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Do rural health worker incentive schemes work? Evidence from Thailand

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Abstract

This paper studies supply-side health interventions, which increased the monetary incentives and number of health professionals in the Deep South provinces of Thailand, and provides evidence on the effectiveness of provision of primary care providers on the health care utilization of the community. We use a difference-in-differences approach to estimate effects of this policy on child health by evaluating the probability of immunizations in the policy affected areas using two rounds of the Multiple Indicator Cluster Surveys (MICS). We find that after the policy implementation, there is a decrease in immunizations that are given to children within 2 months and 1 year of their date of birth between 6.8 to 17.9 percentage points, controlling for cohort specific time-invariant unobservables. However, we note an increase in BCG vaccinations that are administered at the time of birth. Event studies suggest no presence of pre-trends before the policy implementation. We also observe heterogeneity of effects along the dimensions of residence, ethnicity, and education of the caretaker with children belonging to rural areas, non-Thai ethnicity, and uneducated caretakers experiencing stronger effects. We investigate the quality of services as a mechanism to explain these findings using Thai Health and Welfare Surveys (HWS) and find a shift from small government facilities to large government facilities for in-patient services, indicating a decrease in demand due to lower quality.

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1. Introduction

Historically, Thailand suffers from a lack of health workers, especially in the public system and rural areas. In 2003 and 2004, the doctor to population ratio in Thailand was 0.3 doctors per 1,000 population compared to the 0.4 and 2.9 in other Southeast Asian countries and Europe, respectively (Thinakorn and Pagaiya 2009). Starting in 2004, political unrests became increasingly intense in the country's three southern-most provinces: Yala, Pattani, and Narathiwat. To recruit and retain health workers in the area, the government announced an extra hardship monetary allowance and a special medical student recruitment program in May 2005. The extra hardship allowance for the Deep South was considerably large relative to the hardship allowance already in place and those elsewhere in the country. Prior to this policy, the hardship allowance for doctors and dentists in extremely remote areas was 20,000 baht per month, while the hardship allowances in other remote areas and in non-remote rural areas were 10,000 and 2,000 baht per month, respectively.[1] The new policy added an extra 10,000 baht per month to the hardship allowance for doctors and dentists in the Deep South and an extra 2,800 baht per month for some non-remote rural areas. Nurses and pharmacists also received the extra hardship allowance, though in smaller amounts.

In addition to the extra hardship allowance, the government started a local recruitment program in which 30 additional slots in a nearby medical school were granted to local high school students. These students are required to return and serve their area after graduation. This recruitment program was planned for 2005-2013, and the first batch of students graduated in March 2011. Later in 2007, the government also initiated a similar recruitment program for nurses in which 3,000 local students were sent to nursing schools all over the country. These students also graduated and started working in the area in 2011. Given that these policies were implemented due to political unrest rather than lack of doctors and worse health outcomes in the area per se, we use this natural experiment to study the impact of an increase in supply of doctors and nurses in the affected areas.[2]

This paper studies these supply-side health interventions and provides evidence on the effectiveness of provision of primary care providers on healthcare utilization of the community. We use a difference-in-differences (DiD) approach to estimate effects of this policy on child health by looking at the probability of immunizations and anthropometric outcomes in the policy affected areas. Our main source of data is two rounds of the Multiple Indicator Cluster Surveys (MICS). Since this is not a panel dataset, we develop household-cohorts to control for cohort specific time-invariant unobservables. Our key assumption for identification is that this policy change was driven by political motivations at the province level and hence was exogenous to household cohort health-related behaviors. We find no evidence of pre-trends in our data and a large change once the policy is in effect. We find that after the policy implementation, there is a *decrease* in immunizations that are given to children within 2 months and 1 year of their date of birth. On the other hand, we record an increase in BCG immunization, which is given at the time of the birth.

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[1] In this period, hospitals were initially categorized into three hardship levels based only on distance and travel time to nearest towns and cities. For this reason, hospitals in the deep south fell into all hardship levels. The categorization gradually changed every year. By 2008, all district hospitals in the deep south fell under the extreme hardship (Hardship II) category.

[2] There is a marked increase in the number of nurses available per thousand population and increasing trend in number of the doctors in the treatment areas after 2011 in our data (see Figure 1). Before the policy implementation, we check the distribution of doctors per 1000 population ratio and see that the treated areas are at the mode of the distribution in both 2003 and 2004. We also do not observe any statistically significant differences in vaccinations administered after 2 months of birth between treated and control provinces, before the treatment was implemented.

