Effects of Public Health Insurance in Nepal*

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Expanding access to health insurance in low- and middle-income countries is a policy priority, but evidence on its effects remains limited. This paper provides new and timely evidence on the effects of government-led health insurance program in Nepal, a country uniquely suited given the program's staggered rollout across districts over time. Using novel and rich administrative health data from 2014-2022, I examine program's impacts on health care utilization, health outcomes and access to higher quality health care. To ensure a clean identification, I exploit a natural experiment created by a staggered rollout. The differences in differences design compares districts that have introduced the insurance program with districts that have yet to do so. I employ the Callaway and Sant'Anna (2021) estimator to address the potential biases from treatment effect heterogeneity, and as long as the parallel trends hold between these two groups, I can isolate the causal effect of health insurance.

Keywords: Health Insurance, NHIP

JEL-Classification: H51, I12, I13, I14, J16, O15

*Correspondence: sabin.subedi@strath.ac.uk. This paper is a work in progress and only preliminary results are presented. It is submitted in this format rather than as an extended abstract because of the need to explain the background about the health insurance program. All mistakes are my own.

1 — Introduction

The development of a well-functioning health care system marks an essential step down the path of national economic development. A common roadblock facing lower-middle income countries in this progression is the presence of high out-of-pocket medical costs, which leave households financially vulnerable to health shocks (Chetty and Looney 2006). Accordingly, the expansion of health insurance is often a paramount priority for developing nations (Kurowski et al. 2023; Miller, Pinto, and Vera-Hernández 2013), with the establishment of Universal Health Coverage (UHC) as the ultimate objective. While previous authors have outlined the importance of UHC in improving both public health (Kurowski et al. 2023; WHO and Bank 2023) and health care utilization (Das and Do 2023; Fitzpatrick and Thornton 2019; Huang and Liu 2023; Miller, Pinto, and Vera-Hernández 2013), there remains no consensus as to the impact of health insurance on health outcomes in lower-middle income countries.

To address this absence, I study the launch of the National Health Insurance Program (NHIP), a Nepalese public health insurance program that aimed to prevent health-related expenditures driving households into poverty and achieve UHC in Nepal. It was intially piloted in three districts in 2016 and gradually expanded to all 77 districts by 2022. I study this rollout by compiling monthly data from all the districts from 2014 to 2022 on health care utilization and various health outcomes. Overall, this unique dataset - the first of its kind compiled in Nepal - allows me to study the impact of health insurance on health care seeking behaviours. Further, I study the disparities in accessing health care and also impact on population health outcomes.

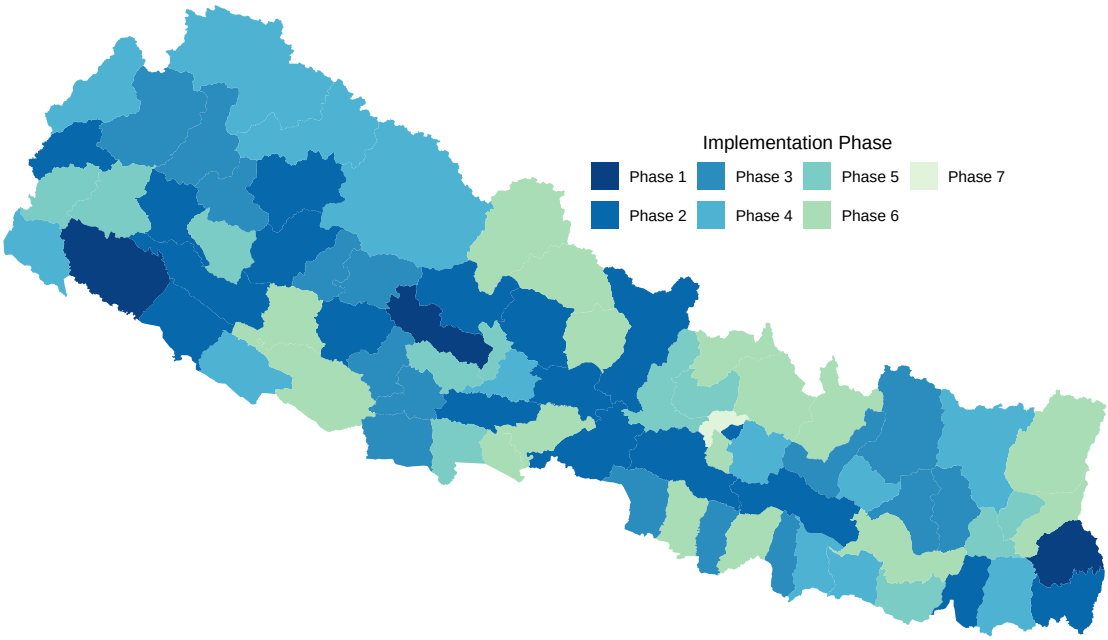
I use differences in differences methodology to get the causal impact of eligibility on health insurance by exploiting this natural experiment where the insurance was rolled out in phases over the years, and employ the Callaway and Sant'Anna (2021) estimator to address methodological challenges in analyzing staggered policy rollouts, providing more credible causal estimates by accounting for treatment effect heterogeneity.

