Ayushman Bharat Health Insurance Scheme and Maternal And Infant Mortality Rates In India: Causal Inference Using Wild-Cluster Bootstrap

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Keywords: causal inference, difference in differences, identification, parallel trends, cluster robust inference, wild cluster bootstrap, state-time panel data, fixed effects, random effects, quasi experimental designs, policy analysis, Ayushman Bharat Yojana, PM-JAY, Infant Mortality Rate IMR, Maternal Mortality Rate MMR

ABSTRACT

This paper studies short-run causal effect of Republic of India's public health insurance scheme adopted in 2018, called "Ayushman Bharat Yojana" (ABY) which allows citizens below a certain income level to get free health insurance and avail health care at private facilities at no cost.

Out of total 36 states in India, four did not adopt it, presenting a natural experimental setting to study causal effect of scheme on health outcomes in treated states, i.e. the states which adopted the scheme in 2018. Health outcomes studied are MMR (Maternal Mortality Rate) and IMR (Infant Mortality Rate). Causal effect is isolated using Diff-in-diff and Triple differencing estimators on three-year, unbalanced panel dataset using state fixed effects. Assuming idiosyncratic heterogeneity (Sate Fixed Effects), cluster-robust analysis is done to obtain the results. Wild cluster bootstrap is used to adjust p values on Wald-statistics since the number of groups is just 36, considered too few in literature on panel data.

ABY being a new health-benefit scheme, giving free access to better health facilities to those who can ill afford these otherwise, the treatment is expected to give better health outcomes in states which adopted the scheme. That must translate into reduction in Infant and Maternal Mortality Rates in treatment states compared to control states. The coefficients on DD estimates are anticipated to be negative, and statistically significant.

I find statistically significant causal effects of ABY on IMR but in the opposite direction. However, these effects disappear after wild-cluster bootstrap is deployed to account for the problem of too few clusters. No statistically significant effects of ABY are found on MMR. However, this is a very short-run study measuring outcomes just in the next year of implementation of policy. We may expect positive changes in health outcomes in treatment states once the scheme matures, and people become more aware of the benefits of the scheme and get comfortable with delivery structures and rules of access.

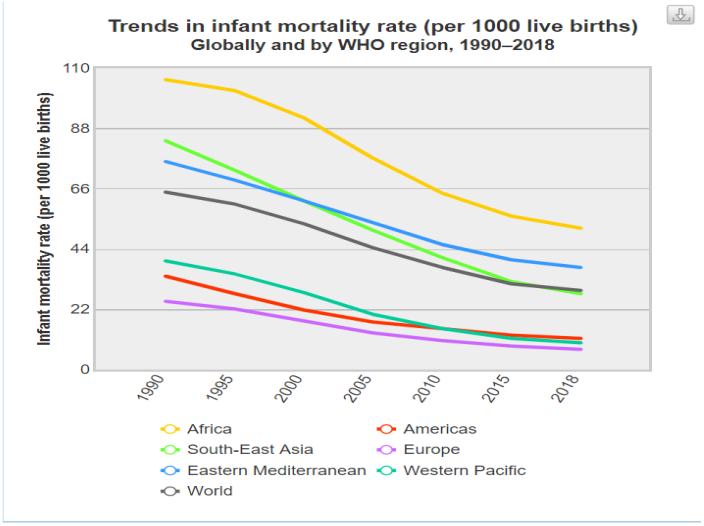
I. Introduction

The third Sustainable Development Goal of United Nations (SDG-3) aims to ensure healthy lives and promote well-being for all at all ages by 2030. UN report of 2019 on the progress of the goal claims 'major progress has been made in improving the health of millions of people, increasing life expectancy, reducing maternal and child mortality, and fighting against leading communicable diseases'. Reproductive, maternal, newborn and child health is a major global touchstone to measure level, quality, and progress of health care. Two major indicators to assess quality of overall population health, and an accurate measure of availability of Reproductive and Child Health Services, are Infant Mortality Rate (IMR) and Maternal Mortality Rate (MMR).

The report further says quality access to essential health services is an issue for millions across the globe, and many of those who do, suffer undue financial hardship, potentially pushing them into extreme poverty. Concerted efforts are required to achieve universal health coverage and sustainable financing for health, to address the growing burden of disease in all nations of the world.

According to WHO globally, the Infant Mortality Rate has decreased from an estimated rate of 65 deaths per 1000 live births in 1990 to 29 deaths per 1000 live births in 2018. IMR is the number of deaths per 1,000 live births of children under one year of age. The rate for a given region is the number of children dying under one year of age, divided by the number of live births during the year, multiplied by 1,000.

Unequal development indices across nations reflect in huge disparity in these rates among them. The risk of a child dying before completing the first year of age was highest in the WHO African Region (52 per 1000 live births), over seven times higher than that in the WHO European Region (7 per 1000 live births). The leading causes of death among children under five in 2017 were preterm birth complications, acute respiratory infections, intrapartum-related complications, congenital anomalies, and diarrhea.



Source: UNICEF, WHO, World Bank, UN DESA/Population Division. *Levels and Trends in Child Mortality 2019*. UNICEF, 2019.

Fig 1: Global trends in IMR by WHO region

Attached to 17 SDG goals are 169 concrete targets measured by 232 specific indicators. 35 of these indicators are directly related to children.

By 2030, SDG3 targets to end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce neonatal mortality (NMR) to at least as low as 12 per 1000 live births and under-5 mortality (UFMR) to at least as low as 25 per 1000 live births. It does not specify IMR separately, and it is safe to adopt target for NMR as the one to aspire for as NMR is main contributor of IMR.

According to UN Inter-agency Group for Child Mortality Estimation (IGME), IMR for India in 2019 was 29.94.

MMR refers to deaths due to complications from pregnancy or childbirth per 100,000 live births. WHO says Maternal mortality as measured by MMR is unacceptably high. About 295 000 women died during and following pregnancy and childbirth in 2017. The vast majority of these deaths (94%) occurred in low-resource settings, and most could have been prevented. The high number of maternal deaths in some areas of the world reflects inequalities in access to quality health services and highlights the gap between rich and poor.

The MMR in low income countries in 2017 is 462 per 100 000 live births versus 11 per 100 000 live births in high income countries.

SDG 3 aims at reducing the global MMR to less than 70 per 100 000 births, with no country having a maternal mortality rate of more than twice the global average.

MMR in India **in 2019 is categorized as low by UNICEF at 145.**

Addressing inequalities in access to and quality of reproductive, maternal, and newborn health care services, and ensuring universal health coverage for comprehensive reproductive, maternal, and newborn health care is the foremost strategy recommended by WHO for ending 'Preventable Infant and Maternal Mortality'. Further, under specific Health Targets for SDG3, aim is to achieve universal health coverage, including financial risk protection, access to quality essential health-care services and access to safe, effective, quality and affordable essential medicines and vaccines for all.

Recognizing the pivotal importance of SDGs, the Indian National Health Policy, 2017 (NHP) aims at equity, affordability, universality and partnership in health care services in India. India's public health system attempts to assure availability of free, comprehensive primary health care services, for all aspects of reproductive, maternal, child and adolescent health and for the most prevalent communicable, non-communicable and occupational diseases in the population. Since public health services in India struggle with quality coverage, and access of most vulnerable still remains very poor, we aim to fill the gaps through ensuring improved access and affordability, of quality secondary and tertiary care services through a combination of public hospitals and well measured strategic purchasing of services in health care deficit areas, from private care providers, especially the not-for profit providers.

NHP aims to reduce UFMR to 23 by 2025 and MMR from current levels to 100 by 2020. Further it targets to reduce IMR to 28 by 2019 and NMR to 16 and still birth rate to "single digit" by 2025.

Among public programs targeting women and children under Indian National Health Mission, Janani Shishu Suraksha Karyakram (JSSK: Mother and Child Safety Program) makes a provision for all RCH (Reproductive and Child Health) services free of cost to all. Ayushman Bharat Yojana (ABY: Literal translation- Long live India) is one of the schemes under NHP, 2017 for universalization of health care in India, and includes RCH coverage as well. It is a flagship scheme of Government of India for achieving Universal Health Coverage (UHC). A brief on the scheme is given below in background.

I attempt to measure the causal effect of adoption of ABY on IMR and MMR to study the impact of policy on important health outcomes. In a resource constrained middle-income country like India, optimal expenditure of budgetary resources is essential owing to higher opportunity costs. We cannot afford to mid-direct constrained public resources when these can be used for equally deserving alternative schemes. Such a study also helps to assess the gaps and scope for improvement and helps policy makers to redress these gaps early so that benefits of the scheme reach the group targeted, and desired outcomes are achieved.

Three-year (2017-19) data is collected on outcomes, other health related and socio-economic features from official government sources, 2018 being the treatment year when the policy was rolled out on the all-India level.

Difference-in-differences estimation of treatment effect of ABY on IMR finds statistically significant causal effect, but the direction of the effect is opposite to what is anticipated, i.e. a

positive and beneficial effect of improved access to RCH facilities by poor mothers and children leading to a fall in the numbers of infants dying out of total babies born in that year. When I apply Wild-Cluster Bootstrap on the results, the significant effects disappear and causal relationship between ABY and IMR is abolished.

Adoption of ABY is not shown to have significant causal effects on MMR in treated states using the same methodology.

The paper is organized as follows. Section II gives a background on the ABY scheme and observed heterogenous trends in health statistics and socio-economic indicators in different states of India. Section III describes the data and empirical approach used. Section IV reviews my results. Section V concludes.

II. Background

A. Ayushman Bharat: Pradhan Mantri Jan Arogya Yojana (PM-JAY)

ABY is designed to establish a continuum of care framework for healthcare in India. It has two inter-connected components-

1. Health and Wellness Centers (HWCs)

Beginning February 2018, ABY aims to establish 150000 by revamping existing Primary Health Centers (PHCs) and Sub-centers. These shall provide comprehensive primary health care services including maternal and child health services. All essential drugs and diagnostic services are free for all at these centers. These expanded range of health facilities shall be available to communities close to their homes.

2. Pradhan Mantri Jan Arogya Yojana (PM-JAY)

(Literal translation: Prime Minister's Public Health and Wellness Scheme)

This scheme was launched on 23rd September 2018. This is claimed to be the largest health assurance scheme in the world. It aims at providing a health cover of Rs. 5 lakhs (USD 6579) per family per year for secondary and tertiary care hospitalization to over 107.4 million poor and vulnerable families (approximately 500 million beneficiaries) that form the bottom 40% of the Indian population. The households included are based on the deprivation and occupational criteria of Socio-Economic Caste Census 2011 (SECC 011) for rural and urban areas.
It provides cashless access to health care services for the beneficiary at the point of service, that is, the hospital. Hospitals allowed are secondary and tertiary care hospitalization across public and private empaneled hospitals in India.
PM-JAY envisions to help mitigate catastrophic expenditure on medical treatment which pushes nearly 60 million Indians into poverty each year.
The benefits are on a family floater basis and all pre-existing diseases are covered.
As of 17 May 2020, 21,508 hospitals have been empaneled, 124,638,433 e-cards (health insurance cards) have been issued and 9,957,014 hospitalizations recorded under PM-JAY. (Scheme website)

B. RCH epidemiological trends in our units of study: States of India

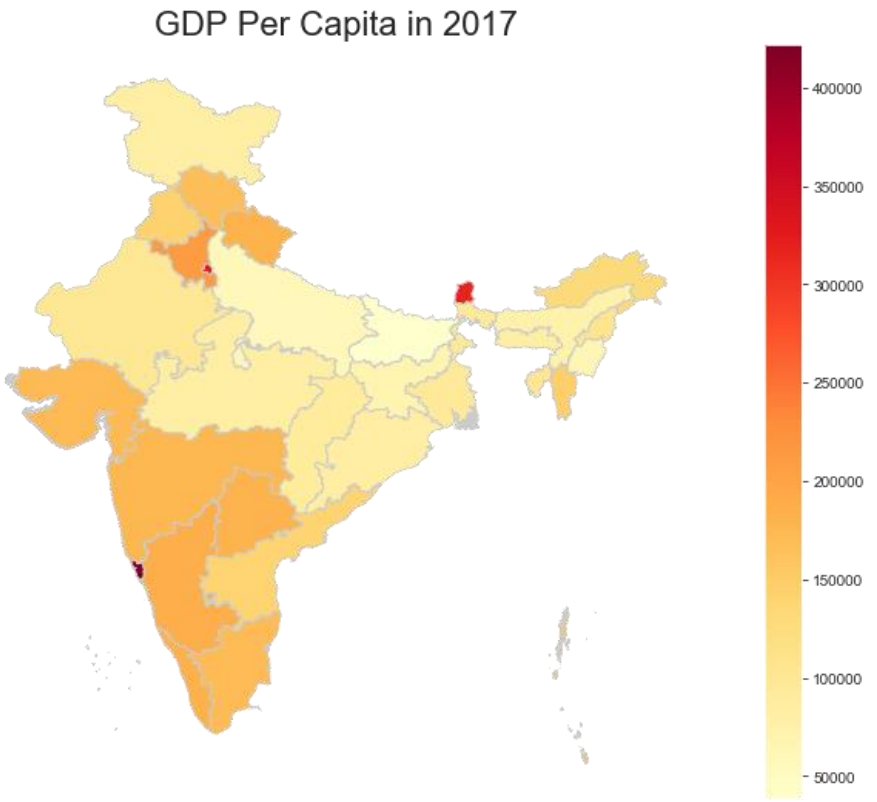
India is variously referred to as 'Nations within a Nation', given geographical expansiveness and tremendous diversity in culture, languages, ethnicity, religions, and most relevant for our study - socio-economic indicators.