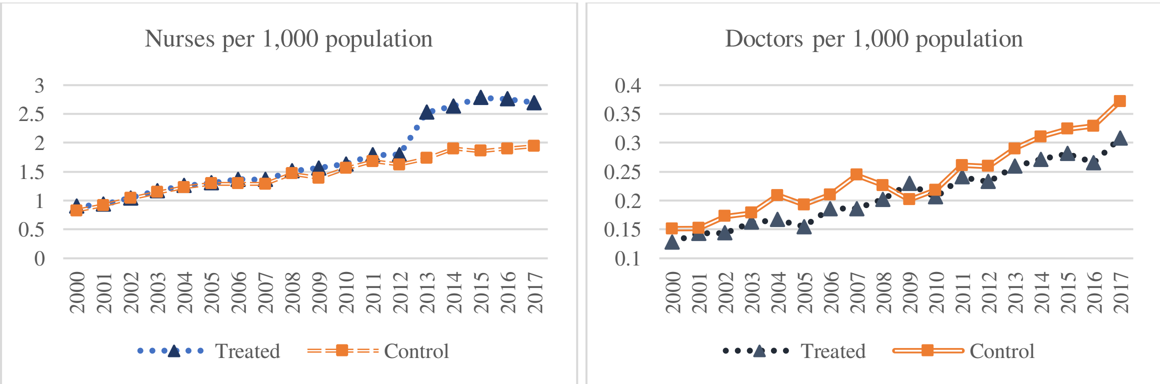
We then explore channels through which our results are realized, and we present the quality of care as the main driver. Filmer et al. (2000) find mixed evidence in the literature looking at the effect of access to hospitals, doctors, public sector clinics, health centers, and rural health workers on health status. They bring out two key intertwining perspectives to understand the effectiveness (or the lack of it) of health policy— incentives and choices. While the government focuses on quantity or delivery of services, the quality of services could be lacking leading to health services having no impact on health. Just the presence of healthcare facilities or improvement in the number of doctors may not bring significant differences in health outcomes as is documented in different country settings (Frankenberg 1995; Rosenzweig and Schultz 1982). There is also a rich health economics literature that documents the importance of quality on health outcomes. Björkman and Svensson (2009) show that the community monitoring of the health care provider lead to an improvement in child health and increase in healthcare utilization. Barber, Gertler and Harimurti (2007) demonstrate that private nurses offer below-average care and private physicians provide high quality care in Indonesia. Das et al. (2008b) find that the quality of care in low-income countries as measured by what doctors know is very low, and that the problem of low competence is compounded by low effort. The low quality of services, despite recruitment of doctors and nurses is documented in various developing countries due to low or no accountability of physicians or nurses leading to long wait times, absence of doctors, and limited consultation hours (Lewis et al. 1996; The World Bank 1994). When the quality of services is low, it acts as a disincentive for individuals to use those services and instead individuals bypass them for better services elsewhere, known in the literature as the bypassing hypothesis. Consistent with the bypassing hypothesis, we find evidence of a shift from small government facilities to large government facilities, conditioning on needing medical services.

Our paper fits in well in a literature on preventive care interventions. Many supply-side health interventions in developing countries are focused on primary health care which is used by the rural and poor population. Review of the literature suggests that the effectiveness of the intervention may vary by country and local characteristics. Many studies assess effects of access to services on child or infant mortality in various countries, and find mixed evidence (Lavy et al. 1996; Pitt et al. 1993; Rosenzweig and Schultz 1982). In this literature, it can be hard to disentangle the demand and supply sides of effects given the strong interrelationship between the two. A higher demand for health care leads to higher provision of health care facilities and a higher demand is observed when good quality healthcare is provided. Our paper complements this literature and offers an opportunity to partially disentangle the demand and supply effects. Thailand rolled out a universal health insurance coverage in 2001 which takes into account incomes, prices, and demand for specific services. Gruber et al. (2014) find that the increased funding to hospitals and reduced copays due to this program led to a significant increase in healthcare utilization and a fall in infant mortality. Given the universal health coverage in Thailand, everyone is guaranteed a basic access to health care, so demand-side variations are mostly driven by preferences for quality, not by affordability of health care. In the context of Thailand, a number of papers in economics and public health have examined effects of rural doctor incentives and a rural doctor recruitment program on rural doctor retention (Pagaiya et al. 2015; Techakehakij and Arora 2017). Our paper also completes the picture in this literature by showing how these incentive structures translate into changes in healthcare utilization and health outcomes in the population.

2. Data

We first present evidence that the policy was successful in increasing the number of doctors and nurses in the treatment areas. This is presented in Figure 1 and the data is collected from the Reports on Public Health Resource by Ministry of Public Health, Thailand. We see a clear jump in the number of nurses available per thousand population in the treatment areas after 2011 when the new graduates started working. There is also an increasing trend in the number of doctors in the treated areas since 2005, however not as stark as the increase in number of nurses. These two policies combined significantly increased health workers in the area at all facility levels; however, rural clinics were probably still not regularly staffed with doctors and many of the procedures were being performed by nurses. This could lead to lower quality of services provided in these facilities.