2 — Background

2.1. The National Health Insurance Program of Nepal

National Health Insurance Program (NHIP) is a public health insurance program implemented by the governemtn of Nepal starting in 2016 with the major objective of reducing out-of-pocket (OOP) health expenditure of households. In 2017, Health Insurance Board (HIB) was established to implement health insurance nationwide with a mandate of covering every citizen under health insurance. Figure 1 shows the phasewise implementation of health insurance in various districts from 2016 to 2022.

Figure 1 — Coverage of Health Insurance in Nepal



Source: Authors own calculations based on the data collected from annual reports, press released and notices.
Notes. This figure illustrates the spatial variation of the coverage of National Health Insurance Program across different districts from 2016 to 2022

NHIP is a voluntary insurance program, where it receives contribution from households and has to be renewed annually. A family of five members can register for health insurance at the annual premium of NRs 3,500 (USD 25.23) [1], with any additional member costing NRs 700 (USD 5.05). Once registered the members of NHIP are entitled to free care upto maximum of NRs 100,000 (USD 720.96) per family per year. And additional members get coverage of NRs 20,000 (USD 144.19). Alongside this, government also provides subsidies to ultra-poor, senior citizens, disabled and patient of selected terminal diseases. Elderly members above the age of 70 with selected terminal diseases receive additional coverage of NRs 100000 (USD 720.96) (HIB 2024).

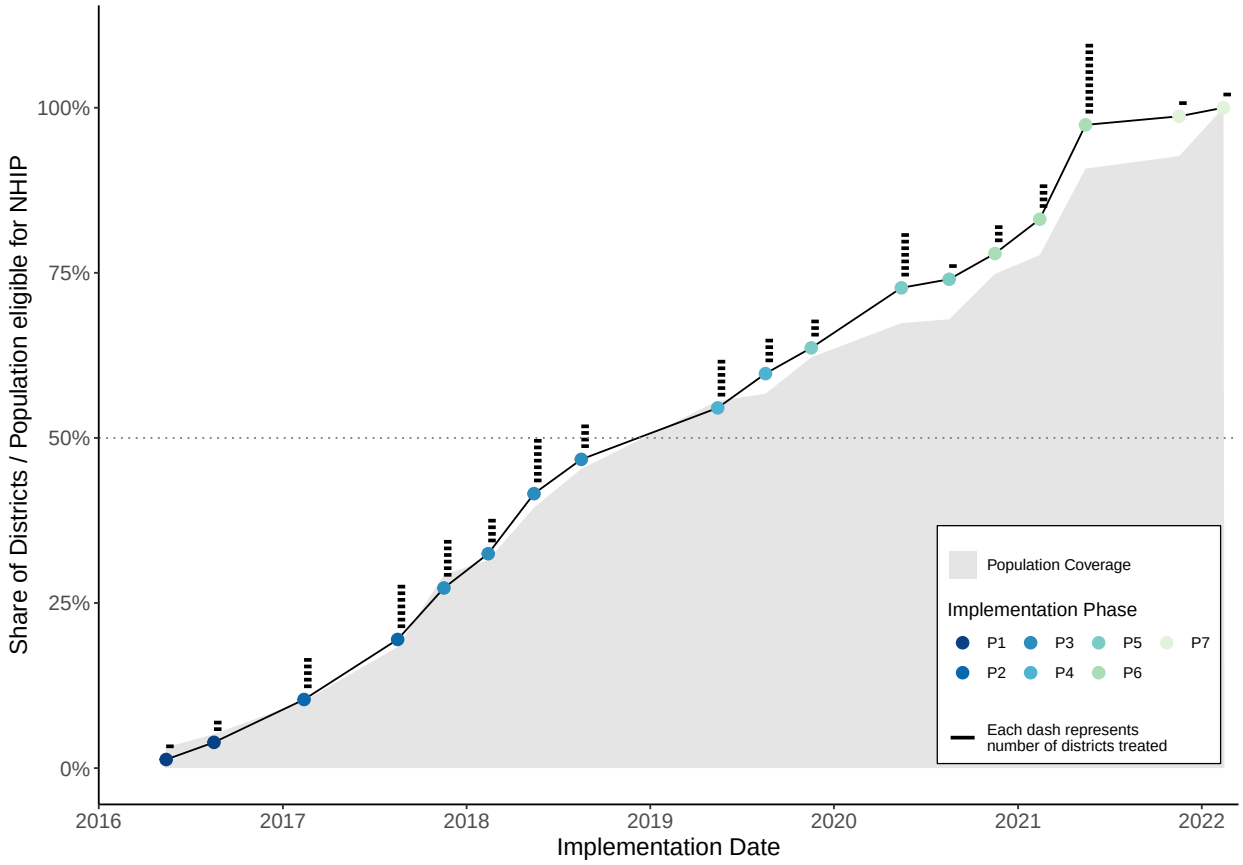
NHIP generously covers all preventive, curative, promotive, inpatient, emergency, surgery, medicines, diagnostics, rehabilitation and health aid equipments, alongside covering upto NRs 2000 (USD 14.42) of emergency ambulance service. It excludes services like expensive medical aid equipments, plastic surgery, most dental services and artificial insemination. Households during the registration select their preferred first point of contact (health care centers), which provides them facilities and if needed refers them to secondary care. It is a completely cashless system which does not require any payment at any point.

