A thesis submitted for the degree of Doctor of Philosophy

Essays in Health and Development Economics

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Declaration of Authorship for Co-authored Work

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I confirm that the thesis I am presenting has been co-authored with Professor Melanie Lührmann. Within this partly co-authored work, I declare that the following contributions are entirely my own work:

I declare that the first chapter of my thesis is co-authored. The Center for Health Financing Policy and Health Insurance Management, Faculty of Medicine, University of Gadjah Mada (PKP-MAK) granted a license to use the National Socio-Economic Survey (Susenas) and the Village Census Data (PODES), and I have conducted some of the analyses under the supervision of Professor Melanie Lührmann.

I declare that the second chapter of my thesis is not co-authored and it is entirely my own work. I downloaded the data from the RAND Indonesian Family Life Survey (RAND IFLS) and have conducted all of the analyses independently.

I declare that the third chapter of my thesis is not co-authored and it is entirely my own work. I downloaded the data from the Study of the Tsunami Aftermath and Recovery (STAR) and have conducted all of the analyses independently. I also co-authored a separate paper with Dr. Rozana Himaz that investigates the direct and indirect effects of the 2004 tsunami and is submitted for publication.

Daim Syukriyah

Abstract

One of the basic requirements for a country to have strong economic growth is a qualified healthcare system. A healthcare system that emphasises providing high-quality services for everyone especially the poor, is a foundation to improve population health and reduce health inequity. Good health is associated with the economic development of a country (Bloom et al., 2001; Weil, 2014). Healthier individuals are likely more productive, have a higher life expectancy, have more opportunities to cultivate their potential to develop their skills and knowledge, and subsequently, increase demand for their labour. Having high labour productivity, people will be optimal at their work, earn more incomes, and be financially well-off (Jack and Lewis, 2009).

Since health is an important contributor to a country's economic growth, it is the responsibility of the government to improve the health of its people and ensure everyone has access to healthcare services. While many developed countries have an established healthcare system, this is not the case with many developing countries. Indonesia, for example, has faced various challenges to reduce inequality of access to healthcare for everyone across the country. Having around 17,000 islands and being the fourth-largest population, the country has to find the appropriate policies to address specific issues, including health. This thesis comprises three empirical chapters that look into the effects of the Indonesian government's policy reforms on health-related outcomes such as health insurance coverage, healthcare utilisation, private health spending, access to safe drinking water, and its subsequent impact on children's health. The third chapter of the thesis examines the impact of a disastrous tsunami following a 9.3 Richter magnitude earthquake that struck the coastal areas of the Indian Ocean among the affected households living in regions with different damage intensities.

In the first chapter, I assess a policy reform aimed at improving poverty targeting that came effectively in 2013 in Indonesia and extending the country's social health insurance (Jamkesmas) for the bottom 40% of households. Having developed the proxy means testing-based poverty database, Jamkesmas's eligibility was tied to it starting in 2013. I employ an event study method using Indonesia's National Socio-economic Household Survey (Susenas) data from 2011-2013 and utilise quarterly information from the household interview dates to estimate the impacts

of the reform on health insurance coverage, healthcare utilisation, and out-of-pocket healthcare expenditures across five poverty quintiles, constructed from per capita consumption spending. By interacting quarterly period information of the survey with households' poverty quintiles, I am interested in observing whether changes are seen in the aforementioned outcomes of interest after quarter 1 of 2013 relative to the baseline period in quarter 1 of 2011.

In the second chapter, I look at the effects of the first phase of Indonesia's community water supply programme (PAMSIMAS) that was introduced in 110 districts spread across 15 provinces. The programme began in 2008 and was completed in 2012. In its implementation, the programme required the participating communities to meet four district-level criteria and 20% community co-financing to build water infrastructure. I utilise the Indonesian Family Life Survey (IFLS) data from 2 waves, 2007 and 2014 to evaluate the impact of PAMSIMAS by running a difference-in-difference estimator combined with propensity score matching at the household level. The main variables are households' access to safe drinking water, in-house water provision, and distance to the water collection point. In the second part of the chapter, I evaluate the effects of PAMSIMAS on children's health two years after programme was completed using a cohort-based difference-in-difference method at the individual level.

In the third chapter, I am interested in looking at the effect of a mega-tsunami that hit the coastal areas of the Indian Ocean on December 26, 2004, on monthly health expenditures borne by households who lived in areas with different damage levels post-tsunami periods. In this chapter, I compare the health expenses of households living in medium and heavily-damaged areas with those who lived in no or light-damaged regions 5-17 months and 18-30 months after the event by employing the Study of the Tsunami Aftermath and Recovery (STAR) data. Since pre-tsunami health expenditures are not available in the survey, I estimate households' monthly health spending from the mean values of the household health expenses reported in the consumption module conditional on the health conditions of household members and in line with households' wealth index. Besides, I also use information from the detailed spending to look at which healthcare components contributed to the changes in health spending. I analyse the impact of the tsunami on the outcome of interest by employing an inverse-probability weighting

(IPW) model at the household level.

I will discuss all aspects of each chapter in detail in the next sections of the thesis.

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Chapter 1

Improving Health Insurance Coverage for the Poor in Indonesia

Daim Syukriyah, Melanie Lührmann

Abstract

Improving access to healthcare, especially among the poor, is one of the UN's sustainable development goals. We evaluate the effects of a 2013 reform in Indonesia designed to improve poverty targeting, a major challenge in developing countries, and to extend health insurance coverage for the poorest 40% of households. We employ an event study method to estimate the heterogeneous impacts of the reform on (a) health insurance coverage, (b) healthcare utilisation, and (c) out-of-pocket healthcare spending across poverty quintiles, measured directly via per capita consumption rather than proxy mean testing.

Our results suggest that the reform increased insurance coverage among the poorest 20 (40)% substantially - by around 13 (10) percentage points, indicating improved poverty targeting. Yet, increased insurance coverage among the untargeted above the poverty line, especially in the fourth quintile, points to remaining targeting leakages. Households' out-of-pocket spending on health decreased by approximately IDR 141,000 among the poor and near-poor households - suggesting that the reform reduced the financial burdens on these targeted households. However, the reform led only to limited increases in healthcare utilisation across household quintiles, which do not vary by local healthcare infrastructure capacity.

1.1 Introduction

Insufficient access to healthcare services among the poor is one of the key obstacles to "ensure healthy lives and promote well-being for all at all ages", one of the UN's sustainable development goals. Less than half of the world's population had access to essential healthcare services in 2017 (World Health Organization et al., 2017). Financial constraints and insufficient public healthcare provision are primary barriers to medical treatment faced by the poor. Over the last decades, many governments in Latin America and Asia have introduced large, subsidised or free public healthcare insurances to improve access to medical services.

One of these is the Indonesian social health insurance programme, Jamkesmas which has offered free health insurance to the poorest 40% of households since 2008. Yet, it effectively insured only about 50% of those classified as poor (Sumarto, 2012). One suspected reason for this insurance gap among the poor was inefficient poverty targeting, a challenge facing many developing countries (Alatas et al., 2012; Bah et al., 2018; Galasso and Ravallion, 2005; Tohari et al., 2019). Means-testing, a common approach for the targeting of social insurance and social welfare programmes in high-income countries, hinges on accurate measurement of households' income or consumption, and warrants more focus on barriers to take up (Finkelstein and Notowidigdo, 2019). Yet, large informal economic sectors and lack of reliable income or expenditure data, sometimes combined with weak institutions prevent effective programme implementation, and hence, require alternative methods to identify the poor in developing countries (Harimurti et al., 2013). These alternatives often rely on community selection or employ proxy-means testing (PMT) approaches for poverty targeting. The former relies on local information available to community leaders to identify who the poor are while the latter often relies on inventories of households' ownership of a wide array of assets to capture poverty. Such a method is also typically combined with survey data on households' expenditures to generate poverty rankings based on households' wealth proxies and define cutoff thresholds to identify poor households eligible for targeted schemes.

In this chapter, we evaluate the impact of an update of the poverty database in Indonesia in 2013, consisting of the abandonment of community selection methods and revision of their

PMT method. The resulting poverty database was the basis for the expansion of eligibility to be entitled to social health insurance (Jamkesmas), intended to close Indonesia's health insurance gap. Employing an event study approach, we analyse whether the reform led to an increase in health insurance coverage among the poorest 40% households and expanded the number of beneficiaries. We further examine whether the reform increased healthcare utilisation, and reduced out-of-pocket (OOP) health spending in line with the aim to reduce financial barriers to accessing healthcare.

Chapter 1 contributes to two strands of literature. First, we provide new evidence on the impacts of a switch from a hybrid targeting approach that combines community selection with a poverty database determined through PMT towards an updated, purely PMT-based identification method, on recipiency of one of the flagship programmes of Indonesia's welfare system, Jamkesmas. In line with evidence from a randomised-controlled trial (RCT) conducted in the early 2000s, we show that PMT-based poverty targeting improved the accuracy of targeting (Alatas et al., 2012). Our results suggest that enrolments of Jamkesmas among the poorest 20% and 40% were higher by 13 and 10 percentage points (ppts) respectively in comparison to the baseline in the first quarter of 2011. This better targeting also led to changes in monthly healthcare expenditures by IDR 141,000 less among the targeted households relative to the same baseline of health expenditure in quarter 1 of 2011.

Second, to the best of our knowledge, this chapter is the first study that evaluates the effects of the poverty-targeting reform developed by PMT on health insurance enrolments, health expenditures, and healthcare utilisation by observing any discontinuity from the interaction between the poverty quintiles and quarterly information of the household survey's interview months in our event study analysis. Between 2011-2014, Susenas data - the national household survey used in this study - were collected quarterly before it was combined into a yearly release. We exploit this feature by observing changes among the estimated outcomes of interest after the launch of the Unified Poverty Database (UDB) at the beginning of 2013 to observe if the reform improved insurance coverage, healthcare utilisation and reduced private health spending.

The remainder of Chapter 1 is organised as follows. Section 1.2 describes the health insurance and healthcare setting in Indonesia, and provides details on the 2013 reform. The data and methodology used to identify the impact of the reform are described in Sections 1.3 and 1.4. Section 1.5 presents the event study results. Section 1.6 concludes.

1.2 Institutional Setting and Literature

In this section, we first give a short overview of Indonesia's social health insurance and its evolution over time (section 1.2.1). Then we describe the targeting strategy used to identify eligible, i.e. poor, households (Section 1.2.2), and the new targeting method introduced in 2013 alongside an expansion in the eligibility base for *Jamkesmas* (Section 1.2.3).

1.2.1 Indonesian Social Health Insurance

Over the last decades, Indonesia has made progress in providing health protection for the poor as part of its goal to achieve equitable health care regardless of people's background. The first steps towards introducing social health insurance were taken in the mid-1990s, which covered about 10% of the country's population by 2005 (Sparrow et al., 2013). This was scaled up in 2005 - following the enactment of the social security system law - with the introduction of Social Health Insurance for the Poor (Askeskin), covering the poorest 20% of the population.

Jamkesmas, the focus of this paper, commenced in 2008 to substitute Askeskin. It doubled the targeted beneficiaries to the poorest 40% of households, by extending social insurance to near poor households. It covered around 76.4 million people, around 33% of the population (Rokx et al., 2009b). The new scheme was launched with a full, government-funded subsidy for the poor.

The purpose of Jamkesmas was to improve access to healthcare services for those considered poor.[1] Financial barriers often prevent the poor from seeking medical treatment, producing large inequalities in healthcare utilisation and health outcomes (Gakidou and King, 2000; O'Donnell et al., 2007). With limited financial capacity, poor people tend to fulfill and maintain their subsistence needs rather than spend money to take care of their health when one of their family

[1] Askeskin and Jamkesmas also targeted employees in the informal sector.

members is sick. Through Jamkesmas, the Indonesian government intended to help them by offering free healthcare for the poor.

Jamkesmas provided insurance to all family members of poor households. Insurance holders were eligible for basic medical services in primary healthcare centres, public hospitals, and some registered private healthcare facilities. These included ambulant and inpatient care in third-class rooms at public hospitals and some appointed private hospitals, newly covered prescriptions (Harimurti et al., 2013), comprehensive maternity care such as pre-and post-natal care as well as hospital delivery (Rokx et al., 2009b). Reflecting the introduction of free medication and the expansion in healthcare providers, Jamkesmas beneficiaries could access, government funding per capita increased relative to the previous Askeskin scheme, from IDR 5,000 (circa USD 6.67) in 2005 to IDR 6,500 (circa USD 8) per month in 2011 per person (Bi et al., 2014).

Similar to other developing countries, this non-contributory scheme, providing free health insurance for the poor, is flanked by two contributory pillars covering public sector employees (called Askes) and those working in the formal sector (Jamsostek)(Giedion et al., 2013).[2] Table 1.1 summarises each pillar.

1.2.2 Poverty Targeting

In the aftermath of the Asian financial crisis, i.e. after 1997, Indonesia launched several social assistance programmes to reduce the risk of extreme poverty and improve access to basic social services, including healthcare services. Targeting mechanisms and eligibility criteria for these social welfare programmes were programme-specific. The urgency to provide fast response support during the crisis made a rigorous targeting approach difficult. Consequently, social welfare programmes such as Jamkesmas often relied on community targeting methods before 2013. According to Alatas et al. (2012), these lead to about 33% of the population being incorrectly targeted.

From 2008 to 2012, Jamkesmas targeted 76.4 million individuals, or about 30% of Indonesia's population, without any expansions in the number of beneficiaries. Eligibility of households for

[2] In 2014, Indonesia introduced universal health coverage (JKN) which integrated all pillars (Sato and Damayanti, 2015).

Table 1.1: Three Flagship Health Insurance Schemes in Indonesia

Characteristics	***Askes***	***Jamsostek***	***Jamkesmas***
Year Initiated	1968	1992	2008
Coverage	19.5 million (7.8% of population)	5.6 million (2.3% of population)	76.4 million (30.7% of population)
Members	Civil servants, retired, armed forces, veterans and families	Formal private employees of firms with >10 workers	Poor and near poor
Dependents	Spouse plus 2 oldest children < 21 years (if unmarried and not employed)	Spouse plus 3 oldest children < 21 years (if unmarried and not unemployed)	Spouse and all children within family
Participation	Mandatory	Voluntary Employers may opt-out and choose private health insurance	Poorest 40% of the population as identified by poverty registry
Monthly Contribution	2% of the payroll, 1% government top-up	6% (3%) of wages for married (single)	IDR 6,500 (USD 8) per capita
Benefit Coverage	Outpatient and inpatient treatment	Comprehensive but with limitations	Comprehensive, medication covered within formulary
Cost Sharing	Yes, for non-listed treatments, e.g. a class upgrade of care, unprescribed drugs, transplantation, cardiac surgery, and hemodialysis	No, payment for high medical care like cancer treatment, cardiac surgery, and hemodialysis. Drugs outside formulary	None
Reimbursement	Capitation	Fee-for-service	Fixed fee for diagnosis-related groups (INA-DRGs)
Providers	Public facilities (health centres and hospitals)	Approved list of public and private facilities; inpatient only at public	Approved list of public and private facilities
Management	State-owned health insurance firm (*PT. Askes*) for profit	State-owned enterprise (*PT. Jamsostek*) for profit	Ministry of Health

Source: Achadi et al. (2014), Trisnantoro et al. (2014),Aji et al. (2013)

Jamkesmas was determined ad-hoc based on community selection. Local governments acted as programme administrators and compiled a list of potential beneficiaries according to local poverty indicators (Bah et al., 2019). They distributed insurance cards to those deemed eligible, conducted social campaigns, and were in charge of monitoring and evaluation. Similar to other pro-poor government programmes, households could show a poverty letter issued by their village head as evidence of their poverty status to prove their eligibility (World Bank, 2012b). Intransparent and unsystematic eligibility criteria and poverty letters without an expiry date led to substantial "leakage", i.e. (continued) benefit recipiency of non-poor households and non-recipiency among some of the poor (Sparrow et al., 2013). Similar methods have been used, for example, in the Bangladesh Food- for -Education programme (Galasso and Ravallion, 2005), working on the presumption that communities have more information about their residents whose socio-economic status may be hard to conceal from community members or officials. Critics of the approach suggest that elite capture may lead to corruption in the selection of the poor, resulting in inefficient poverty targeting (Alatas et al., 2012). Community selection continued after the launch of Jamkesmas in 2008, leading to nearly 50% of the poor being excluded from social assistance programmes (Sumarto, 2012).

In 2011, Indonesia followed the growing trend in lower-middle-income countries (LMICs) to adopt a single poverty targeting database - developed using PMT methods - that can be universally used to target recipients for any pro-poor programme (Fiszbein and Schady, 2009; Honorati et al., 2015). For example, Mexico applied PMT to identify the poor for their conditional cash transfer programme (PROGRESA). Poverty status is determined via a "proxy" for household consumption expenditure, a common indicator of socio-economic status in developing countries, that relies on a large list of easily observable indicators, such as measures of asset ownership.

This alternative is popular as several reasons preclude standard means-testing based on income. First, 60% to 70% of Indonesian workers are employed in the informal economy. Informal sector workers are more likely to experience financial instability and poverty, and reliable recording of earnings information is difficult. Second, verifiable census data on consumption expenditure or income is also lacking - particularly among the poor. Household surveys usually collect such information. However, they 1) typically cover only a sample of the population, and 2) are prone to measurement error,[3] especially under-reporting if it becomes known that

[3] A larger disparity of the shares of non-food expenditure between the national accounts and Susenas estimates suggests that the richer households were under-represented in Susenas and if they were surveyed, they tended to under-report their expenditures (Booth et al., 2019).

reported quantities will be used for poverty targeting.

Both measurement errors in consumption data and the lack of administrative income or earnings data pose challenges for accurate poverty targeting in many developing countries, and make it difficult to maintain up-to-date poverty databases.

The Indonesian PMT strategy focused on collecting information about households' wealth from a set of households' asset and housing characteristics and then using it in conjecture with estimated PMT scores to proxy households' expenditure across the population. The list of households surveyed is obtained from the population census.[4] Households are then ranked by their proxy expenditure and defined as poor if their rank is lower than the poverty threshold.

PMT used information on asset ownership and demographic characteristics which are more easily observable compared to earnings, especially among households who live from subsistence farming activities. Enumerators can more easily ask about and verify asset items than record household expenditure or earnings (Alatas et al., 2012).

The PMT model was developed using a representative sample of the population, the respondents of Susenas, for whom both asset ownership and demographic characteristics and reliable expenditure information are available. A statistical model is then used to estimate so-called PMT scores for each asset item or characteristic to predict household expenditure. District-level specific PMT scores account for local differences in asset ownership and cost of living. Out-of-sample predictions generate a population distribution of predicted household expenditures which is then used to classify households into poor and non-poor.[5] The resulting UDB consists of 24.7 million poor households or 96.7 million poor individuals.

There are some improvements in the development of the UDB compared to the old targeting system. First, the variables used as indicators of proxy household minimum expenditures of basic needs increased from 14 to 26 items. Second, in its implementation, it took a two-stage data collection process. (1) The household targeting step to determine household quota referred

[4] Population Census in Indonesia is conducted every 10 years. The latest one before the establishment of UDB was in 2010.

[5] In the construction of UDB, the poor refers to those targeted households belonging to the bottom 40% of households and non-poor refers to the top 60% of households according to the households' total consumption distribution.

to the list of households and the number of households that were going to be surveyed in each region. This activity was done via a "small area poverty mapping estimation" approach introduced by Elbers et al. (2003) by using the 2010 population census, 2010 Susenas, and 2008 PODES. (2) The enumeration process was done by visiting the listed households and collecting social demographic information in the Data Collection for Social Protection Programme (PPLS 2011). Third, the PMT model is district-specific consumption-based poverty estimations. Out of 497 districts, the PMT models used in the development of UDB were 482 district-specific models.[6] Lastly, the household coverage in the UDB also expanded to the poorest 40% (24.7 million households) nationwide (TNP2K, 2015).

Its construction can be summarized as follows:

1. The government generated enumeration quotas of poor households to be surveyed in each region that were estimated from the province to the village level based on the geographic distribution of the 40% poorest households. The purpose of this activity is to ensure a high level of accuracy in estimating the distribution of poor households across the country by undertaking a poverty mapping starting from the smallest community. The consumption expenditure per capita was used to generate the target enumeration quota of households to be surveyed in each district. This process was conducted using Susenas combined with PODES.

2. The characteristics of these poorest 40% obtained from (1), were then matched to the same variables that appeared in the 2010 population census using a means testing model (Poverty Targeting Model) to identify poor households based on the predicted per capita consumption expenditure. Through this process, the 'pre-listed' households to survey were gathered including their names and addresses according to the lowest 40% of predicted consumption expenditures.

3. After the pre-listed households were available, the 'additional' households were added from

[6] The government decided to apply a universal targeting approach to the remaining 15 districts with high poverty rates by assigning all households to be included in the poverty database, except for those with government employees and army personnel(Tohari et al., 2017).

(a) the existing beneficiaries used in the old targeting system[7] using *matching* process and (b) based on community suggestions and consultation. Information from the community helped to improve the accuracy and verify if pre-listed households were really poor or if any other poor households were not yet included. The pre-listed households obtained from (2) were then combined with the additional households based on the community consultation.

4. The first stage of the UDB construction process includes (1) to (3). At this stage, the total household coverage was 43% nationwide which varied at the regional levels. Subsequently, after the list of eligible households for the PPLS 2011 survey was ready, PPLS 2011 enumerators visited these households and collected information on the social demographic characteristics of the households including asset ownership, education, occupation, housing quality, sanitation, household composition, and access to social welfare programmes. The provincial office of statistics recorded all information from the PPLS 2011 data collection and sent it to the Central Office of Statistics (BPS).

5. The National Team for the Acceleration of Poverty Reduction (TNP2K) together with the BPS and the World Bank processed the data. In each district, household welfare was predicted using its specific PMT formula. The predicted expenditure was found after finding fitting models from each district by accounting for the diversity of socio-economic status across districts. This means each district has its unique significant variables that could be different from other districts to generate household welfare. Households were then ordered from the lowest predicted expenditure up to the highest one to account for 40% poorest population i.e. up to decile 4. These households were then entered into the national poverty register, the UDB. The number of households to be included in the UDB across districts varied depending on the district's poverty incidence (TNP2K, 2015).