Figure 1: Nurse and Doctor Population in Thailand



Note: The graphs show the trends in nurses and doctors per thousand population in the treated and control areas overtime.
Data Source: Reports on Public Health Resource, Ministry of Public Health, Thailand

We use two repeated cross-sectional health surveys in this paper: The Multiple Indicator Cluster Surveys (MICS) and the Thai Health and Welfare Surveys (HWS). The MICS were designed to collect information on children and women around the world. In this paper, we focus on immunization and anthropometric outcomes from the children module in the 2005-06 and the 2016 14-province datasets. The 2005-6 wave covers all provinces in Thailand while the 2016 wave only contains 14 selected provinces from all areas of the country. The children module in both waves covers children age between 0–5 years. Given the nature of the surveys and that the survey is carried out once in a decade, most treatment data come from the 2016 MICS survey while most pre-treatment data comes from the MICS 2005-06 survey. In addition to the MICS, we also tap on the HWS for healthcare utilization outcomes. The HWS is a national-representative cross-sectional survey covering several aspects of public health. In this paper, we use the data from 2001, 2003, 2009, 2011, and 2013.

We analyze if the policies affected healthcare utilization by focusing on vaccinations children received. The vaccination data in the MICS mostly come from each child's vaccination card. To make the data consistent between the two waves, we exclude children without the vaccination cards.[3] Our main results focus on five vaccinations: Bacillus Calmette-Guern (BCG) for tuberculosis; the first oral polio vaccine (OPV1); the first vaccine for diphtheria, tetanus toxoids and pertussis (DTP1); the first hepatitis B vaccine (H1); and the first vaccine against measles, mumps and rubella (MMR1). For all vaccinations except the BCG, our outcome for each vaccination is a dummy indicator that is equal to one if a child has got that vaccine. Children who are too young and not yet eligible for the vaccine are excluded. The BCG is given at birth, and almost every child got the BCG. For this reason, we instead use a dummy variable for whether a child got it on time (within 3 days of birth). The OPV1, DTP1,

[3] Around 86% of all children got a vaccination card. We tested for selection based on the vaccination card availability and found that children in the treated area were less likely to have the vaccination card after the policies were implemented. By excluding the children without the vaccination cards, our results would be the lower bound.

and H1 are administered to the child after 2 months of birth and the MMR is administered to the child from 9 months to 1 year of birth. We also look at some standard anthropometric measures like HAZ and WAZ scores to look at malnutrition and health outcomes for children.[4]

Table I: Summary Statistics of Key Variables from the 2005-2006 MICS Data

	Treated Group			Control Group			
Variable	Mean	SD	N	Mean	SD	N	p-value
Vaccinations							
BCG	1.000	0.000	508	0.993	0.082	1,177	0.002
BCG (on time)	0.642	0.480	508	0.861	0.346	1,177	0.024
OPV1	0.986	0.119	489	0.990	0.098	1,135	0.006
DTP1	0.986	0.119	489	0.990	0.098	1,135	0.006
H1	0.994	0.078	489	0.996	0.066	1,135	0.004
MMR1	0.948	0.222	423	0.965	0.183	980	0.012
Anthropometry							
Weight	11.585	3.848	683	12.155	4.057	1,339	0.184
WAZ	-0.204	1.635	677	0.053	1.567	1,335	0.076
Height	84.813	14.535	680	85.911	14.473	1,336	0.684
HAZ	-1.000	1.753	680	-0.696	1.369	1,336	0.077
Child characteristics							
Female	0.486	0.500	689	0.492	0.500	1,395	0.023
Age	2.007	1.421	688	1.984	1.395	1,390	0.066
Household's and caretaker's characteristics							
Rural	0.579	0.494	689	0.518	0.500	1,395	0.023
Low income	0.936	0.245	689	0.871	0.335	1,394	0.013
Thai ethnicity	0.226	0.419	689	0.860	0.347	1,395	0.018
Caretaker's age	31.792	7.984	689	33.654	10.706	1,395	0.418
Female caretaker	0.997	0.054	689	0.988	0.110	1,395	0.004
Caretaker > elementary educ	0.091	0.288	689	0.153	0.361	1,395	0.015

Notes: p-values are from two-sample *t*-tests for differences in means.

Table I contains summary statistics of key variables from the 2005-2006 MICS data and shows that our treated group differed from others in almost every dimension prior to the policy changes. These differences, however, do not pose serious threats to our identification as pre-treatment trends in outcomes are similar among the two groups (shown in Appendix A1). In our sample, most children get the required vaccinations. In both the treated and control groups, we do not find severe cases of stunting or wasting. Children seem to be better nourished in the control group than the treated, with mean WAZ being 0.05 and mean HAZ being -0.7. About half of our sample is female children with an average age of about 2 years. The treated group is more rural, poor, and less educated. The caretaker is overwhelmingly female and above 30 in the sample. The treated region also has less people of Thai ethnicity than the control group.

[4] Height-for-Age Z Score (HAZ) is the number of standard deviations of the actual height of a child from the median height of the children of his/her age as determined from the standard sample. Weight-for-Height Z Score (WAZ) is the number of standard deviations of the actual weight of a child from the median weight of the children of his/her height as determined from the standard sample.