2.2. Rollout of NHIP

The rollout of the National Health Insurance Program (NHIP) was implemented in phases at the district level which are second level of administrative division as shown in Figure 1. Figure 2 shows the rollout of the NHIP program from 2016 to 2022. The rollout of the insurance does not have any specific dates every year when it is implemented due to administrative factors, and there was no prior public knowledge of when the health insurance would be started or in which group of districts. There was a delay of 3 months between the registration into health insurance and the use of health insurance.

1. USD 1 = NPR 138.7 at the time of writing

Figure 2 — Rollout of the National Health Insurance Program



Source: Authors own calculations based on the data collected from annual reports, press released and notices.
Notes. This figure illustrates the implementation of the National Health Insurance Program across different districts from 2016 to 2022. Dash at each point indicates the number of districts that were newly covered by health insurance at that time.

3 — Data

3.1. NHIP Rollout

I track the implementation of health insurance through survey of annual health reports of Department of Health Serives (DoHS), notices and press releases from HIB. I create a rollout data for each district including exact date of commencement of registration and the date of implementation of health insurance.

3.2. District Health Information System

I use comprehensive data from District Health Information System (DHIS2) for this study. DHIS collectes monthly data on visits, use of health services, referrals, family planning services, immunization and data related to diseases like malaria, leprocy, HIV Aids, Tuberculosis among others. It collects data for both public and private health services, but it is not compulsory for private sector. However, preceding the implementation of health insurance collection of data via DHIS2 was one of the priorities. Almost all of the empaneled health care institutions provide data through DHIS2.

4 — Empirical Method

4.1. Empirical Strategy

My primary goal is to indentify the causal effect of health insurance on various important outcomes. Simply comparing districts that implement health insurance to those who do not implement health insurance results in bias because those districs that implement health insurance might differ in many unobservable ways that also correlate with each of their potential outcomes.

To get away from this bias, I use the gradual rollout of the health insurance and use a Difference in Differences (DID) method for casual identification of the effect of health insurance program. This method exploits the variation in timing of implementation, with some districts implementing earlier than others. It compares the evolution of outcomes for the earlier treated groups with groups not yet treated, controlling for district time invariant confounders and time-specific effects that impact all districts.

4.2. Estimator

Prior literature has shown that the popular two-way fixed effects (TWFE) estimator, where the outcome is regressed with the group and time fixed effects, can be biased in a staggered timing setup because it imposes an assumption of homogenous effects in treatment timing and homogenous effects in groups. This homogeniety is unlikely because of various reasons including that districts that implement health insurance earlier might get efficient with time with better enrollment strategies and service delivery. If there is any treatment timing heterogeneity, the static TWFE estimator can be biased due to negative weight problem (Borusyak et al., 2024; de Chaisemartin

and D'Haultfœuille, 2020; Goodman-Bacon, 2021) (see Roth et al. (2023) for elaboration). There are various estimators for different set of situations in a staggered adoption of DID. And the specific choice of estimator will depend on the type data, data quality and context.

I use Callaway and Sant'Anna (2021) (CS) estimator in this study to deal with treatment timing and treatment group heterogeneity to estimate the intention-to-treat (ITT) effects of health insurance eligibility. I do so firstly by aggregating the data at quarterly level. Y_{it} is the outcome for district *i* at time *t*. CS estimator estimates the ATT effects for group *g*, which is treated at time *t*. In my estimation *g* is defined as the cohort of units *i* (districts) that implement the treatment in the same period *t* (quarter-year). CS estimator works with a relatively more intuitive set of control groups, which in my case are those districts who have not implemented the health insurance by time t, known as "not yet treated" groups in the literature. CS estimator also imposes a weaker parallel trends assumption because it only relies on post treatment parallel trends, rather than imposing parallel trends for all the districts and time and is more efficient when the outcome might be serially correlated like in this scenario (Roth et al. 2023). CS estimator also provides an easy way of incorporating anticipation periods. And although I argue that the timing of treatment is quasi-random, CS estimator also accommodates the inclusion of covariates in case parallel trends assumption is only satisfied under inclusion of covariates.