The introduction of the new PMT method led to the UDB containing 24.7 million households or 96.7 million individuals (around 38-40% of the population). Tohari et al. (2019) finds significant reductions in undercoverage, suggesting a reduction of type I errors in the targeting method.

[7] This data includes households listed in the waiting list to receive the Family Hope Programme (PKH)

1.2.3 The Targeting Reform from 2013

Starting in 2013, eligibility for Jamkesmas was harmonised and tied to the UDB, with the potential to significantly raise the fraction of the population with health insurance, as prior to the reform insurance rates were low - in spite of the stated target from 2008 to reach the poorest 40% (Tohari et al., 2019).

Insurance cards were distributed to individuals in late 2012. From January 2013, Jamkesmas card holders could receive health fee waivers for healthcare services.[8] For those who had obtained an insurance card previously but were not listed in the poverty database and hence no longer eligible, their entitlement to free healthcare ceased in February 2013 (TNP2K, 2013).

We expect the targeting reform to increase health insurance coverage rates among the extreme and near poor via two channels: Firstly, if the aim of more efficient targeting of the poorest 40% was achieved, undercoverage of the poor should reduce. Secondly, households were recorded in the new poverty database with their address, allowing their automatic subscription to social assistance programmes. In consequence, Jamkesmas insurance cards were distributed via postal mail to households in the poverty database instead of the previous system which required the household to request to be subscribed to the programme by seeking a community letter as evidence of being poor.

Similarly, as previous leakage reduces, insurance coverage among those above the poverty line may decrease, unless households who lose free health insurance through Jamkesmas substitute with other forms of health insurance.[9]

1.3 Data

Our analysis is based on Indonesia's Susenas. Susenas is a nationally representative household survey that collects individual and household information on consumption, education, health,

[8]https://www.kemkes.go.id/article/view/2201/kemenkes-distribusikan-kartu-jamkesmas-untuk-864-juta-penduduk-indonesia.html

[9](Bah et al., 2018) study the changes in the pool of beneficiaries of two large social welfare programmes (the unconditional cash transfer programme (BLT) and Jamkesmas) from the targeting reform. They find that while prior to the reform around 40% of recipient households did not belong to the poorest 40%, this leakage reduced by 15 percentage points.

dwelling conditions, and other socio-economic characteristics. It is a repeated cross-section of around 300,000 households annually, which are randomly drawn by two-stage stratified sampling.

We remove households with a household head below 16 years old to obtain a sample of 851,337 households observed between 2011 and 2013. Of the total observations, 567,345 households are observed before and 283,992 after the 2013 reform. In its construction, the sampling methodology of Susenas uses the probability proportional to size technique (PPS) to select census blocks from the master sampling frame of the population census and the selection of households to be surveyed within each block by systematic random sampling (Statistic Indonesia (BPS), 2012). To ensure that any estimation or calculation employed by Susenas is representative of the country's population and households, any calculation using Susenas should apply either individual or household weights depending on the level of analysis used. As in our study, we will analyse our model at the household head level, household weights are used in our analysis which relies on district-level variation throughout this chapter.

We exploit quarterly interview information of Susenas[10] to conduct an event study, and estimate the reform effects for the poor (i.e. the poorest 20%), the near poor (the second quintile), and non-poor quintiles of the population. We define households' five economic statuses (quintiles) using per capita consumption that households reported in the consumption module of the survey.

While poverty targeting is frequently achieved through means testing in developed countries, the existence of large informal sectors and a lack of verifiable earnings or income records prevents the use of income measures in many developing countries (Banerjee et al., 2020). In addition, high levels of subsistence farming also mean that per capita expenditure may provide a more accurate indicator of households' socio-economic status (Deaton, 1997; Meyer and Sullivan, 2012). In consequence, we base our poverty quintiles on direct measurements of per capita consumption expenditure. One of the strengths of Susenas is that it collects information on per capita consumption directly based on households' food and non-food consumption expenditures. The recall period for food consumption was one week before the survey took place and for

[10] Between 2011-2014, Susenas was fielded quarterly in March, June, September, and December.

non-food consumption was one month, 2 months, and 3 months before the survey. Census data used to identify the poor usually relies on PMT methods which approximate per capita expenditure through easily verifiable, and more available measures of asset holdings, and other easily observable household characteristics (Filmer and Pritchett, 2001; Sahn and Stifel, 2003). In fact, Susenas which records per capita expenditure and information on asset wealth and other household characteristics is the database used for PMT by the government and to define the cutoff thresholds between the extremely poor, near poor, and non-poor. The method is then applied to census data to form the poverty database.

Our key outcomes of interest are 1) the insurance status of the household head, 2) an indicator of healthcare utilisation and 3) the household's OOP health expenditure. In the first instance, we investigate whether the targeting reform and social insurance expansion increased access to healthcare via an increase in insurance coverage, and for whom. Susenas records health insurance coverage (HIC), including the type of insurance.[11] Generally, health insurance is given to individuals but the identification of potential beneficiaries was obtained through households' welfare status or at the household level. On average, 43% of households had some type of health insurance in 2011, rising to 52% in 2013.

Secondly, as insufficient healthcare infrastructure or social barriers may prevent healthcare access in a system of notional eligibility for free services for the poor, we test whether the reform achieved its aim to increase the utilisation of healthcare, particularly among population groups who became newly eligible. We use three outcome variables, HIC, healthcare utilisation and private health spending. We construct the HIC from Susenas question asking if a household held any health insurance and from another question that did not ask about the insurance card but if they received free healthcare services.[12] For the healthcare utilisation indicator, we employ outpatient visit frequency to the public and private hospitals and health centres in the past month before the survey. In Susenas, there is a question asked to household members if they

[11]The question provides a list of health insurance types in Indonesia, with options such as subsidised health insurance (Jamkesmas), specific insurance schemes for veterans and public sector employees, and non-government health insurance.

[12]This question is usually to capture responses from people in remote regions or the elderly who are often not familiar with the names of the social welfare programmes.

received any outpatient care from visiting either public or private hospitals, or community health centres (CHCs) one month before the survey. Since the head of the household was the one who answered the question on behalf of their family members, for our analysis, only visits made by the heads of households are counted. We compute the total of these ambulatory care visits to create the healthcare utilisation variable.

Finally, an expansion of the provision of free social insurance may reduce financial hardship for the poor paying for critical healthcare services out of pocket. Hence, we also investigate reform impacts on households' private healthcare expenditure. For the healthcare spending, we calculate the average monthly expenditure from any expenses spent at public and private hospitals, health centres, seeing a doctor, traditional care (herbal medication), maternal care, vaccinations, medication (drugs), birth control and contraception, purchases of eyeglasses, medical check-up, and other general healthcare costs. We take the average of these expenditures from the past 3, 2 and 1 months instead of the past month of the survey as our households' health expenditure variable in our analysis. This approach creates a more accurate measure of spending on health-related medical care which can vary month by month.

In addition, we obtain healthcare infrastructure information from the 2011 release of the PODES which we link to the Susenas sample at the district level.[13] PODES collects and documents statistical information of village characteristics and is conducted every four years. The 2011 census, consisting of around 77,000 villages, contains information on the number of hospitals, maternity hospitals, doctor-led clinics, CHCs and auxiliary CHCs in or near the villages. We capture the supply of health facilities by aggregating across these different providers, and calculate the number of local healthcare providers per person at the district level to determine the local healthcare supply.

In all our estimates we control for individual and household characteristics such as age, gender, marital status, household size, residential area (urban/rural), educational attainment (including primary, junior high school, senior high school and college attendance), and employment status. Table 1.2 provides summary statistics for these before and after the UDB reform.

[13] We obtain information from PODES at the village level and aggregate it into the district level so we can merge it with Susenas.

Table 1.2: Descriptive Statistics of Variables

Variable Names	**Pre-UDB Reform**		**Post UDB Reform**	
	Mean	Std. Deviation	Mean	Std. Deviation
Health Insurance Rates				
Health Insurance rate (%)	0.43	0.50	0.52	0.50
Healthcare Utilisation				
Outpatient visit (%)	0.11	0.54	0.11	0.50
Out-of-Pocket Spending				
Healthcare spending (IDR)	192,070.77	1,378,149.87	240,504.5	1,718,004
Demographic Characteristics				
Age (years)	46.93	13.75	47.94	13.65
Urban (%)	0.42	0.49	0.43	0.49
Married (%)	0.82	0.38	0.81	0.39
Male (Household Head) (%)	0.86	0.35	0.85	0.36
Household size	3.91	1.75	3.85	1.72
Education Attainment				
Primary (%)	0.49	0.50	0.49	0.50
Junior High School(%)	0.15	0.35	0.15	0.36
Senior High School (%)	0.21	0.41	0.22	0.41
College (%)	0.15	0.36	0.14	0.35
Employment Status				
Work (%)	0.89	0.31	0.89	0.32
Household Head Observations	567,345		283,992	

Source: Susenas, Author calculation.

1.4 Methodology

We employ an event study approach to identify the impact of the UDB reform on health insurance coverage across the population quintiles. First introduced by Fama et al. (1969), event studies have recently gained general popularity due to the rising availability of large datasets at more granular frequency.[14]

An event study or event-history analysis is a powerful research design for treatment effect estimation where we primarily are interested in change after the treatment or in this chapter, after a policy reform. Usually, we measure the change on our variable of interest after an "event time" or the exact timing when a policy or an event occurs (Miller, 2023). To estimate the effects of an event (treatment), a key assumption underlying the use of an event study approach is the implementation period of such an event (treatment) is not systematically related to any unobserved factors affecting the outcomes (Dursun et al., 2021). In the absence of an event or a policy that we regard as "treatment", we expect the variable of interest would have continued to stay the same as those before the event. Ideally, if we plot our summary of estimation results on a graph, we will see that the line before the event is trendless. When pre-trends are present, any deviations from flat trends may indicate a potential problem of other confounding factors, model misspecification, or other expectation effects that may influence the outcomes (Dursun et al., 2021; Miller, 2023). Hence, our pre-treatment terms will serve as a falsification test to detect any potential problems that may lead to biased estimated effects in our model.

In this chapter, we aim to establish whether the UDB targeting reform 1) increased HIC and healthcare utilisation in the bottom 40% population, 2) reduced OOP health expenditure among the targeted 40% poorest. Our identification strategy is to examine the reform's effects using an event study by estimating changes in those three outcomes obtained from the quarterly information of the households' interview dates of Susenas. Secondly, using quintiles of household expenditure, the underlying poverty measure that PMT seeks to proxy,[15] we wish to investigate

[14] For example, Dursun et al. (2021) uses it to investigate the impact of the US educational reform on infant health, and Chorniy et al. (2018) to estimate the impact of (a switch to) managed care on child healthcare access.

[15] The Susenas sample was indeed used in the estimation of the PMT scores, as it is an independent (non-governmental) survey containing information on both assets and expenditures.

whether type I and II errors in the targeting process lead to leakage and undercoverage in the recipiency of Jamkesmas. Note that our outcome variable captures actual insurance status, and is hence a takeup rather than eligibility measure.

We estimate the following linear probability model:

$$Y_{igt} = \alpha + X'_{igt}\beta + \sum_t \gamma_t Q_t + \sum_q \delta_q \cdot P_{qgt} + \sum_t \sum_q \theta_{tq} \cdot Q_t \cdot P_{qgt} + \mu_g + \epsilon_{igt} \tag{1.1}$$

where Y_{igt} denotes our key outcomes of interest for household i living in district g in period t. X_{igt} are characteristics of the household and its head, and Q_t denotes quarters prior to and after the UDB reform. Overall, our event period covers 8 quarters before the reform, and 3 quarters afterwards. Quarter 0 denotes Q1 in 2013, the quarter in which the UDB reform was implemented for Jamkesmas. For the sake of brevity, when we present the analysis results, we start from quarter 3 of 2011 to 2013 to make our results easier to read. We will observe if pre-trends are present from any quarters before 2013. P_{qgt} denotes the respective per-capita consumption quintile, which we use to characterise relative poverty, henceforth referred to as $P20, P40, P60, P80$, and $P100$. $P20$, the poor and $P40$, termed near-poor, comprise the target population. The three remaining quintiles, $P60, P80$, and $P100$ denote the non-poor who were not targeted by Jamkesmas. Our key parameters of interest are θ_{0q}. Finally, we control for district fixed effects μ_g to filter out time-constant heterogeneity across districts. ϵ_{igt} denotes idiosyncratic errors.

We include control variables and district-fixed effects to help capture certain factors such as omitted variables and confounders (that may vary at the district level) that might influence the outcome variables. By observing our pre-trends (falsification test) and controls for other variables in our event study model, we expect that we can isolate the reform effects and thus, our coefficients are credible.

If the UDB reform instigated a substantial change in, say, insurance coverage among the poor (and only among them), then we would expect θ_{0q} to be substantially and statistically significantly higher than in the previous quarters for the poor and near poor, and near zero and not statistically significantly different from pre-reform coefficients for the non-poor.

1.5 Empirical Results

In Section 1.5.1, we investigate in an event study framework whether the UDB reform, applied to Jamkesmas in Q1 of 2013, led to changes in health insurance coverage of the poor and non-poor, i.e. if undercoverage and leakage changed and if the reform presents, as planned, an overall expansion in insurance coverage. Subsequently, we investigate whether the hypothesised increase in insurance coverage improves healthcare utilisation (Section 1.5.2), and alleviates financial pressures for households by reducing OOP health expenditures (Section 1.5.3).

1.5.1 Health Insurance Coverage

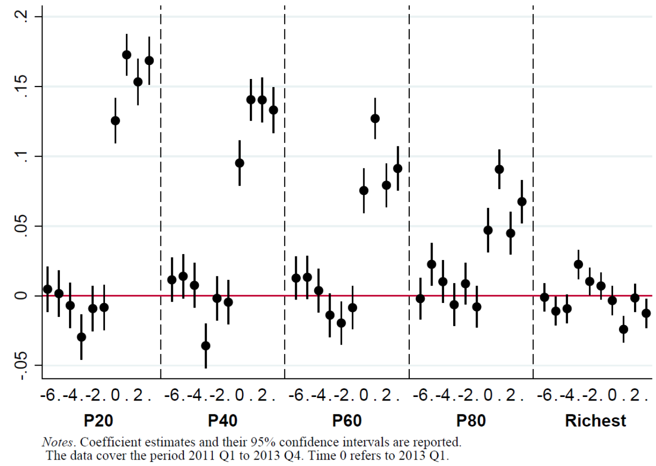
We estimate equation (1.1) in three specifications. In our baseline specification, we ignore household controls and district-fixed effects. In specification (2), we introduce individual and household characteristics, and in the specification (3) we add district-fixed effects. In Figures 1.1 a to c, we present the estimated coefficients (and confidence intervals) for the interaction term between the quarter dummies and the quintiles separately for each of the five socio-economic groups, the poorest (P20), the vulnerable (P40), middle (P60), the rich (P80) and the richest quintile.[16]

We find that after the roll-out of the new eligibility criteria for Jamkesmas under the newly targeting reform, insurance coverage of P20 increased by nearly 13 ppts in the first quarter of 2013 relative to the baseline in the first quarter of 2011 and subsequently rose to 17 ppts in the last quarter of 2013. Implementation of the UDB also improved the enrolment in Jamkesmas among the targeted vulnerable households by approximately 10 and 13 ppts in the first and last quarter of 2013 respectively. These results suggest that the UDB reform indeed increased health insurance coverage substantially among the target population, the poorest 40%. Note, however, that this only amounted to a modest closing of the insurance gap among the poor, and increased the insurance coverage to about 52% of the poor.

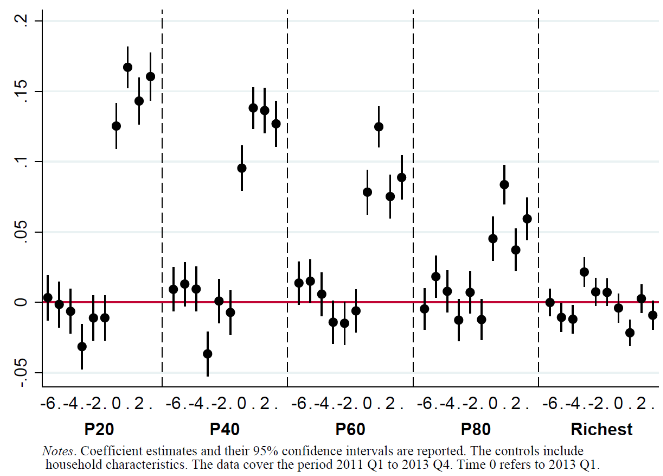
Controlling for household (head) characteristics: age, gender, household size, residential area, educational attainment, and employment status, the estimated improvements on HIC among the

[16]Even though we use all quarters of the study period in the estimation, we present 2011's Q3 (denoted by -6) to 2013's Q4 in the graphs where quarter 0 refers to the timing of reform introduction in 2013's Q1.

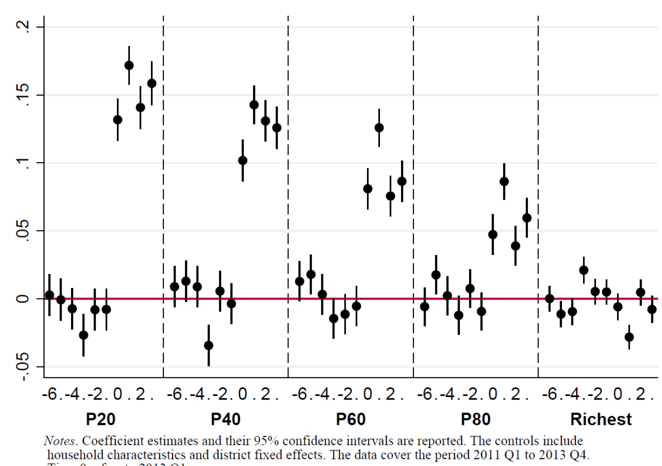
Figure 1.1: Event study estimates for health insurance status, by quintiles of per-capita expenditures



(a) Baseline specification



(b) Including (head of) household characteristics



(c) Adding district fixed effects

Source: Q1.2011-Q4.2013 Susenas, Author calculation

poorest 20% slightly decreased by circa 1 ppt in the last quarter of 2013 relative to the baseline year (2011 Q1), but did not change substantially (see Figure 1.1 b). The HIC among the near poor 40% remained unchanged either after including individual (household head) and household characteristics. Our results are robust when we include district-level fixed effects (see Figure 1.1 c). HIC among the poorest households increased by 13 ppts in quarter 1 of 2013 or on average by 15 ppts across 2013 relative to the baseline. Similarly, we estimate a 10 ppts increase in the second quintile, followed by a subsequent 3 ppts increase across 2013.

Yet, we also notice that the insurance rates among the poor and near-poor households decreased slightly around 3% in the second quarter of 2012 - shown by period -3 or (.) in the horizontal line of the graph. This decline could be a subsequent response that was related to the government's plan to slash the fuel subsidies from April 2012. Details on this fuel subsidy reform will be discussed in section 1.5.3 when we present the results on the households' health expenses.

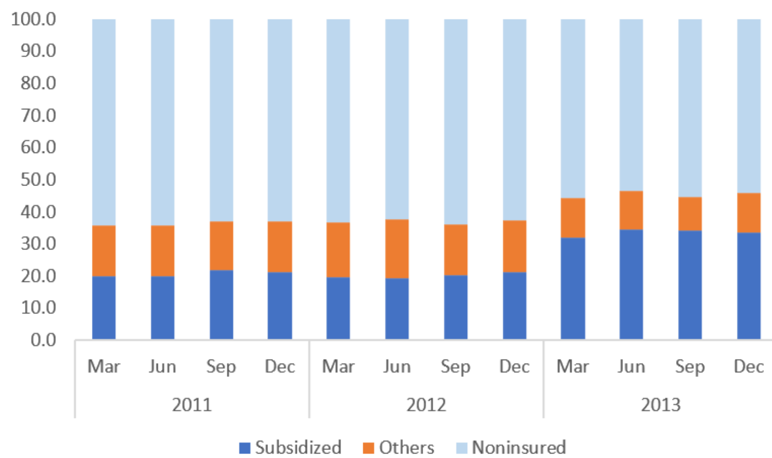
Figure 1.1 also shows - consistently across all three specifications - that the intended improvement in poverty targeting has not eliminated the aforementioned leakage in Jamkesmas beneficiaries. While we observe no discernible change in insurance rates after the reform among the richest 20% of the population, we observe statistically and economically significant increases in insurance coverage among the (not targeted) 3rd and 4th quintiles (P60 and P80). In comparison to the first two poorer household groups, these increases are smaller and decrease across quintiles - i.e. an 8 ppts increase in P60 and around 5 ppts among P80 relative to 2011 Q1.

HIC may have increased across the non-poor for other reasons than targeting leakage. It may be that non-poor households who lost their free healthcare access (due to becoming ineligible), obtained health insurance from the contributory schemes or purchased private health insurance. To investigate this, we decompose our dependent variable, health insurance status, by insurance type. Figures 1.2 a and b represent the proportion of households without insurance, and those receiving subsidised insurance (i.e. Jamkesmas),[17] or other types of insurance (such as the

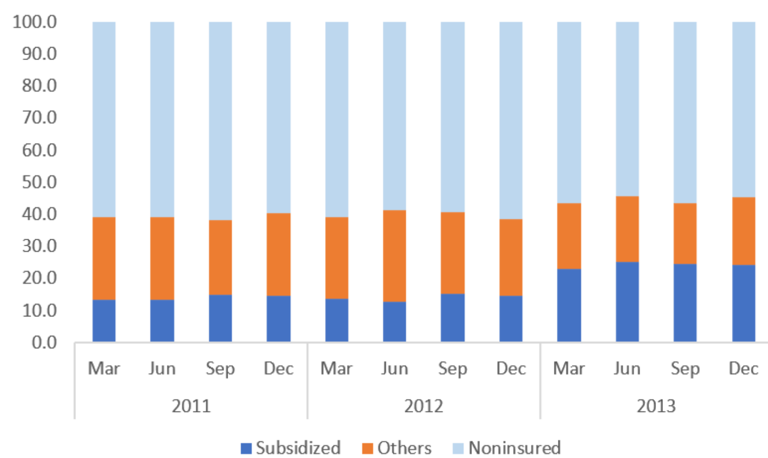
[17] In the questionnaire, the social health insurance is also listed names of the old subsidised programme such as Health Card or Poor Card, but all these names refer to Jamkesmas because respondents, especially in the rural regions were still not familiar with the new programme name, in this case, Jamkesmas.

contributory public insurance schemes or private insurance). The share of households receiving subsidised health insurance in quintiles 3 and 4, increased contemporaneously with the reform implementation, suggesting continued non-negligible leakage rather than substitution into other forms of insurance. We do not present the richest quintile because, from our earlier result, we do not observe any change in HIC for this group.

