which was close to the average premium charged across the country during that year.

TABLE B1 District rollou.

Variables	(1) By 2008	(2) By 2009	(3) By 2010	(4) By 2011	(5) By 2012	(6) By 2013	(7) By 2014	(8) Total years
Nightlights	−0.0013	−0.0025	−0.0029	−0.0025	0.0017	0.0021	0.0037	0.0006
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.014)
Sex ratio all	0.0001	−0.0006	−0.0004	0.0001	0.0002	−0.0003	−0.0004	−0.0015
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Pecent men illiterate	0.2919	0.6855	0.3144	0.2628	−0.0010	−0.0255	−0.1723	1.3303
	(0.403)	(0.776)	(0.761)	(0.472)	(0.416)	(0.466)	(0.431)	(2.179)

TABLE B1 (Continued)

Variables	(1) By 2008	(2) By 2009	(3) By 2010	(4) By 2011	(5) By 2012	(6) By 2013	(7) By 2014	(8) Total years
Percent women illiterate	−0.3416	−0.7909	−0.3440	−0.5180	−0.1743	0.0350	0.1246	−1.9742
	(0.370)	(0.637)	(0.641)	(0.471)	(0.372)	(0.413)	(0.412)	(2.183)
Population density	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sex ratio - child	0.0008	0.0002	0.0011*	0.0004	0.0009	0.0005	0.0004	0.0047*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.003)
SCST population share	0.0734	0.2244	−0.1434	−0.1893	−0.0718	−0.1599	−0.1056	−0.5321
	(0.102)	(0.187)	(0.142)	(0.135)	(0.083)	(0.125)	(0.094)	(0.523)
LFP men	−0.1857	−0.2536	0.3525	−0.0705	−0.2934	−0.4810	−0.6331	−2.0459
	(0.431)	(0.521)	(0.592)	(0.378)	(0.361)	(0.404)	(0.470)	(2.219)
LFP women	−0.0656	−0.1319	−0.0178	0.4035	0.1159	0.1451	0.1169	0.7111
	(0.252)	(0.208)	(0.362)	(0.309)	(0.247)	(0.180)	(0.177)	(1.146)
Percent men (labor) in ag sector	0.0000	−0.0000	0.0000	0.0000**	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Percent women (labor) in ag sector	0.0000	0.0000	0.0000	−0.0000**	−0.0000	−0.0000*	−0.0000*	−0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Percent men (labor) in nonag sector	−0.0000	−0.0000**	−0.0000**	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Percent women (labor) in nonag sector	0.0000	0.0000**	0.0000**	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural hospitals (2011)	−0.0007	−0.0024	0.0018*	0.0009	−0.0004	−0.0007	−0.0009	−0.0031
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Urban hospitals (2011)	−0.0000	−0.0001	−0.0002	−0.0022**	−0.0021*	−0.0004	−0.0003	−0.0057
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)
Rural paramedics (2011)	0.0000	−0.0000	−0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban paramedics (2011)	0.0000	0.0000	−0.0000	0.0000	0.0001	0.0001	0.0001	0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural doctors (2011)	0.0000	−0.0002	−0.0000	−0.0001	−0.0000	0.0001	0.0001	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban doctors (2011)	0.0000	0.0001	0.0004***	0.0003**	0.0001	−0.0000	−0.0000	0.0010
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Rural clinics (2011)	−0.0000	0.0002***	0.0001	0.0000	0.0000	−0.0000	−0.0000	0.0002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban clinics (2011)	−0.0000	−0.0000***	0.0000	0.0000**	0.0000	0.0000	0.0000	0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban hospital beds (2011)	−0.0000**	−0.0000**	0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Aligned with UPA	−0.6032***	−0.4156	−0.0294	0.1025	0.6976***	1.1374***	1.2008***	3.2274**
	(0.217)	(0.306)	(0.268)	(0.255)	(0.203)	(0.243)	(0.278)	(1.201)
Percent seats won by UPA	−0.6021**	−0.7821**	−0.8096*	−1.1210***	−0.4451	−0.0739	0.0101	−3.8974**
	(0.287)	(0.353)	(0.457)	(0.363)	(0.276)	(0.227)	(0.271)	(1.559)

TABLE B1 (Continued)