I define G as the first quarter when a district *i* becomes first treated. I set up the estimation using potential outcomes framework where $Y_{it}(0)$ is the untreated potential outcome of the district *i* at time *t* if they remain untreated. $Y_{it}(g)$ is the potential outcome of the district *i* at time *t* if they are first treated in quarter *g*. $G_{ig}(0)$ is a dummy variable that takes the value 1 if district *i* is eligible at quarter *g*. The first cohort to be treated in my case is on quarter 9. Thus, $g=9,..,\tau$.

So the potential and observed outcomes for district *i* can be defined as follwing:

$$\mathrm{Y}_{it} = \mathrm{Y}_{it}(0) + \sum_{g=9}^{\tau} (Y_{it}(g) - Y_{it}(0)) \cdot G_{ig} \tag{1}$$

I will be estimating group-time ATT effect defined as:

$$\mathrm{ATT}_{gt} = \mathbb{E}_{gt}[Y_t(g) - Y_t(0) \mid G_g = 1] \tag{2}$$

CS estimator allows aggregation of all the group-time ATT effects to get a summary measure

of the effect of health insurance on the outcome. For the main analysis I use "group" aggregation as the measure of overall ATT effect. The group overall ATT effect can be defined as:

$$\theta^0_{sel} = \sum_{g \in G} \theta_{sel}(g) P(G = g \mid G \leq \tau) \tag{3}$$

where

$$\theta_{sel}(\tilde{g}) = \frac{1}{\tau - \tilde{g} + 1} \sum_{t=\tilde{g}}^{\tau} ATT(\tilde{g}, t) \tag{4}$$

$\theta_{sel}(\tilde{g})$ is the average ATT effect of health insurance eligibility among all the districts *i* in cohort $\tilde{g}$ across all post treatment effects. Thus θ^0_{sel} first calculates the average ATT effect for each cohort across all time periods, and then averages across all cohorts to give the summary measure.

I also estimate dynamic ATT, which are event study type estimates that show how the effects evolve over time. Assuming *e* as quarter since adoption such that, *e* = *t*-*g*, dynamic ATT can be defined as:

$$\theta_{es}(e) = \sum_{g \in G} 1\{g + e \leq \tau\} P(G = g \mid G + e \leq \tau) \cdot ATT(g, g + e) \tag{5}$$

$\theta_{es}(e)$ is the average effect for all the districts that are treated exactly *e* period, weighted by the probability that a district was eligible for health insurance in quarter *g*, conditional on being observed for *e* quarters after the treatment.

There are various key assumption that is essentialy for the validity of my identification strategy. The first assumption is that the treatment is irreversible, meaning that once the health insurance is implemented these districts do not go back to not having health insurance eligibility. This is a non-issue in our case, because once the treatment switches on, it is always treated. Second, this strategy Equation 2 provides a causal interpretation if conditional parallel trends assumption Equation 6 holds. When there is a known $\delta \geq 0$, for each $g \in G$ and each $(s, t) \in \{9, \ldots, T\} \times \{9, \ldots, T\}$ such that $t \geq g - \delta$ and $t + \delta \leq s < g$,

$$\mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid X, G_g = 1] = \mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid X, D_s = 0, G_g = 0] \tag{6}$$

Here δ captures anticipation effects. CS estimator has limited anticipation assumption which means that the individuals do not change their behaviour just before the implementation of health insurance in anticipation of health insurance or even if they do, it is within a clearly defined period. In my context during the first time of implementation the difference in time of registration and eligibility to use health insurance is about 3 months. So I use one quarter as anticipation period to account for this delay. Equation 6 imposes parallel trends assumption between group g and group not yet treated by time $t + \delta$, meaning that in the absence of NHIP implementation, the difference in potential outcomes between health insurance eligible and not yet eligible districts would have evolved similarly. And using one quarter as anticipation period means that the parallel trends assumption is now evaluated relative to period before registration. This is likely to hold because I argue that the timing of implementation can be considered as quasi-random because the order of rollout was not in any public domain knowledge, and the actual timing of implementation also was the function of administrative delays. This assumption cannot be tested directly, but I will inlcude event study like plots to visually inspect pre-trends. However, pre-trends is neither necessary nor sufficient to prove parallel trends, so I include some falsification tests to show that health insurance has no effect on unrelated outcomes. It is important to note that Equation 6 restricts the observed pre-treatment trends, meaning that the outcomes evolve parallelly both in earlier and later periods.

4.3. Inference

CS estimator can be estimated using outcome regression, inverse probability weighting (IPW) and doubly roubust methods. Although the identification remains the same with all the methods, doubly robust method is more robust to misspecification compared to the other two (Sant'Anna and Zhao 2020). Therefore in all my specification I use doubly robust method, with standard errors clustered at the district level with bootstrapping for 1000 iterations. All the confidence bands reported are simultaneous confidence bands, which are wider than the pointwise confidence bands. I use them because they take into account the dependency across group-time average treatment effect and asymtotically cover the whole path of these effects (Callaway and Sant'Anna 2021). I use short gaps (varying base period) for the dynamic ATTs, which means that I estimate the treatment effect if the treatment had occurred in that period. However, choosing short gap

over long differences (universal base period) does not affect my interpretation or the look of the event study plot, which is mainly because the post adoption ATTs are same regardless of the base period.