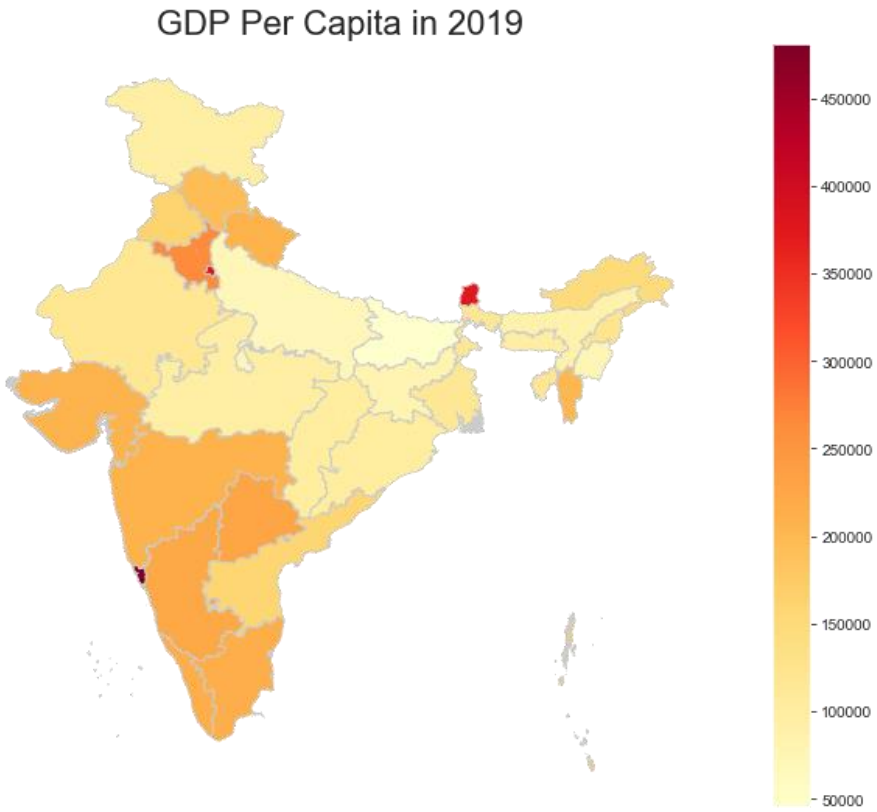
Fig 2: Map of India depicting different States and Union territories

Optimal health status is both the cause and consequence of the development status of a country. Development per se stands for an improved quality of life through gains in health, education, living standards and higher income (Basch, 1999).
According to UNDP's Human Development Reports, 2019, India stands at 129 among 193 nations of the world, with HDI value of 0.647. Our life expectancy at birth is 69.4 with Gross National Income at PPP $ of 6,829. 27.9% of Indian population is categorized as poor.

As per Subnational Human Development Report of Global Data Lab, the 2017 HDI scores indicate that the States like Kerala, Goa and Punjab occupy the top three positions while States like Bihar, UP and MP are in the bottom of the rank. HDI of state of Kerala at 0.779 is comparable to the best in the world, and Bihar at 0.57 to the worst.

However, if we look at the change in ranks for all the States between 1990 to 2017, Haryana, Himachal Pradesh, Tamil Nadu and Karnataka have seen a significant jump in their HDI rank, while most of the North Eastern states like Nagaland, Meghalaya and Manipur have seen slippages in the ranking. Both UP and Bihar have continued to remain at the bottom of the rank in the last 27 years. Another interesting fact is that the States who were the worst performing states in HDI during 1990s are presently doing well in the social parameter since 2014. For example, Rajasthan, UP, Odisha & MP have seen the largest jump in change in HDI value among the 25 major States in India.





Figs 3 & 4: GDP per capita at current prices (INR) across Indian States in pre and post treatment period (Source: Author's calculations from Government of India data)

See Table 1 of means of IMR, MMR and GDP per capita in current prices reflect some of the trends reflected in HDI of individual states.

Depending on the socio-economic development status of the respective states, their health outcomes as measured by IMR and MMR had idiosyncratic trends before implementation of ABY in 2018. This fact justifies the choice of a state-time panel data fixed effects model to isolate the causal effect of ABY scheme on two major health outcomes, believably reflecting the general trends in overall health status of the population of a state.
(Details of Indian States are linked in appendix with list of state names)

Table 1: Mean of IMR, MMR and GDP_PC (INR) in current prices for states in India

AYUSHMAN BHARAT HEALTH INSURANCE SCHEME AND MATERNAL AND INFANT MORTALITY RATES IN INDIA: CAUSAL INFERENCE USING WILD-CLUSTER BOOTSTRAP

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index	State Name	2017	2018	2019	Total
1	A & N Islands				
	IMR	21.16333	11.26667	23.29333	18.57445
	MMR	313.7633	119.7867	372.2033	268.5844
	GDP_PC	159664	167647	176029	167780
2	Andhra Pradesh				
	IMR	10.88539	10.94462	12.39923	11.40974
	MMR	79.01923	57.95539	65.32385	67.43282
	GDP_PC	139679	151173	158732	149861.3
3	Arunachal Pradesh				
	IMR	5.7855	5.7265	4.175	5.229
	MMR	87.8095	12.417	38.4255	46.21733
	GDP_PC	130197	139587	146567	138783.7
4	Assam				
	IMR	21.11222	20.41593	20.6937	20.74062
	MMR	186.2507	162.8093	150.9552	166.6717
	GDP_PC	74183	82078	86182	80814.33
5	Bihar				
	IMR	6.381053	5.664474	4.948947	5.664825
	MMR	74.81579	61.50316	55.84526	64.05474
	GDP_PC	38630	43822	46013	42821.67
6	Chandigarh				
	IMR	46.8	53.94	46.97	49.23667
	MMR	20.73	52.1	63.38	45.40333
	GDP_PC	296434	329208	345669	323770.3
7	Chhattisgarh				
	IMR	17.95741	17.39852	20.33815	18.56469
	MMR	156.2685	115.0826	154.2682	141.8731
	GDP_PC	89812	96886	101731	96143
8	Dadra & Nagar Haveli				
	IMR	27.88	27.65	25.57	27.03333
	MMR	108.05	110.62	67.6	95.42334
	GDP_PC	114958	126406	134432	125265.3
9	Daman & Diu				
	IMR	7.385	11.4	9.575	9.453333
	MMR	103.095	15.475	0	39.52333
	GDP_PC	114958	126406	134432	125265.3
10	Delhi				
	IMR	15.39636	16.15182	17.55091	16.36636
	MMR	135.5782	149.1564	152.4146	145.7164
	GDP_PC	328985	365529	383805	359439.7
11	Goa				
	IMR	5.66	8.48	6.03	6.723333
	MMR	83.605	66.49	38.4	62.83167
	GDP_PC	422155	458304	481219	453892.7
12	Gujarat				
	IMR	22.59636	17.9597	17.54879	19.36828
	MMR	90.92818	81.26727	83.46303	85.2195
	GDP_PC	173079	197446	207319	192614.7
13	Haryana				
	IMR	10.18045	20.07682	23.42818	17.89515
	MMR	103.2446	120.7427	142.61	122.1991
	GDP_PC	211525	236146	264206	237292.3
14	Himachal Pradesh				
	IMR	11.22833	13.85583	16.75083	13.945
	MMR	58.91417	80.765	60.34583	66.675
	GDP_PC	167044	179187	195255	180495.3
15	Jammu & Kashmir				
	IMR	8.124545	7.59	8.170455	7.961667
	MMR	67.45636	48.16091	70.55045	62.05591
	GDP_PC	82709	91882	96476	90355.67
16	Jharkhand				
	IMR	6.261667	6.739583	7.914167	6.971806
	MMR	132.175	116.9525	140.2588	129.7954
	GDP_PC	69264	76018	79820	75034
17	Karnataka				
	IMR	12.48267	11.117	11.43633	11.67867
	MMR	75.84167	66.45967	77.15467	73.152
	GDP_PC	187649	210886	221431	206655.3
18	Kerala				
	IMR	5.264286	3.306429	3.104286	3.891667
	MMR	59.61929	24.78143	42.195	42.19857
	GDP_PC	183435	204105	214310	200616.7
19	Lakshadweep				
	IMR	17.92	12.96	6.43	12.43667
	MMR	0	0	385.6	128.5333
	GDP_PC	114958	126406	134432	125265.3
20	Madhya Pradesh				
	IMR	23.31177	24.97843	24.97529	24.42183
	MMR	144.7871	147.5698	158.5651	150.3073
	GDP_PC	82941	90998	95548	89829
21	Maharashtra				
	IMR	11.35086	11.14629	10.40514	10.96743
	MMR	62.86371	62.65	79.18343	68.23238

	GDP_PC	176102	191736	207727	191855
22	Manipur				
	IMR	5.571111	2.868889	3.476667	3.972222
	MMR	76.37222	51.43445	53.09111	60.29926
	GDP_PC	65008	69978	73477	69487.67
23	Meghalaya				
	IMR	29.31455	22.69091	29.23636	27.08061
	MMR	287.3391	189.2418	199.6509	225.4106
	GDP_PC	81098	89023	98151	89424
24	Mizoram				
	IMR	21.85667	19.26111	20.48333	20.5337
	MMR	114.3844	125.2322	38.93556	92.85074
	GDP_PC	146764	168625	201741	172376.7
25	Nagaland				
	IMR	7.992727	8.237273	7.09	7.773333
	MMR	133.8118	66.67091	101.4691	100.6506
	GDP_PC	104680	116882	122726	114762.7
26	Odisha				
	IMR	23.57133	21.74833	20.15433	21.82467
	MMR	161.4927	99.06933	97.82633	119.4628
	GDP_PC	84495	95163	101586	93748
27	Puducherry				
	IMR	11.3625	11.0675	7.18	9.87
	MMR	66.2525	27.215	9.582501	34.35
	GDP_PC	203583	220460	237278	220440.3
28	Punjab				
	IMR	10.38955	8.516818	7.805	8.903788
	MMR	147.895	123.2709	109.7123	126.9594
	GDP_PC	142476	154995	162746	153405.7
29	Rajasthan				
	IMR	13.54182	22.40697	21.02909	18.99263
	MMR	93.40061	99.80546	103.5697	98.92525
	GDP_PC	99366	110605	118158	109376.3
30	Sikkim				
	IMR	22.1	19.7475	14.4475	18.765
	MMR	82.7325	224.78	328.3175	211.9433
	GDP_PC	317133	357643	375525	350100.3
31	Tamil Nadu				
	IMR	8.47875	7.7975	11.325	9.200417
	MMR	62.76844	49.66875	45.95688	52.79802
	GDP_PC	171582	193749	214236	193189
32	Telangana				
	IMR	4.94	6.780323	5.410968	5.71043
	MMR	43.53968	53.25258	83.90258	60.23161
	GDP_PC	180494	204487	228216	204399
33	Tripura				
	IMR	17.21375	13.9675	15.89875	15.69333
	MMR	135.6925	83.18375	70.76625	96.5475
	GDP_PC	100476	113102	118757	110778.3
34	Uttar Pradesh				
	IMR	4.281067	3.392	3.064	3.579022
	MMR	147.1745	134.8717	110.8948	130.9804
	GDP_PC	58821	66511	70418	65250
35	Uttarakhand				
	IMR	6.263077	8.100769	8.777692	7.713846
	MMR	97.14769	113.16	124.3846	111.5641
	GDP_PC	182320	198738	208675	196577.7
36	West Bengal				
	IMR	20.0387	19.23348	17.9387	19.07029
	MMR	97.40783	87.70435	79.31044	88.14087
	GDP_PC	93710	109491	114966	106055.7
37	Total				
	IMR	12.74591	12.82305	13.05298	12.87398
	MMR	111.1508	95.59939	101.3063	102.6855
	GDP_PC	122534.5	136286.7	145793.2	134871.4

III. Data Description and Empirical Approach

This is a novel project having no prior references. All data are aggregated and analyzed from primary Government of India sources.

District, state and national level statistics are available at my app at the link http://indiainstats.herokuapp.com/

A. Data Source (Column Wise):

1. Following Columns are imported from the Section named "Performance of Key HMIS Indicators(up to District Level)" available at https://nrhm-mis.nic.in/hmisreports/frmstandard_reports.aspx for different years-

'% Institutional deliveries to Total Reported Deliveries',

'Total Number of reported live births',

'% live birth to Reported Birth',

'% Newborns having weight less than 2.5 kg to Newborns weighed at birth',

'% Newborns given OPV0 at birth to Reported live birth',

'% Newborns given BCG to Reported live birth',

'% Newborns given Hep-B0(Birth Dose) at birth to Reported live birth',

'% Infants 0 to 11 months old who received Measles+ MR vaccine to reported live births',

'No of children 16-24 months age given Measles Rubella Vaccine 2nd dose',

'Total Number of Infant Deaths reported', 'Total no. maternal deaths',

'Total number of pregnant women Registered for ANC'

2. Doctor data is calculated from "Rural Health Statistics" section available at https://nrhm-mis.nic.in/SitePages/HMIS-Publications.aspx for different years.