Variables	(1) By 2008	(2) By 2009	(3) By 2010	(4) By 2011	(5) By 2012	(6) By 2013	(7) By 2014	(8) Total years
Annual precipitation (2005)	−0.0025	−0.0019	0.0006	−0.0008	−0.0028	0.0010	0.0009	−0.0046
	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.010)
Aridity (2005)	0.0089	0.0099	0.0001	0.0059	0.0138**	−0.0020	−0.0015	0.0330
	(0.007)	(0.013)	(0.020)	(0.010)	(0.006)	(0.005)	(0.004)	(0.043)
Day land surface temp (2005)	0.0061	0.0042	−0.0012	0.0001	−0.0010	0.0092	0.0110	0.0376
	(0.010)	(0.009)	(0.012)	(0.008)	(0.009)	(0.009)	(0.008)	(0.045)
Diurnal temperature range (2005)	0.0077	−0.0103	0.0327	0.0097	0.0093	−0.0056	−0.0090	0.0291
	(0.015)	(0.018)	(0.024)	(0.020)	(0.016)	(0.014)	(0.014)	(0.086)
Enhanced vegetation index (2005)	−0.0001	−0.0000	−0.0001	−0.0000	−0.0000	−0.0000	0.0000	−0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Frost days (2005)	0.0017	−0.0059	−0.0139	−0.0106	−0.0054	−0.0032	0.0004	−0.0402
	(0.013)	(0.013)	(0.012)	(0.010)	(0.011)	(0.009)	(0.009)	(0.058)
PET (2005)	0.0080	0.0836	0.0113	0.0621	0.0980	−0.0003	−0.0157	0.2466
	(0.081)	(0.076)	(0.101)	(0.074)	(0.066)	(0.051)	(0.056)	(0.298)
Rainfall (2005)	−0.0000	−0.0000	0.0000	0.0000	−0.0000	−0.0000	−0.0000	−0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Travel times (2000)	−0.0002	−0.0000	0.0000	0.0000	−0.0002	0.0000	0.0000	−0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Observations	635	635	635	635	635	635	635	635
R-squared	0.288	0.616	0.678	0.778	0.829	0.813	0.811	0.848
Sample	AllDists	AllDists	AllDists	AllDists	AllDists	AllDists	AllDists	AllDists
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E cluster	State	State	State	State	State	State	State	State

Note: These are district-level regressions where the independent variable is a categorical variable taking a value of one if RSBY was implemented in the district in that calendar year. Example - BY 2008—means that the district had RSBY by 2008 and by 2011 includes all districts that received RSBY by 2011. Columns 1–7 are linear probability models. The last column is calculated as the total number of years during which RSBY was available. Districts that started RSBY in 2008, received a value of 8 and districts that started RSBY in 2011 would receive a value of 5, etc. This column is a OLS model. Clustered standard errors are in parentheses. * on coefficient imply ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). Data sources - variables starting from the sex ratio till percent working in the non-agriculture sector comes from the 2011 census of India. Hospital indicators are from SHRUG's data base for 2010. Political variables on elections was gathered from online archives. Climate related variables were obtained from the NFHS 4 climate data.

Abbreviations: ag, agriculture sector; LFP, Labor Force Participation; nonag, non-agriculture sector; OLS, ordinary least squares regression; PET, precipitation, evaporation, transpiration; SCST, scheduled caste and scheduled tribe; Travel times, Time taken to reach the nearest town in the district; UPA, United Progressive Alliance.

TABLE B2 Summary statistics.

	N	Mean	S.D.	Min	Max
Enrollment rate (%)	431	47.47	22.93	0.00	90.83
Number of hospitals per 1000 enrolled	431	0.74	4.41	0.00	90.06
% share of private hospitals	431	47.97	30.43	0.00	100.00
Hospital spending per capita enrolled	431	171.25	231.34	0.00	1853.33
Average amount spent per hospital (in ’000 of Rs.)	431	847.26	1652.51	0.00	13,367.34

Note: Program Administrative Data.

TABLE B3 Summary statistics.

	All		RSBY in district				No RSBY in district	
			Exposed		Not exposed			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.
Outcome = mortality per 1000								
Neo-natal mortality	19.94	139.80	20.20	140.68	21.20	144.06	17.27	130.29
Infant mortality	30.65	172.37	30.56	172.11	33.46	179.84	26.54	160.73
Under-2 mortality	32.81	178.13	32.48	177.28	36.14	186.65	28.49	166.36
Under-5 mortality	35.53	185.12	34.79	183.25	39.85	195.62	30.80	172.78
Child characteristics								
Year of birth	2011	2.62	2013	1.98	2009	1.48	2011	2.59
Single birth	0.98	0.12	0.98	0.12	0.99	0.12	0.98	0.12
Girl child	1.03	0.71	1.01	0.71	1.05	0.70	1.05	0.70
Birth order	2.31	1.49	2.32	1.51	2.43	1.56	2.08	1.27
Month of birth	5.55	3.21	5.57	3.23	5.46	3.21	5.61	3.12
Mother characteristics								
Mother's age at birth	24.86	5.09	24.98	5.06	24.79	5.24	24.64	4.92
No education = 1	0.34	0.47	0.32	0.47	0.40	0.49	0.30	0.46
Primary education = 1	0.15	0.36	0.15	0.36	0.17	0.38	0.14	0.35
Secondary education = 1	0.43	0.49	0.44	0.50	0.38	0.48	0.47	0.50
Mother's BMI-Z score	−1.98	0.99	−2.02	0.99	−2.01	0.98	−1.81	1.01
Any health insurance of mother	0.24	0.43	0.21	0.41	0.29	0.45	0.25	0.43
Household characteristics								
1st (Lowest) wealth quintile = 1	0.26	0.44	0.26	0.44	0.27	0.44	0.23	0.42
2nd wealth quintile = 1	0.22	0.42	0.22	0.41	0.23	0.42	0.22	0.41
3rd wealth quintile = 1	0.20	0.40	0.19	0.39	0.20	0.40	0.20	0.40
4th wealth quintile = 1	0.17	0.38	0.17	0.38	0.17	0.37	0.19	0.39
Hindu = 1	0.72	0.45	0.73	0.44	0.71	0.45	0.72	0.45
Scheduled caste = 1	0.19	0.40	0.21	0.41	0.19	0.39	0.16	0.37
Scheduled tribe = 1	0.21	0.41	0.19	0.39	0.23	0.42	0.23	0.42
Other backward aste = 1	0.38	0.49	0.39	0.49	0.37	0.48	0.38	0.49
Mtrbike owned = 1	0.49	0.50	0.51	0.50	0.52	0.50	0.37	0.48
Car owned = 1	0.06	0.24	0.07	0.25	0.06	0.23	0.07	0.25
No toilet in hh = 1	0.31	0.46	0.32	0.47	0.32	0.46	0.29	0.46
Piped water in hh = 1	0.27	0.44	0.26	0.44	0.24	0.43	0.34	0.47
BPL card = 1	0.44	0.50	0.41	0.49	0.45	0.50	0.52	0.50
BPL card = 1	0.44	0.50	0.41	0.49	0.45	0.50	0.48	0.50
Urban = 1	0.24	0.43	0.24	0.43	0.21	0.41	0.23	0.42
Percent covered by RSBY								
Covered at birth	0.51	0.50						
Observations	929,969		478,073		275,208		176,688	