Figure 1.2: Health insurance composition among the non-poor



(a) P60



(b) P80

Source: Q1.2011-Q4.2013 Susenas, Author calculation

In summary, our results indicate that targeting accuracy (or takeup) has improved, as Indonesia successfully expanded health insurance coverage among the poor. However, the results also show that unintended "benefit leakage" remains a concern (at least from a fiscal perspective), as we see moderate increases in health insurance coverage also among the 3rd and 4th quintiles. Furthermore, while the reform led to a sizeable increase in poor recipients, about an increase of one-third, the HIC gap among the poor remains large.

1.5.2 Healthcare Utilisation

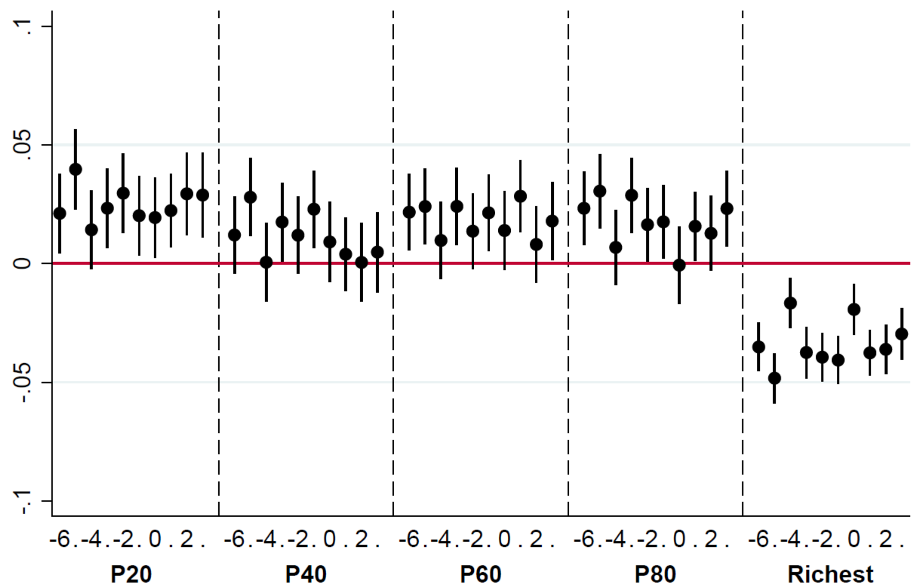
In this section, we address the question of whether the targeting reform led not only to increased notional HIC, but also improved actual access to healthcare services among the poorest 40% of the population.

We use, as the first indicator, the extent to which households use outpatient care. Specifically, we measure the frequency of ambulatory care visits by the household head in the last month, either to public or private hospitals or to community health centres. The question in the survey asked everyone in the household, but for our analysis, only visits made by the heads of households are counted because the head of household was the one who answered the question on behalf of their family members. We focus on outpatient care as there is no utilisation limit to seek medical treatment within the scheme, and no referral is required (unlike for inpatient care). Before the reform, those who could not afford medical treatment due to the consultation fee may have opted to use a traditional medication method or alternative herbal medicines. Two earlier studies evaluate the role of health insurance memberships on healthcare services, taking into account the accessibility, quantity, and quality of the services (Johar, 2009a; Vidyattama et al., 2014). In our case, we focus on the frequency of the visits.

For the causal effect of the reform on the number of outpatient visits, we replicate our event study model specification in (1.1) to see if the reform has affected the access to healthcare services directly and replace the dependent variable with the healthcare utilisation parameter. Apart from the baseline, the remaining two models also incorporate a set of individual and household characteristics and 497 district dummies as our controls. Our results are consistent across all these three specifications and we present our result from the last specification that includes household characteristics and 497 district dummies in Figure 1.3.

As we can see from the graph, the number of outpatient visits to any medical facilities increased by less than 5 ppts after the introduction of the reform among the lowest quintile. However, access to these facilities seemed to rise far before the reform took place. Meanwhile, no

Figure 1.3: Event study estimates for outpatient visits



Notes. Coefficient estimates and their 95% confidence intervals are reported. The controls include household characteristics and district fixed effects. The data cover the period 2011 Q1 to 2013 Q4. Time 0 refers to 2013 Q1.

Source: Q1.2011-Q4.2013 Susenas, Author calculation

changes were seen for the remaining population quintiles. Our findings are similar to Vidyattama et al. (2014) which observe the impact of holding any health insurance membership on healthcare services using the 2007 Basic Health Research Survey (Riskesdas) and Susenas. They find that the insurance increased healthcare utilisation by 8 ppts among those who were sick and this goes down to 5 ppts if they account for everyone.

Two reasons could possibly cause this limited healthcare service utilisation. First, the economic development disparity across regions in Indonesia remained significant (Vidyattama, 2013), which then led to an inequality gap in access to healthcare providers and poor provision of healthcare services. Second, the limited capacity of the existing public health system prior to the UDB reform has already reached capacity and is unable to increase the number of appointments with additional demands to healthcare services (World Bank, 2012a).

1.5.3 Out-of-pocket Spending on Health

The cost of medical visits or consultation fees was considered to be one of the factors preventing the poor from seeking medical treatment when they needed it before the reform. Under limited financial capacity, poor households often must choose between fulfilling their basic needs such as food, housing, clothing, and education and going to seek medication if one of their family members is in ill-health condition (Knaul et al., 2006; Van Minh et al., 2013). If there is a family member of a poor household sick, such a family has to shift some of their non-health consumption budgets to health spending allocation. Alternatively, the poor household may also look for help by borrowing money from friends or relatives to survive financially (Dhanaraj, 2016; Flores et al., 2008; Nguyen et al., 2012; Sparrow et al., 2014). Hence, a small health expense can pose a threat to exacerbate the economy of poor households (Su et al., 2006). Consequently, low-income households are commonly reluctant to visit healthcare facilities and forgo medications if their family members are in poor health.

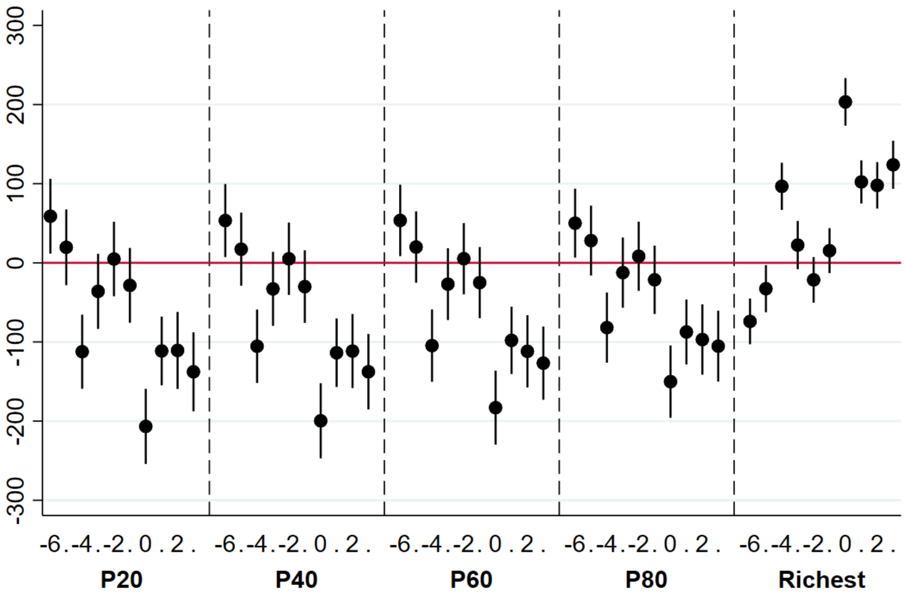
In 2012, private spending contributed a lion's share of total healthcare expenditure approximately 60.4%[18] and OOP expense made up more than 70% of this private healthcare spending or approximately 51% of 2012's total health expenditure. A high share of OOP spending can impoverish households' financial ability when it surpasses their consumption expenditure threshold and cause households to fall into poverty or even push them into an extreme one (Mclntyre et al., 2006; Sangar et al., 2019; Van Doorslaer et al., 2006; Xu et al., 2007, 2003).

The government through its provision of subsidised health insurance aimed to ease the financial burden of the poor. The reform allows us to examine whether there was some progress in the access to medical treatment with the free scheme.

To see changes made in private spending on health after the reform, we run a similar model to (1.1), used for the effects on health insurance coverage. The dependent variable is the average health expenditure of the past 3, 2, and 1 months before the survey or quarterly spending on health. The numbers are the total expenses spent on consultation visits to public and private hospitals, community health centres, doctor-led clinics, medication/drug costs, and preventive care. The result of the estimation that incorporates the individual characteristics and district fixed effects is displayed in Figure 1.4. To help readers understand the result in the graph, we transform the monetary unit of the spending by dividing households' health expenditures by

[18] World Health Organisation. World Health Statistics 2015 (accessed August 25, 2019). Available from: ⟨https://www.who.int/gho/publications/world_health_statistics/en/⟩

Figure 1.4: Event study estimates for out-of-pocket (OOP) spending on health



Notes. Coefficient estimates are in thousands IDR and their 95% confidence intervals.
The vertical line represents '000 IDR. The controls include household characteristics and district fixed effects.
The data cover the period 2011 Q1 to 2013 Q4. Time 0 refers to 2013 Q1.

Source: Q1.2011-Q4.2013 Susenas, Author calculation

IDR 1,000 in Figure 1.4.

Consistent with the HIC result, the result shows that total private spending on health decreased on average by about IDR 141,000 across the first lowest quintiles (P20 and P40) relative to the 2011 Q1's spending starting from the first quarter of 2013 onward. The average health spending for the poorest and near-poor households was IDR 51,500 before 2013. With the average reduction of IDR 141,000, household recipients of subsidised health insurance might benefit up to more than 100% with the improvement of poverty targeting, particularly those with expenses below the average amount of reduction. Except for the richest group, we can see that the better-off households also had reductions in their health expenditure after the roll-out of the new Jamkesmas programme.

If we look at figure 1.4, there was a smaller reduction in health expenses, around half of that reduction in the first quarter of 2013 among households except for the richest in 2012 Q1. Such a reduction was short-lived and returned to similar amounts of the old health expenditure until the last quarter of the year. This small decline in health expenditure could be associated with the government's plan for the fossil-fuel subsidy reform in early 2012. Indonesia has provided fuel subsidies for decades so that people can buy fuel at cheaper prices. Yet, the cost of fuel subsidies continuously increased and became a heavy burden for the country's public finances where in 2011, the subsidies for fuel products accounted for USD 1.8 billion or 22% of the revised state budget of the fiscal year 2011(Indriyanto et al., 2013; Pradiptyo and Sahadewo, 2012).[19] Meanwhile, the benefit of cheaper fuel prices predominantly benefitted the better-off consumers with more than 40% of the fuel subsidies going to the top 10% of households and less than 1% went to the poorest 10% (Diop, 2014). Consequently, the government had limited fiscal space for investment in other sectors including health, education, infrastructure, and defence (Pradiptyo and Sahadewo, 2012). In January 2012, the government sought to cut down the fuel subsidies by (1) raising fuel prices by IDR 5,000 per litre, or around one-third of 2012's fuel prices, and (2) restricting subsidised fuel consumption for certain types of vehicles to be effective per April 1, 2012 (Indriyanto et al., 2013). Even though the plan was postponed due to strong public resistance, the government's announcement might affect households' decisions indirectly to reduce their healthcare consumption already as their strategy to anticipate the rise of consumer goods prices and other costs of living.[20]

Additionally, the small decline in OOP expenses on health in the first quarter of 2012 also coincides with a slight drop in the outpatient visit estimate in Figure 1.3 for the same quarter (shown by period -4 in the horizontal line of the graph), suggesting that households' health expenses reduction in 2012's first quarter was caused by a reduction in the healthcare services utilisation. The decline in health insurance coverage among the first two bottom households is instead seen to appear in the second quarter of 2012 in Figure 1.1, which likely was a continuation effect of the same government's subsidy reform plan.

Meanwhile, the richest population had a temporary increase in OOP health spending in the same quarter 1 of 2012 when the low and middle-income households' OOP expenses decreased following the government's plan on the fuel subsidy cut. Even though it needs further observation, the richest might not lower their healthcare consumption even if there was speculation

[19] 1 USD is equivalent to IDR 9,150 March exchange rate.

[20] The consumer price index inflated between May to June 2012 by 0.62%. Price increases occurred in all expenditure groups between January to June 2012. Inflation in the health group was 0.21% with the highest price increase seen in the food group by 1.57% (BPS, 2012).

for expected inflation over the plan.[21] This decision was reflected in the healthcare utilisation pattern of the richest in the same period where in 2012 Q1, outpatient visits of this household group slightly went up in Figure 1.3. Yet, this small increase was not statistically significant.

After the implementation of the targeting reform in Jamkesmas in 2013, the monthly health expenses of the richest group increased by IDR 200,000 in 2013 Q1 relative to the baseline before it went down and was consistent at approximately IDR 100,000 for the remaining quarters in 2013. We might argue that under the revised targeting, some of the richest who previously received benefits from subsidised health insurance were excluded under the new eligibility criteria. Subsequently, they had to pay for the healthcare services after the reform. One of the goals of establishing the UDB was to improve its targeting accuracy and reduce the *leakage* where the non-poor population were included as programme beneficiaries. However, since our data is cross-sectional, we are unable to verify if those who experienced an increase in OOP health expenditure after the reform were the former beneficiaries of Jamkesmas. Hence, it still needs to be analysed further using other data such as panel data to understand why the richest faced health expenditure increases after the new poverty database used in Jamkesmas.

1.5.4 Heterogeneity in Healthcare Infrastructure Provision

This chapter so far has shown in section 1.5.2 that the effects of the UDB reform on the number of outpatient visits were indiscernible among all population groups. In analysing the healthcare services utilisation, it is important to look at the enabling factors for the insurance holders to access the health facilities in their vicinity. Apart from the affordability factor, whether there is an adequate number of basic healthcare providers available and facility locations that are acceptable in terms of distance to reach from the targeted recipients of the Jamkesmas programme. Johar et al. (2018) highlighted supply-side constraints in the country regarding healthcare infrastructure, with no subsequent expansion between 2011 and 2014. Since the free health insurance scheme was introduced at the beginning of 2013, limited healthcare services

[21] After the government announced its plan to reduce fuel subsidies by raising fuel prices, Indonesia's currency weakened by 1.3% against the USD in February 2012 (Muhandri, 2012). As the government planned to increase fuel prices, it also proposed a compensation fund for the poor. The waiting time for the parliament's approval of the cash transfer to limit the potential impact of the fuel-subsidy plan would lead to uncertainty in the financial markets and price increases of consumption goods and services even before the policy took place (Basri, 2016).

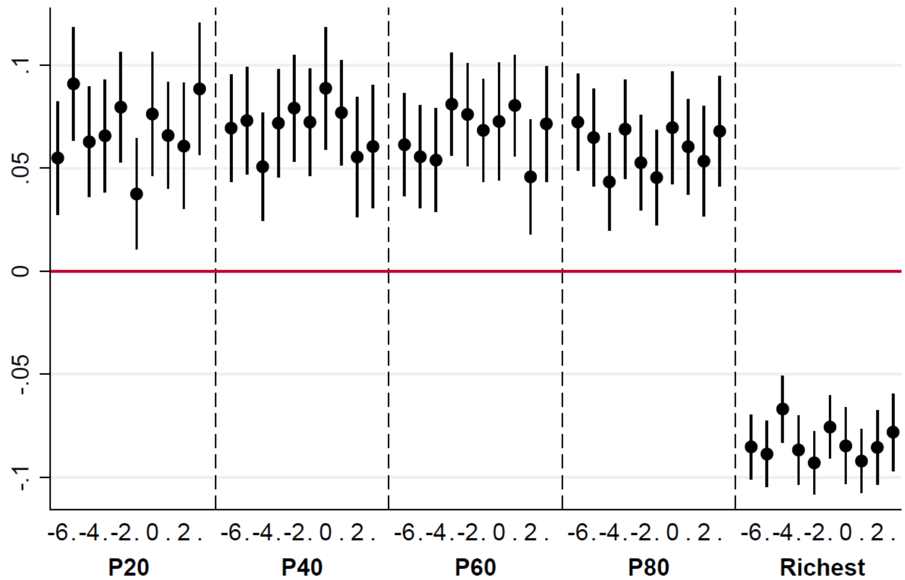
utilisation increases coupled with supply-side constraints demonstrated by Johar et al. (2018) could mean that there was no new investment being made post-reform.

Uneven distribution of healthcare facilities can also contribute to limited improvements in healthcare delivery and accessibility. Some studies on a number of countries reveal accessibility to healthcare facilities was relatively low in less-developed regions like rural areas and concentrated more in urbanized ones (Agbenyo et al., 2017; Buor, 2003; Okafor, 1990). So, even if there was no expansion during the study period, it is possible for districts equipped with a relatively better supply of healthcare infrastructure to perform better after the reform was implemented.

Using data from PODES, we create an indicator that provides information about the availability of local healthcare providers per person. We develop this indicator from the total number of hospitals, maternity hospitals, polyclinics, community health centres, and auxiliary community health centres in each village and aggregate them at the district level. The total number of these health facilities is then divided by the total district population. We then split districts based on the median value of this variable to differentiate between districts with a high and low supply of healthcare facilities. To observe if a higher supply of healthcare providers is sufficient to increase access to healthcare usage we run the same estimation on the number of outpatient visits as in section 1.5.2 separately for these two district categories.

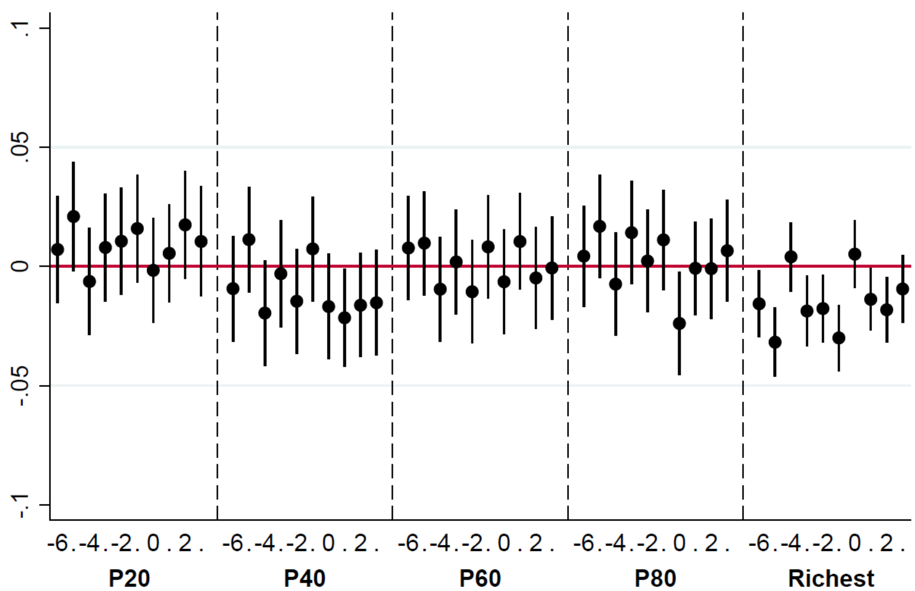
Our results in Figures 1.5 a and b unveil no significant improvements in the number of outpatient care visits after the reform in either of these districts. People who lived in the districts with high levels of healthcare providers seemed to easily access medical treatment years before the reform took place (fig.1.5 a). Meanwhile, regions with low levels of healthcare providers did not experience any changes throughout our study period for all household groups. We do not find any evidence of heterogeneous impacts of the reform on healthcare utilisation by local healthcare infrastructure disaggregation between these two district categories.

Figure 1.5: Event study estimates for outpatient visits by district medical care supply



Notes. Coefficient estimates and their 95% confidence intervals are reported. The controls include household characteristics and district fixed effects. The data cover the period 2011 Q1 to 2013 Q4. Time 0 refers to 2013 Q1.

(a) Districts with above-median number of local healthcare providers per person



Notes. Coefficient estimates and their 95% confidence intervals are reported. The controls include household characteristics and district fixed effects. The data cover the period 2011 Q1 to 2013 Q4. Time 0 refers to 2013 Q1.

(b) Districts with below-median number of local healthcare providers per person

Source: Q1.2011-Q4.2013 Susenas, Author calculation

1.6 Conclusion and outlook

At the beginning of 2013, Indonesia's government launched the use of a single poverty registry through the implementation of the country's social health insurance (Jamkesmas). This database consists of the poorest 40% households that was developed using a PMT method and offered a more accurate measure to determine the eligibility of targeted recipients into a social programme. This reform is in place to replace the fragmented targeting mechanism used before 2013. In addition to correcting its beneficiaries, 2013's Jamkesmas also expanded its targeted beneficiaries by 10%.