3. Methodology

We explore effects of the incentive programs using an event study analysis and a Difference-in-Difference (DiD) approach. The treated group includes children living in the Deep South: the provinces of Yala, Pattani, and Narathiwas. The control group consists of children in the rest of the 14 provinces. The time period under both approaches is defined based on exposure to the policies and hence varies with outcomes. The effects of the policy are staggered. First, during 2005–2010, only the extra hardship allowance was effectively in place because the newly recruited medical and nursing students were still in training. The first batch of the students graduated in March 2011 and started working in April–May 2011, so we see the cumulative effects of both the policies after the first quarter of 2011. Therefore, we divide the DiD treated period into two sub-periods: 2006 to the first quarter of 2011, and the second quarter of 2011 onward to accurately measure the impact of the policies. Lagarde et al. (2013) performed a discrete choice experiment on young doctors in Thailand and found that the doctors preferred an easy access to specialty training over a low to moderate hardship allowance. However, doctors with rural background were more responsive to the financial incentives than other doctors. Given the staggered implementation of different incentives and previous literature documenting differential impact of incentives on attracting health personnel (Lagarde et al. 2013), the treatment indicator is devised to capture these differential effects.

Let Y_{ict} be the outcome of interest for child i belonging to household-cohort c at time t. Then, the main DiD estimating equation can be written as

$$Y_{ict} = \beta_0 + \beta_1 Treat_p + \sum_{\tau=I,II}(\beta_2^{\tau} Post_t^{\tau} + \beta_3^{\tau} Treat_p * Post_t^{\tau}) + \delta' X_{ict} + \mu_c + \gamma_t + \epsilon_{ict}, \quad (1)$$

where $Treat_p$ is a dummy indicator equal to 1 if a child i lives in the treated province, p. ${Post^{I}}_t$ and ${Post^{II}}_t$ are dummy indicators for the two treated periods. X_{ict} is a vector of individual and household control covariates like caretaker's age, caretaker's education, gender of the child, and birth order. μ_c and γ_t are household-cohort and time fixed effects, respectively. The household cohorts are sets of households belonging to particular province, ethnicity, and income levels.[5] The error term ϵ_{ict} may be correlated within provinces, so we use province-clustered standard errors in all of our estimation.

By using household cohorts, we are controlling for household cohort specific time invariant characteristics. In essence, we are creating a pseudo panel which tracks household belonging to a particular province, Thai ethnicity, and wealth strata. The MICS survey has details on the assets of the household and not the income. Given the asset details and using principal component analysis, we create a wealth indicator and group households into three broad categories – low, middle, and high income – which we then use to create household cohorts. Since asset creation takes time and there is in general low mobility between wealth strata, we can observe households in a province with particular ethnicity and wealth levels to display similar unobserved behavior overtime. By creating these cohorts, we are better able to control for these time invariant unobservables since households belonging to these cohorts are expected to display similar time invariant characteristics. However, it should be kept in mind that since we are not observing the same caretaker over two rounds of survey, this analysis is unable to control for family level time invariant unobservable like child rearing ability of the caretaker.