3. Following Columns are imported from the Section named "Data Reporting Status (Up to District Level)" available at https://nrhm-mis.nic.in/hmisreports/frmstandard_reports.aspx for different years-

'Sub Centers', 'PHCs: Primary Health Centers', 'CHCs: Community Health Centers', 'Sub Divisional Hospitals', 'District Hospitals', and 'Total Health Centers'

4. GDP Per Capita is taken from http://mospi.nic.in/sites/default/files/press_releases_statements/State_wise_SDP_28_02_2020.xls provided by Ministry of Statistics and Program Implementation, GOI. and economic survey of Maharashtra and Himanchal Pradesh. Also, missing fields where data of previous year is available are compensated by putting 105% of the previous year.

For Dadra and Nagar Haveli, Daman and Diu and Lakshadweep National GDP per capita at current price of India is used due to non-availability of data.

In short data taken from Government of India - Ministries of Health and Family Welfare, Statistics & Program Implementation and Finance.

The data munging codes, STATA.dta file and do files are available on my GitHub page https://github.com/Nemeiralal/CausalProjectABY_MMR_IMR_20

B. Model and Identification

Inference with Cluster-Robust, Wild Bootstrapped, Differences-in-Differences and Triple Differencing using State-Year Panel Data of 36 states over three years

The data structure is three-year (2017-19) panel data of Indian states, 36 in number. Each state has various numbers of districts, the lowest administrative unit in federal structure, akin to a county. There are 704 districts in India. This generates 704*3= 2112 district-year cells, and 36*3=108. Number of districts range from just 1 in both Chandigarh and Lakshadweep, to 75 in Uttar Pradesh, the largest state, with an average of 19.5 districts per group. District level data within each state is available for all entries, and the panel is temporally balanced. However, the number of districts vary within each state, and the panels are thus contemporaneously unbalanced.

Expecting state fixed effects given the considerable heterogeneity of states in India affecting the districts within the states in idiosyncratic manner, uncorrelated with districts in other states, Cluster-Robust inference is used. Clustered errors have two main consequences: they (usually) reduce the precision of $\hat{\beta}$, and the standard estimator for the variance of $\hat{\beta}$, $\hat{\mathrm{V}}[\hat{\beta}]$, is (usually) biased downward from the true variance. Computing cluster-robust standard errors is a fix for the latter issue. (Cameron and Miller, 2015)

Clustering is done over State variable as suggested by Bertrand, Duflo, and Mullainathan (2004). Their study suggests that, because of serial correlation, conventional DD standard errors may grossly understate the standard deviation of the estimated treatment effects, leading to serious over-estimation of t-statistics and significance levels.

by Bertrand, Duflo, and Mullainathan (2004) highlight that in data structures, like the one used in this study, clustering on state-year shall be very inadequate, since it imposes the restriction that observations are independent if they are in the same state but in different years. Indeed, if the data is aggregated at the state-year level, there is only one observation at the state-year level, so this is identical to using heteroskedastic-robust standard errors, i.e. not clustering at all. They advocated clustering on states.

Use of Wild Cluster Bootstrapping for inference is necessitated by the fact that I am estimating over 36 unbalanced clusters. According to Cameron and Miller, 2015, current consensus appears to be that $G = 50$ is enough for state-year panel data. Bertrand, Duflo, and Mullainathan (2004, Table 8) find in their simulations that for a policy dummy variable with high within-cluster correlation, a Wald test based on the standard CRVE with critical value of 1.96 had rejection rates of .063, .058, .080, and .115 for number of states (G) equal to, respectively, 50, 20, 10 and 6. The simulations of Cameron, Gelbach and Miller (2008, Table 3), based on a quite different data generating process but again with standard CRVE and critical value of 1.96, had rejection rates of .068, .081, .118, and .208 for G equal to, respectively, 30, 20, 10 and 5. In both cases the rejection rates would also exceed .05 if the critical value was from the $T(G-1)$ distribution.()

Recent papers by Carter, Schnepel, and Steigerwald (2013) and Imbens and Kolesar (2012) provide theory that also indicates that the effective number of clusters is reduced when observations varies across clusters. Wild Cluster Bootstrap is prescribed in literature as an effective method to redress the problem of a few clusters. Cameron, Gelbach, and Miller (2008) found that in Monte Carlos with few clusters the pairs cluster bootstrap did not eliminate test over-rejection. The authors proposed using an alternative percentile-t bootstrap,

the wild cluster bootstrap, that holds the regressors fixed across bootstrap replications. (Cameron and Miller, 2015)

The basic idea behind bootstrap to generate a large number of bootstrap samples that mimic the distribution from which the actual sample was obtained. Each of them is then used to compute a bootstrap test statistic, using the same test procedure as for the original sample. The bootstrap P value is then calculated as the proportion of the bootstrap statistics that are more extreme than the actual one from the original sample. (Roodman, McKinnon etal, 2018)

Wild cluster bootstrap (WCB), was proposed in Cameron, Gelbach, and Miller (2008) and the validity of which was proved in Djogbenou, MacKinnon, and Nielsen (2018). It is a generalization of the ordinary wild bootstrap (WB), which was developed in Liu (1988) for the non-clustered, heteroskedastic case, following a suggestion in Wu (1986) and commentary thereon by Beran (1986).

The boottest package performs wild bootstrap tests of linear hypotheses by default, boottest generates 999 wild cluster bootstrap samples using the Rademacher distribution, with the null hypothesis imposed. It reports the t-statistic from the Wald test and its bootstrapped P value (by default, symmetric).

It then automatically inverts the test and reports the bounds of the confidence set for the default level of confidence, which is normally 95%. Finally, it plots the "confidence curve" underlying this calculation, that is, the bootstrap P value for the hypothesis $\hat{\beta} = c$ as a function of c. It marks the points where the curve crosses 0.05, which are the limits of the confidence set. (Roodman, McKinnon etal, 2018)

For our estimate to be statistically significant, it must lie outside the confidence limits set on the p-value by the wild cluster bootstrap.

1. DD Estimator with state and time fixed effects

Model:

Without Covariates

$$IMR_{ist}/\ MMR_{ist} = \alpha + \theta*ABY + \eta*State + \tau*Time + \delta*Time*ABY + \varepsilon_{ist}$$

With Covariates

$$IMRist/\ MMRist = \alpha + \theta*ABY + \eta*State + \tau*Time + \delta*Time*ABY + \beta*Xist + \varepsilon ist$$

IMR is the Infant Mortality rate at time t (Year), in district I for the group 's' (State).

MMR is the Maternal Mortality rate at time t (Year), in district I for the group 's' (State).

X are other covariates like immunization status, Maternal mortality rate, health infrastructure and per capita GDP of the district etc.

Independent variable State captures unobservable State level fixed effects which are the time in-varying effects influencing all districts in the state uniformly like effective governance, transport infrastructure, urbanization etc.

Independent variable Time captures time varying effects on the dependent variable which do not vary at the state level like income shocks affecting the entire country uniformly, effects of a pandemic in a certain year etc.

ABY is the binary treatment variable which shall be 1 if the state had implemented the health scheme in a particular year, 0 otherwise.

δ is the Diff-in-Diff estimator of interest which captures average post treatment effect of implementation of scheme between treatment and control states, holding all else fixed.

$$\delta = (Y^1_{ABY,2019} - Y^0_{ABY,2017}) - (Y^1_{NABY,2019} - Y^0_{NABY,2017})$$

ABY: Treatment states which adopted the ABY scheme
NABY: Control states which did not adopt the ABY scheme

DD is a quasi-experimental technique used to understand the effect of a sharp change in the economic environment or government policy. It is used in conjunction with a natural experiment. One of the identifying assumptions is independence in assignment of units to treatment and control groups. In a natural experiment, this is automatically achieved.

The key to any program evaluation is estimating the counterfactual: what would have happened had the treated not been treated or if the controls were treated? Therefore, evaluation requires we estimate the counterfactual. Since the fundamental problem of causal inference makes this ideal estimation impossible, we try to obtain a good estimate of the counterfactual by the random assignment. We assume there is no self-selection in the treatment group. This is true for our DGP as states of India, which chose not to implement ABY, did not do it based on their pre-existing health status but for political reasons, making health related outcomes and treatment unrelated. We also assume there is no manipulation as the scheme is a benefits program and was equally available to all for adoption.

Since acceptance of ABY by treatment and control states in India was not a response to existing health status, so we may safely assume any differences observed in treatment group from control group in post treatment period, if significant, indicate causality and are not merely due to chance.

Further, we are taking care of any state level fixed effects, say an overall healthy hill climate of less urbanized state, giving better baseline health to population within that state, and therefore confounding our results. These effects are done away with by doing cluster robust inference through fixed effects estimation.
The confounding effects of other features like high socio-economic status of states those have higher per-capita GDP, vaccination status of infants, quantum of institutional deliveries where mothers are assisted by trained health professionals, maternal mortality etc. are controlled by including these variables in the regression.

The expression in terms of sample means connects the regression to potential outcomes and shows that, under a common trends assumption, a two-group/two-period (2x2) DD identifies the average treatment effect on the treated. (Andrew, Goodman-Bacon, 2018)

Another concern in state-year panel is serial correlation i.e. group level unobservables (ε_{ist}) may be correlated over time among groups, leading to Omitted Variables Bias (OVB) in future time periods. Bias would be positive if certain factors like recruitment of a health consultant in one year by a state, which will likely affect the health outcomes positively over future periods. Similarly, negative shocks like a natural calamity may have prolonged effects via downward bias of estimates over many future periods. We correct it by including a time dummy variable, which avoids omitted time trends.

In short, DD estimator takes care of cross-sectional differences and time-series differences by differencing away any permanent differences between the groups and any common trend affecting both groups.

Key assumption behind DD is the Parallel Trends assumption. It implies, in the absence of treatment, the average change in the response variable, in our case the IMR or MMR, would have been the same for both the treatment and control groups. It is tested by inspecting pre-treatment era growth rates in these variables. Since we do not have the data to test this, we assume that states in India have retained their regular and stable trajectories of trends in health statistics prior to the scheme. There have really not been any evidence of sudden jumps in health outcomes in recent past in states in India.

2. Difference-in-difference-in-differences: DDD Estimator with state and time fixed effects

Without covariates

$$IMRist/\ MMRist = \alpha + \theta*ABY + \eta*State + \tau*Time + \lambda*Poor + \delta*Time*ABY*Poor + \varepsilon ist$$

With Covariates

$$IMRist/\ MMRist = \alpha + \theta*ABY + \eta*State + \tau*Time + \lambda*Poor + \delta*Time*ABY*Poor + \beta*Xist + \varepsilon ist$$

λ measures effect of binary poor which is 1 if the district has per capita GDP below the median, 0 otherwise.

δ is the Diff-in-diff-in-diff parameter of interest which measures average treatment effect of implementation of health scheme among districts which adopted the scheme. Both treatment and control states are also differenced on poor vs not poor as defined by having per capita GDP below the median.

$$\delta = \{(Y^1_{ABY,2019} - Y^0_{ABY,2017}) - (Y^1_{ABY,\ poor} - Y^0_{ABY,\ not\text{-}poor})\}$$

- $\{(Y^1_{NABY,2019} - Y^0_{NABY,2017}) - (Y^1_{NABY,\ poor} - Y^0_{NABY,\ not\text{-}poor})\}$

ABY: Treatment states which adopted the ABY scheme
NABY: Control states which did not adopt the ABY scheme

Under similar assumptions of randomness in selection and parallel trends, Difference-in-difference-in-differences estimates difference between DD of interest and the other DD. It acts like a sensitivity test on DD estimation as if the outcome here is significantly different from original DD, we have to wonder whether the original DD is unbiased. In our case, we have used differencing on per capita income using a binary variable poor, which is one of the states has per capita income below the median, and zero otherwise. This estimator purges away the confounding effect of income on health outcomes in state which varies state-by-year level. There is a risk it may difference out some of the 'true' effects of the scheme on

health outcomes if there are spillover effects of income on adoption of scheme (Bitler and Carpenter, 2011). This does not seem to be the case in our DGP.

Treatment= implementation of ABY in 2018

Pre-treatment year - 2017

Post-treatment year -2019

IV. Results

To decide between fixed or random effects I ran Hausman tests where the null hypothesis was that the preferred model is random effects vs. the alternative the fixed effects. It basically tests whether the unique errors (idiosyncratic heterogeneity component of overall error) are correlated with the regressors, the null hypothesis is they are not. The results for both regressions, i.e. IMR and MMR on ABY returned significant results, with p-values 0.0342 and 0.0281, which are less than 0.05, enabling us to not accept the null. This establishes that the model is correctly specified as fixed effects.