This chapter examines whether the UDB reform improved the health insurance coverage among the poorest 40% of households after the reform was introduced. We evaluate the reform's effects using an event study approach by observing changes in our three variables of interest estimates from quarter 1 of 2013 and the poorest quintiles. We use the first quarter of 2011's estimates as our baseline category. To the best of our knowledge, our study is the first to evaluate the effects of poverty targeting from PMT on HIC among the poor using quarterly information from household interview dates to identify improvement shown from a different pattern in insurance coverage following the introduction of a new poverty database.

Our findings suggest that on average, the HIC of the poorest quintile increased by 13% in the first quarter of 2013 relative to 2011 Q1's HIC and continued to increase reaching 17% by the last quarter. The HIC among the near-poor households (P40) also improved by about 10% in 2013's Q1 relative to the baseline and reached 13% by Q4. However, we also see an increase in insurance enrolment among non-poor households indicating that the poverty targeting has not eliminated leakage. Overall, the government's decision to make an expansion in the eligibility criteria for the provision of health insurance for the poor had a positive impact on improving health protection.

Subsequently, we further investigate whether the targeting reform through the increase of HIC effectively improved the poor's healthcare utilisation given that there was a limited investment into the healthcare infrastructure provision at the time of reform was introduced and even after the next policy reform in 2014 (Johar et al., 2018). The findings inform us that there was a small increase in the number of outpatient care visits after the reform and current variations in healthcare infrastructure provision are still unable to explain why the improvements are so limited. The effects of the reform on private spending on health seem more positive instead as the reform directly leads to approximately IDR 141,000 reduction of household expenditure across the first four quintiles. This result supports the goal of rolling out free health insurance to reduce the financial burdens of the insurance holders as OOP spending on health was perceived as a barrier for the poor to seek medical treatment. We also find that the richest faced increased monthly health expenditures in the subsequent months which needed to be further investigated.

To sum up, this study can provide an example and alternative for other countries facing similar issues of lacking reliable data on the potential beneficiaries of a social health programme to adopt the PMT approach that the Indonesian government has successfully constructed. The country's revised targeting reform has shown a positive direction of HIC improvements among the poor, who after being entitled to free healthcare services have reductions in their health expenses.

Chapter 2

Health Impacts of a Community Water Supply Intervention

Daim Syukriyah

Abstract

Access to safe water remains a significant global challenge, with one in four people excluded. I study the impact of PAMSIMAS a large-scale rural and peri-urban water supply programme in Indonesia, on households' access to safe drinking water and children's health outcomes. The key feature of the programme is central and sub-national governments' subsidies combined of up to 80% with a 20% contribution from the community to build water infrastructure. I employ a difference-in-difference estimator combined with propensity score matching using IFLS. I find that the share of households with access to safe drinking water and in-house water supply living in treated communities increased 7 ppts two years after programme completion. These results suggest a narrowing of the water access gap, but even large subsidies alone are insufficient to close it. However, I find instant improvements in childhood health, such as reduced sick days among primary school children by 10% - 11%.

2.1 Introduction

Lack of access to clean water sources costs approximately USD 260 billion every year globally.[1] According to Damania et al. (2019), this situation potentially limits economic growth by one-third in some countries. However, by 2020, approximately 2 billion people worldwide still experienced unsafe water supplies,[2] with 771 million lacking basic water services (WHO and UNICEF, 2021).[3] Consequently, approximately one in four individuals do not have proper access to clean water (Ritchie and Roser, 2021), and eight in ten people in rural areas have limited access to basic water services (WHO and UNICEF, 2021).

Limited access to safe water sources is widely associated with health risks (Calzada and Iranzo, 2021; Duflo et al., 2015; Prüss-Ustün et al., 2018). Children are relatively susceptible and less resistant to water-borne illnesses than adults and bear the most significant burden from unsafe water consumption (Burström et al., 2005; Howard et al., 2003; Zwane and Kremer, 2007). The most common disease due to exposure to unsanitary water is diarrhea (Black et al., 2003; Prüss et al., 2002; Zwane and Kremer, 2007), one of the major causes of mortality among children under 5 years old in LMICs accounting for 1,200 deaths per day and 60% of deaths in this age group worldwide (Prüss-Ustün et al., 2018; UNICEF, 2016).

Poor health conditions due to water-related infections often prevent children from performing their daily activities and sometimes, this condition requires medication and forces children to remain in bed due to sickness. Evidence shows that areas with a high prevalence of diarrhoea are likely to have high school absenteeism and low enrolment (Komarulzaman et al., 2019). As pathogens usually transmit to unprotected water sources, locations of drinking water sources play an essential role in ensuring freshwater availability and improving its quality. Previous studies have observed a positive relationship between access to piped water, especially via a tap in the premises of household houses, and child health (Jalan and Ravallion, 2003; Lee et al.,

[1] https://water.org/our-impact/water-crisis/economic-crisis/

[2] With 1.4 billion lived in areas with considerably high risks of physical water scarcity

[3] According to WHO and UNICEF, water services are defined as improved ones when they are easy, accessible to reach by the users, and are not contaminated by dangerous substances to health. If users still have to travel within 30 minutes to reach the water premises even if they are considered to be improved sources such as piped water, protected dug wells, etc, the service is categorized to be "basic". Limited service is access to improved water premises that exceed 30 minutes of journey.

1997; Mangyo, 2008). However, evidence on interventions that successfully increase water access and their impact on subsequent health outcomes is still limited.

In this chapter, I first estimate the impact of the first phase of Indonesia's Water Supply and Sanitation Programme for Low-Income Communities (*Program Air Minum dan Sanitasi Berbasis Masyarakat, PAMSIMAS*), a large-scale community-focused water-supply programme targeting rural and peri-urban communities in Indonesia, on 1) safe drinking water access, 2) in-house water supply and 3) distance to the nearest water source. In the second step, I quantify its impacts on primary-age children's sick days and days in bed, including self-rated health conditions, two years after programme implementation. I employ a difference-in-difference (DID) estimator combined with propensity score matching (PSM) to compare household and children's outcomes in treated and control communities. I combine microdata from the 2007 and 2014 waves of the IFLS, a representative household panel, with 2008 and 2014 rounds of PODES - census data that provides village characteristics information.

To ensure access to reliable water supplies and improve sanitation in low-income communities, the government of Indonesia (GoI) launched PAMSIMAS in 2008. The GoI prioritised the programme implementation based on four district-level criteria: 1) poor regions with low and medium fiscal capacity, 2) low availability of drinking water and sanitation, 3) high prevalence of water-borne diseases, and 4) never received a similar project within the last two years. The GoI offered grants of up to 80% as subsidies from central and local governments, including training, to eligible communities to build water infrastructure, but required communities to contribute the remaining funds and manage the project. To date, there have been three phases of PAMSIMAS aiming to reach universal access coverage within each participating district by 2019.[4] This chapter focuses on the first phase, which started in 2008 and was completed in 2012.

This study employs a sample of 4,027 households. Subsequent analysis of health impacts is based on a sample of 10,142 children observed in these households. The findings suggest that the share of households with access to safe drinking water in treated communities and with

[4]The first phase began in 2008-2012 in 110 districts across 15 provinces followed by the second phase with an expansion to 233 districts in 32 provinces running between 2013-2015. The third phase started in 2016 with an implementation in 396 districts and 11 cities of 34 provinces where initially targeted to be completed in 2019 but then extended to 2021 due to the Covid-19 pandemic situation.

in-house water provision increased by 7 ppts each over the baseline of 66% and 21% respectively, two years after implementation. On top of that, the number of days missed from doing primary activities among children further declined by 11% - 13% from its baseline of 4 days gone due to poor health.

This chapter makes two main contributions to existing evidence. First, it evaluates one of the largest water infrastructure interventions in the developing world and estimates its impact on households' access to safe drinking water. Few similar studies have analyzed the effects of rural or communal water organizations in Peru (Calzada and Iranzo, 2021), in western Kenya (Crow et al., 2012) and in Bolivia, Peru, and Ghana (Whittington et al., 2009) but with smaller coverage of population than the Indonesian water programme or operated by a private company like in Argentina (Galiani et al., 2005). In the case of PAMSIMAS, the programme covered nearly 5,000 villages in 15 provinces, and the total project cost amounted to USD 321 million during its first phase of implementation. As Indonesia had a population of nearly 240 million people by 2007, PAMSIMAS was deemed the largest and longest nationwide community-driven water programme globally. I show that PAMSIMAS improved households' access to safe drinking water services and in-house water provision in the programme districts by 7 ppts each by 2014. Despite not yet meeting the universal water access goal, this figure narrowed the water access gap between the treated and non-treated communities, two years after its first phase project finished.

Second, I identify the causal impacts of such interventions on child health that are relatively sparse. While several studies have documented the association between safe water access, primarily pipeline services and children's health and mortality, they mostly were not conducted using individual children data and not panel data (Jalan and Ravallion, 2003; Lee et al., 1997; Merrick, 1985; Thomas and Strauss, 1992), or observational data (Galiani et al., 2005). A study by Mangyo (2008) is the only exception that measures the child health effect from within-community distance to a water source in China using child-level fixed effects but in a smaller sample of 1,192 children. I provide direct evidence on the impact of the intervention on the number of days missed from conducting primary activities of a large sample of young children between 0 to 12 years old living in treated communities and their self-rated health condition post-PAMSIMAS phase I.

A study done previously about PAMSIMAS focuses more on the relationship between the project's unique feature of community mobilisation and its positive influence on the sustainability of the water programme operation (Al Djono and Daniel, 2022). In its implementation, PAMSIMAS adopted a bottom-up water project approach where recipient communities formulated a strategy according to their needs and resources, and were responsible for construction, monitoring and implementation (World Bank, 2015). With the cost-sharing model between the government with its large subsidies and community contributions, the provision of labour and materials at the beginning of the project construction and financial contributions such as water tariff collection from users helped maintain the water project run. My paper further investigates whether the targeted communities benefitted from PAMSIMAS measured by increased water access of households living in the targeted communities and produced other outcomes related to health 2 years post-project implementation.

The remainder of the chapter is structured as follows. Section 2.2 details the PAMSIMAS programme and its features. Section 2.3 describes the data and variables used in this project, followed by Section 2.4 which outlines the empirical model. I present the empirical impacts of PAMSIMAS on water access in Section 2.5.1 and children's health outcomes in Section 2.5.2. Section 2.6 concludes.

2.2 The Intervention

In 1990, Indonesia's population with access to improved[5] water services reached 70% nationwide, similar to water coverage in other LMICs and one-fifth lower than in upper-middle-income economies (Herrera and Post, 2014). However, water access was considerably poorer in rural areas at 61%, where the share of those with piped-water connections was very low (2%) (WHO

[5]According to WHO-UNICEF Joint Monitoring Program (JMP), improved water sources refer to any water sources that can produce and deliver free-contaminated water either by nature of design such as protected springs, rainwater collection or by man-made construction including household piped water, public standpipe, boreholes, protected dug wells, or packaged water by delivery. In addition, the water services should ensure the need of each individual for at least 20 litres/day.

and UNICEF, 2013). Therefore, despite the claim of having access to improved water services, the remaining rural population relied on other water sources that were unprotected and not necessarily safe for consumption. Meanwhile, access to improved sanitation was even worse at 35% nationwide, and 40% of the population still defecated openly in an unprotected environment (WHO and UNICEF, 2014). After nearly two decades, the population coverage with at least basic services did not improve significantly, with approximately a 6 percentage point increase in 2007.

The main challenge to accelerate progress in improving access to water and sanitation services was the country's geographical setting, with 17,000 islands that stretch 5,110 kilometres from west to east comprising plains, mountains, and coastal areas (Cribb, 2013). Considering the diverse geographical regions, the GoI could not apply a one-size-fits-all approach and needed to acknowledge its geographical heterogeneity when implementing development projects, with no exception for the water and sanitation projects.

Moreover, it is commonly seen in developing countries that most of the poor were located in rural and remote areas, suggesting that provinces with high poverty rates were likely to have lower safely managed water access coverage. However, when I break down access to 2007's improved water services coverage of Indonesia as seen in Figure 2.1, it is not always the case that regions with higher poverty rates will have lower water access coverage. The horizontal line of the figure represents access to safe water services, while the vertical axis represents the poverty rates in percentages (%). The national poverty rate in 2007 was approximately 17%, shown by the dashed horizontal line and the country's average access to safe water was nearly 49% seen by the solid vertical line in the middle. Looking at the graph, particularly in the lower right corner of the panel, wealthier provinces such as DKI Jakarta (the capital), Bali, and Riau Island reached more than 70% water access coverage compared to other regions. Yet, I can also observe that other provinces with lower poverty rates than the national figure also had relatively lower access to safely managed water sources as seen in the lower-left panel of the graph. As Indonesian provinces comprise districts with diverse socioeconomic conditions and there is no data available for access to safe water services at the district level, I cannot elaborate further on whether high-poverty level districts tended to have lower water access coverage than those relatively less-poorer districts. Nevertheless, we can still see from the graph that none of these provinces met the universal target coverage of access to safe water services.

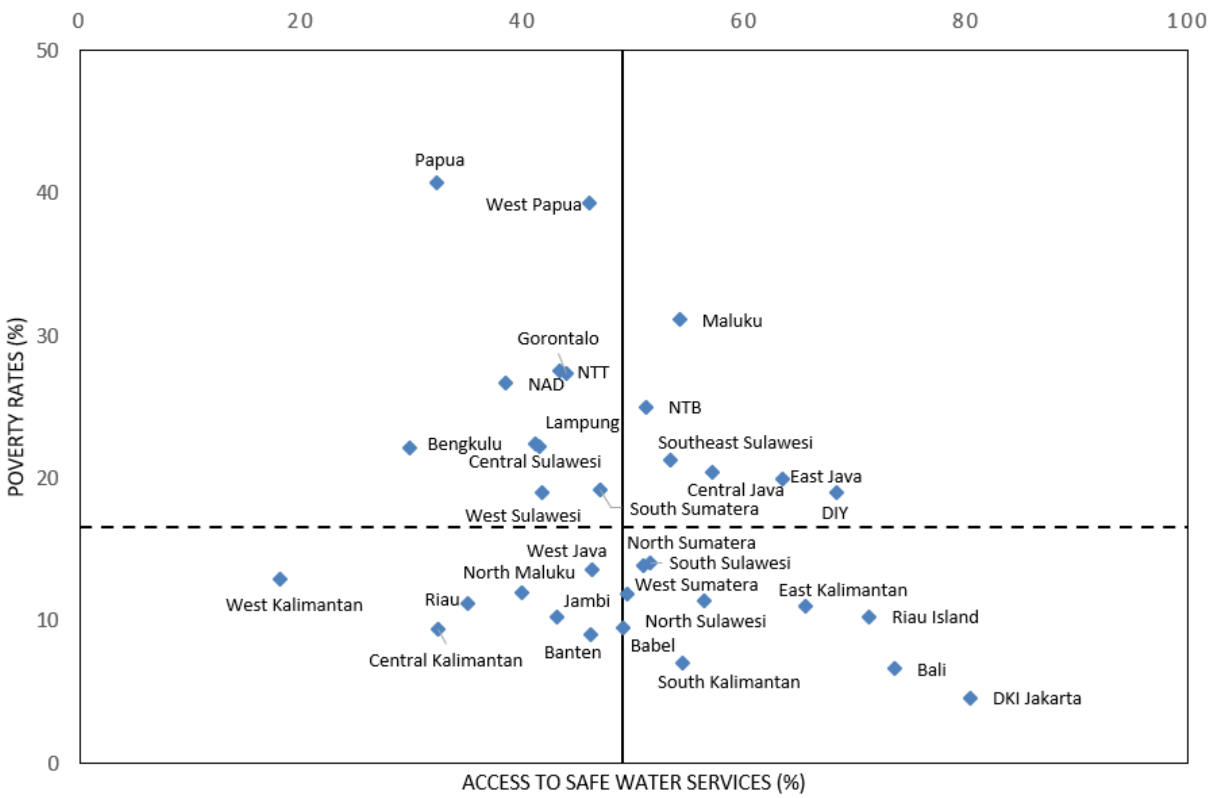


Figure 2.1: Access to basic water across provinces with different poverty rates in 2007

Note: The national average of poverty and access to safe water are 17% and 49%, respectively. The lower right quadrant of the graph shows provinces having lower poverty rates than the national figure and a higher percentage of access to safe water than the national mean.
Source: World Bank's Indonesia Database for Policy and Economic Research, 2007.

Given the inequality in access to improved water services between urban and rural across provinces, the GoI felt the urgency to minimise the inequality gap and improve its public service delivery. If this gap were closed, the country would benefit from the economic gain of improving the full coverage of water availability by saving 2.45% of its gross domestic product (GDP) in 2045 (World Bank, 2021), equivalent to USD 29 billion.[6] To mitigate this loss, in 2008, the government launched a public-led community-based water-supply initiative called PAMSIMAS, with the primary objective of increasing the provision of clean water-supply services and sani-

[6]calculated from 2021's Indonesia GDP of USD 1,186 billion.

tation practices among the rural and peri-urban low-income communities with limited access to safe water and sanitation.

PAMSIMAS began in 2008 and covered 5,000 villages in 110 districts spread across 15 provinces targeting rural and peri-urban communities. Since the programme favoured the poor, the government applied selection criteria to determine the program villages, including 1) a high level of poverty, 2) limited access to drinking water and basic sanitation, 3) a high incidence of diarrhoea, 4) no other similar programme or project in the past 2 years (World Bank, 2015). In the selection process of village beneficiaries, based on those criteria, district governments and representatives of civil society groups screened which villages were eligible and convinced the targeted communities to participate in the programme. The district governments consisted of representatives from the district office of public works (Dinas PU), the local development planning agency (BAPPEDA), the local agency for community empowerment (PMD) together with the relevant local non-governmental organisations (NGOs) and academics (Thapa, 2019).

As a community-led project, PAMSIMAS employed communities as the main actors to run the programme operations rather than the government that built and maintained the sustainability of the water infrastructure in the programme locations. In its implementation, the village's water management board were responsible for carrying out and organise the water project and piped-water system to run (Daniel et al., 2021). The project also required that at least 40% members of the board are women although only one-fifth of all PAMSIMAS projects complied with this policy (Al Djono and Daniel, 2022). As a community-driven approach, below are the project's main components:

1. The government offered technical and institutional capacity enhancement through technical skill and community facilitator training to assist communities in planning and project preparation.

2. The government allocated grants and technical assistance to incentivise local communities to implement the project plan.

3. Technical support was provided via monitoring and evaluation while developing a grievance system about the project delivery.

The key feature that made PAMSIMAS interesting and distinguished it from any other government programme was that the programme had communities play an active role in its programme implementation from the start. Often, the provision of piped water and sanitation facilities improvement to rural communities can be relatively expensive. Thus, by giving communities more responsibility to create a sense of ownership, the sustainability of the programme is maintained (Marks and Davis, 2012; Zwane and Kremer, 2007). Hence, PAMSIMAS required the targeted communities to contribute at minimum 20% of the total construction costs in the form of 16% in-kind support, including labor and 4% cash. Therefore, beyond monetary contributions, all community members were actively involved in building the water infrastructure facilities and toilets in their villages during the construction phase. Furthermore, the subnational governments allocated 10% of the total cost for each programme village. Meanwhile, the central government made the lion's share of the total programme, financing 70% earmarked from the national budget and a World Bank loan.

During the project implementation, the government allocated USD 20,000-30,000 per village depending on the proposed Community Work Plan (RKM) that varied across villages due to geographical diversity (LP3ES, 2007).[7] The government made an initial transfer of 25% of the village's project cost if the targeted beneficiaries via their water board committees could show that the 4% cash community contribution got collected (PAMSIMAS, 2013). The government made the next fund payments when the available balance of the village's bank account indicated below 10% and subsequently transferred the remaining fund if the government observed physical progress up to 75%.

Before the project began, the community also decided on the monthly water fee according to their affordability to maintain the water system operations outside their early cash contribution to the project. This decision was agreed during the village hall meeting when all community members discussed their community work plan. Although PAMSIMAS was designated to provide water access to under-serviced and rural communities, the regular monthly payment improved the functionality of the water system and the amount fee was cheaper than the regular tariff

[7] converted into 2007 prices or between IDR 195-280 million. 1 USD equals to IDR 9,400 in 2007.

charged by the urban water utility company (Al Djono and Daniel, 2022).[8]

Based on each village's respective community work plan that had been approved by the district facilitator, the water board committees along with the communities primarily built household connections using pipelines from their main water sources to houses in the targeted villages. It started with the construction of public water storage and public taps and connected the main water storage tank to a house connection, usually by installing a pipeline water metre. It also aimed to increase the use of proper sanitation facilities and promoted the adoption of hygiene practices. Hence, the programme also supported communities when they were willing to construct sanitation infrastructure. However, due to geographical, socio-economic, and cultural variations, PAMSIMAS had to adjust their solutions to these challenges during the programme implementation and gave the communities a choice to use the water system technology that best suited them.

(a) Public Water Tap. (b) Permanent Squat Toilet.

Figure 2.2: Examples of Pamsimas products taken by the World Bank (2015).

To ensure that PAMSIMAS ran well with communities acting as the principal agents in the programme operations, the GoI allocated grants for the preparation and construction of the water-supply facilities and public toilets in the programme villages. Although communities were responsible for building and customising the water-supply facilities according to their specific needs and village topography, they might have lacked institutional knowledge and skills during the implementation. To help formulate the plan and establish its associated institutional re-

[8] USD 0.11 per cubic meter (Destarian and Pigawati, 2015)

quirements, the government offered technical support and training for community facilitators to provide their capacity building in the implementation and sustainability of the facilities post-construction. This service also benefitted communities if they wanted to expand the water and sanitation facilities to offer broader community coverage in the future. Since PAMSIMAS was a transformation process to increase public health for all community members, the government followed an inter-sectoral approach, establishing active coordination among numerous government agencies, including regional offices, the private sector, and non-governmental organisations.

Between 2008-2019, there were three phases of PAMSIMAS, starting with phase I which spanned from 2008-2012, phase II from 2013-2015, and phase III during 2016-2019.[9] The coverage areas of PAMSIMAS I (2008-2012) initially included 110 districts in 15 provinces. By the second scheme of the program, the government added the number of provinces summing up to 220 districts located in 32 provinces. The final PAMSIMAS covered 396 districts in nearly 34 provinces, or 77% of all districts in Indonesia.