Note: Mortality is calculated as a recorded death (=1) or not(=0). If a child died within 30 days of birth, it is considered as a Neo Natal death. If the child died within the first 365 days of birth, it is considered as an infant death. If a child died within 730 days (2 years) of birth, it is considered as a death by age 2. A child death by the age of 5 is considered in the calculation of the under-5 morality. Mortality per 1000 births can be calculated by multiplying the mean values by 1000. Abbreviations: RSBY, Rashtriya Swasthya Bima Yojana; BMI, Body Mass Index; Any variable marked as " = 1" is a dummy variable that is one if the label is true.

TABLE B4 Fertility rates.

Variables	(1) Num births	(2) Num births	(3) Num births	(4) Num births	(5) Num births	(6) Num births
Post RSBY	−0.00316*	−0.00319	−0.00552**	−0.00242	−0.00219	−0.00437*
	(0.00184)	(0.00198)	(0.00222)	(0.00199)	(0.00215)	(0.00244)
R-squared	0.006	0.006	0.011	0.011	0.075	0.082
Observations	428,332	378,059	428,332	378,059	428,332	378,059
Sample	YOB>=2007	YOB>=2008	YOB>=2007	YOB>=2008	YOB>=2007	YOB>=2008
Data level	Clust-month	Clust-month	Clust-month	Clust-month	Clust-month	Clust-month
Fixed effect	State	State	District	District	Cluster	Cluster
S.E cluster	State	State	District	District	Cluster	Cluster
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: In all of these specifications the outcome of interest is number of births in a cluster and birth-month. The data comes from the NFHS 4 survey, and all regressions include fixed effects. *RSBY*, that takes a value of one if birth month was after RSBY implementation was implemented and zero otherwise. Standard errors are clustered. * Significant at 10 percent. ** Significant at 5 percent. *** Significant at 1 percent.

TABLE B5 Deliveries by region and hospital type.

	Full sample			Urban only			Rural only		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Any hosp.	Pvt.	Govt.	Any hosp.	Pvt.	Govt.	Any hosp.	Pvt.	Govt.
Born after RSBY	0.046***	0.001	0.046***	0.029***	0.009	0.020**	0.049***	−0.001	0.050***
	(0.005)	(0.003)	(0.005)	(0.006)	(0.008)	(0.009)	(0.005)	(0.003)	(0.006)
r2	0.23	0.26	0.14	0.21	0.27	0.20	0.23	0.22	0.15
N	343,798	343,798	343,798	78,806	78,806	78,806	264,992	264,992	264,992
Mean	0.85	0.21	0.64	0.95	0.36	0.59	0.81	0.16	0.65

Note: The data comes from the NFHS 4 survey & NFHS 5, and all (linear probability model) regressions include district fixed effects, along with the full set of controls. The outcome variables take the value = 1 if the the category described in the column is true, else it is 0. Any Hosp. refers to any institutional deliveries (as opposed to home births), Govt. refers to births in government health centers and Pvt. refers to births in private health centers. The data comes from the NFHS 4 survey, and regressions include all controls. *RSBY*, that takes a value of one if birth month was after RSBY implementation was implemented and zero otherwise. Sample sizes are smaller since this information is only collected for the most recent delivery. Standard errors are clustered. * Significant at 10 percent. ** Significant at 5 percent. *** Significant at 1 percent.