A. ABY and IMR

As we can observe from Table.2 (Col.1), the regression coefficient estimated by fixed-effects regression using cluster robust standard errors regressing outcome variable IMR on treatment ABY, interacted with year 2019, without using other covariates, i.e., the Diff-in-diff estimate is statistically significant, but the sign on the parameter is counterintuitive. Logically, ABY being a health benefit scheme offering free insurance to poor families, and granting them access to better medical facilities must decrease adverse outcomes, measured here by IMR. But our results point in the opposite direction.

Treatment States i.e. the states which adopted the scheme see an increase in Infant Mortality Rate, on an average, of 1.41, after they were treated with policy variable ABY, which is statistically significant at 1.8%, holding all else fixed.

When we include the covariates likely affecting health outcomes besides the policies like better care of pregnant mothers reflected in percentage covered by institutional deliveries, immunization coverage and socio-economic status captured in GDP per capita, the causal effect of treatment becomes insignificant, indicating that some of these variables contributed to biasing the original estimate by being correlated with the diff-in-diff interaction term.

In the second regression (Col.2), the DD estimator is statistically significant, but the sign on the parameter is counterintuitive.

Treated states i.e. the states which adopted the scheme see an increase in Infant Mortality Rate, on an average, of 3.05 which is statistically significant at less than 1% level, holding all else fixed.

The results in columns 4 and 5 are significant from theoretical point of view as these confirm the fact that use of default standard errors in estimation, and failure to account for correlation of unobservable heterogeneity at group level in multi-period panels leads to an over rejection of null hypothesis, and significance in causality/correlation observed is spurious (Bertrand, Duflo and Mullainathan, 2004).

The significant results of column 1 and 2 are upended when we correct for having too few clusters by Wild-cluster bootstrapping. Fig.8 presents the 95% confidence intervals on

insignificant DD estimates obtained without covariates, and Fig.9 does the same for regression with covariates.

Results of WCB on regression of IMR on ABY without covariates:

Bootstrap results in Fig.8 on Col.1 regression of Table.2 shows that Wald t test statistic in our primary regression was bigger than bootstrapped values 21.82% times out of total, thus rendering our initial results spurious.

T (35) = 2.4670

Prob>|t| = 0.2182

Wild cluster bootstrap indicates that the DD estimator is insignificant at 22% level of significance indicating there is no statistically significant causal effect of adoption of new health scheme on IMR in treatment group of states compared to control states, on an average, holding all else fixed.

95% confidence set for null hypothesis expression: [-1.352, 4.341], meaning that our estimate has to lie beyond these two limits, i.e. it has to be less than -1.359, or greater 8.654 to be statistically significant at level 0.05.

Our estimate of causal effect of 1.418 lies within the region of insignificance, and thus the null that adoption of treatment policy has no statistically significant causal effect on IMR cannot be rejected.

Results of WCB on regression of IMR on ABY with covariates:

Bootstrap results on Col.2 regression shows that Wald t test statistic in our primary regression was bigger than bootstrapped values 12.39% times out of total, thus rendering our initial results spurious.

T (35) = 2.8246

Prob>|t| = 0.1239

Wild cluster bootstrap indicates that the DD estimator is insignificant at 12% level of significance indicating there is no statistically significant causal effect of adoption of new health scheme on IMR in treatment group of states compared to control states, on an average, holding all else fixed.

95% confidence set for null hypothesis expression: [-1.359, 8.654], meaning that our estimate has to lie beyond these two limits, i.e. it has to be less than -1.359, or greater 8.654 to be statistically significant at level 0.05.

Our estimate of causal effect of 3.05 lies within the region of insignificance, and thus the null that adoption of treatment policy has no statistically significant causal effect on IMR cannot be rejected.

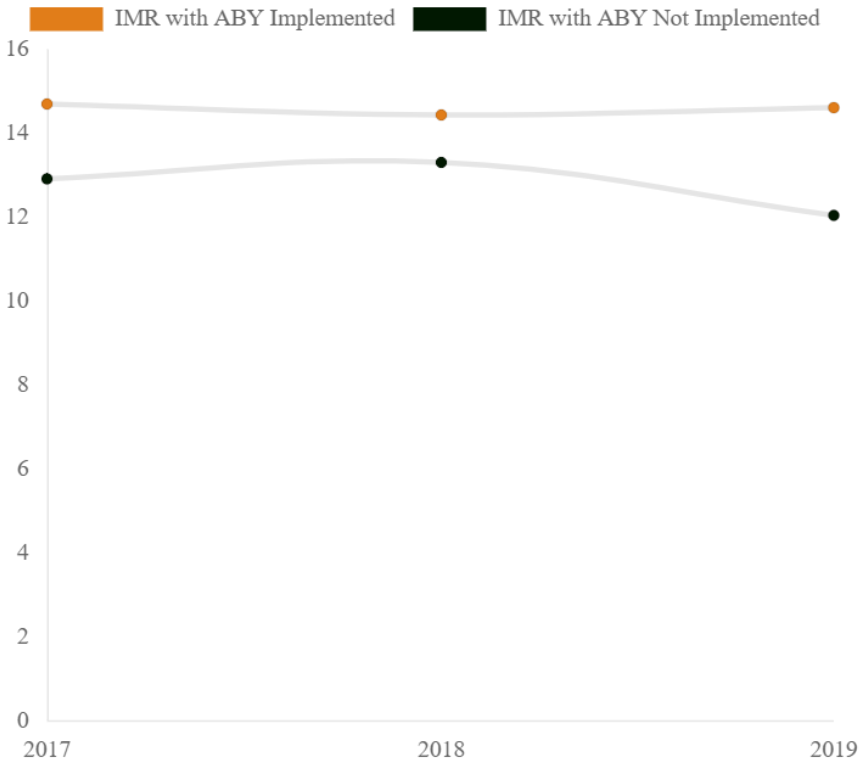
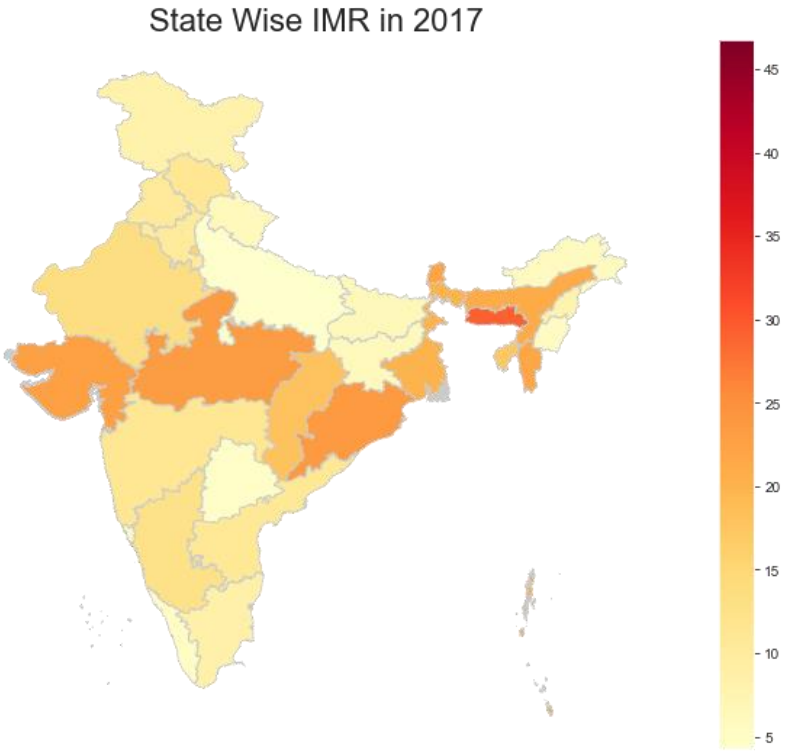
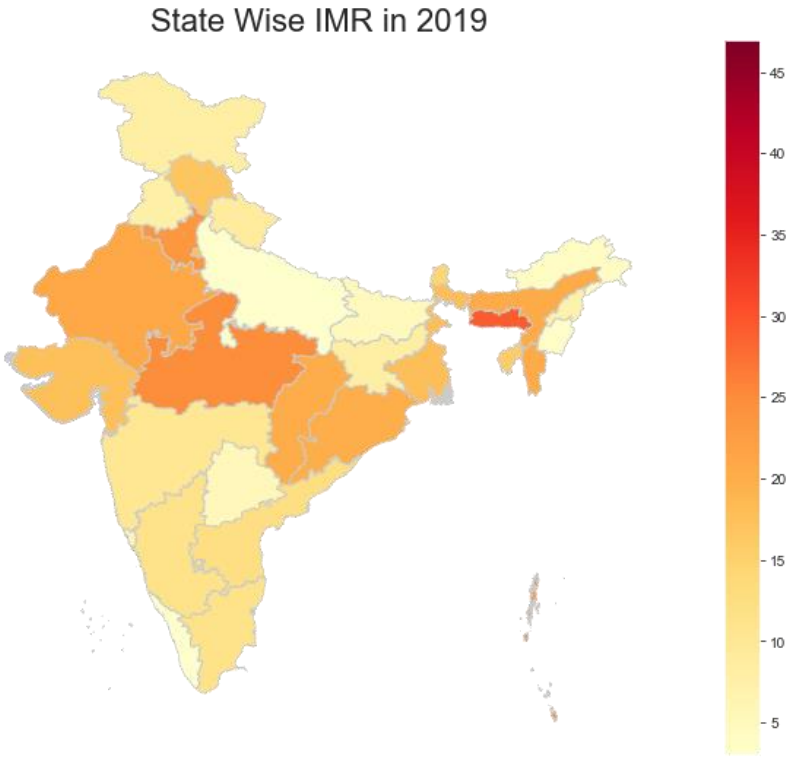


Fig 5: Comparison of IMR between treatment and control states on an average at the national level. 2018 is the year of adoption of ABY- the treatment policy variable





Figs 6 & 7: Infant Mortality Rates across Indian States in pre and post treatment period

(Source: Author's calculations from Government of India data)

Table 2: Fixed-effects and Random-effects, state-time panel data regressions of Infant Mortality rate (IMR) on Health Scheme (ABY) treatment and other variables

	Fixed effects without Covariates (clustered se's)	Fixed effects with Covariates (clustered se's)	Random effects with Covariates (clustered se's)	Fixed effects with Covariates (Default se's)	Random effects with Covariates (Default se's)
	(1)	(2)	(3)	(4)	(5)
IMR					
Treatment Var: Indicator for whether a state adopted the Central Health Benefit	-0.648 (0.525)	-.640 (0.616)	-0.0321 (0.938)	-0.640 (0.628)	-0.741 (0.550)
Interaction term, DD estimator: If a state had the scheme in year 2019	1.418* (0.018)	3.05 (0.007)	0.311 (0.450)	3.051* (0.025)	2.840* (0.033)
_Iyear_2018	0.662 (0.373)				

_Iyear_2019	-0.387 (0.648)				
% Institutional deliveries to Total Reported Deliveries in a year		-.0631 (0.039)	-0.0772*** (0.000)	-0.0634** (0.003)	-0.0648** (0.002)
% live births of Total Reported Births		-3.72 (0.000)	-4.439*** (0.000)	-3.724*** (0.000)	-3.837*** (0.000)
% Newborns having weight less than 2.5 kg to Newborns weighed at birth		.290 (0.000)	0.336*** (0.000)	0.290*** (0.000)	0.305*** (0.000)
% Newborns given Oral Polio Vaccine (OPV) at birth to Reported live births		.007 (0.723)	0.00432 (0.797)	0.00735 (0.655)	0.000580 (0.972)
% Newborns given BCG (Tuberculosis vaccine) to Reported live births		-.012 (0.376)	-0.00578 (0.496)	-0.0116 (0.218)	-0.0129 (0.167)
% Newborns given Hepatitis-B vaccine (Birth Dose) at birth to Reported live births		.027 (0.170)	0.0368* (0.017)	0.0269 (0.078)	0.0313* (0.039)
% Infants 0 to 11 months old who received Measles, Mumps and Rubella vaccine		.004 (0.695)		0.00408 (0.318)	0.00315 (0.440)
No of children 16-24 months age given Measles Rubella Vaccine 2nd dose		-.000 (0.065)		-0.0000232* (0.041)	-0.0000234* (0.033)
Maternal Mortality Rate: mother deaths per 100,000 live births		.020 (0.000)		0.0201*** (0.000)	0.0204*** (0.000)
Total doctors in public health system at state level averaged		.0071984		0.00720 (0.461)	0.00366 (0.627)

for districts		(0.319)			
most peripheral health facility in Indian Public Health System		-.002 (0.582)		-0.00174 (0.412)	-0.00183 (0.378)
Primary Health Centre: state-owned rural single doctor facilities		-.003 (0.866)		-0.00263 (0.785)	-0.000225 (0.981)
First referral health units, accepts patients referred from phc's		-.018 (0.011)		-0.0179** (0.004)	-0.0166** (0.007)
hospital at sub-district level		.03 (0.000)		0.0322** (0.001)	0.0280** (0.005)
final referral centers for the primary and secondary levels of the public health		.037249 (0.726)		0.0372 (0.560)	0.0242 (0.705)
per capita GDP at current prices		.000 (0.858)		0.0000138 (0.648)	0.00000470 (0.530)
year=2017				0 (.)	0 (.)
year=2018		.768 (0.696)		0.768 (0.592)	1.038 (0.393)
year=2019		-2.26 (0.501)		-2.263 (0.269)	-1.479 (0.331)
Constant	12.75*** (0.000)	377.1*** (0.000)	452.7*** (0.000)	377.1*** (0.000)	390.5*** (0.000)

Observations	2112	2112	2112	2110	2110

p-values in parentheses

Notes: This table compares Diff-in-Diff coefficients to study Average Treatment Effect of implementation of Central Government Health Insurance Scheme ABY on Reproductive and Child Health outcomes measured by IMR in different states of Republic of India. The treatment year is 2018. The estimates measures DD coefficients using one year each pre (2017) and post treatment (2019), and their significance across five different regressions. It uses primary official data from Government of India.