5 — Results

5.1. Effects of health insurance on health visits

I show the effects of eligibility of health insurance on hospital visits in Table 1. The outcome is aggregated at the quarterly periods for each districts and I use group aggregate group time effect (AGGTE) from the CS estimator for the analysis of overall treatment effect. In Table 1 all of the outcomes are log transformed for easy interpretation. I show that log transformation does not change my interpretation in Table A1, where I show the untransformed effects compared to the pre-treatment averages which are comparable to log transformed results. Following Roth and Sant'Anna (2023), event studies are shows for log transformed outcomes.

I find that eligibility of health insurance increases the total clients served (which includes all inpatient, outpatient and emergency services) by health service providers by 15.87 percent. In our dataset we also have information about total new clients served, which essentially calculates visits from patients that did not visit hospital in the past. This distinction allows us to also glance if the effect is driven only by people that already used to visit these health serivce providers, which could be those people that can either afford these health services or are already sick. I see that health insurance increases the total new clients served by about 14 percent. Although it is yet unclear from these estimates if these visits are from those population that was the main target of health insurance. I see similar effects on Total outpatient department (OPD) visits, which increases by 15 percent and new OPD visits increase by 14 percent.

Table 1 — Health Insurance Eligibility on Health Visits

	Total Clients Served	Total New Clients Served	Total OPD Visits	Total New OPD Visits
Model:	(1)	(2)	(3)	(4)
Group Aggregation				
Is NHIP eligible = 1	0.1331***	0.1052***	0.1281***	0.1169***
	(0.0234)	(0.0240)	(0.0307)	(0.0358)
Fit statistics				
Number of Cohorts	17	17	17	17
Number of Time Periods	30	30	30	30

Note: All of the outcomes are log transformed

Clustered (District) standard-errors in parentheses bootstrapped with 1000 iterations.

Estimation Method: Doubly Robust.

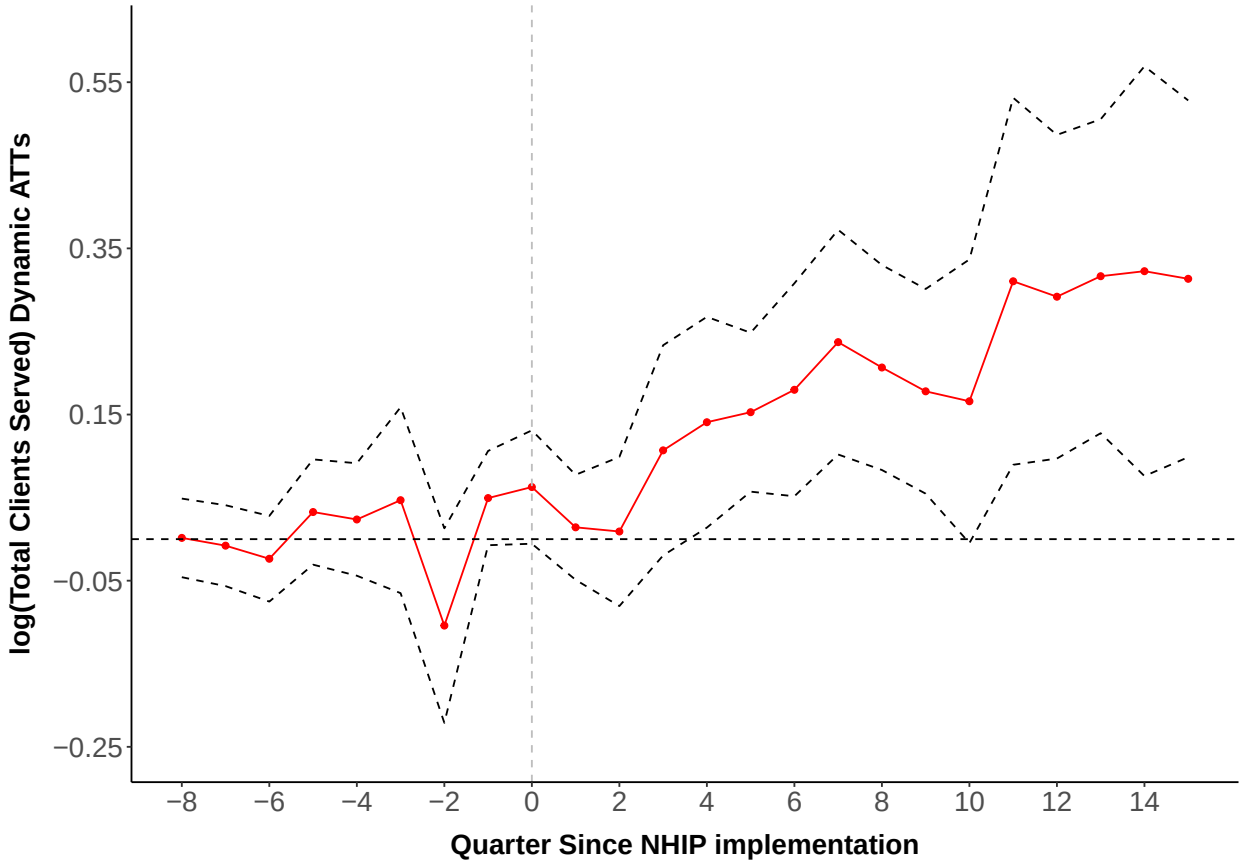
Control Group: Not Yet Treated, Anticipation Periods: 1.