2.3 Data

The main analysis of this study will be based on the IFLS, with panel household data comprising relevant questions about individual and household characteristics, such as main water sources for drinking, types of latrines, distances to water points, types of water sources, gender, ages, education, types of dwellings, household assets, and monthly expenses for foods and non-foods. IFLS tracked the same 7,200 households living in 13 out of 26 provinces and all their family members starting in 1993 and maintained a high household recontact rate above 90% until the latest wave in 2014 (Strauss et al., 2016). The sample is representative of 83% of the Indonesian population with approximately 40,000 and 50,000 individuals covered in the 2007 and 2014 waves, respectively. For this analysis, I will use these two waves (see Figure 2.3).

As explained in the previous section, there are three phases of PAMSIMAS with phase I starting from 2008-2012, followed by its second phase between 2013-2015, and the last phase from 2016-2019. Meanwhile, IFLS is only available until the 2014 wave with approximately a

[9]since there was a Covid-19 pandemic in the first quarter of 2020, the government decided to prolong the program until 2021 to help provide some facilitation support to avoid adverse effects.

seven-year gap between surveys. Because of such data limitation, this study primarily focuses on evaluating the first phase of PAMSIMAS during 2008-2012, with all households residing in districts treated in Phase I as the treatment group. Since Phase II began in 2013, households from this phase were partly treated until 2014, the last wave of the IFLS. Therefore, I exclude these respondents from the analysis. The untreated group will come from the remaining rural districts targeted by PAMSIMAS (i.e. those eligible to participate in Phase III, but did not receive any treatment by 2014). In total, I employ 4,027 households as my final data set, consisting of 2,282 treated households living in 77 districts out of 110 PAMSIMAS districts and 1,745 not-yet-treated households from 70 districts.[10] Figure 2.3 depicts the timeline of the three PAMSIMAS phases and the coverage period under study.

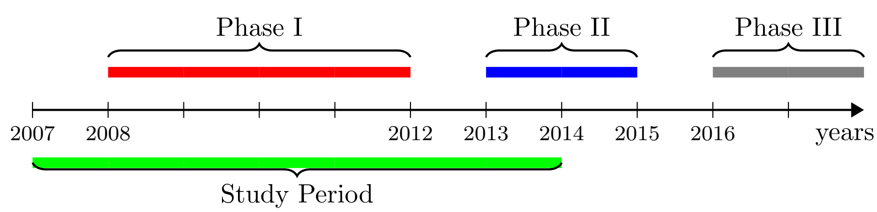


Figure 2.3: PAMSIMAS phases and the study period

In addition, I incorporate village and district-level characteristics to capture information used as selection criteria for targeted communities to receive the treatment. I obtain the village-level variables from PODES and 2007's district poverty rates from Indonesia's Database for Policy and Economic Research (Indo-Dapoer), World Bank.[11] Furthermore, I evaluate the impact of PAMSIMAS across three key indicators:

1. **The share of households with access to safe drinking water.** This indicator measures water access coverage. I construct this variable from the number of households with safe drinking water sources following the definition of the World Health Organization (2017) divided by the total households in the districts. PAMSIMAS was implemented at the village level within the programme districts, so instead of having a binary variable,

[10] We use all PAMSIMAS districts that are available in the survey that matched between 2007 and 2014

[11] The poverty rates used in this study are calculated based on the official district poverty rates released by BPS. BPS computes the district poverty rates every quarter using a basic needs approach (a poverty basket) from Susenas.

households with access to safe water sources are replaced by the corresponding proportion of households within the programme districts receiving PAMSIMAS relative to the total district population. According to PAMSIMAS, safe water sources mean water sources that can deliver free-contaminated water from faecal or chemical contamination, including water pipelines, protected dug wells, and borehole pumps. Meanwhile, protected springs and rainwater were not considered improved sources by PAMSIMAS, although they were considered safe by the World Health Organisation (WHO). Hence, I exclude these two types of water sources in constructing this indicator.

2. **The share of households with in-house water supply.** This indicator measures the enhancement of the water-supply provision because improved water sources also mean that the water collection point has to be reasonably easy to reach (WHO and UNICEF, 2021). I compute this variable from the number of households with the location of safe water sources inside their houses and then divide it by the number of households within the districts. I then apply the proportion of households within the districts relative to the total population to those who answered that their safe water sources were located inside their houses.

3. **Distance to the water collection point.** This indicator measures whether the journey distance to collect water decreased in the respondents' villages after the programme commenced. The water distance is calculated as the round trip from houses to the safe water collection points in metres. When a household answered that the location of their water source was inside of their house, the distance to collect water was recorded as zero metres in the survey. Because there are households with zero metres in water fetching distance, I cannot use the regular logarithmic function because it cannot read 0 values of distance and it will create a problem in running the analysis. Instead, I transform this distance measure using an inverse hyperbolic sine function (IHS) because such a function can read non-negative values including zeros, and thus, IHS is an appropriate transformation for the distance variable. Hence, I then convert the values using the inverse hyperbolic sine function and employ the transformed values in my analysis.

These three outcome variables reflect the key aims of PAMSIMAS. Outcome 1 captures whether the programme widened access to safe and improved water sources, while outcomes 2 and 3 capture two dimensions of reduced distances to water collection. All these together mean access enhancement to safe water sources, which later on contributes to individuals' health and indirectly can lead to higher school attendance, labour market participation, more leisure time, and less conflict due to competition to fetch water. Moreover, better health can also lower families' healthcare expenses and improve households' living standards. At the macro level, these improvements are expected to create a healthy society, induce productivity in the workforce, and boost the national economy.

Since PAMSIMAS also empowered communities to adopt hygiene practices and supported the elimination of poor sanitation, I will use the share of households who still defecated openly (in an open or unprotected setting). This indicator will be a proxy for unprotected and poor sanitation practices reduced after PAMSIMAS. Table 2.1 describes all outcome variables of interest for this study.

Table 2.1: Description of Outcome Variables

	Variable	**Description**
1	Access	The change in shares of access to water between 2007-2014
2	In-house Water Supply	The change in shares of in-house water supply between 2007-2014
3	Distance to Water	The change in the water fetching distance between 2007-2014
4	Open Defecation	The change in shares of open defecation practices between 2007-2014

Source: IFLS, Author definition

Then, in the next analysis, I investigate PAMSIMAS's impact on child health outcomes. I used data from individual children living in the sample households. Of 4,027 households, the sample consists of 10,142 children between 0-12 years old, with 5,523 kids belonging to the treated districts and 4,619 observations in the not-yet-treated ones. Young children are deemed vulnerable and susceptible to water-related illnesses because of their little knowledge to avoid exposure to diseases (Burström et al., 2005; Howard et al., 2003; Zwane and Kremer, 2007). Three health outcomes I observe are 1) the number of days missing from primary daily activities due to poor health in the past 4 weeks, 2) the number of days staying in bed in the past 4 weeks, and 3) the self-rated health status in the past 4 weeks of the survey. I particularly examine these three health indicators to assess if, in general, the kids' health in treated communities improved after PAMSIMAS, where the programme helped communities access to safe water with protected, in-house water facilities. For the last child health outcome, the self-rated health status, I examine another cohort covering up to junior-school-aged children if their general health status improved after PAMSIMAS. Therefore, in addition to 10,142 children, I use 12,041 individuals from 0 to 15 years old. The children's health outcomes are presented in Table 2.2.

Table 2.2: Description of Child Health Outcome Variables

	Variable	**Description**
1	Sick days	Number of days missing primary activities due to sickness in the past 4 weeks
2	Stay in bed	Number of days staying in bed due to sickness in the past 4 weeks
3	Health status	1 = if the respondent reported quite healthy and very healthy, 0 = if somewhat unhealthy and unhealthy

Source: IFLS, Author definition

Table 2.3 presents the variables and their respective definitions in the participation model to generate propensity scores. As an archipelago, the country's socio-economic and geographical variations might have hindered the programme's implementation (World Bank, 2015). In the model, I control for village information, such as the share of villages with hilly areas and villages with asphalt roads, two variables possibly reflecting the challenging physical conditions of the corresponding village residents to reach the water sources. In addition, since PAMSIMAS applied specific criteria for communities to receive the programme, I include the proportion of family members that had diarrhoea or stomachache in the past four weeks prior to the survey to control for diarrhoea prevalence and district-level poverty rates to capture socio-economic differences across districts. I also add a binary variable of having access to safe drinking water in 2007 in the model to control for the baseline access to safe water sources in my sample and help eliminate systematic differences between the treated and non-treated groups.

I also include the household representative's age, gender, marital status, education, and literacy status in the model because they reflect individual variations that might influence the final community action plan. PAMSIMAS required targeted communities to be involved in the design and plan, construction and maintenance of the water and sanitation facilities that met their needs and geographical features. Thus, rural members held meetings at the village hall to discuss their action plans (World Bank, 2015). Their decisions and ideas varied among individuals, especially about installing a private house connection from the main water storage. Control variables include *smoking* to capture information if respondents had a smoking habit, as smoking can be used as a proxy for unobserved risk preferences (Pfeifer, 2012). There is also a dummy variable called *full-time* if respondents were employed either working for others or in their businesses an average of 35 hours or higher per week. The *full-time* estimates full-time employment used to measure the opportunity cost for water collection and participation in the water and sanitation project construction.

In many countries, female family members, from children to adult women, commonly have a higher burden of domestic housework than their male household counterparts, including water collection tasks (Hutton et al., 2007; Irianti and Prasetyoputra, 2019). It is then expected that families with a higher share of female members will be more likely to have improved access to water and sanitation facilities. The water collection task becomes heavier if fewer members are available within the family to take responsibility as water carriers. Thus, I create several household characteristics to reflect households' demographic structures, including the proportion of adults above 15 years old in the family, the dependency ratio and house density measured by the number of family members relative to the house size in square metres.

In the economic literature, measuring household socio-economic status commonly uses numeric measures, such as household income or expenditures and wealth. In developed countries, information on incomes and assets is relatively reliable and readily available. By contrast, in developing countries, the socio-economic status of a household is not always determined by income or expenditure measures and is often not reliable (Kolenikov et al., 2004), partly because most of the population works in the informal sector of employment. In Indonesia, according to BPS, of those with informal employment, approximately 70%-80% work in the agricultural sector and reside in rural regions for whom monetary possessions do not always define wealth because they do not receive regular salaries like their urban counterparts. Instead, they receive a portion of

Table 2.3: Description of Independent Variables of Probit Participation Model

	Variable	Description
1	Asphalt roads	Share of villages with asphalt roads
2	Hills	Share of villages with hilly or mountainous areas
3	Diarrhoea incidence	Share of households with members suffering from diarrhoea or stomachache in the past 4 weeks
4	Poverty rates	District poverty rates
5	Safe water	1 if the household had access to safe drinking water in 2007
6	Age	Age of respondent
7	Male	1 if respondent's gender is male and 0 otherwise
8	Married	1 if respondent is married and 0 otherwise
9	Smoking	1 if respondent still smoked until the interview took place, 0 has never smoked or smoked but successfully quit
10	Full-time	1 if respondent worked on average 35 hours or above per week
11	Primary	1 if the highest level of education is primary or lower
12	University	1 if the highest level of education is college or equivalent to higher education level
13	Literate	1 if respondent can read and write the Indonesian Language
14	House density	Average of family members per metre square living in the house
15	Dependency ratio	The ratio of working age relative to non-working age family members
16	Adults	Share of family members in the households aged 1 year old or above
17	Share of female	The proportion of females in the family
18	House ownership	Wealth index reflecting household assets with higher loading contributors are from own house assets and perennial crop harvest
19	Household appliances	Wealth index reflecting household assets with higher loading contributors are household appliances such as TVs, refrigerators, computers, DVDs, sewing machines and washing machines.
20	Household expenditure	Monthly household consumption expenditure in IDR in logarithmic values

Source: IFLS and PODES, Author definition produce from their harvest in return. In addition, some rely on subsistence farming, only leaving a little surplus for sale. Moreover, during surveys, respondents can sometimes be sensitive and reluctant to reveal information about their incomes to enumerators who are strangers to them.

Hence, the survey collects information on a selection of durable assets of these households to solve this issue and find a relatively reliable proxy measurement to determine households' socio-economic status. Their wealth structure is primarily based on the ownership of durable household assets, the possession of cattle and livestock, family members' employment and access to service. These assets help inform the relationships and patterns of households' socioeconomic positions in a set of steady variables because they show households' affordability to acquire these assets over the years.

First, I use monthly household expenditures in logarithmic values to measure wealth. Since this study focuses on the programme that targeted rural communities, household assets often will help identify households' socio-economic status. Hence, in addition to the household expenditure, I also need household assets to measure wealth and might help explain the socio-economic backgrounds of households that participated in the programme. However, we need to ensure the right number of variables and which household variables explain the information of households' socio-economic status. Otherwise, if we incorporate many variables in our regression model, it will result in higher dimensional data and may overfit the model, making it difficult to interpret the direction of these variables on the households' socio-economic status. Besides, if among variables that I include in the model to represent households' socio-economic status are highly correlated, the model will suffer from multicollinearity and subsequently, it will create a redundancy in some of the variables due to overlapping. Consequently, a lack of information per parameter in a regression will inflate the standard errors and curtail the statistical power, which in turn, the parameter estimates of the regression become large and cause unreliable inferences (Daoud, 2017).

Since I have 14 household variables representing assets and housing quality, and to avoid the aforementioned issues, I need to reduce the inclusion of all 14 variables and only add in a few factors that characterise household wealth. To do so, I will construct a household wealth index by combining a series of household assets in a few numbers to avoid urban bias (Martel et al., 2021) and compensate for any measurement errors due to household expenditures (Kolenikov et al., 2004). To help identify the right number of variables or common factors that parsimoniously explain the covariation (correlated variation) among 14 variables of household assets and characteristics, I will generate a set of observed household assets using Factor Analysis (FA). Later, I will refer to this set of household assets or factor solutions according to FA as the household wealth index.

In reducing complex data and extracting pertinent information from a set of variables, FA is preferable to Principal Component Analysis (PCA) (Costello and Osborne, 2019). While PCA's objective is merely data reduction, FA aims to explain the correlations among variables and describe the structure of the data in terms of a smaller set of variables which provides easier interpretations (Bandalos and Boehm-Kaufman, 2010). In addition, the standard FA (or PCA) uses the Pearson correlation coefficients that assume variables employed are multivariate normal distributed, which is only suited to deal with continuous and interval-level measures (Holgado-Tello et al., 2010; Martel et al., 2021). In this study, the 14 variables that I use to develop factor solutions of household wealth index include house and land possession, livestock/fish ponds, hard stem plants (coconut, coffee, rubber, and cloves plants), possession of durable goods, and other variables that inform housing quality such as the type of house's wall, floor, roof, number of rooms in the dwelling, and the floor size of the house. As these variables are in categorical or ordinal terms, the standard FA method is less suitable for calculating the correlation among categorical variables or discrete data (Holgado-Tello et al., 2010). To correctly extract factor solutions of household wealth proxies from these types of variables, I perform a factor analysis using a polychoric correlation matrix in the computation.

The standard FA will not fit ordinal data because it will ignore discreteness when ordinal data is present. If there are categorical or binary variables in our data and we compute factor solutions using the standard FA, the correlations calculated using Pearson correlation will tend to be underestimated Byrne 2013, p.129. The polychoric correlation coefficient is instead designed to fit ordinal data as it requires less restrictive assumptions. Polychoric coefficient assumes each discrete data as a binned continuous value from a normally distributed data point using a maximum likelihood procedure which asymptotically is efficient (Olsson, 1979). Hence, I construct socio-economic proxies using this polychoric-FA method as detailed in section A.2 of the Appendix (Tables B1 - B3).

For the subsequent estimations on children's health outcomes, I will incorporate variables used in the main analysis, mostly household characteristics, village- and district-level information listed in Table 2.3. In addition, I will also control for child-level characteristics described in Table 2.4 for child health outcome estimations.

Table 2.4: Description of Independent Variables of the Probit Participation Model

	Variable	Description
1	Child age	Age of the child respondent.
2	Child male	1 = if child respondent is male, 0 = if female.
3	Child primary	1 = if child respondent attended a primary school, 0 = otherwise.
4	PAM	1 = if child respondent lived in treated communities receiving PAMSIMAS.
5	CHILD	1 = if child respondent belong to a specific age cohort: (i) 0-12 for outcomes 1, 2 and 3, and (ii) 0-15 for outcome 3.

Source: Author definition

2.4 Empirical Model

2.4.1 Propensity Score Matching-Difference in Difference Method (PSM-DID)

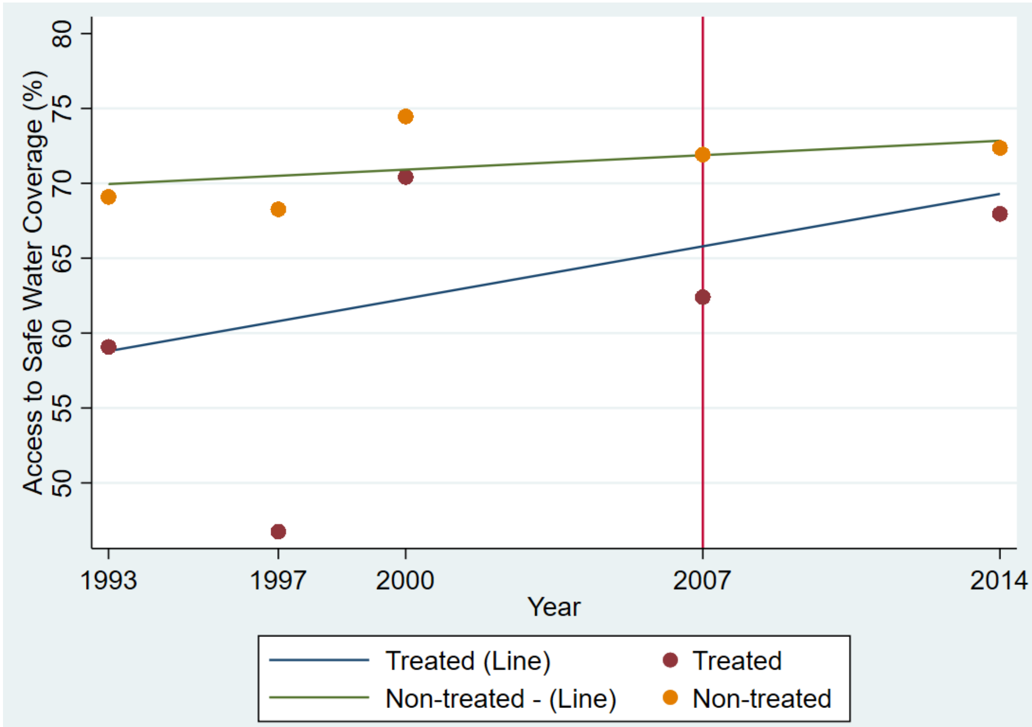
PAMSIMAS is a government programme designed to provide water access to safe drinking water and improve sanitation facilities in rural communities based on specific pro-poor criteria. Hence, the programme was not randomly assigned to rural communities. This paper mainly aims to obtain the average treatment on the treated (ATT) of the average impact of receiving PAMSIMAS on access to safe drinking water among households in districts during PAMSIMAS phase I. I employ a combination of the PSM method and DID technique to obtain the ATT.

PSM is a policy evaluation approach that uses observational data in a non-experimental setting where the treatment assignment is not random (Rosenbaum and Rubin, 1983). To obtain a non-biased estimate effect in such a setting, I should have compared the outcomes of the same household in two states, conditional on receiving and not receiving the treatment simultaneously (Smith and Todd, 2005). Since this is infeasible, the evaluation requires me to mimic a randomised experiment as closely as possible and uses not-yet-treated households (i.e. those in villages targeted in phase III) as a comparison to exploit a counterfactual outcome of the treated households. However, selection bias will occur from simply comparing the treated and non-treated households' outcomes due to the non-random assignment of receiving PAMSIMAS. Indeed, certain characteristics of the treatment group might have desirable features that generate a positive bias toward the outcomes.

Rubin and Thomas (1996) suggest that matching using the linear propensity scores effectively reduces and corrects any potential self-selection problem in the intervention effects. In doing so, PSM produces a probability score of treatment assignment conditional on the baseline observed covariates so that the distribution between the treatment and control groups is statistically similar and balanced (Rosenbaum and Rubin, 1983). Therefore, the use of PSM in this paper will be consistent with the technique developed by Heckman et al. (1997); Rosenbaum and Rubin (1983) and Smith and Todd (2005).

Meanwhile, the DID will allow me to eliminate potential bias arising from time-invariant unobservable factors using the double difference of the estimator in both groups on the access take-up and bias due to time trends that are unrelated to the intervention. Additionally, the DID also helps to deal with any potential endogeneity problems (Silva et al., 2012). Hence, combining PSM with the DID will help improve the quasi-experimental evaluation method (Blundell and Costa Dias, 2000).

Besides, the parallel trend of households' access to safe water coverage in the treated and not-yet-treated communities is unmet which then rules out the use of the DID technique alone to observe the outcomes of the PAMSIMAS programme. The validity of DID to be used alone in eliciting the impact of PAMSIMAS on its expected outcomes requires "a common trend" between treatment and control groups, implying that the observed and unobserved factors between these two groups are not different pre-programme intervention and thus, may not change either after the programme in the absence of the PAMSIMAS. As seen in Figure 2.4, I plot the share of



Note: The graph describes the shares of access to safe water among households living in treated and non-treated districts from 1993, 1997, 2000, 2007, and 2014 waves. Some districts in 1993, 1997, and 2000 waves might not be the same as in 2007-2014 due to the regional autonomy policy commencing in 1999 which resulted in some district proliferation. The vertical axis denotes the share of households' access to safe drinking water coverage in percentage and the horizontal axis represents the year of data collection. The vertical red line marks the year 2007, one year before PAMSIMAS started in 2008. Visually, there were pre-intervention trends between the treated and non-treated households' access to safe water.