Stars ***, **, * denote statistical significance at the 1%, 5% and 10% respectively.

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

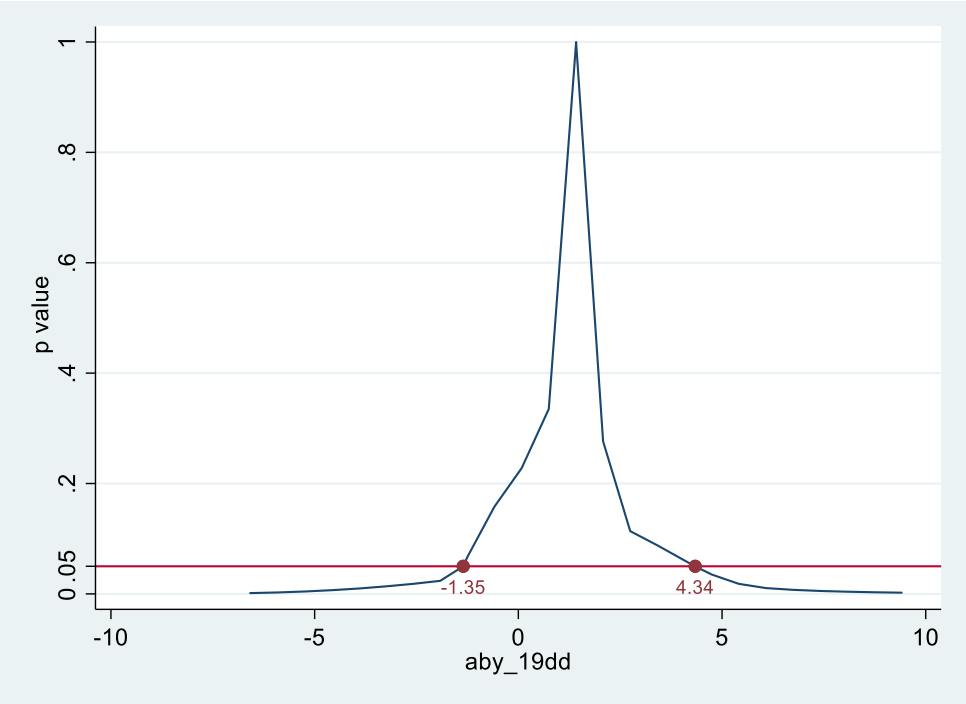


Fig 8: Result of Wild-cluster Bootstrapping on Wald test statistic: IMR on ABY without covariates (Diff-in-Diff)

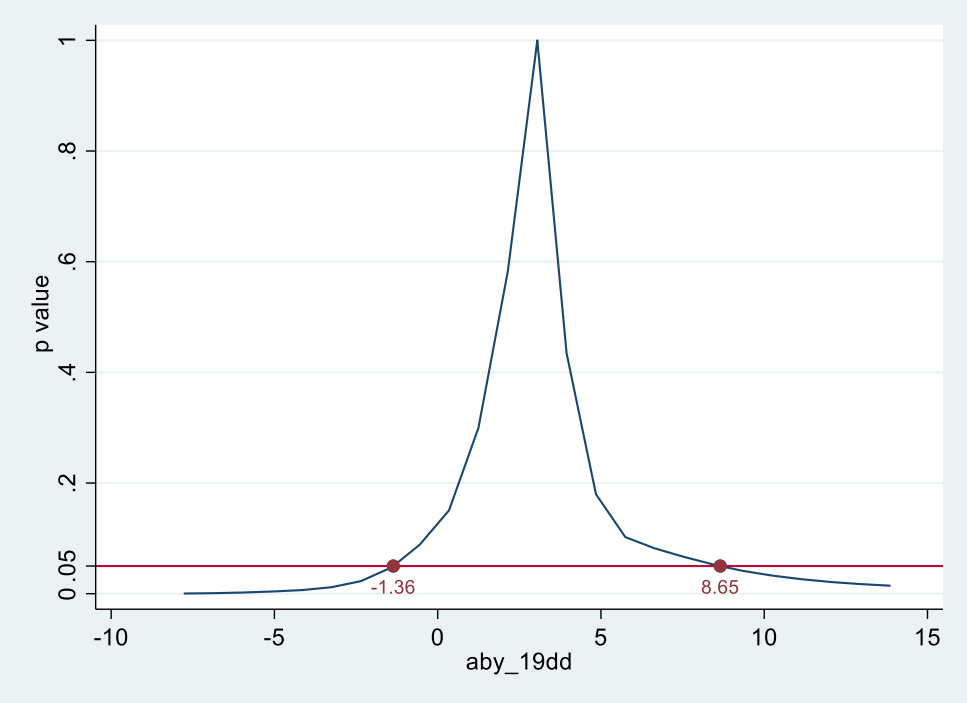


Fig 9: Result of Wild-cluster Bootstrapping on Wald test statistic: IMR on ABY with covariates (Diff-in-Diff)

B. ABY and MMR

As we can observe from Table.3 (Col.1), the regression coefficient estimated by fixed-effects regression using cluster robust standard errors regressing outcome variable MMR on treatment ABY, interacted with year 2019, without using other covariates, i.e., the Diff-in-diff estimate at -5.280, is not statistically significant, but the sign on the parameter is in the correct direction as anticipated.

Treated states i.e. the states which adopted the scheme see a decrease in Maternal Mortality Rate, on an average, of 5.28 but it is not statistically significant at any level of significance, holding all else fixed.

Even when we include the covariates likely affecting health outcomes besides the policies like better care of pregnant mothers reflected in percentage covered by institutional deliveries, immunization coverage and socio-economic status captured in GDP per capita, the causal effect of treatment remains insignificant, as seen in regression results in Col.2.

Treatment States i.e. the states which adopted the scheme see a decrease in Maternal Mortality Rate, on an average, of 5.53 but it is not statistically significant at any level of significance, holding all else fixed.

The results in columns 4 and 5 are significant from theoretical point of view as these confirm the fact that use of default standard errors in estimation, and failure to account for correlation of unobservable heterogeneity at group level in multi-period panels leads to an over rejection of null hypothesis, and significance observed is spurious (Bertrand, Duflo and Mullainathan, 2004). In the case of MMR regression, the results of cluster robust and standard results are almost similar (Col.1 and Col.4). We may infer absence of idiosyncratic fixed effects, but a look at Col.2 and 5 cautions against it. Here, the unadjusted standard errors are seen to inflate

the significance of results, and the results are tempered down by using cluster robust standard error estimates.

Results of WCB on regression of MMR on ABY without covariates:

T (35) = -0.4239

Prob>|t| = 0.7985

Wild cluster bootstrap results and Fig.13 indicate that the DD estimator at 5.28 is insignificant at 80% level of significance indicating there is no effect of adoption of new health scheme on IMR in treatment group of states compared to control states, on an average, holding all else fixed.

95% confidence set for null hypothesis is [-30.79, 34.52], and our estimate needs to be outside the bounds to be significant at 5%, which it is not.

Results of WCB on regression of MMR on ABY with covariates:

T (35) = -0.7499

Prob>|t| = 0.5113

Wild cluster bootstrap results and Fig.14 indicates that the DD estimator at 5.53 is insignificant at 51% level of significance indicating there is no effect of adoption of new health scheme on MMR in treatment group of states compared to control states, on an average, holding all else fixed.

95% confidence set for null hypothesis expression is [-24.09, 21.78], and our estimate lies within it, rendering it insignificant.

We observe that there are no statistically significant causal effects of adoption of ABY policy on Maternal Mortality Rates in states which adopted the scheme. Since the period under study is very short, we may not conclude that the policy is useless. The analysis may be repeated after a reasonable period of two to three more years to gauge the results again, as health of a community has some stickiness due to underlying demographics and behaviors. The policy make take time to penetrate and become easily understood by people for whom it is targeted.

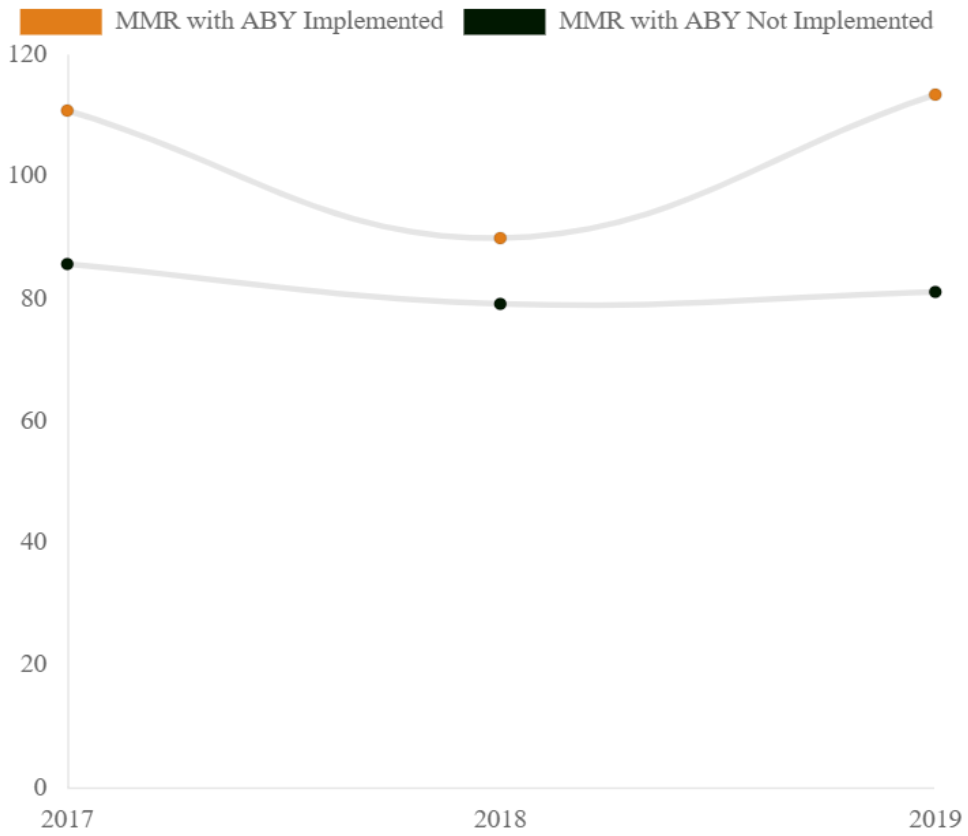
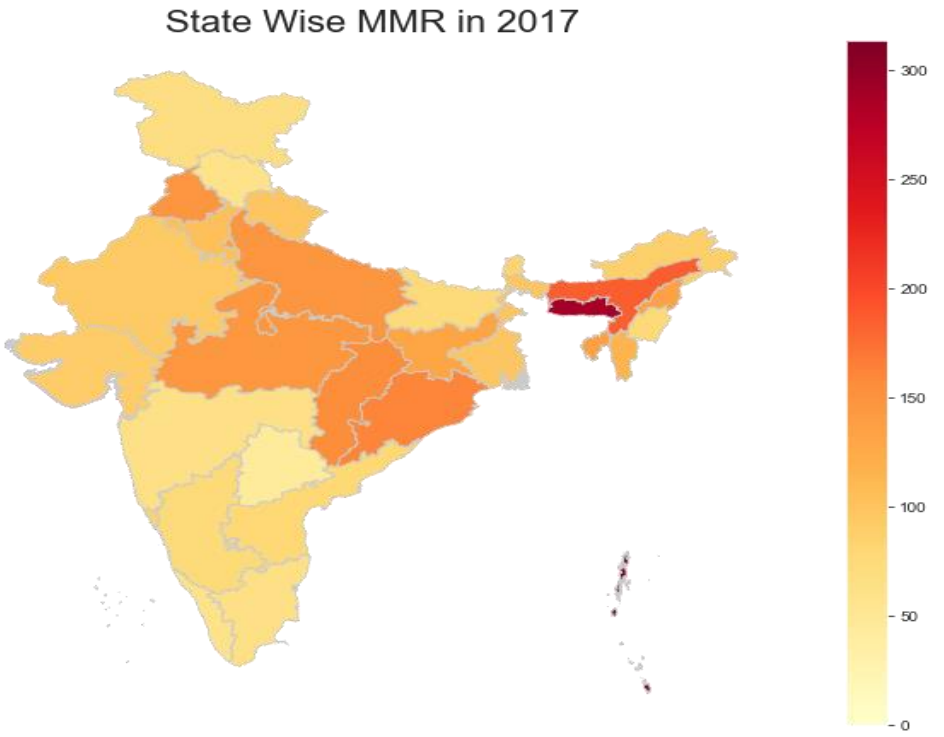
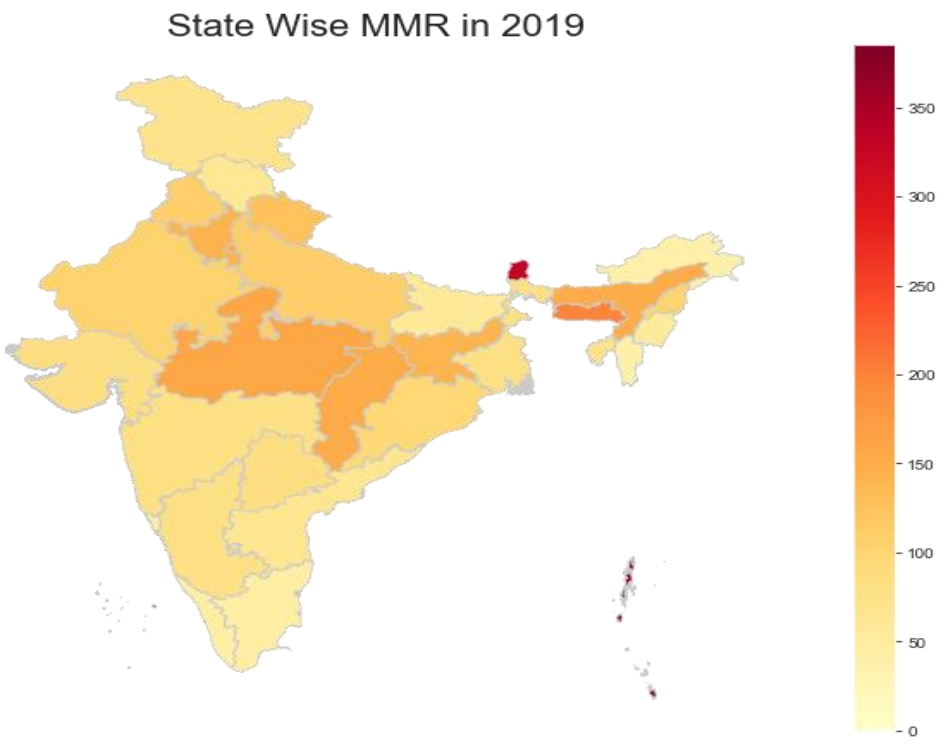