Signif. Codes: *** 99% ** 95% * 90% uniform confidence band does not include 0.

5.2. Dynamic ATT

I show dynamic ATT from the CS estimator in Figure 3 . It is a event study like plot, that also allows to see pre-trends. I show dynamic ATT for untransformed outcomes in Figure A1. For these dynamic ATTs, I use varying period as an option. It means that I am essentially estimating short-gaps instead of long differences like in TWFE event studies. In other words with a varying base period,the estimates are the estimated treatment effect if the treatment had occurred in that period. It shows how the effects evolve over time. I see that the effects of health insurance are large. The effect starts to become significant after five quarters of implementation. The dynamic ATTs for all the outcomes in Table 1 behave in the same way. This could possibly be due to two reasons, firstly the coverage is not that high early on, and also the awareness about the usage of insurance also picks up after the implementation.

Figure 3 — Total Clients Served Dynamic ATTs



Notes. This figure shows dynamic ATTs for total clients served by health service providers. The outcome is log-transformed total clients served, x-axis shows weeks since NHIP implementation, quarter 0 being the first implementation quarter. The black dotted lines represent a 95% uniform confidence interval.

5.3. Female Share

Table 2 — Health Insurance Eligibility on TCS age group

	1	2	3	4
Model:	(1)	(2)	(3)	(4)
Group Aggregation				
Is NHIP eligible = 1	0.0917***	0.1461***	0.1420***	0.1812***
	(0.0245)	(0.0292)	(0.0241)	(0.0296)
Fit statistics				
Number of Cohorts	17	17	17	17
Number of Time Periods	30	30	30	30

Note: All of the outcomes are share of female visits

Clustered (District) standard-errors in parentheses bootstrapped with 1000 iterations.

Estimation Method: Doubly Robust.

Control Group: Not Yet Treated, Anticipation Periods: 1.

Signif. Codes: *** 99% ** 95% * 90% uniform confidence band does not include 0.

5.4. Falsification Exercise

Although NHIP funded for pregnancy-related delivery services, I do not expect NHIP to have any substantial effect on outcomes related to maternal mortality, still births, institutional delivery among others. This is because of Safe Motherhood Program that was launched in 2009 to reduce maternal/neonatal moribidity and mortality, increase institutional delivery, increase the share of births attended by skilled professionals and other factors related to safe pregnancy. It was implemented nationwide at the community level providing incentives for institutional delivery via free transportation, incentivising antenatal care and providing institutional delivery services for free. It was eligible in any public health facility with a birthing facility for any mother and newborn who are a Nepali citizen. In this sense, the Safe Motherhood Program elminated any financial barriers that NHIP would have otherwise addressed in accessing these kind of services. I show the results of the falsification exercise in Table 3. Consistent with the expectations, I

show that health insurance has no effect on outcomes related to the safe motherhood program across range of different outcomes. I show the effects with various simple, group and calendar aggregation and all the estimates cannot be distinguished from zero.

Table 3 — Health Insurance Eligibility on Safe Motherhood

	Share of home delivery	Share of delivery attended by SBA	Maternal Mortality Ratio	Ratio of still birth (per100 birth)
Model:	(1)	(2)	(3)	(4)
Simple Aggregation				
Is NHIP eligible = 1	-1.0325	1.5733	12.4370	0.6529
	(0.7063)	(1.0995)	(7.6634)	(1.6171)
Group Aggregation				
Is NHIP eligible = 1	-0.3403	1.5517	6.8191	1.6647
	(0.7386)	(0.8783)	(6.2901)	(1.7483)
Calendar Aggregation				
Is NHIP eligible = 1	-0.5074	0.9444	7.8861	0.4202
	(0.6344)	(0.9356)	(5.4218)	(1.4762)
Pre-Treatment Mean	7.16	89.17	12.27	17.11
Fit statistics				
Number of Cohorts	17	17	17	17
Number of Time Periods	30	30	30	30

Note: Clustered (District) standard-errors in parentheses bootstrapped with 1000 iterations.