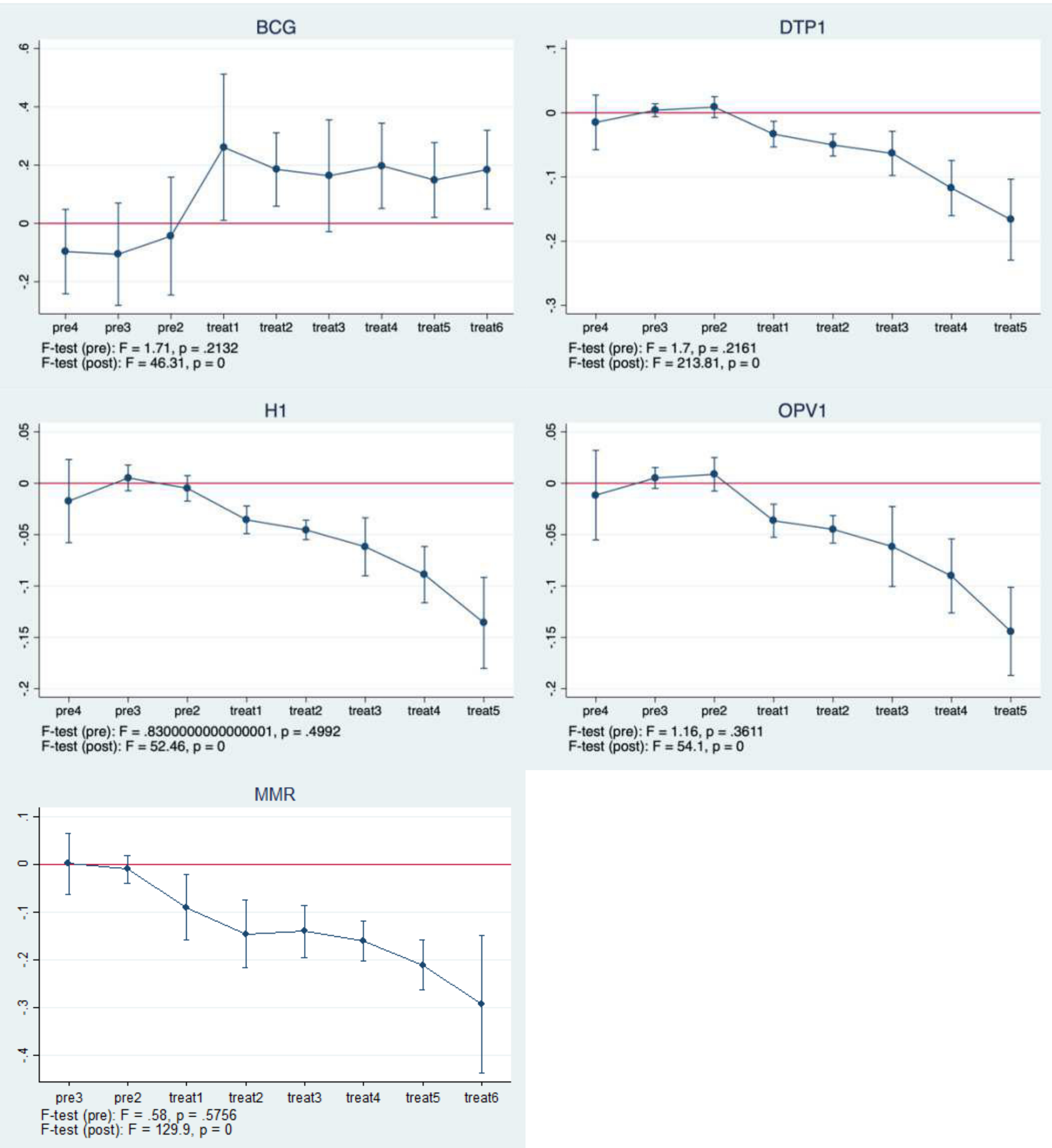
[5] These three variables are significant in all the OLS specifications, which makes us choose these three to create household cohorts. We also check for different specifications of cohorts including different characteristics and do not find a difference in the main results. These results are presented in Appendix A4.

Next, in section 6, we also explore heterogeneity in our regression results. We estimate equation (1) by subsamples and report $\hat{\beta}_3^{II}$. We also report the p-value for $\hat{\eta}_3^{II}$ from a pooled regression following equation (2) to illustrate if a difference between the two subsamples is statistically significant. Let V_{ict} be a dummy variable, such as a child's sex, that separates the sample into the subsamples, then the pooled regression equation takes the following form:

$$Y_{ict} = \beta_0 + \beta_1 Treat_p + \eta_1 Treat_p * V_{ict} + \sum_{\tau=I,II}\left(\beta_2^{\tau} Post_t^{\tau} + \beta_3^{\tau} Treat_p * Post_t^{\tau} + \eta_2^{\tau} Post_t^{\tau} * V_{ict} + \eta_3^{\tau} Treat_p * Post_t^{\tau} * V_{ict}\right) + \eta_4 V_{ict} + \delta' X_{ict} + \mu_c + \gamma_t + \epsilon_{ict}. \quad (2)$$

4. Event Study

Figure 2: Event Study Graphs for the Treated Provinces



Note: The graphs show the trends in BCG, DTP1, H1, OPV1, and MMR vaccines before and after the treatment. For each time period, we show a point estimate for the effect as well as a 95% confidence interval constructed from province-clustered standard error. The F-statistics for pre and post periods are noted below each graph.

We create an event-study graph for the treated provinces to show the effect of the policy on vaccinations.[6] Using the same notation as in (1) and (2), the estimating equation for the event study analysis can be written as

$$Y_{ict} = \alpha_0 + \sum_{\tau=-n}^{-2} \beta_\tau \, treat_p * I(t=\tau) + \sum_{\tau=1}^{m} \beta_\tau \, treat_p * I(t=\tau) + \delta' X_{ict} + \mu_c + \gamma_t + \epsilon_{ict}, \quad (3)$$

where τ is an index for the years before and after the treatment became effective. τ is equal to zero in the period that the policy became effective, is negative for the periods before that, and is positive for the periods after. We omit the period immediately preceding the effective period to eliminate any anticipatory effects that may be present due to the informal announcement of the policy before it is implemented. Using this study, we could test for the joint significance of pre-treatment years using the F-statistic.

The results are presented in Figure 2. After controlling for household cohorts and time fixed effects, we find that there are no noticeable trends in the pre-treatment period for vaccines. Consequently, F-test rejects the null hypothesis of joint significance of pre-treatment year effects. The vaccination rates for vaccinations given at 2 months from date of birth (DTP1, H1, OPV1) and after 1 year from the date of birth (MMR) fall after the implementation of the policy. However, we observe a marked increase in BCG vaccinations after the treatment. We also do an event study for other health care outcomes; however, we cannot rule out the presence of pre-trends in the variable of interest especially in HAZ scores. These graphs are presented in Appendix A2.