Fig 10: Comparison of MMR between treatment and control states on an average at the national level. 2018 is the year of adoption of ABY- the treatment policy variable





Figs 11 & 12: Maternal Mortality Rates across Indian States in pre and post treatment period (Source: Author's calculations from Government of India data)

Table 3: Fixed-effects and Random-effects, state-time panel data regressions of Maternal Mortality rate (MMR) on Health Scheme (ABY) treatment and other variables

	Fixed effects without Covariates (clustered se's)	Fixed effects with Covariates (clustered se's)	Random effects with Covariates (clustered se's)	Fixed effects with Covariates (default se's)	Random effects with Covariates (default se's)
	(1)	(2)	(3)	(4)	(5)
MMR					
Treatment Var: Indicator for whether a state adopted the Central Health Benefit	-18.38* (0.025)	-7.909 (0.328)	-8.705 (0.278)	-7.909 (0.593)	-8.705 (0.525)
Interaction term, DD estimator: If a state had the scheme in year 2019	-5.280 (0.672)	-5.533 (0.455)	-12.69 (0.120)	-5.533 (0.717)	-12.69 (0.390)
year==2018	1.031 (0.869)	-17.79 (0.150)	-4.088 (0.572)		
year==2019	11.50 (0.504)	-10.67 (0.580)	20.41 (0.201)		
% Institutional deliveries to Total Reported Deliveries in a year		-0.272 (0.606)	-0.357 (0.490)	-0.272 (0.258)	-0.357 (0.123)
% live births of Total Reported Births		-20.71** (0.002)	-21.93*** (0.001)	-20.71*** (0.000)	-21.93*** (0.000)
% Newborns having weight less than 2.5 kg to Newborns weighed at birth		0.659 (0.202)	0.506 (0.296)	0.659 (0.145)	0.506 (0.241)
% Newborns given Oral Polio Vaccine (OPV) at birth to Reported live births		0.0608 (0.752)	0.0563 (0.769)	0.0608 (0.742)	0.0563 (0.756)
% Newborns given BCG (Tuberculosis vaccine) to Reported live births		-0.0763 (0.778)	-0.0556 (0.836)	-0.0763 (0.470)	-0.0556 (0.591)

% Newborns given Hepatitis-B vaccine (Birth Dose) at birth to Reported live births	0.0389 (0.820)	0.00753 (0.964)	0.0389 (0.820)	0.00753 (0.964)
% Infants 0 to 11 months old who received Measles, Mumps and Rubella vaccine	0.255 (0.140)	0.250 (0.132)	0.255*** (0.000)	0.250*** (0.000)
No of children 16-24 months age given Measles Rubella Vaccine 2nd dose	0.000149 (0.158)	0.0000802 (0.451)	0.000149 (0.243)	0.0000802 (0.512)
Infant Mortality Rate: number of deaths per 1,000 live births under one year	2.526*** (0.000)	2.525*** (0.000)	2.526*** (0.000)	2.525*** (0.000)
Total doctors in public health system at state level averaged for districts	-0.146 (0.148)	-0.179* (0.044)	-0.146 (0.180)	-0.179* (0.027)
most peripheral health facility in Indian Public Health System	-0.0432 (0.051)	-0.0389 (0.064)	-0.0432 (0.068)	-0.0389 (0.091)
Primary Health Centre: state-owned rural single doctor facilities	0.173 (0.197)	0.159 (0.218)	0.173 (0.110)	0.159 (0.138)
First referral health units, accepts patients referred from phc's	-0.00107 (0.978)	0.000663 (0.986)	-0.00107 (0.988)	0.000663 (0.992)
hospital at sub-district level	-0.0339 (0.774)	-0.0150 (0.892)	-0.0339 (0.760)	-0.0150 (0.892)
final referral centers for the primary and secondary levels of the public health	2.099 (0.237)	2.106 (0.227)	2.099** (0.003)	2.106** (0.003)
per capita GDP at current prices	0.000803 (0.125)	1.54e-09 (1.000)	0.000803* (0.017)	1.54e-09 (1.000)

year=2017				0 (.)	0 (.)
year =2018				-17.79 (0.267)	-4.088 (0.761)
year =2019				-10.67 (0.642)	20.41 (0.221)
Constant	111.2*** (0.000)	2020.1** (0.002)	2246.7*** (0.000)	2020.1*** (0.000)	2246.7*** (0.000)
Observations	2112	2110	2110	2110	2110

p-values in parentheses

Notes: This table compares Diff-in-Diff coefficients to study Average Treatment Effect of implementation of Central Government Health Insurance Scheme ABY on Reproductive and Child Health outcomes measured by MMR in different states of Republic of India. The treatment year is 2018. The estimates measures DD coefficients using one year each pre (2017) and post treatment (2019), and their significance across five different regressions. It uses primary official data from Government of India.

Stars ***, **, * denote statistical significance at the 1%, 5% and 10% respectively.

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

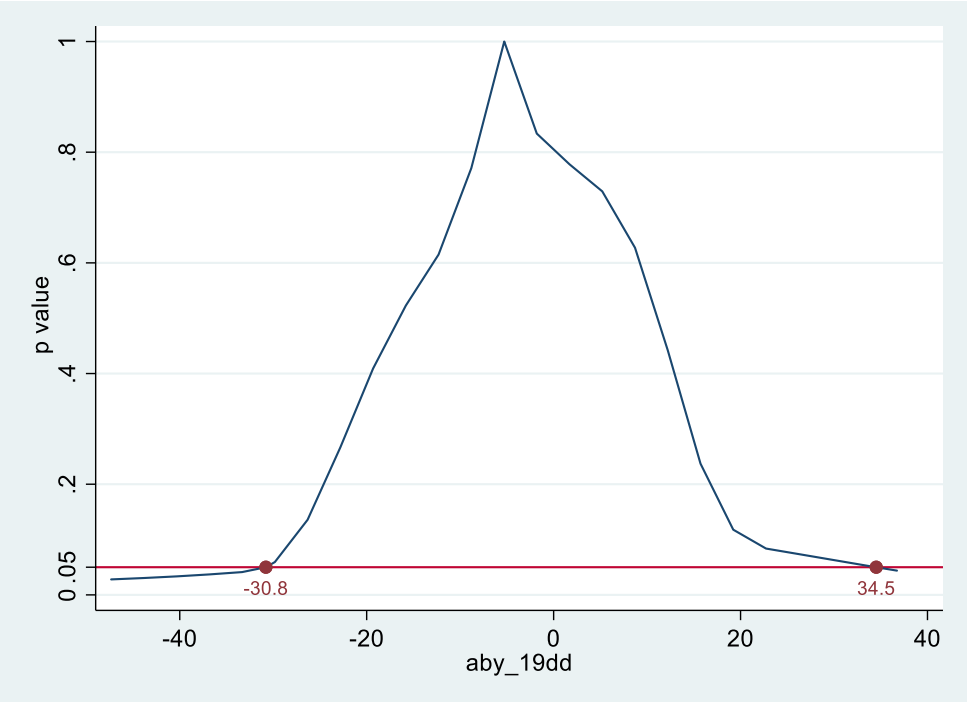


Fig 13: Result of Wild-cluster Bootstrapping on Wald test statistic: MMR on ABY without covariates (Diff-in-Diff)

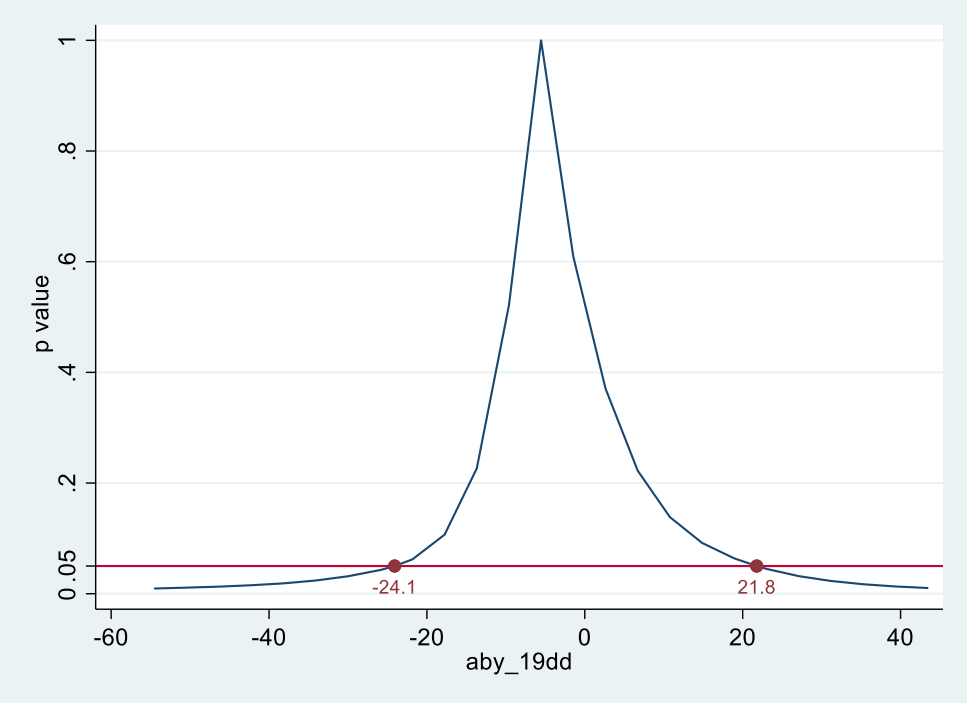


Fig 14: Result of Wild-cluster Bootstrapping on Wald test statistic: MMR on ABY with covariates (Diff-in-Diff)

Robustness Tests

A. DDD Estimation

(i) IMR on ABY

The DDD estimator of regression without covariates in column 1 of Table 4 is not statistically significant but indicates favorable result.

Treated states i.e. the states which adopted the scheme and are poor as well, see a decrease in Infant Mortality Rate, on an average, of .11 due to policy but it is not statistically significant at any level of significance, holding all else fixed.

The results of WCB read with observation of Fig.15 are-

T (35) = -0.1269

Prob>|t| = 0.9063

WCB indicates that the DDD estimator is insignificant at 90% level of significance indicating there is no effect of adoption of new health scheme on IMR in treated group of states compared to control states, on an average, holding all else fixed.

95% confidence set for null hypothesis expression: [-2.072, 1.858], and our estimates lies within interval of insignificance.

Similarly, in regression with covariates, the DDD estimator in column 2 is statistically significant, but the sign on the parameter is again counterintuitive.

Treated states i.e. the states which adopted the scheme and are poor as well, see an increase in Infant Mortality Rate, on an average, of 1.93 which is statistically significant at 5% level, holding all else fixed.