Figure 2.4: Parallel trend graph from IFLS 1993-2014

Source: IFLS, Author calculation

households with access to safe water across years pre-PAMSIMAS to post-treatment in 2014. From the IFLS survey, there are 4 pre-treatment waves collected in 1993, 1997, 2000, and 2007, and 1 year after the PAMSIMAS period in 2014. In the pre-intervention period of PAMSIMAS commencement, the observed trends between access to safe water coverage between the treated and non-treated households are not parallel, hence undermining the parallel trend assumption for employing DID alone. Using a matching technique can overcome these non-parallel trends by finding matches between households in the treatment and comparison groups under common support regions (Ryan et al., 2019).

In this study, PSM is needed to adjust confounders to find a balance between the treated and not-yet-treated groups. Hence, by combining PSM and DID, the ATT estimates will be unbiased and meet the common time trend (Dehejia, 2005). Several studies have used PSM-DID method in their empirical research. Specifically, those evaluation studies on health, including Rabbe et al. (2021), Chen et al. (2020), Tsuji (2015) and Chen and Jin (2012).

In conducting PSM-DID, I aim to obtain unbiased estimators; hence, I need to ensure balanced covariates are used in the matching process. In the first step, I perform individual t-tests over all variables that I use in the matching analysis to see if each variable is statistically the same for both the programme and comparison groups. In addition, I also conduct Romano-Wolf multiple hypothesis testing suggested by Clarke et al. (2020) and Mckenzie (2020) to evaluate if jointly all variables statistically have similar demographic structures in both groups. Romano-Wolf tests can correct the probability of falsely rejecting the true null hypotheses or, particularly the family-wise error rate (FWER) asymptotically using a bootstrap resampling procedure (Clarke et al., 2020). If the adjusted p-values from Romano-Wolf tests are statistically not significant, it means the treatment and comparison groups are balanced. Our Romano-Wolf test suggests that three out of four outcome variables are balanced but not for *Access to Water*. This result matched our single t-test outcomes. Furthermore, individual and Romano-wolf tests are necessary to feed the second step when I specify the participation model using either logit or probit regression to correct the imbalance and achieve covariate balance.

Looking at the results in Table 2.5, the characteristics among individuals in treatment and control groups are similar except for the gender status of the respondents, where *male* in the treatment group is slightly smaller than that in the comparison group at the 5% level. All household representatives with higher education are quite the same in both groups. Nevertheless, those with primary highest education attainment are slightly lower in the control districts. Regarding household compositions, 71% of households in the control districts have a larger share of adult members within households than their counterpart treatment districts, with 69%. While the adult members' composition is higher in the comparison group, the share of female family members is larger in the treatment districts. Even though the shares of adult members and females in the family are significantly different between the two groups, the household density that measures individuals living in a household per unit of area, is the same between

Table 2.5: Descriptive Statistics of Variables

	Control Districts		***Treated Districts***		***t-Test Statistic***
	Mean	Std.Dev.	Mean	Std.Dev.	
Village Characteristics					
Asphalt road	0.68	0.01	0.67	0.00	1.66
Hills	0.15	0.00	0.25	0.00	-16.97
Diarrhoea incidence	0.09	0.00	0.11	0.00	-2.24
District Level Indicators					
Poverty rates	15.80	6.84	18.59	7.54	-12.12
Demographic Characteristics					
Age	42.60	14.60	43.07	14.25	-1.03
Male	0.74	0.44	0.71	0.45	2.31
Married	0.87	0.34	0.86	0.35	0.91
Smoking	0.55	0.50	0.53	0.50	1.10
Full-time	0.56	0.50	0.52	0.50	0.39
Literate	0.82	0.38	0.84	0.36	-1.62
Education					
Primary	0.58	0.49	0.61	0.49	-2.16
University	0.07	0.26	0.06	0.24	1.47
Household Composition					
Adults	0.71	0.22	0.69	0.22	3.54
Share of female	0.49	0.21	0.51	0.22	-2.18
House density	16.79	20.75	17.04	18.96	-0.41
Household Assets					
House ownership	6.29	4.57	6.78	4.20	-3.54
Household appliances	2.01	2.75	2.53	2.51	-6.25
Household expenditure	14.11	0.65	14.15	0.64	-2.25
Baseline Outcomes					
Households with safe water	0.71	0.34	0.66	0.39	4.90
Households with in-house water	0.24	0.28	0.21	0.27	3.29
Water distance	13.54	28.40	12.41	25.19	1.33
Households with open defecation	0.09	0.18	0.08	0.17	0.19
Outcomes in 2014					
Households with safe water	0.72	0.35	0.73	0.36	-1.56
Households with in-house	0.33	0.32	0.41	0.35	-7.53
Water distance	11.29	26.14	7.02	20.27	2.68
Household with open defecation	0.02	0.09	0.02	0.08	0.69

Source: IFLS, Author calculation

treatment and control districts.

To compare household economic status in two groups, I use three socioeconomic indicators:

Table 2.6: Romano-Wolf Multiple Hypotheses Testing

Variables	Model p-value	Resample p-value	Romano-Wolf p-value
Access to Water	0.0001	0.0020	0.0040
In-house Water Supply	0.5287	0.5564	0.7652
Distance to Water	0.1693	0.2078	0.4466
Open Defecation	0.4972	0.4985	0.7652

Source: IFLS, Author calculation.
Notes: In running the test, I include all covariates listed in Table 2.5 from village characteristics to household assets as my control variables.

monthly household expenditures and two asset-based indices constructed using FA. As seen in the table, while the log household expenditures are relatively similar for both groups, two wealth indices show that households in the treatment districts are relatively wealthier. However, at the district level, programme districts are considered much poorer, on average, with district baseline poverty rates at 18.59% compared to 15.80% for the control regions.

The last section of the table describes t-test results of the outcomes of interest both for the baseline and end-line periods. In the pre-matching stage, I only need to check the similarity of baseline outcomes (2007 variables). Since this study uses PSM combined with DID, I also present 2014's outcome variables as the dependent variables, taking the form of the differences between the 2007 and 2014 outcomes, as previously seen in Table 2.1.

In the baseline year, the share of households having access to improved drinking water for the non-program districts is higher by 5 ppts than households in the treatment districts with 66% coverage. This difference almost disappears in 2014. Not only do the treatment districts have a lower share in access coverage, but the share of those living with in-house water provision is also slightly higher at 24% in the non-programme districts compared to 21% in the treatment districts. While having higher access and more households with in-house water source locations, the table shows that two other baseline journey distance and sanitation practices are statistically similar between the two groups.

2.4.2 Estimation Model

This section provides steps on how to conduct the matching model for this study. The first procedure is to estimate a binary nonlinear model of household participation in the PAMSIMAS programme. The probit model aims to obtain the propensity scores by controlling factors, simultaneously affecting the decision to participate in the programme and the outcomes of interest (Rosenbaum and Rubin, 1983). In conducting a matching strategy, I should impose the conditional independence assumption (CIA), requiring an independent relationship between the outcome variables and the assignment of the treatment conditional on the propensity scores (Caliendo and Kopeinig, 2008). Therefore, the inclusion of variables used in the models should satisfy this CIA by selecting factors affecting the participation decision. Otherwise, omitting variables will lead to biased estimated results (Heckman et al., 1997). The baseline covariates for this study appear in Table 2.3, and the probit model generating propensity scores for the matching analysis is given below:

$$Prob\left(Pams_{igt} = 1 | X_{igt-1}, VI_{gt-1}\right) \tag{2.1}$$

where $Pams_{igt}$ is a dummy variable representing PAMSIMAS programme, $Pams_{igt} = 1$ for households i who lived in the districts g at time t that received PAMSIMAS and $Pams_{igt} = 0$ for households i in the non-programme districts g at time t that were not-yet-treated in PAMSIMAS I. X_{igt-1} denotes selected individual and household characteristics, while VI_{gt-1} are poverty rates and other village-level characteristics such as the shares of asphalt roads and hilly areas aggregated at the district level considered to affect the decision to receive PAMSIMAS from the baseline year in 2007.

The next procedure is to estimate the four expected outcomes after PAMSIMAS was implemented. Specifically, I am interested in whether there is: 1) an increase in the share of households with access to safe drinking water services, 2) an increase in the share of households with in-house water supply, 3) a shorter distance to collect water and 4) a lower share of households who defecated openly or in an unprotected setting. To estimate these outcomes, I mainly run the DID method in Equation (2.2) below to evaluate the policy effect by accurately comparing the changes in each outcome among households living in the treated and non-yet-treated districts.

$$W_{igt} = \beta_0 + \beta_1 Pams_{igt} + \beta_2 T_t + \varphi(Pams_{igt} * T_t) + \sum_{i=1}^{N} X'_{igt}\beta_3 + \sum_{g=1}^{G} VI'_{gt}\beta_4 + \zeta_{igt} \tag{2.2}$$

where W_{igt} is the outcome of interest for household i living in district g and year t. T_t is a dummy variable referring to the post-programme implementation period. $Pams_{igt} = 1$ refers to households that lived in districts of programme communities receiving the treatment, while $Pams_{igt} = 0$ otherwise. The interaction between the dummy variable of PAMSIMAS assignment and post-programme period; $Pams_{igt} * T_t$ captures the policy effect of PAMSIMAS that is denoted by φ. Please note that this coefficient term represents the estimated effect of PAMSIMAS from the double difference between 2007 and 2014. This average effect of participating in the PAMSIMAS programme among households or technically, the ATT becomes the central aim of this analysis. Below, I will explain how this estimated coefficient is derived from the main equation.

The treatment effect estimate is the result of the outcomes between two groups of households, $W_{ig,14}$ and $W_{ig,07.}$ $W_{ig,14}$ is the expected outcome post-programme implementation and $W_{ig,07}$ is the pre-programme period outcome. Thus, the ATT is ideally can be written as follows:

$$\varphi = E\left(W^1_{ig,14} | Pams_g = 1, X_{ig,07}, VI_{g,07}\right) - E\left(W^0_{ig,07} | Pams_g = 1, X_{ig,07}, VI_{g,07}\right) \tag{2.3}$$

where the second term describes the expectation of outcome with the underlying assumption that the treated household i-th would have not been treated. In other words, the second term is a counterfactual outcome because the same household i cannot be in two different states at the same time. Thus, I need a proxy of the i-th household in the second term to estimate φ in (2.3).

If the assignment to the treatment, in this case, PAMSIMAS is random, then $X_{ig,07}, VI_{g,07}$ and $Pams_g$ in (2.3) are independent. Hence, equation (2.3) can be re-specified by assigning everyone in the second term of the equation by j as a proxy for the treated households where these households j are part of the non-treated group:

$$\hat{\varphi} = E\left(W^1_{ig,14} | Pams_g = 1\right) - E\left(W^0_{jg,07} | Pams_g = 0\right) \tag{2.4}$$

However, as PAMSIMAS allocation is not random and other confounding factors may affect the treatment, the selection bias potentially influences the estimated effect. Following Rosenbaum and Rubin (1983), PSM will eliminate this potential bias by matching the propensity scores obtained from (2.1) between the treatment and comparison groups. As such, the propensity scores generate the estimated policy effects between the treatment and non-treatment groups with similar characteristics. Furthermore, since this study employs panel data, the impact estimates generated from PSM-DID analysis will be more effective and free from potential unobserved factors including those related to time-trends (Tsuji, 2015). Similar to Todo (2011) and Tsuji (2015), the ATT or now I call it the PSM-DID estimator as proposed by Heckman et al. (1998a, 1997) and Heckman et al. (1998b) is described below:

$$\varphi^{\{PSM-DID\}} = \frac{1}{N} \sum_{i \in Pams_g = 1} \left(\Delta W^1_i - \sum_{j \in \{Pams_g = 0\}} w Pr(X_{ig,07}, V_{g,07}) Pr(X_{jg,07}, V_{g,07}) \Delta W^0_j \right) \tag{2.5}$$

where $\Delta W^1_i = W^1_{i,14} - W^1_{i,07}$ and $\Delta W^0_j = W^0_{j,14} - W^0_{j,07}$. N is the number of observations. A weight w imposing on the not-yet-treated households is determined according to the distance of the propensity scores between the treated (i) and the matched not-yet-treated (j) households.

As dependent variables in this study are continuous, $\varphi^{\{PSM-DID\}}$ is the difference in mean outcome from the treated and not-yet-treated households. Rosenbaum and Rubin (1985) suggests nearest neighbour matching is useful if we want to match treated and non-treated participants whose closest distance propensity scores, so I will use this method in the main analysis of this study. This means, the weight w employed in (2.5) stores the frequency or the number of observations from the matched control group for every treated household in the treated group and averages the matched outcome across the number of observations. In the nearest neighbour matching, each treated observation or household will be matched to a single non-treated household (Silva et al., 2012).[12]

2.4.3 Propensity Scores Matching Results

The probit model is used in the participation model to generate propensity scores. The propensity score represents the probability of study participants receiving PAMSIMAS based on relevant village and rural household characteristics. Once propensity scores are obtained, the matching model will compute the estimated causal effects of the programme. To comply with the CIA assumption discussed in Section 2.4.2, I select the listed variables in Table 2.3 that capture information on the institutional setting of how the PAMSIMAS programme was implemented.[13]

Building on this matching strategy assumption and previous research, the propensity score estimation results from the probit model appear in Table 2.7. Some variables' signs align with expectations, such as *hills*, *diarrhoea incidence*, *poverty rates* and *share of females*. Villages with a higher proportion of hilly or mountainous segments were more likely to participate in the programme. It was likewise for the prevalence of diarrhoea or stomachache within the region *(diarrhoea incidence)* and district poverty level *(poverty rates)*. The larger the proportion of female members within households, the higher the assignment probability into the treatment.

However, a few variables generate opposite directions, such as employment variable *(full-time)*, although it is not statistically significant. Commonly, having full-time employment encourages people to have a closer or in-house water supply. Walking far away to collect water is an opportunity cost for those who work over 35 hours a week. Nevertheless, the *full-time* variable shows a negative sign for participating in the treatment. This outcome could be due to the type of employment that these rural people had, where most worked in the agricultural sector as farm workers. It could be because they were still unaware of the indirect benefits of improved access, considering that people with higher literacy *(literate)* were more willing to im-

[12] For the 1:1 nearest neighbour matching with replacement, weight=1.

[13] As suggested by Bryson et al. (2002), it is important to note that the selection of variables to be included in the model must aim to obtain a precise and correct model and avoid an over-parameterized model specification by having extra and irrelevant variables. The price of having a non-parsimonious participation model is a higher estimator variance even though the estimation results are still consistent and unbiased

prove their water access. The willingness to participate in the programme could be due to some expectations to acquire more working hours or equivalent to being a full-time worker once access to safe water sources was established. Furthermore, the decision to participate in PAMSIMAS was made at village halls as a consensus with some consultations given by the local governments and PAMSIMAS facilitators after being appointed as targeted communities. Therefore, even if some rural residents were initially unaware of the importance of better access to safe and clean water, they eventually agreed and were assigned to receive the treatment.

Table 2.7: Estimation Results of the Probit Model at the Household Level

Variable Names	Marginal Effects	Variable Names	Marginal Effects
Demographic Information		***Village Characteristics***	
Age	-0.00	Asphalt roads	-0.10
	(-0.67)		(-0.97)
Male	0.01	Hills	2.01***
	(0.19)		(13.51)
Married	-0.16**	Diarrhoea incidence	0.40***
	(-2.33)		(3.12)
Smoking	-0.10*		
	(-1.86)		
Full-time	-0.07		
	(-1.60)		
Literate	0.20***		
	(3.12)		
Education		***District-level Indicators***	
Primary	0.06	Poverty rates	0.02***
	(1.14)		(6.91)
University	-0.12		
	(-1.30)		
HH Composition			
Adults	-0.42***		
	(-2.88)		
Share of female	0.22**		
	(2.03)		
House density	-0.01***		
	(-3.14)		
Dependency ratio	-0.03		
	(-0.59)		
HH Assets		***Baseline Outcomes&Cons***	
House ownership	-0.21***	Safe water	0.01
	(-9.51)		(0.10)
Household appliances	0.39***	Constant	-2.91***
	(11.34)		(-5.11)
Household expenditure	0.23***		
	(5.82)		
Household Sample	4,027		

t statistics in parentheses

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: IFLS, Author's calculation

2.4.4 Post-Matching Balance Test

After obtaining the propensity scores from the sampling matching, the next step is to check the matching quality of the model to determine whether the characteristics of all covariates in both treatment and control groups are well-balanced and approximate to random assignment.

Following Caliendo and Kopeinig (2008), I use three indicators to assess if all covariates are balanced in the post-matching estimation. First, a single t-test of each variable difference from means of both the treatment and control groups. Second, the joint significance of all regressors followed by pseudo R-squared pre- and post-matching estimations. Lastly, the absolute standardised bias calculation needs to be below 25% and the ratio of variances of the propensity score between the treated and matched non-treated groups (R) needs to lie between 0.5 and 2 after the matching procedure (Rubin, 2001). The last two numerics will inform if, the matching procedure sufficiently ensures similar characteristics before the DID-matching estimation is conducted and produces a balance between the two groups.

Having run the probit model and testing the matching quality using three indicator benchmarks, I observe that the absolute standardised bias figure is 18.3, below 25, satisfying the balance condition. Subsequently, after matching the pseudo-R-squared needs to be adequately low to inform me that all variables can explain well the participation probability (Caliendo and Kopeinig, 2008). The result suggests that the pseudo-R-squared number is fairly low at 0.006. Meanwhile, the joint hypothesis of all regressors post-matching is significant at 1% ($LR-\chi^2$=21.68) and meets the requirement that the $LR-\chi^2$ has to be rejected after matching (Caliendo and Kopeinig, 2008). The standardised bias is 1.03, which is between 0.5 and 2, so all these tests confirm that the treatment and control groups are similar and have no significant discrepancies.

In performing the matching model, I use all observations of 4,027 households to obtain a balance between the treatment and comparison groups. Overall, the estimation achieves balance, except for the variable *poverty rates*, which is significant at 10%. Table 2.8 shows the matching quality results, as explained above.

To verify that I achieve balance apart from numerical computation, I also perform graphical

Table 2.8: Balance Test Results of the Matching Model

Covariates	Matching (M/U)	Mean		Bias (%)	Reduct Bias (%)	T-test	
		Treated	Control			t	$p > \|t\|$
Demographic Information							
Age	U	43.069	42.598	3.3		1.03	0.303
	M	43.092	42.519	4.0	-21.6	1.02	0.308
Male	U	0.708	0.741	-7.4		-2.31	0.021
	M	0.710	0.729	-4.3	41.2	-1.09	0.275
Married	U	0.856	0.866	-2.9		-0.91	0.361
	M	0.869	0.863	1.8	38.7	0.46	0.645
Smoking	U	0.529	0.547	-3.5		-1.10	0.270
	M	0.526	0.535	-1.7	51.4	-0.43	0.665
Full-time	U	0.518	0.558	-8.0		-2.50	0.012
	M	0.525	0.532	-1.5	80.5	-0.39	0.694
Literate	U	0.843	0.824	5.1		1.62	0.105
	M	0.832	0.846	-3.9	23.6	-1.02	0.310
Education							
Primary	U	0.609	0.575	6.9		2.16	0.031
	M	0.583	0.615	-6.6	4.0	-1.68	0.092
University	U	0.062	0.074	-4.6		-1.47	0.142
	M	0.073	0.058	6.1	-31.9	1.59	0.113
HH Composition							
Adults	U	0.703	0.726	-10.7		-3.36	0.001
	M	0.707	0.694	1.8	83.4	0.45	0.652
Share of female	U	0.518	0.503	7.5		2.34	0.020
	M	0.511	0.515	-1.5	79.9	-0.39	0.698
House density	U	17.044	16.788	1.3		0.41	0.683
	M	16.28	16.019	1.3	-1.7	0.40	0.688
Dependency ratio	U	0.700	0.639	10.3		3.24	0.001
	M	0.677	0.673	0.6	93.8	0.16	0.874
HH Assets							
House ownership	U	6.777	6.285	11.2		3.54	0.000
	M	6.512	6.272	5.5	51.1	1.63	0.104
House appliances	U	2.534	2.013	19.8		6.25	0.000
	M	2.278	2.195	3.1	84.2	0.95	0.341
Household expenditure	U	14.151	14.105	7.2		2.25	0.024
	M	14.140	14.106	5.2	26.8	1.37	0.171
Village Characteristics							
Asphalt roads	U	0.666	0.678	-5.2		-1.66	0.098
	M	0.655	0.648	3.4	34.0	0.88	0.380
Hills	U	0.247	0.149	55.8		16.97	0.000
	M	0.171	0.165	3.5	93.8	1.17	0.243
Diarrhoea incidence	U	0.112	0.099	7.1		2.24	0.025
	M	0.103	0.108	-2.7	61.9	-0.69	0.491

Source: IFLS, Author calculation.

Table 2.8: Balance Test Results of the Matching Model (*Continuation*)

Covariates	Matching (M/U)	Mean		Bias (%)	Reduct Bias (%)	T-test	
		Treated	Control			t	$p > \|t\|$
District Level Indicators							
Poverty rates	U	18.594	15.799	38.8		12.13	0.000
	M	17.013	16.496	7.2	81.5	1.93	0.054
Baseline							
Safe water	U	0.769	0.826	-13.9		-4.35	0.000
	M	0.816	0.807	2.1	84.8	0.55	0.581
Baseline Outcomes & Cons							
Access to water	U	0.656	0.713	-15.7		-4.90	0.000
	M	0.710	0.704	1.7	88.9	0.45	0.652
In-house supply	U	0.211	0.240	-10.4		-3.29	0.001
	M	0.214	0.215	-0.2	98.4	-0.04	0.966
Water distance	U	2.217	2.133	3.7		1.15	0.249
	M	2.314	2.322	-0.4	89.8	-0.09	0.925
Open defecation	U	0.085	0.086	-0.6		-0.19	0.849
	M	0.081	0.090	-5.1	-739.8	-1.27	0.206

Sample	Ps R^2	LR chi^2	p> chi^2	MeanBias	MedBias	B	R
Unmatching	0.106	582.24	0.000	10.5	7.2	78.3*	1.56
Matching	0.006	21.69	0.653	3.0	2.7	18.3	1.03

Source: IFLS, Author calculation.
Notes: 1. M/U refers to matched (M)/unmatched (U) observations, 2. Ps R^2 is Pseudo-R^2, and 3. * if B>25%, R outside [0.5;2].

balance diagnostics to confirm if there is a large enough common support between the treatment and non-treatment groups (Lechner, 2008). Based on the minima and maxima criterion, the propensity score lies within the interval of 0.11 - 0.99, verifying adequate overlapping among observations (Caliendo and Kopeinig, 2008). These graphical diagnostics appear as scatter plots of all covariates, side-by-side box plots, and non-parametric density plots between the treatment and control groups. The graphical displays illustrate that all covariates look balanced and convergence in all graphs infers achieving a balance of the variables post-matching. These graphical diagnostics are presented in Figures B.2, B.3, B.4, and B.5 of the Appendix.