5. Results

The regression results based on equation (1) affirm the findings from the event study analysis—children were *less likely* to receive most vaccinations after the policy changes. In Table II, Columns (1)-(3), we gauge the effect of the treatment on vaccinations taken after 2 months of birth date and find a significant decrease in DTP1, OPV1, and H1 vaccinations, not controlling for household cohorts. In Table II, (4)-(7), we add household cohorts as additional controls and find a larger decrease in vaccination rates. The combined effect of the policies leads to a decrease in children getting the DTP1 vaccine by 8.4 percentage points, OPV1 vaccine by 7.5 percentage points, and H1 vaccine by 6.8 percentage points as seen in Table II columns (4), (5), and (6) respectively. The effect is even greater for MMR vaccine, which is given to the child at the age of 1 year. In Table II (7), we observe a decrease in probability of receiving MMR vaccine by 17.9 percentage points. The results are consistent across different specifications.[7]

We also look at immunizations received at birth, specifically the BCG vaccination. We find an increase in the BCG vaccination received on time across specifications after the policy is in effect. The onset of extra hardship monetary allowance immediately led to an increase in BCG vaccination rates, and the further influx of new health worker graduates in 2011 led to another round of increase in the BCG vaccinations. Columns (1) and (2) in Table III do not control for household-cohorts and find an increase in the vaccination rates by 0.23–0.25 percentage points after the first period and another increase by 0.2 percentage points after the second treatment in 2011. The results hold as we control for household-cohorts in specification (3) and (4) in Table III. The vaccination results overall point to the importance of the timing of the vaccination delivery. If the vaccination is delivered at birth, like the BCG, we see that the

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[6] Additionally, we also test the parallel trend assumption embedded in a DiD analysis to find if the evidence is causal. These graphs are presented in Appendix A1.

[7] The full set of results for all the vaccinations are presented in Appendix A3 for the interested reader.

policy is effective in increasing healthcare utilization. However, if the vaccinations are provided later on in a child's life, we see a decrease in utilization of the healthcare services.

Table II: After- Birth Vaccinations

	All Sample						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	**DTP1**	**OPV1**	**H1**	**DTP1**	**OPV1**	**H1**	**MMR**
Treat 1	0.00353 (0.945)	0.00312 (0.953)	0.000390 (0.964)	-0.0171 (0.758)	-0.0203 (0.719)	-0.0206* (0.051)	-0.0964 (0.209)
Treat 2	-0.0675*** (0.000)	-0.0488*** (0.000)	-0.0461*** (0.000)	-0.0840*** (0.000)	-0.0748*** (0.000)	-0.0682*** (0.000)	-0.179*** (0.000)
Explanatory Variables	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	NO	NO	NO	NO
Household Cohort FE	NO	NO	NO	YES	YES	YES	YES
Number of provinces	14	14	14	14	14	14	14
Observations	8589	8616	8616	8589	8616	8616	7843

Note: p-values in parentheses.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table III: At-Birth Vaccinations

	(1)	(2)	(3)	(4)
Dependent Variable	**BCG**	**BCG**	**BCG**	**BCG**
Treat 1	0.234** (0.001)	0.249*** (0.001)	0.277*** (0.000)	0.285*** (0.000)
Treat 2	0.197*** (0.001)	0.213*** (0.001)	0.231** (0.001)	0.237** (0.002)
Explanatory Variables	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Province FE	YES	YES	NO	NO
Household Cohort FE	NO	NO	YES	YES
Control provinces	All	All but South	All	All but South
Observations	8179	6901	8179	6901

Note: p-values in parentheses.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

We also explore the policy's second order effects on child health via the WAZ and HAZ scores. We do not find any statistically significant second order effect on child's weight and wasting. We do find some effect on child's HAZ scores, but pre-trends in these specifications cannot be eliminated and therefore should be interpreted cautiously. We present these results in Appendix A2. We also run various specifications of the estimation models as robustness checks and our results remain qualitatively similar to our main estimations. Our results are robust to an alternative definition of control units. We also test for the validity of the results if we do not include other southern provinces in our control units to account for spillover effects. We also check at the district level if the treatment is demand driven or endogenous and do not find any evidence.[8]

6. Heterogeneity and Channels

We find significant differences in vaccination rates for children being in the rural area, caretaker being educated, and being of Thai ethnicity. Table IV panel (A) shows stronger effects in rural areas than in urban areas, with rural population having a greater decrease in vaccinations like OPV1, H1, and MMR. OPV1 vaccination rate falls by around 8.7 percentage points for rural children while children in urban areas see a decrease of about 3.9 percentage points. Similarly, the rural population is 20.6 percentage points less likely to receive MMR while the effect on the urban population is only 8.7 percentage points. The combined effects of the policies lead to a higher decrease in DTP1, OPV1, and H1 vaccinations in non-Thai population by 3.4–5.5 percentage points vis-à-vis the Thai population as shown in Table IV panel (C). The non-Thai population also have a significantly higher probability of receiving the BCG vaccination on time. Given that the treatment region has a higher proportion of non-Thai population, we see more concentrated effects for this population. Heterogeneity by education are presented in Table IV panel (D). A child with a caretaker who is not educated would be less likely than the control group to receive the DTP1, H1, and OPV1 vaccinations by 12.5 percentage points, 11.1 percentage points, and 8.9 percentage points respectively. These effects are larger in magnitude than those for the educated subsample by 3–7.8 percentage points.