WCB results:

T (35) = 2.0107

Prob>|t| = 0.0853

WCB results read with Fig. 16 indicate that the DDD estimator is insignificant at 8.5% level of significance indicating there is no effect of adoption of new health scheme on IMR in treatment group of states compared to control states, on an average, holding all else fixed.

95% confidence set for null hypothesis expression: [-.2786, 3.994]. Our estimator lies within it.

Table 4: Fixed-effects and Random-effects, state-time panel data regressions of Infant Mortality rate (IMR) on Health Scheme (ABY) treatment and other variables: Triple Differencing Estimation

	Fixed Effects without covariates (with cluster se's)	Fixed Effects with covariates (with cluster se's)
	(1)	(2)
IMR		
Treatment Var: Indicator for whether a state adopted the Central Health Benefit	0.326 (0.809)	1.412 (0.385)
per capita GDP below median value of 110605 INR (USD 1455, 76 INR=1USD)	-2.793 (0.357)	-4.131 (0.097)
Triple Difference estimator: Interaction term: 1 If a state had the scheme in year 2019 and was poor	-0.116 (0.899)	1.929 (0.050)
year==2018	-0.424 (0.690)	-1.905 (0.442)
year==2019	-0.233 (0.847)	-3.063 (0.391)
% Institutional deliveries to Total Reported Deliveries in		-0.0626*

a year	(0.039)
% live births of Total Reported Births	-3.734*** (0.000)
% Newborns having weight less than 2.5 kg to Newborns weighed at birth	0.286*** (0.000)
% Newborns given Oral Polio Vaccine (OPV) at birth to Reported live births	0.00594 (0.772)
% Newborns given BCG (Tuberculosis vaccine) to Reported live births	-0.0105 (0.417)
% Newborns given Hepatitis-B vaccine (Birth Dose) at birth to Reported live births	0.0273 (0.160)
% Infants 0 to 11 months old who received Measles, Mumps and Rubella vaccine	0.00333 (0.750)
No of children 16-24 months age given Measles Rubella Vaccine 2nd dose	-0.0000209* (0.045)
Maternal Mortality Rate: mother deaths per 100,000 live births	0.0202*** (0.000)
Total doctors in public health system at state level averaged for districts	-0.00373 (0.652)
most peripheral health facility in Indian Public Health System	-0.00191 (0.531)
Primary Health Centre: state-owned rural single doctor	-0.00241 (0.878)

facilities		
First referral health units, accepts patients referred from phc's		-0.0181** (0.009)
hospital at sub-district level		0.0326*** (0.000)
final referral centers for the primary and secondary levels of the public health		0.0257 (0.788)
per capita GDP at current prices		0.0000694 (0.456)
Constant	14.29*** (0.000)	374.3*** (0.000)
Observations	2112	2110

p-values in parentheses

Notes: This table compares Diff-in-Diff-in-Differences coefficients to study Average Treatment Effect of implementation of Central Government Health Insurance Scheme ABY on Reproductive and Child Health outcomes measured by IMR in different states of Republic of India. The treatment year is 2018. The estimates measures DDD coefficients using one year each pre (2017) and post treatment (2019), and their significance across five different regressions. It uses primary official data from Government of India.

Stars ***, **, * denote statistical significance at the 1%, 5% and 10% respectively.

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

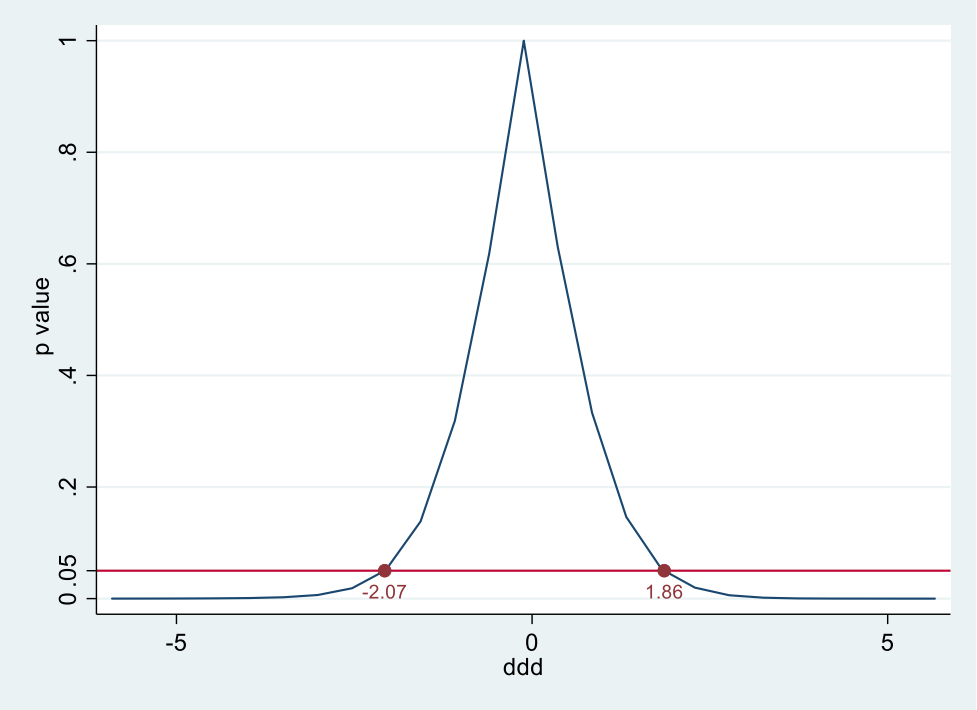


Fig 15: Result of Wild-cluster Bootstrapping on Wald test statistic: IMR on ABY without covariates (Triple Differencing)

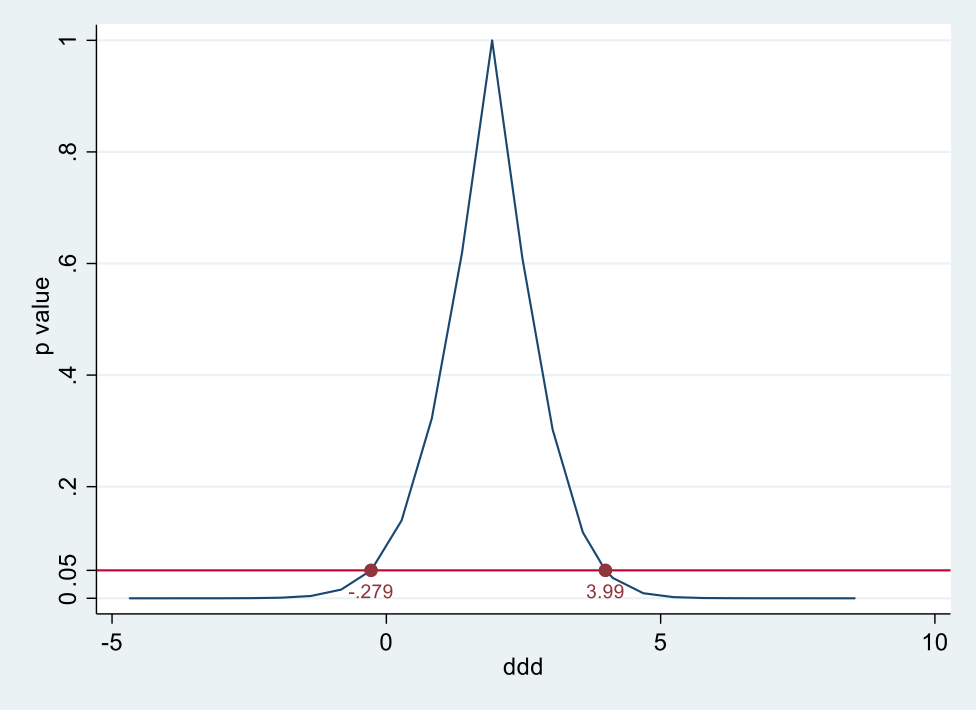


Fig 16: Result of Wild-cluster Bootstrapping on Wald test statistic: IMR on ABY with covariates (Triple Differencing)

(ii) MMR on ABY

The DDD estimator of regression without covariates in column 1 of Table 5 is not statistically significant, but the sign on the parameter is correct.

Treated states i.e. the states which adopted the scheme and are poor as well, see a decrease in Maternal Mortality Rate, on an average, of 13.61 which is not statistically significant at less than 15% level, holding all else fixed.

WCB results read with Fig.17:

t (35) = -1.4603

Prob>|t| = 0.2102

Wild cluster bootstrap indicates that the DDD estimator is insignificant at 21% level of significance indicating there is no effect of adoption of new health scheme on IMR in treatment group of states which are poor, compared to control states, on an average, holding all else fixed.

95% confidence set for null hypothesis expression: [-33.86, 8.028]. Out DDD estimator from the first regression without covariates at 13.31 lies outside the region of insignificance. But when we read it with p-value on Wald statistics of WCB results, we conclude that the estimate is not statistically significant at 21% level.

The DDD estimator of regression with covariates in column 2 of Table 5 is not statistically significant, but the sign on the parameter is correct.

Treatment States i.e. the states which adopted the scheme, and are poor as well, see a decrease in Maternal Mortality Rate, on an average, of 6.6 which is not statistically significant at less than 49% level, holding all else fixed.

WCB results read with Fig.18:

T (35) = -0.6959

Prob>|t| = 0.5171

Wild cluster bootstrap indicates that the DD estimator is insignificant at 52% level of significance indicating there is no effect of adoption of new health scheme on IMR in treatment group of poor states compared to control states, on an average, holding all else fixed.

95% confidence set for null hypothesis expression: [-27.02, 13.37]. Our estimator lies within it and thus is insignificant.

Table 5: Fixed-effects, state-time panel data regressions of Maternal Mortality rate (MMR) on Health Scheme (ABY) treatment and other variables: Triple Differencing Estimation

	Fixed Effects without covariates (with cluster se's)	Fixed Effects with covariates (with cluster se's)
	(1)	(2)
MMR		
Treatment Var: Indicator for whether a state adopted the Central Health Benefit	-18.57 (0.106)	-12.38 (0.215)

per capita GDP below median value of 110605 INR (USD 1455, 76 INR=1USD)	10.71 (0.514)	11.07 (0.294)
Triple Difference estimator: Interaction term:1 If a state had the scheme in ye	-13.61 (0.150)	-6.597 (0.487)
year==2018	1.986 (0.841)	-10.86 (0.502)
year==2019	14.11 (0.231)	-4.974 (0.810)
% Institutional deliveries to Total Reported Deliveries in a year		-0.272 (0.606)
% live births of Total Reported Births		-20.60** (0.002)
% Newborns having weight less than 2.5 kg to Newborns weighed at birth		0.665 (0.197)
% Newborns given Oral Polio Vaccine (OPV) at birth to Reported live births		0.0654 (0.735)
% Newborns given BCG (Tuberculosis vaccine) to Reported live births		-0.0796 (0.767)
% Newborns given Hepatitis-B vaccine (Birth Dose) at birth to Reported live births		0.0365 (0.830)
% Infants 0 to 11 months old who received Measles, Mumps and Rubella vaccine		0.257 (0.137)

No of children 16-24 months age given Measles Rubella Vaccine 2nd dose		0.000147 (0.164)
Infant Mortality Rate: number of deaths per 1,000 live births under one year		2.540*** (0.000)
Total doctors in public health system at state level averaged for districts		-0.124 (0.219)
most peripheral health facility in Indian Public Health System		-0.0428 (0.053)
Primary Health Centre: state-owned rural single doctor facilities		0.172 (0.204)
First referral health units, accepts patients referred from phc's		-0.000507 (0.990)
hospital at sub-district level		-0.0353 (0.765)
final referral centers for the primary and secondary levels of the public health		2.128 (0.229)
per capita GDP at current prices		0.000612 (0.334)
Constant	105.2*** (0.000)	2024.3** (0.002)
Observations	2112	2110

p-values in parentheses

Notes: This table compares Diff-in-Diff-in-Differences coefficients to study Average Treatment Effect of implementation of Central Government Health Insurance Scheme ABY on Reproductive and Child Health outcomes measured by MMR in different states of Republic of India. The treatment year is 2018. The estimates measures DDD coefficients using one year each pre (2017) and post treatment (2019), and their significance across five different regressions. It uses primary official data from Government of India.

Stars ***, **, * denote statistical significance at the 1%, 5% and 10% respectively.