2.4.5 Estimation Model of Children Health Outcomes

As child-related health measures are age-specific, I estimate health impacts using a cohort-based DID approach (i.e. comparing the health outcomes of younger cohorts living in treated districts to those of earlier-born cohorts in treated districts whose health outcomes were not affected by PAMSIMAS) and compare the change in health outcomes to those among the same cohorts in control districts.

To observe the effect of PAMSIMAS on children's health indicators, I run an OLS model and specify the econometric model below:

$$H_{igt} = \mu_0 + \mu_1 PAM_{gt} + \mu_2 CHILD_{igt} + \vartheta(PAM_{gt} * CHILD_{igt}) + \sum_{i=1}^{N} X'_{igt}\mu_3 + \sum_{g=1}^{G} VI'_{gt}\mu_4 + \xi_{igt} \tag{2.6}$$

where subscript i indexes a child of the household respondents, subscript g indexes district, subscript t indexes year. H_{igt} is each health outcome measure: 1) forgone days due to poor health, 2) stay in bed, and 3) self-rated health status. PAM_{gt} is a dummy variable representing the PAMSIMAS district indicator, with $PAM = 1$ if a child lived in a PAMSIMAS district and $PAM = 0$ if otherwise. $CHILD_{igt}$ is a binary variable representing a specific age cohort used in the estimation (0-12 years old). I compile a sample of all children from the 2007 and 2014 IFLS, and define those born between 2002 and 2014 as treated cohorts *(CHILD=1)*, while those born between 1995 and 2007 become the control cohorts *(CHILD=0)*. To capture the effect of PAMSIMAS on the child health indicators, I interact with the PAMSIMAS district indicator *(PAM)* and the children's cohort *(CHILD)*. When estimating the model, I also control for several children's characteristics, household-level information, and village-level variables used from the main analysis.

When analysing the health outcomes among the 0 to 12-year-old cohort of children as in Equation (2.6), there is a cohort of children born between 2002 and 2007 that was observed in both panel waves. These children were fully present since PAMSIMAS commenced until its completion. I will use this smaller subsample of children to verify whether the result from (2.6) is robust because these children's health outcomes allow me to estimate within-person changes in health outcomes. However, I will report these results as sensitivity checks due to power concerns. I specify the estimation model for this cohort of children below:

$$H_{igt} = \alpha_0 + \alpha_1 POST_t + \alpha_2 CHILD_{igt} + \delta(POST_t * CHILD_{igt}) + \sum_{i=1}^{N} X'_{igt}\alpha_3 + \sum_{g=1}^{G} VI'_{gt}\alpha_4 + \epsilon_{igt} \tag{2.7}$$

Similar to Equation (2.6), H_{igt} denotes a health outcome indicator. $POST_t$ refers to a binary variable that equals 1 if the year represents the post-programme period (2014). Slightly different from the previous model of (2.6), I define a variable $CHILD_{igt} = 1$ if children aged between 0 to 12 years old (born between 2002 to 2007) who lived in treated communities and $CHILD_{igt} = 0$ for 0-to-12-year-old children who lived in not-yet-treated communities. The coefficient of interest, δ comes from the interaction term $POST_t * CHILD_{igt}$ that will inform whether the three health outcome measures among these children changed after PAMSIMAS. Children and household characteristics as well as district poverty rates are denoted by X_{igt} and VI_{gt} respectively.

2.5 Results

2.5.1 Impacts on Households' Access to Safe Water

Table 2.9 presents the estimation results of all primary outcomes employing the 1:1 nearest matching model based on the estimation model (2.2), one of the most common, suggested by Rubin (1973). The estimated coefficients calculated using the nearest neighbour matching are the ATT that is derived from equation (2.5). I find that the share of household access to drinking water improved by 7 percentage points 2 years after the project's completion in 2012. This increase is significant at 1% and is relatively robust when I change the caliper tolerance and apply multiple neighbours,[14] in which increased access translates as an 11% improvement from 66% at the baseline.

Two indicators for water availability within household reach I use here are having an in-house water supply and the distance to water sources. The findings show that the proportion

[14]The magnitude estimates of employing multiple neighbours do not change but standardized bias increased slightly. When I change to have a higher caliper and maintain a single neighbour, our result does not achieve the variables balance and higher bias with the estimated coefficients reduced to 5%.

Table 2.9: Results of One-to-One Nearest Matching with Replacement

	U/M Sample	*Treated*	*Control*	*Diff (ATT)*	*S.E*	*t-val*
Access to Water	U	0.08	0.00	0.08	0.01	7.34
	M	0.09	0.01	**0.07*****	0.02	3.53
In-house Water Supply	U	0.20	0.09	0.11	0.01	9.18
	M	0.17	0.10	**0.07*****	0.02	3.15
Distance to Water	U	-0.72	-0.28	-0.44	0.09	-4.81
	M	-0.70	-0.31	**-0.40*****	0.17	-2.34
Open Defecation	U	-0.06	-0.06	-0.00	0.00	-0.14
	M	-0.06	-0.06	**0.00**	0.01	0.99
Observations(N)	4,027					

Note: U/M Sample refers to the Unmatched or Matched sample of households. **Treated (Control)** column shows the estimated mean difference between the 2014 and 2007 outcomes of interest among households in the treated (non-treated) communities. The **Diff (ATT)** column refers to the estimated effect of PAMSIMAS on the outcome interest (e.g. access to water) between the treated and non-treated communities (double difference).

Source: IFLS, Author's calculation

of households who built their water sources inside their houses increased by 7 ppts 2 years after post-programme completion compared to the baseline at 21%. In line with this improvement, the journey distance to collect water became shorter by around 7 metres less than the average distance people in the non-targeted rural communities and, conditionally, excluding those with zero metres of journey distance.[15]

One of the economic costs of accessing safe water in many developing countries is the travel time needed to the water points. The WHO and UNICEF have suggested that improved access to water services requires a 30-minute walking distance to the nearest water premises. As our study suggests, the water premises are located inside the house, reducing the distance to fetch the water, which suggests that the water sources are protected, and the duration to collect water is also diminished. Considering that this improvement in the location of water supply is about 32% from the baseline of 21% in 2007, households in the programme districts should expect

[15] I run two other estimations using the absolute distance and logarithmic values apart from the inverse hyperbolic sine function and the results are similar

enormous subsequent benefits after PAMSIMAS.

While the first three outcomes are statistically significant at the 1% and 5% levels, the share of households where the family members still defecated openly in unprotected settings is not significant. This result is robust when I estimate using other matching algorithms applying different callipers and multiple neighbours. As PAMSIMAS promoted the behaviour change to adopt better sanitation and hygiene practices, this result infers that this objective is unmet. The programme did not seem capable of changing behaviours among rural households in the treated districts to adopt better sanitation practices regarding defecation.

Indeed, PAMSIMAS did not finance the water and sanitation facilities construction on an individual basis. Therefore, the treated communities had to decide if they wanted to build water and sanitation facilities reflected in their community work plan, so, it could be that the households in the treated regions were not strongly encouraged to have a proper and protected sanitation facility for their houses or not everyone in the treated communities perceived the urgency of building latrines for access to safe drinking water. Hence, the outcome reflects this weak motivation on the sanitation aspect.

Apart from the main analysis, I conduct sub-group analysis to see if the PAMSIMAS programme is homogeneous among households based on their: 1) water access coverage and 2) welfare status. In the first analysis, I obtain the mean coverage of water access among households and divide my household sample into two groups: a household group with a share of water access around the mean or higher and those with access below the average. Results from estimating the water access outcomes based on mean water coverage, households living with low coverage of water access had a more significant benefit post-PAMSIMAS. They had better access to water coverage by 9 percentage points after the programme was completed or 3 percentage points more than those with 'high' access to water coverage. I also observe a 4 percentage point increase in households with in-house water supplies, while no improvement was seen in the other group. The estimation results of the PAMSIMAS effects based on water access coverage appear in Tables B7 and B8 of the Appendix.

Nonetheless, estimating PAMSIMAS on water access outcomes dis-aggregated by household welfare status provides a different picture. Those who were considered wealthier had better access to water than the non-wealthy group at 6 percentage points. However, both groups had a similar rate of improvement for the in-house water provision at 4 to 5 ppts. Given different socioeconomic characteristics, well-off households slightly benefitted from a larger reduction than those in the first lowest quintiles by possibly investing more in piped-water house connections or switching from purchasing water bottles to connecting to piped water with the commencement of PAMSIMAS. Estimation findings of PAMSIMAS dis-aggregated based on non-rich and richer households are seen in Tables B9 and B10 of the Appendix.

2.5.2 Impact on Health Outcomes

In this section, I further investigate the impact of PAMSIMAS on children's health living in the treated communities. Improved access to safe water and increased in-house water provision were likely to result in more regular consumption of fresh and clean water by household members, reducing the ingestion of water-borne bacteria and germs that are the leading causes of gastroenteritis. In addition, parents, especially mothers could use the time-savings from water fetching to increase parental time investments into their children, leading to health benefits for their children. Finally, children who were used to carrying water would also no longer suffer from physical burdens and injuries that might happen when undertaking the task.

2.5.2.1 Forgone Days and Staying in Bed due to Sickness

Table 2.10 presents the findings of the PAMSIMAS effect on our two health indicators among children based on Equation (2.6). The table shows that the number of days missed from kids' primary activities among children living in treated communities was reduced by 11% from the baseline of 4 days absent due to poor health in 2007 (see column 2). While I observe some improvement in the health of children seen from the lower number of days missed from their main activities such as schooling, I find smaller and statistically not significant impacts of PAMSIMAS for the second health indicator of staying in bed due to illness as seen in Table 2.10 columns 3 and 4.

Exploiting the panel feature of the data, I study the subsample of children born between

Table 2.10: Number of Missed Days of Primary Activities and Days in Bed Due to Poor Health

	(1) Missed Activities	(2) Missed Activities	(3) In Bed	(4) In Bed
PAM	0.083***	0.071**	0.039**	0.030*
	(0.030)	(0.030)	(0.017)	(0.017)
CHILD	0.048	-0.001	0.037**	0.021
	(0.031)	(0.035)	(0.017)	(0.020)
PAM × CHILD	-0.120***	-0.106***	-0.030	-0.021
	(0.040)	(0.040)	(0.023)	(0.023)
Individual/Household Characteristics	No	Yes	No	Yes
Children Sample	10,142	10,142	10,142	10,142
Adj. R^2	0.001	0.048	0.001	0.006

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2002 and 2007, whose health outcomes were observed before and after potential exposure to PAMSIMAS. Precisely, I create a cohort of children born between 2002 and 2007 and received full treatment since PAMSIMAS arrived. This estimation is useful to verify the results presented in Table 2.10. In total, the sample becomes 4,677 children. To capture the effects of PAMSIMAS on the health indicators of days missed from primary activities and staying in bed due to poor health, I run an individual-level effects model by interacting the binary variables *(CHILD)* referring to 1 if the children lived in districts exposed to PAMSIMAS and the post-programme period in 2014, *(POST)* based on (2.7). Using this sub-sample panel of children's data, I use the Hausman test to determine whether the fixed effects model (FE) or the random effects model (RE) is more effective and a better fit to model children's health outcomes analysis from a sub-sample panel data of children. The null hypothesis is that the RE is preferred to FE or the error term (ϵ_{igt}) for children is not correlated with the regressors. If the test is rejected at the 5% confidence level, then FE is more appropriate. Based on our models, the random effects model is selected over the fixed effects model based on the Hausman test to assess the PAMSIMAS effect on the number of days missed from primary activities (p-value = 0.114). As for evaluating the effect of the programme on the number of days in bed, the fixed effects model is in favour of the random effects one (p-value = 0.007). Detailed Hausman test results of both FE and RE models for each health outcome indicator can be seen in the Appendix Section A.2 Tables B11 and B12. I report our selected models based on the Hausman test in Table 2.11 below.

Table 2.11: Number of Days Missed Primary Activities and Staying Bed due to Poor Health

	(1) Missed Primary Activities	(2) Staying in Bed
CHILD	0.107**	0.005
	(0.042)	(0.154)
POST	-0.059	0.364
	(0.076)	(0.280)
POST × CHILD	-0.104*	-0.008
	(0.058)	(0.039)
Individual/Household Characteristics	Yes	Yes
Children Sample	4,677	4,677
Within R^2	0.093	0.012
Between R^2	0.037	0.0003

Standard errors in parentheses

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

Similar to the earlier findings, column 1 of Table 2.11 shows that children living in treated communities experienced lower forgone days of their main activities due to poor health by 10% over the baseline of 4 days being absent from doing their primary activities, or around 1-2 percentage points difference than the coefficients seen in the results of Table 2.10. Likewise, the coefficient of the health variable being in bed due to sickness indicates a smaller reduction but is not statistically significant. These results confirm that PAMSIMAS reduced the number of days missing from kids' main activities due to poor health among 0-to-12-year-old children by approximately 10%-11%.

2.5.2.2 Self-Reported Health Status

Using the same subsample, I investigate if PAMSIMAS helped to improve the overall health status of children between 0-12 years old. Table 2.12 reports our estimation results of this indicator on a set of explanatory variables employed in Section 5.2.1. As seen in columns 1 and 2 of the table, I find no effect of the programme on children's self-reported health status. As a comparison, I expand the sample to 0-15 year-old kids to cover those who embarked on their junior high school. The estimated mean impact of this analysis appears in columns 3 and 4 of the table. The coefficient of the interaction variables indicates that these older kids living in PAMSIMAS districts reported their health conditions improved. However, the results are relatively modest at 2 percentage points.

Table 2.12: Children Self-Reported Health Status

	Age Cohort: 0-12		**Age Cohort:0-15**	
	Better Health	Better Health	Better Health	Better Health
PAM	-0.014	-0.008	-0.022***	-0.016*
	(0.009)	(0.009)	(0.008)	(0.008)
CHILD	-0.022*	-0.027**	-0.025***	-0.023**
	(0.009)	(0.011)	(0.009)	(0.010)
PAM × CHILD	0.014	0.008	0.026**	0.019*
	(0.012)	(0.012)	(0.011)	(0.011)
Individual/Household Characteristics	No	Yes	No	Yes
Children Sample	10,142	10,142	12,041	12,041
Adj. R^2	0.000	0.018	0.001	0.016

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Overall, the findings on children's health support the hypothesis that the PAMSIMAS programme produced a positive outcome on health, possibly due to improved in water accessibility, particularly among children. This result is consistent with findings from other studies where water sources in the housing compound lead to improved children's health (Cameron et al., 2021; Irianti et al., 2019; Jalan and Ravallion, 2003; Mangyo, 2008). Similar to what I do here using individual children, Mangyo (2008) examines the effect of in-yard water sources and finds a positive impact on the height and weight of the children, especially among educated mothers in China. Moreover, Jalan and Ravallion (2003) study that piped-water sources reduced diarrhoea prevalence among rural children in India. Finally, Cameron et al. (2021) and Irianti et al. (2019) find that an in-house water supply reduced stunting rates.

2.6 Discussion and Conclusion

This chapter evaluates PAMSIMAS, possibly the largest water supply intervention in developing countries. The intervention was implemented at scale with central and local government subsidies of up to 80%, involving communities from the start by putting them in charge of implementation and requiring 20% community co-financing - delivered through a combination of cash and in-kind contributions. In particular, I estimate the impact of the PAMSIMAS programme on households' access to safe drinking water, in-house water supply, the journey distance to collect water, and open defecation practices. Water provision programmes are expensive, requiring significant subsidies to invest in such a communal project to operate and maintain, especially in developing countries with limited fiscal capacity. This study's findings show an increase in access to safe drinking water by 7 ppts, corresponding to 11% over the baseline.

Using 1:1 nearest-neighbour matching, I demonstrate that the share of water supply access improved by approximately 7 ppts, along with a modest reduction in the distance to fetch water. PAMSIMAS, with the adoption of community involvement besides a large subsidy, has shown that the programme's first phase positively impacted access to water. The increase in the share of households with access to safe water sources and in-house water provision narrowed the water access gap two years post-programme. Thus, the programme has the significant potential to minimise an estimated loss of 2.5% of Indonesia's GDP by 2045 if the country cannot meet universal water coverage (World Bank, 2021).

Access to safe drinking water sources improved human health (Howard et al., 2003). The location of the water sources closer to the dwelling has also been associated with the improved quality of children's health (Mangyo, 2008). Several previous studies by Cameron et al. (2021); Irianti et al. (2019); Jalan and Ravallion (2003); Lee et al. (1997); Mangyo (2008) and Thomas and Strauss (1992) particularly connected the relationship between water accessibility and child health. In this chapter, I further estimate if the increased water access and in-house water provision augmented child health using individual children's data from households living in the PAMSIMAS districts. The health indicator is the number of days having poor health, where the results indicate that children of the treated households were likely to have an 11% - 13% reduction from missed days due to poor health than their counterparts of not-yet-treated children. In addition, children also reported that their overall health conditions improved. PAMSIMAS provides empirical evidence that a community-driven water project involving community contribution can positively affect child health from increased water accessibility among the users.

Chapter 3

Effects of Tsunami Intensities on Household Financial Wellbeing

Daim Syukriyah

Abstract

The 2004 Indian Ocean Tsunami led to devastating damage and severe loss of life. This paper examines the effect of this 2004 tsunami on health-related expenditures at the household level in the short-and medium-term after the incident. To do so, it uses STAR survey data collected 5 to 17 months and 18 to 30 months after the tsunami. Employing inverse-probability weighting (IPW) regression analysis, I find that health-related spending estimates among heavily affected households increased by 34% between 5 to 17 months post-tsunami. Further analysis of the detailed spending on five healthcare components suggests that households in heavily damaged regions had higher expenses mostly on outpatient care visits and self-treatment care, while those living in medium-level damaged areas spent more on health products and other services. Even though this higher spending effect was short-lived not going beyond 1.5 years after the tsunami, the government should use such estimates to mitigate consequences of similar post-disaster events to speed up the affected population recovery process.

3.1 Introduction

Most natural disasters are unpredictable and hence, they represent a major threat to human life. The Emergency Events Database (EM-DAT) records that the average number of natural disasters between 1990 and 2000 was approximately 348 events each year, killing in total 544,000 people and causing an annual damage of USD 68 billion. The figure rose by a quarter for the following two decades between 2001-2021 to 427 annually, killing 1.4 million people and costing USD 140 billion. Based on the type of disaster, between 1995-2004, the number of geological disasters caused by earthquakes and tsunamis in Asia was 193, being the largest out of 299 events worldwide. Among these, the 2004 Tsunami triggered by a subduction earthquake of 9.3 Richter magnitudes striking off the coastal areas of the Indian Ocean on Boxing Day, remains to this day as the deadliest on record. The disastrous tsunami, with an epicentre near the west coast of Sumatra Island, Indonesia, and a focal depth of 30 km under the Indian Ocean, impacted more than 10 countries in Asia and Africa where the Province of Aceh and some parts of North Sumatra Province in Indonesia were severely affected. Total human casualties from this catastrophe were up to 300,000 deaths or missing persons and the total economic damage amounted to USD 4.45 billion[1] (Masyrafah and McKeon, 2008; World Bank, 2005) - around 2.14% of the country's GDP (Sawada, 2007) or 80% of Aceh's GDP (Himaz, 2022). Nangroe Aceh Darussalam (Aceh), the worst affected province, accounted for more than 50% of the total deceased and missing persons, with more than 530,000 people being displaced.[2]

The immense scale of damage caused by the tsunami prompted international responses to provide immediate, large-scale assistance from the first week of the disaster, ranging from humanitarian missions, food, and medical aid to financial assistance. By the end of 2007, the total amount of disaster support received from the international community was equivalent to USD 6.4 billion (Masyrafah and McKeon, 2008), of which USD 892 million was devoted to emergency action. With the influx of emergency health assistance and rapid actions from the government together with other parties including volunteers, international teams, such as the

[1] https://sos.noaa.gov/catalog/datasets/tsunami-wave-heights-indian-ocean-december-26-2004/

[2] https://dibi.bnpb.go.id/kbencana/index

WHO, and NGOs, no large disease outbreaks emerged among the survivors after the tsunami, aside from the extensive loss of life and assets and damaged infrastructure (Carballo et al., 2005; Zipperer, 2005). The fear of epidemic diseases such as malaria, cholera, and dengue was anticipated to happen. However, based on a surveillance report, there was a cluster of 106 tetanus cases observed in four districts of Aceh during the first-month post-tsunami (Jeremijenko et al., 2007). The case-fatality ratio (CFR) was 18.9% (20/106), relatively lower than similar epidemics of the 2005 South Asia earthquake (CFR=29.5%) and the 2006 Yogyakarta earthquake (CFR=38.7%). Even though external disaster assistance was generous, the inflation in Aceh occuring post-tsunami - reaching 41% in November 2005 - affected the delivery of efforts from the initial plans. In addition, with more than 500 agencies in place, the implementation of recovery and reconstruction activities faced challenges in being able to coordinate with local actors (Masyrafah and McKeon, 2008). Hence, although the provision of medical services, government welfare assistance, and external sources of support was available, little is known if health-related risks due to the tsunami with varying intensity levels of damage impacted further household spending post-disaster.