We also check for differences along the dimensions of income and gender of the child in Table IV panels (B) and (E). We do not find significant differences in vaccination rates along these dimensions. This could be partly explained by the prevalence of universal health insurance in Thailand such that any demand side mechanisms for health that may originate out of wealth of a family are taken care of. Thailand does not also display any son preference that is typical of some other Asian countries like India and China (Panda 2019; Jayachandran and Pande 2017; Das Gupta et al. 2003). These results suggest that the vaccination that is given along with the delivery of child like the BCG benefits from the presence of doctors and nurses in the area, and this positive effect is generally stronger in low socioeconomic status (SES) groups. However, we see evidence of a larger decrease in demand for vaccinations that are given 2 months after birth in the low SES population relative to those with higher SES.

In terms of policy implementation, we see a higher concentration of nurses in the rural areas while a higher concentration of doctors in the urban areas. The observed results are in line with the literature pointing towards low quality of services leading to mixed outcomes (Das et al. 2008; Filmer et al. 2000). Due to lower quality, people can decrease their demand for health care and/or substitute public facilities with private facilities providing higher quality care (Filmer et al. 2000). To explore this quality mechanism, we use the HWS Dataset to look at healthcare utilization in the three Deep South provinces. Table V presents these results. An indicator of quality of public facility, for which data is available in the HWS dataset, is preventive care. We observe evidence of a decline in the demand for preventive care by 3.1 percentage points in the affected provinces, possibly due to the lower quality of services in Table V (1). Table V (2) shows that the probability of households going for medical checkups decreased by 2.32 percentage points after the policy is in effect. Overall, people seek less care.

[8] Results available on request.

Table IV: Heterogeneity Analysis

		(1)	(2)	(3)	(4)	(5)
	Dependent Variable	**DTP1**	**OPV1**	**H1**	**MMR**	**BCG**
(A)	**Rural**	-0.030 (0.444)	-0.087** (0.002)	-0.0896*** (0.000)	-0.206*** (0.000)	0.276*** (0.000)
	N	4566	4880	4880	4439	4665
	Urban	-0.0542** (0.006)	-0.039** (0.044)	-0.0209*** (0.042)	-0.0871** (0.001)	0.209** (0.028)
	N	3721	3736	3736	3404	3514
	p-value	0	0.0002	0	0.025	0.259
(B)	**Low Income**	-0.083*** (0.000)	-0.076*** (0.001)	-0.065*** (0.000)	-0.181*** (0.000)	0.233** (0.003)
	N	3883	3895	3895	3498	3784
	High Income	-0.099*** (0.000)	-0.059*** (0.000)	-0.066*** (0.000)	-0.164*** (0.000)	0.198*** (0.000)
	N	4706	4721	4721	4345	4395
	p-value	0.2995	0.71	0.58	0.6523	0.741
(C)	**Thai**	-0.0348 (0.136)	-0.0284** (0.010)	-0.0312** (0.011)	-0.150*** (0.001)	-0.0260 (0.724)
	N	6568	6583	6583	6048	6252
	Non-Thai	-0.069** (0.004)	-0.083** (0.002)	-0.0713** (0.001)	-0.190*** (0.000)	0.259** (0.006)
	N	2021	2033	2033	1795	1927
	p-value	0.06	0.0016	0.0041	0.198	0.047
(D)	**Educated**	0.0473 (0.229)	-0.046*** (0.000)	-0.0585*** (0.000)	-0.174*** (0.000)	0.0676 (0.235)
	N	4621	5034	5034	4589	4734
	Not Educated	-0.125*** (0.000)	-0.111** (0.001)	-0.0885** (0.003)	-0.175*** (0.000)	0.278*** (0.000)
	N	3569	3582	3582	3254	3445
	p-value	0.0002	0.0021	0.0024	0.116	0.3964
(E)	**Female**	-0.0190 (0.839)	-0.0768*** (0.000)	-0.0648*** (0.000)	-0.193*** (0.000)	0.291*** (0.001)
	N	3870	4201	4201	3816	3972
	Male	-0.0882*** (0.000)	-0.071** (0.001)	-0.0672*** (0.001)	-0.161*** (0.000)	0.191** (0.004)
	N	4405	4415	4201	4027	4207
	p-value	0.8395	0.6291	0.85	0.8717	0.2118

Note: All the columns represent different regressions on various vaccinations in the second treated period. The first and third numbers in each cell are $\hat{\beta}_3^{II}$ from (1) estimated using two subsamples. Their respective p-values are reported in the parentheses. The p-values row states the p-value for $\hat{\eta}_3^{II}$ from (2) using the pooled sample. Stars denote statistical significance in the subsample estimates (*** at 1% level, ** at 5% level, * at 10% level).