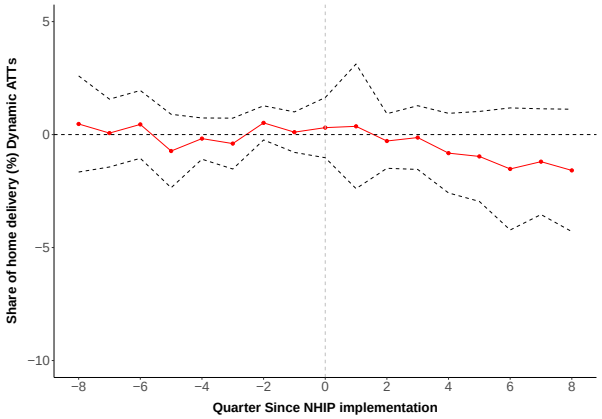
Estimation Method: Doubly Robust.

Control Group: Not Yet Treated, Anticipation Periods: 1.

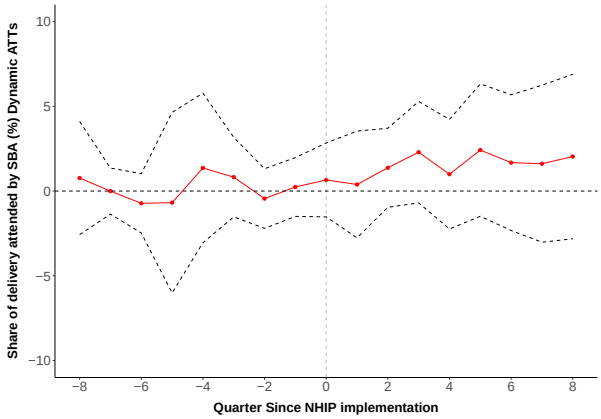
Signif. Codes: *** 99% ** 95% * 90% uniform confidence band does not include 0.

I show the dynamic ATTs in Figure 4. The dynamic ATTs further show that the effect on these variables cannot be distingushed from zero throughout the study period.

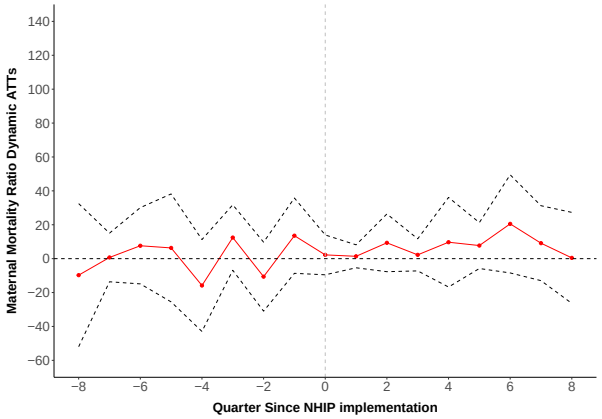
Figure 4 — Dynamic ATTs for Safe Motherhood outcomes



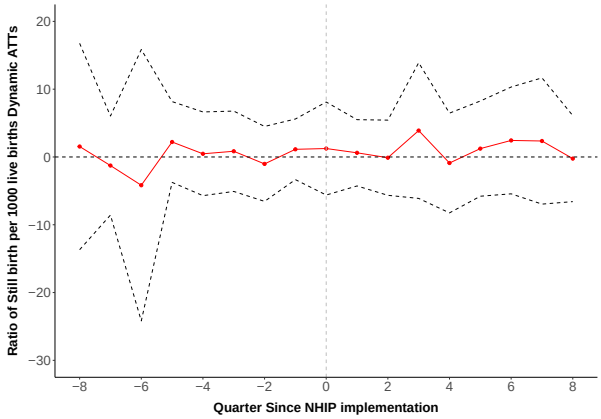
(a) Share of home delivery



(b) Share of delivery attended by SBA



(c) Maternal Moratlity Ratio



(d) Ratio of Still Birth

Note: Panel (a) shows the dynamic ATTs for share of home delivery. Panel (b) shows dynamic ATTs for share of delivery attended by skilled birth attended. Panel (c) shows dynamic ATTs for maternal mortality ratio. Panel (d) shows dynamic ATTs for ratio of still births per 1000 live births. These dynamic ATTs are from CS model, where x-axis is quarter since NHIP implementation and y-axis is outcome. The black dotted lines represent a 95% uniform confidence interval.

This null result supports that the main results are not driven by broad improvements in healthcare services or district-specific trends, making the causal interpretation of the main results credible.

6 — Conclusion

This paper provides preliminary evidence on the effects of Nepal's National Health Insurance Program using a staggered difference-in-differences design. Our findings indicate that health insurance eligibility increases healthcare utilization across multiple measures, with total clients served increasing by approximately 15.87% and new clients by 14%. These effects become significant after approximately five quarters of implementation, suggesting a gradual adoption process.

As this is ongoing research, several aspects remain to be explored. Future iterations will examine heterogeneous effects across demographic groups, analyze impacts on specific health outcomes, investigate cost-effectiveness, and further explore potential mechanisms driving these results. Additional robustness checks and placebo tests will also be conducted to strengthen causal claims. This preliminary analysis suggests that government-led health insurance in Nepal has meaningful impacts on healthcare access, contributing to the broader literature on health insurance effects in developing economies.