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

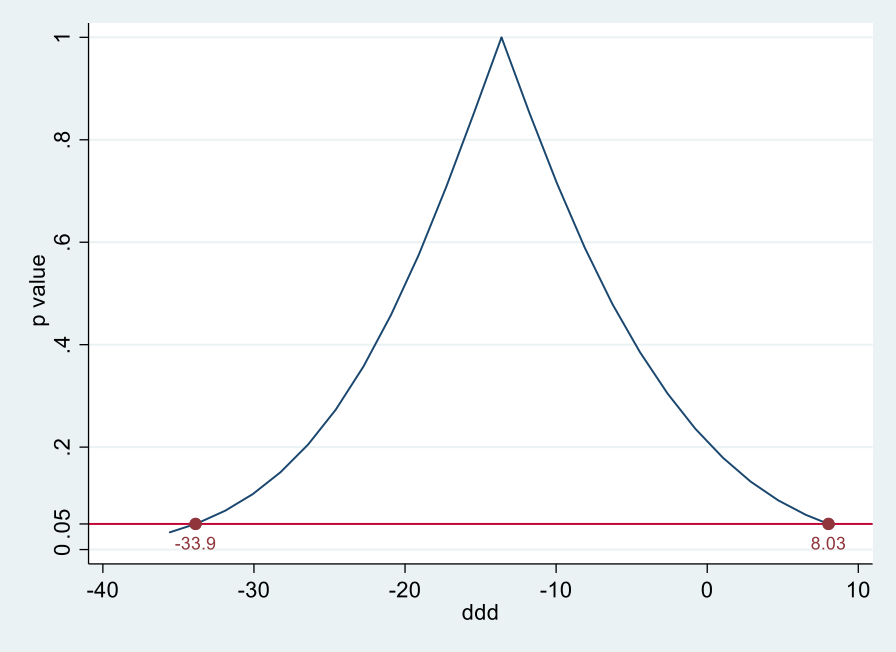


Fig 17: Result of Wild-cluster Bootstrapping on Wald test statistic: MMR on ABY without covariates (Triple Differencing)

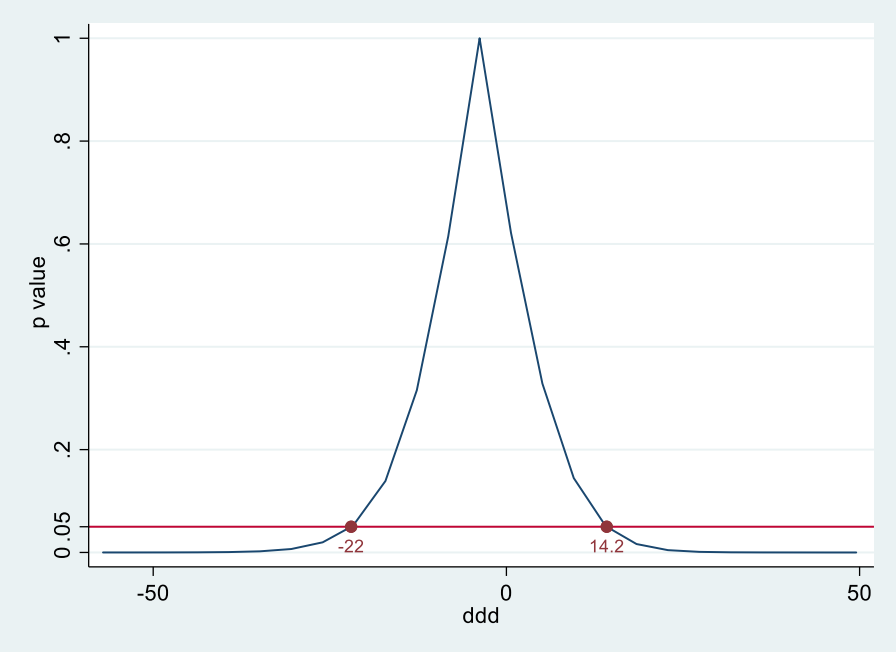


Fig 18: Result of Wild-cluster Bootstrapping on Wald test statistic: MMR on ABY with covariates (Triple Differencing)

The triple differencing estimation in all four DDD regressions in Tables 4 and 5 did not yield significant results helping us to conclude that our DD estimator is unbiased.

B. Placebo Test

Regressing GDP per capita on treatment and other covariates: The null hypothesis is: H0- the parameter on treatment must be statistically insignificant to claim that the treatment had specific effect on outcomes of interest only and did not affect other features of the treatment unit too which are completely unrelated to the outcomes.

As we see that the result of both the regressions, with or without covariates, of GDP per capita on treatment related features is insignificant at 1,5 and 10% levels. Bootstrapping (Fig.19) too does not alter the results on significance.

Thus, we find no evidence that the policy changes direction of existing trend of GDP per capita in a state, whether control or treated, in any direction in post treatment period significantly. Thus, our treatment variable passes the placebo test, and is assumed to affect only variables of interest- IMR and MMR.

Change in health policy which is beneficial to people and gives them access to greater physical well-being is very likely to bring in economic improvement by reducing the days people call sick on work, and by increasing productivity of human capital in the long run. In that sense, this regression suffers from problem of endogeneity. However, in very short term like our DGP, we assume exogeneity and safely conclude that regression results are free from bias due to endogeneity.

Table 6: Fixed-effects, state-time panel data Placebo Diff-in-Diff regressions of GDP per capita on Health Scheme (ABY) treatment and other variables

	Fixed Effects without covariates (with cluster se's)	Fixed Effects with covariates (with cluster se's)
GDP	(1)	(2)
Treatment Var: Indicator for whether a state adopted the Central Health Benefit	-10079.8**	-11139.2**
	(0.009)	(0.001)
Interaction term, DD estimator: If a state had the scheme in year 2019	-7614.1	-5747.0
	(0.151)	(0.332)
Year=2017	0	0
	(.)	(.)
Year =2018	22844.0***	24368.9***

	(0.000)	(0.000)
Year =2019	39218.4***	39083.6***
	(0.000)	(0.000)
% Institutional deliveries to Total Reported Deliveries in a year		-49.41**
		(0.004)
% Newborns having weight less than 2.5 kg to Newborns weighed at birth		-2.077
		(0.921)
% Newborns given Oral Polio Vaccine (OPV) at birth to Reported live births		-3.766
		(0.822)
% Newborns given BCG (Tuberculosis vaccine) to Reported live births		22.62*
		(0.014)
Maternal Mortality Rate: mother deaths per 100,000 live births		3.333
		(0.137)
Infant Mortality Rate: number of deaths per 1,000 live births under one year		5.140
		(0.890)
% Newborns given Hepatitis-B vaccine (Birth Dose) at birth to Reported live births		25.05
		(0.186)

% Infants 0 to 11 months old who received Measles, Mumps and Rubella vaccine	-5.903
	(0.102)
No of children 16-24 months age given Measles Rubella Vaccine 2nd dose	-0.0967**
	(0.005)
Total doctors in public health system at state level averaged for districts	20.18
	(0.662)
most peripheral health facility in Indian Public Health System	-3.817
	(0.542)
Primary Health Centre: state-owned rural single doctor facilities	10.22
	(0.270)
First referral health units, accepts patients referred from phc's	-0.111
	(0.987)
hospital at sub-district level	-4.584
	(0.165)
final referral centers for the primary and secondary levels of the public health	-8.818
	(0.875)
Total public health facilities, does not include private clinics and hospitals	6.676
	(0.228)

Constant	122534.5***	120731.9***
	(0.000)	(0.000)
Observations	2112	2110

Notes: This table compares Diff-in-Diff coefficients to study Average Treatment Effect of implementation of Central Government Health Insurance Scheme ABY GDP per capita in different states of Republic of India. The treatment year is 2018. The estimates measures DD coefficients using one year each pre (2017) and post treatment (2019), and their significance across five different regressions. It uses primary official data from Government of India.

Stars ***, **, * denote statistical significance at the 1%, 5% and 10% respectively.

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

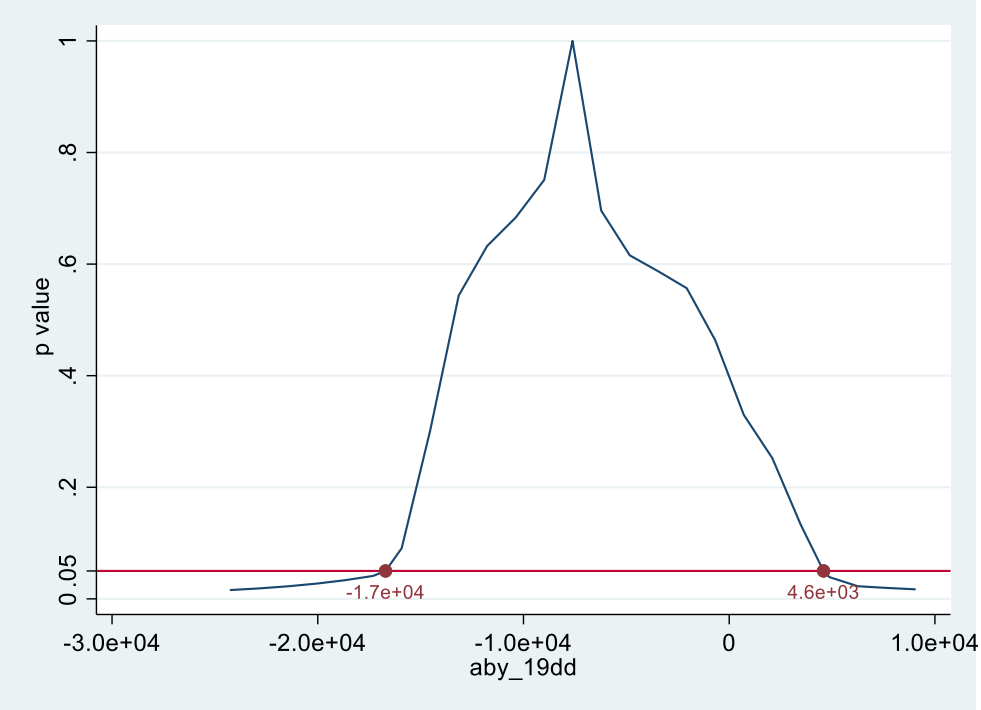


Fig 19: Result of Wild-cluster Bootstrapping on Wald test statistic: GDP per capita on ABY with covariates (Diff-in-Diff)

V. Conclusion

The results of different regressions in the paper suggest there are no statistically significant effects of adoption of ABY in treatment states on IMR and MMR. Perhaps it is too early in the lifetime of policy to achieve a significant effect on health outcomes of the population in states which have adopted the scheme.

On the theoretical side, we observe that causal interpretations may suffer from bias in case there are too few clusters in the panel data. Addressing the problem by effective use of WCB has reversed the significance of results in regressions involving IMR as outcome variable of interest. In absence of bootstrapping, we may erroneously conclude that the policy has a negative causal relation with IMR and leads to more deaths of babies in states which adopt the scheme, a result which may mar adoption of a potentially beneficial policy. It may also become a handle in the hands of detractors to lobby for

repeal of a good policy and embarrass the government. Therefore, we need to be very careful in interpretation of causal results if we have very few clusters, especially if the exercise is not merely academic.

Finally, as a corollary, we observe the necessity of deploying cluster-robust inference as use of default standard errors in our regressions clearly leads to over rejection of true null and inflates the significance leading to spurious interpretation of results.

Given the short run nature of the analysis, a repeat of the same study is recommended after the policy is significantly into its implementation, say after two years of adoption. Higher awareness of all the stakeholders and wider access by users of health insurance in better health facilities might allow us to see significant effects of policy on health outcomes in the populations of treated states.

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Acronyms

ABY Ayushman Bharat Yojana
HWCs Health and Wellness Centers
IMR Infant Mortality Rate
INR Indian National Rupee
MDG Millennium Development Goals
MMR Maternal Mortality Rate
NHP National Health Policy of India, 2017
NMR Neonatal Mortality Rate
PMJAY Pradhan Mantri Jan Arogya Yojana
RCH Reproductive and Child Health
SDG Sustainable Development Goals
UFMR Under Five Mortality Rate
UN United Nations
USD US Dollars (1USD = 76INR)
WHO World Health Organization

Appendix

States of India (Capitals in Parentheses): Control States are highlighted

- Andhra Pradesh (Hyderabad)
- Arunachal Pradesh (Itanagar)
- Assam (Dispur)
- Bihar (Patna)
- Chhattisgarh (Raipur)
- Goa (Panaji)
- Gujarat (Gandhinagar)
- Haryana (Chandigarh)
- Himachal Pradesh (Shimla)
- Jharkhand (Ranchi)
- Karnataka (Bangalore)
- Kerala (Thiruvananthapuram)
- Madhya Pradesh (Bhopal)
- Maharashtra (Mumbai)
- Manipur (Imphal)
- Meghalaya (Shillong)

- Mizoram (Aizawl)
- Nagaland (Kohima)
- Odisha (Bhubaneshwar)
- Punjab (Chandigarh)
- Rajasthan (Jaipur)
- Sikkim (Gangtok)
- Tamil Nadu (Chennai)
- **Telangana (Hyderabad)**
- Tripura (Agartala)
- Uttarakhand (Dehradun)
- Uttar Pradesh (Lucknow)
- **West Bengal (Kolkata)**

Union Territories

- Andaman and Nicobar Islands (Port Blair)
- Chandigarh (Chandigarh)
- Dadra and Nagar Haveli and Daman & Diu
- **The Government of NCT of Delhi (Delhi)**
- Jammu & Kashmir
  (Srinagar-S*, Jammu-W*)
- Ladakh (Leh)
- Lakshadweep (Kavaratti)
- **Puducherry (Puducherry)**

PS**:**For the purpose of analysis I have counted Union Territories as states, and the only difference is modality of governance. UTs are federally administered. Legislations, policies, and guidelines remain the same as others