We also observe a decrease in utilization of health services at small government facilities in the Deep South, conditioning on getting sick. We do not find any evidence of people falling sick less often in the sample, ruling out selection in Table V (3). For the people who do fall sick, there is a decrease in utilization of OPD and IPD services in the small government facilities by 9.9 percentage points and 31.3 percentage points respectively as shown in Table V (4) and (5). At the same time, Table V (6) shows there is an increase in IPD services sought at big government hospitals by around 28.4 percentage points. This implies that people might be bypassing the "lower" quality facilities to higher level ones. It is also possible that the policy might be effective at improving larger facilities, but not smaller ones.

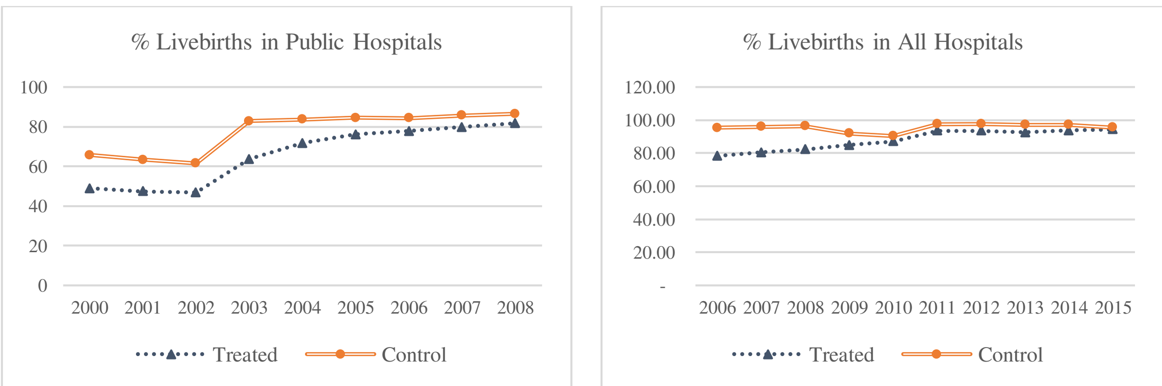
Table V: Channels

	Preventive Care		Utilization			
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**Preventive Care**	**Medical Checkups**	**Sick?**	**OPD (Small Govt.)**	**IPD (Small Govt.)**	**IPD (Big Govt.)**
Treatment	-0.0314**	-0.0232**	-0.0268	-0.0986**	-0.313**	0.284**
	(0.036)	(0.048)	(0.288)	(0.028)	(0.017)	(0.029)
Explanatory Variables	YES	YES	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Sample	Deep South	Deep South	Deep South	Deep South	Deep South	Deep South
Observations	10289	10289	10289	1918	590	590

Note: Explanatory variables include education level of the household, type of health insurance, age, gender, if the person is employed, ownership of the house, and material of the household. p-values are reported in parentheses.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

The only evidence of positive health outcome is increase in on-time BCG vaccinations after the treatment. The data provides two probable explanations. First, in Figure 3 we see an increase in live births at hospitals in the post treatment years. Since the BCG vaccination is given at birth, we see an increase in on-time delivery of the vaccination as people are already in the hospital for the delivery. Second, in Thailand, deliveries are usually done at hospitals while rural clinics are responsible for pre and postnatal care. We observe an increase in demand for delivery and health service utilization in the large government hospitals as they are perceived to be of superior quality than the rural clinics. This also explains the large concentrated decrease in utilization for preventive care services in the rural areas.

Figure 3: Percent Livebirths in Hospitals in Thailand



Note: Increase in births in hospitals after the policy implementation in the treated and control units.
Data Source: Public Health Statistics, Ministry of Public Health of Thailand

7. Conclusion

This paper provides evidence on the effectiveness of a large scale supply side health intervention in Thailand. Using two different household level datasets, we find a decrease in healthcare utilization for preventive care vaccinations that are administered after 2 months and 1 year of birth to the child. At the same time, we observe an increase in on time BCG vaccinations for children. We also observe heterogeneity in the population with more concentrated effects on the rural, uneducated, and non-Thai sections of the population. We explore the channels through which the results are manifested. We provide quality of health care delivery as a mechanism for the reduced utilization in small rural healthcare facilities. This paper emphasizes the need to evaluate the quality of healthcare provision especially for preventive care services in the rural areas and adds to the rich literature on the persistent links between quality, quantity, and impact of health policy.

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