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A — Appendix

Table A1 — Health Insurance Eligibility on Health Visits (per 1000 population)

	Total Clients Served	Total New Clients Served	Total OPD Visits	Total New OPD Visits
Model:	(1)	(2)	(3)	(4)
Group Aggregation				
Is NHIP eligible = 1	39.7522***	17.5118	38.0590***	28.6267***
	(7.3389)	(9.2275)	(7.2238)	(5.6907)
Pre-Treatment Mean	267.71	222.04	239.28	199.67
Fit statistics				
Number of Cohorts	17	17	17	17
Number of Time Periods	30	30	30	30

Note: All of the outcomes are per 1000 population

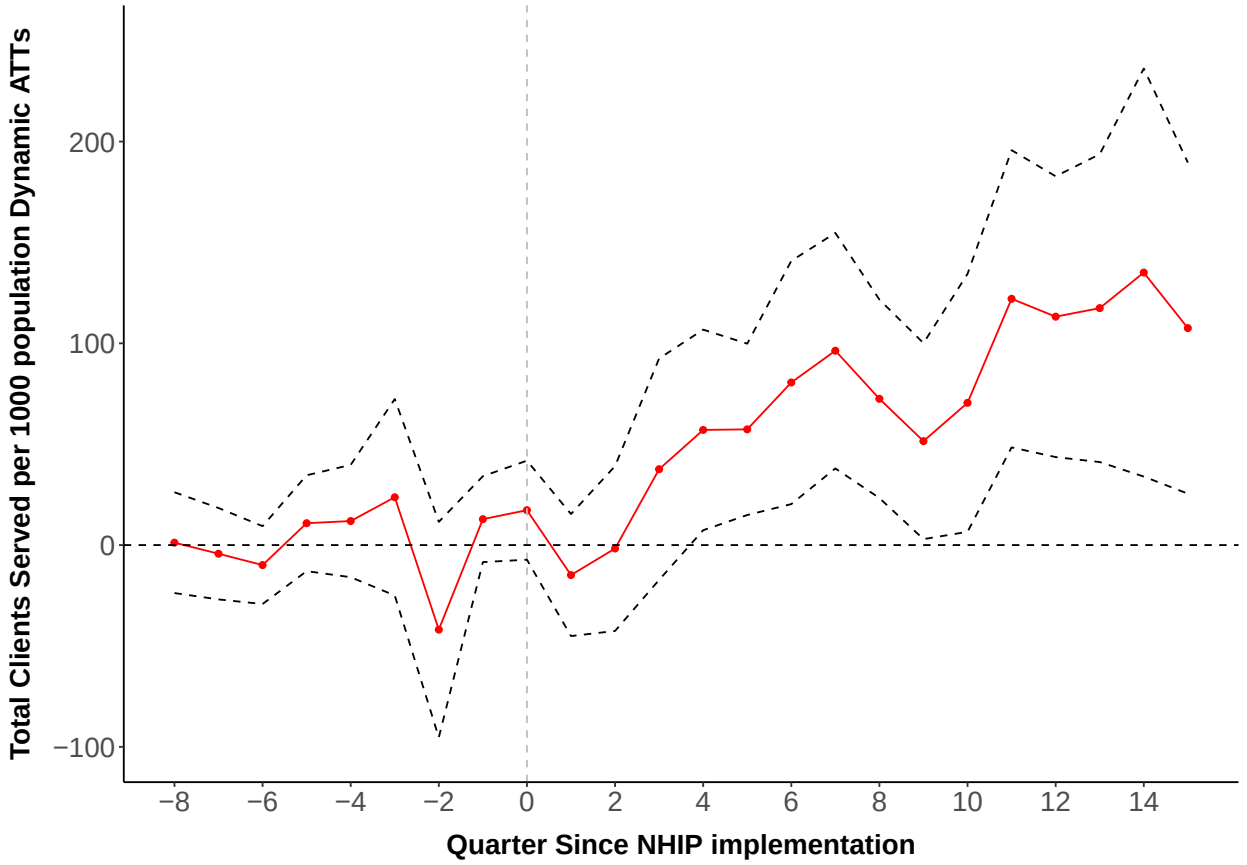
Clustered (District) standard-errors in parentheses bootstrapped with 1000 iterations.

Estimation Method: Doubly Robust.

Control Group: Not Yet Treated, Anticipation Periods: 1.

Signif. Codes: *** 99% ** 95% * 90% uniform confidence band does not include 0.

Figure A1 — Total Clients Served per 1000 population Dynamic ATTs



Notes. This figure shows dynamic ATTs for total clients served per 1000 population by health service providers. The outcome is total clients served per 1000 population, x-axis shows weeks since NHIP implementation, quarter 0 being the first implementation quarter