This study is going to investigate whether different tsunami damage intensities affected household welfare through changes in monetary-health-related spending. This study's findings will contribute to the international literature by examining the effects of natural hazards, in particular, the 2004 Tsunami, on changes in health costs based on hazard intensities experienced according to household location. Since environmental shocks can happen in any country, these results will help better inform any disaster-related policies beyond Indonesia's context on aid and potential risks that will affect households' well-being.

Despite being exogenous in terms of the timing occurrence, disaster events tend to be higher in developing countries than in developed ones, which may cause larger damage and economic consequences (Arouri et al., 2015; De Haen and Hemrich, 2007; Linnerooth-Bayer and Mechler, 2009; Loayza et al., 2012). Disaster preparedness in developing countries is lower due to limited financial resources (Noy, 2009; Noy and Nualsri, 2011), limited access to social safety nets (Linnerooth-Bayer and Mechler, 2007; Sumarto and Syarifah, 2022), insufficient savings

(Mechler, 2009), lack of liquid assets (Krueger and Perri, 2009; Wainwright and Newman, 2011), insurance (Hochrainer-Stigler et al., 2012; Linnerooth-Bayer et al., 2011).

While natural disasters have adverse economic and welfare impacts (Cavallo et al., 2013), their magnitude varies according to factors related to household exposures, capacities to deal with hazards based on socio-economic position (Clark et al., 2022; Krueger and Perri, 2009), and disaster intensities (Skoufias et al., 2017). In the case of tsunamis, for example, geographical regions, the force of waves and how they penetrate the shorelines result in different levels of damage affecting the population concerned. This means that people living in a relatively poor region and with low coping ability for disasters may disproportionately experience a higher impact or be more vulnerable to remaining deprived (Cyr, 2005; Kaplan, 2010), especially those who live in the disaster zones that are severely destroyed. Hence, the location of the disasters determines the level of destructive consequences and is associated with exposure to the event. Yet, finding an effective measure to calculate the economic losses after such incidences is tricky, mainly because of limited information (Sawada, 2007). The 2004 Tsunami demolished 4% of buildings in Aceh province. However, the range of destruction differed depending on the district. For example, the province capital and other two districts; Aceh Jaya and Pidie, had 20% of their buildings destroyed, which is in line with the disaster intensity in the areas (Skoufias et al., 2017).

There is scant empirical research on the impact of natural disasters on household welfare in developing countries. Most studies focus on the macroeconomic effects (Cavallo et al., 2013; Chang, 2010; Guimaraes et al., 1993; Heger and Neumayer, 2019), with limited research on the economic consequences at the household or individual level. A few studies document the household welfare effects of natural disasters. Chang and Meyerhoefer (2022) find that natural disasters are associated with reductions in healthcare usage among farmers who may suffer particularly large income losses. On average, however, food and health expenditures rise after natural disasters, as do poverty and inequality (Bui et al., 2014), which are mostly due to disruptions in the supply chain and road networks. Unsurprisingly, the incidence of physical and mental health issues rises (Escobar Carías et al., 2022). However, there is less evidence for adverse impacts on children's education (Mottaleb et al., 2013).

Arouri et al. (2015) also find large heterogeneity in natural disaster impacts across households, suggesting that some households are more resilient to such shocks than others. They find that smaller, more educated households with a high fraction of working members, and households with access to credit and remittances display higher resilience. This suggests that resilience is strongly linked to protection from subsequent income loss. Households with multiple earners, higher skills, and better risk-sharing arrangements have more risk-diversified income sources and are hence less impacted by financial fallout from natural disasters.

In contrast to resilient households, rural and agricultural households are particularly vulnerable to natural disasters due to their direct impact on harvests (Dartanto, 2022). Results from Escobar Carías et al. (2022) also suggest that poor populations tend to experience longer health problems than their wealthier counterparts.

While these studies exhibit similar findings on the impoverishment of household welfare through foregone earnings, the effects of natural disasters on household spending are mixed. Mottaleb et al. (2013) find that health expenditures among cyclone-affected farmers in Bangladesh with negative income shocks significantly increased. Likewise, Escobar Carías et al. (2022) also observe a 24% increase in medical expenditures among Indonesian households that experienced flooding one year after the disaster. However, large income losses could also lead households to lower their demands for healthcare as evidenced by Chang and Meyerhoefer (2022) among farmers as in response to natural disasters in Taiwan.

This study focuses on the short-and medium-run effects of the 2004 Tsunami on health financing for affected households. Specifically, I explore whether intensity heterogeneity generated by the tsunami led to changes in average household expenditure on health, and further what the size of these changes are, if at all, 1 year and 2 years post-tsunami. I will employ the STAR data from waves 1 and 2, elicited 5-17 months and 18-30 months after the disaster. Information on the damage levels by the tsunami will be important for our identification strategy and the availability of household-level longitudinal STAR data will help compare changes in monthly health expenses of the affected households with changes in the monthly health expenses from households who resided in the no or light damaged-districts. Hence, identification relies on choosing a valid control group of households and matching them to those who were affected by the tsunami, observed by IPW.

Using IPW regression analysis, I observe that households living in heavily damaged regions had higher health-related spending by one-third compared to those with no/light damage to their residence. This increase in health costs happened 5-17 months after the tsunami struck and started to rebound to pre-tsunami spending by 18 months after the event. Further estimation on expenditure components shows that households in heavily damaged regions had higher spending on outpatient and self-treatment care while those living in medium-damaged areas spent more on health-related medication and other services.

This paper proceeds as follows. Section 3.2 describes the background of this study. Section 3.3 explains the data and descriptive statistics of variables employed within the analysis. Section 3.4 discusses the methodological approach and the empirical model of the study. Section 3.5 presents our estimation results and Section 3.6 concludes the study.

3.2 Background

The estimated total damage of the 2004 tsunami for Indonesia accounted for USD 4.45 billion or around IDR 41.4 trillion where housing, agriculture, and fisheries, infrastructure, and environment were the most affected. Out of the total cost of damage, nearly 78% constituted damages and losses accrued to the private sector, including households, and 22% derived from the public sector.

In the health sector, the total impact of the tsunami amounted to USD 91.9 million, of which nearly 75% affected the public sector and around USD 131 million was related to health facilities' reconstructions (BAPPENAS and the International Donor Agency, 2005). Approximately 30 out of 244 health facilities were destroyed, including five hospitals (three public and two private), where 77 and 40 clinics required major and minor renovations, respectively. The World Bank estimates around one-third of village-based health units *(polindes)* and polyclinics were severely damaged. The total number of health professionals who died from the tsunami was approximately 700 from 9,800 personnel, with 30% midwives considered missing (Carballo et al., 2005).

Table 3.1: Pre-disaster health indicators and health professionals

Country	**Infant Mortality**	**Maternal Mortality**	**Doctors**	**Nurses & Midwives**	**Hospital Beds**
	Per 1,000	Per 100,000 livebirths	Per 10,000	Per 10,000	Per 10,000
Indonesia	36.36	261	1.32	8.07	4.5
Malaysia	7.31	33	7.34	17.97	19
Thailand	16.21	44	2.9	13.19	22
Singapore	2.49	13	14.89	42.22	29
Myanmar	60.7	314	3.76	7.65	6
Sri Lanka	13.03	50	5.38	10.6	2.1
United Kingdom	5.32	11	22.01	93.61	39.5

Source: WHO, World Health Statistics, various years.
Notes: 1).Infant and maternal mortality rates are in 2003 2).Figures of health personnel vary between 1998, 2000, 2001, 2002, 2003 and 2004 according to availability; 3). Indonesian health personnel data are in 2003, except for hospital beds in 1998 and 2000.

The damages to Aceh's health facilities and the deaths of health workers posed a significant concern for the country's healthcare system especially in view of the local capacity for addressing injuries and diseases post-tsunami because the number of healthcare workers (physicians, nurses, and midwives) was already low pre-tsunami. There were around 1.32 physicians per 10,000 in Indonesia as compared to 22 per 10,000 in the United Kingdom (UK) in 2003. At the sub-national level, according to the BPS, Aceh had 145 physicians serving a 4-million population in 2002, equivalent to 1 medical doctor per 275,000 persons. The hospital bed ratio was also low nationwide, which again reflected regional disparities in the health sector. In Banda Aceh, the province capital, there were four hospitals, with 750 beds by 1998, referring to a 1:4000 hospital-bed ratio which showed no surge capacity in the province's healthcare facilities to handle an influx of patients such as during emergency situations.

Furthermore, the healthcare system in Aceh before the tsunami depended largely on the central government in Jakarta in terms of direction and funding. Government health expenditure per capita was only USD 26 compared to that of USD 1,610 in the UK in 2002.[3] Prior to the tsunami, people mostly paid for healthcare services because the government left the provision of

[3] https://countryeconomy.com/government/expenditure/health/uk

personal healthcare to the market. Public healthcare providers were available with cheaper fees than private ones because they received a limited subsidy from the government and removed financial barriers to access treatment. Health insurance coverage in the country was also low with two major insurance programmes available for specific groups. First, the government provided health insurance for civil servants, armed forces and their families called Askes since 1968 and the second programme Jamsostek served formal sector workers from 1992.

To minimise access gaps to healthcare and inequalities in access, social health insurance called Health Card *(Kartu Sehat)* became available for poor households in 1994. The cardholders were eligible to receive free healthcare services in all public healthcare facilities. Yet, all users had to visit the primary health centre first, and if they required a higher level of care such as inpatient services, they had to obtain a referral from the relevant health centres as to whether they would be entitled to treatment at a public hospital. In 1998, the government issued a social safety net programme *(JPS-BK)* in healthcare, a temporary rescue programme for low-income groups to access free healthcare services and subsidised medicines in response to the Asian financial crisis (Mahendradhata et al., 2017; Suci, 2006). The government expanded this programme to be Health Insurance for the Poor (Askeskin) from 1999 to 2004 before (Jamkesmas) replaced it in 2004. In its implementation, health insurance among low-income groups remained low and not effective because public health facilities were sparse with poor quality of services and additional transportation cost, which some people in rural regions could not afford (Arifianto et al., 2005; Johar, 2009b, 2010; Saadah et al., 2001). Complex administrative procedures and long waiting times often also made people reluctant to visit formal public medical services, and instead opted for private healthcare providers, self-medicated with medicines purchased over the counter or chose traditional treatment (Brooks et al., 2017; Fles et al., 2017; Marthoenis et al., 2016; Sanjana et al., 2006; Seeberg et al., 2014; Widayati et al., 2015). Overall, pre-tsunami, a majority of the Indonesian population had no health insurance, with only one-fifth being covered (21.3%) (Mulyanto et al., 2019; Rokx et al., 2009a).

Due to the tsunami, nearly 300,000 perished and 530,000 people were displaced. Among the victims, around 7,195 people were seriously injured requiring hospitalisation, with a further

300,000 patients arriving a few weeks after the event (Zipperer, 2005). Without any fast responses from the national government and external support, the local healthcare capacity would have struggled to take care of the victims. Even though the disaster caused a large segment of the population to be vulnerable to epidemic-prone diseases, the fast disaster response during the acute phase of emergency resulted in no major disease outbreaks post-tsunami (Guha-Sapir and van Panhuis, 2009; World Health Organization et al., 2005). The Province Health Office of Aceh, the Ministry of Health, WHO, and partners from the the Global Outbreak Alert Response Network (GOARN) successfully developed a surveillance system that collected information about conditions of potential epidemic cases and respiratory problems from health facilities in affected districts to avoid disease outbreaks. Some cases such as diarrhoea, dengue, typhoid, malaria, meningitis, and measles were detected mostly among displaced populations. In January 2005, a cluster of tetanus cases was identified, delaying further deaths among the tsunami survivors in Aceh, mostly due to the large number of injuries combined with the low coverage of tetanus vaccination in Aceh (Guha-Sapir and van Panhuis, 2009). However, the number of disaster-related health conditions requiring fast and emergency care treatment reduced significantly one month after the tsunami (Guha-Sapir and van Panhuis, 2009).

The tsunami brought unprecedented levels of funding from the international community which is deemed to be the largest recovery effort in the developing world. As an emergency response, the Indonesian government, led by the National Coordinating Agency for Disaster Management (*Bakornas PBP*) and local communities, immediately organised emergency relief operations to prevent a higher death toll and to distribute basic needs such as medical supplies, food, clean water, clothing, and tents to the victims as well as deploying personnel to help with emergency actions. Alongside, the international community, the United Nations, donor organisations, and foreign government and non-government bodies pledged assistance of up to USD 7.7 billion. By the end of 2007, the total tsunami aid collected for relief and recovery projects was USD 6.4 billion with 65% having already been spent. In addition to the provision of health-related services and in-kind assistance, the national government also distributed welfare cash assistance to households, covering USD 0.40/day per person three months after the disaster and direct cash assistance (BLT) to compensate the fuel price subsidy removal (Kelaher and Dollery, 2008). All families not only for tsunami-affected households were eligible for BLT that was launched in October 2005, the same month when the government increased the fuel prices. Each beneficiary received around USD 116.5 (1 USD = IDR 10,295), where the payment was made every three months amounting to nearly USD 10 per month. The government also prepared "cash-for-work" programmes and distributed assets such as small boats and fishing nets, aiming to build livelihoods and provide sustainable resources of income for the affected communities. Some labour-intensive activities such as clearing debris, repairing bridges, or rebuilding houses also helped people to return to their villages quickly while earning an income and re-establishing their lives.

At the end of the relief operations approximately 3 months after the tsunami, the government's agency for reconstruction and rehabilitation *(BRR)* led and coordinated the recovery activities and made impressive progress. Among all sectors, the largest allocation of funds went to housing development, and the health sector had the highest number of projects, with nearly 350 units, followed by the education sector (Masyrafah and McKeon, 2008). During the recovery and reconstruction phase, around 42,000 houses were built along with substantial public infrastructure, such as 113 health facilities, 524 schools (with 2,430 newly recruited teachers), and 490 km of roads (BRR NAD, 2009). While some redevelopment and reconstruction efforts were underway, unexpected inflation appeared and peaked in November 2005 at 41%. Coupled with the fuel subsidy removal in October 2005, increased prices disrupted the reconstruction and rehabilitation process of certain sectors because of the funding gaps, but not with the health sector (Masyrafah and McKeon, 2008). However, considering that healthcare facilities and professionals were under-supply pre-tsunami, it is easy to see how the price hikes in commodities and coordination with local actors might pose a challenge in the implementation of the recovery phase.

3.3 Data

To investigate the relationship between the tsunami damage intensity and its effects on households' OOP spending on health, this study primarily derives from the STAR data waves 1 and 2. STAR data is a longitudinal household survey that asked individuals, households, and communities about immediate and medium-term outcomes of the 2004 Tsunami in 13 districts of two affected provinces, Aceh and North Sumatra, Indonesia. The design of STAR was originally based on 2004 Susenas, a major source of the survey that biannually collects social welfare information of the population. Yet, there was no geographical information in the data that was publicly available for users. Hence, I cannot combine this data with the 2004 Susenas because of the absence of household geographical identifiers. The first wave's STAR data collection took place 5 to 17 months post-tsunami and the subsequent wave was carried out between 18-30 months post-tsunami. I employ the STAR data because it has specific details of questions that I can use to measure the changes in private health spending before and after the tsunami across different levels of destruction. In total, the sample covers 6,155 panel households with information on households' health costs spent over the past month before the survey, three levels of damage caused by the tsunami, urban rural residential areas, and other relevant information such as whether the respondent demographics, including occupation (being a farmer or not), age, gender, and economic well-being such as household assets.

This study looks at the impact of tsunami damage on changes in households' health costs. To measure the damage due to tsunami, the STAR survey team classified respondents' clusters into three levels of destruction according to information from satellite imagery, which were verified by community heads and survey supervisors during enumeration (Frankenberg et al., 2020). According to those three levels of classification, 22% of households lived in areas with no or just light damage, 58% in medium damaged areas and 20% resided in communities that experienced heavy damage.

I also use other information related to household assets to determine the respondents' socioeconomic status that likely influenced changes in private health spending. Households' socioeconomic position can help inform a household's healthcare affordability and accessibility, especially if considering access to healthcare by residential type of location. I use the information on the households' possession of assets before the tsunami and construct households' wealth index using PCA introduced by (Filmer and Pritchett, 2001). STAR data provide information about the possession of valuable goods pre-tsunami, but not on the quality of each property that I can assess to determine household's wealth status such as type of floor, roof, wall, the availability of latrines, and so forth pre-tsunami. Accordingly, to construct a wealth indicator using PCA, I use households' semi-durable and durable properties including possession of a house, land, cattle, vehicles, equipment/furniture, jewellery, cash, stocks, and bonds. In developing the household wealth index, I generate five wealth quintiles based on urban and rural locations.[4]

Studies by Chang and Meyerhoefer (2022); Rozaki et al. (2021) and Mottaleb et al. (2013) show that farmers are vulnerable to environmental shocks and likely to be affected negatively if the hazards destroy their crops. Agriculture is one of the prominent livelihood sectors in Indonesia with predominantly smallholders. Hence, I incorporate the information in the analysis if the respondents were farmers, have had a farm business, or have worked in an agricultural sector since 2004.

Table 3.2 describes the list of variables for the analysis. The first variable is the outcome of interest in this study, the percentage changes in monthly private spending on health. This variable is obtained by taking a percentage term difference from two-period of expenses on health spent by households. The STAR data did not record information on health costs before the tsunami. To obtain changes in health expenses before and after the tsunami, I construct pre-tsunami households' health expenses using relevant information associated with households' economic well-being and the health of family members within the households. I utilise responses provided by households if at least one family member has suffered from deteriorating physical and mental health conditions since the tsunami. Pre-tsunami monthly health expenses of those households with at least one family member had suffered from deteriorating physical and emo-

[4] I also tried to construct another wealth index using a different technique used in Salmanidou et al. (2021) where the index is computed as a fraction between the total number of a household's asset possession and total number of assets listed in the survey questionnaire without assessing their monetary values. The list accounts for house, land, cattle, transport vehicles, furniture, jewellery, and securities. Here, the wealth index comprises eight levels ranging from 0 to 1, with 1 is the highest level of household wealth status. The range of assets owned by a household given by $goods_{min}$ to $goods_{max}$. The results in this study are robust regardless of which index I use.

tional health conditions since the tsunami. I generate pre-tsunami monthly expenses on the health of these households with mean values of health costs spent by their counterpart households within the same wealth quintile category and reported no family members experiencing poorer health since the tsunami. Below, I explained in detail how the pre-tsunami monthly health spending is created along with its underlying assumptions:

1. There are 2 questions in the survey asked about the health conditions of the respondents. The questions asked each household member whether their physical or emotional well-being at the time of the survey was better, the same, or deteriorating compared to their health conditions before the 2004 Tsunami. I created a dummy variable of respondents' health condition denoting 1 if at least there is one family member with poorer health either suffering from physical injuries or worse emotional well-being after the tsunami, and 0 otherwise.

2. As explained above, I also create a wealth index that is constructed using PCA to extract one variable that accounts for common variability of some household assets to represent five quintiles of households' socio-economic status. The household assets that I use to create the wealth index include whether households owned a house, land, livestock, vehicles, household furniture, gold/jewellery, cash, stocks, and bonds.

3. Based on this two information, the pre-tsunami monthly health expenses for households with at least one family member had suffered a worse health condition after the tsunami are created from the average amount of health expenses of their counterpart households belonging to the same wealth index category, without any family member reporting a poorer health condition. For instance, the poorest households with none of their family members reported worse health before and after the tsunami, their average health expenses would be assumed to stay stable pre- and post-tsunami. Meanwhile, for the poorest households with a family member that experienced a deteriorating health condition, their pre-tsunami health expenses would be similar to their counterpart poorest households' average monthly health spending with stable/good health. Under the same wealth quintile group, it is assumed that monthly health expenses among households were approximately

similar to the pre-tsunami period ones. As for post-tsunami health expenses of households with a poorer health condition, the expenses would be their 2005 monthly health expenses obtained from the survey.

4. To anticipate any extreme and spurious outliers, the monthly household spending on health is winsorised at the 1st and 99th percentiles.

5. Once the pre-tsunami and post-tsunami household health spending are available, the changes in health expenses before and after the event are calculated both for changes between the pre-tsunami and short-run health expenses after tsunami or changes between the pre-tsunami and medium-term health expenses.

Table 3.2: Dependent and Independent Variables

	Variable	Description
1	Chinhealth	percentage changes of spending on health between pre and post-tsunami periods
2	Wealth index	households' wealth index calculated based on households' ownership of physical assets
3	Damage	0= if the region got affected by no or light destruction, 1=a medium level of destruction and 2= a heavy level of destruction
4	Rural	1= if household lived in a rural region and 0 otherwise
5	Farming	1 = if respondent's occupation worked in or owned a farm business and 0 otherwise
6	Household size	total number of family members
7	Males between 0-15 y.o	share of male family members under 16 years old
8	Females between 0-15 y.o	share of female family members under 16 years old
9	Males between 16-60 y.o	share of male family members who were considered of productive age
10	Females between 16-60 y.o	share of female family members who were considered of productive age
11	Males above 60 y.o	share of male family members who were older than 60 years old
12	Females above 60 y.o	share of female family members who were older than 60 years old

Source: STAR and author definitions.

Next, I have a variable *damage* in the survey, which denotes three levels of destruction affecting two impacted regions that were collected based on satellite imagery data, combined with information from community leaders and field survey supervisors. Other household characteristics that are used in this study are rural-urban residence of households and household composition.

Table 3.3 presents descriptive statistics of pre-tsunami household demographic information and post-tsunami outcomes. As we can see in Section A, households living in areas that experienced no or light and medium destruction on average were medium-income families belonging to quintile 3. Compared to these households, those who lived in heavily damaged areas were significantly less wealthy, as seen in the last column. Compared to the entire population, around 20% of households lived in heavily damaged areas, and only 55% of them in rural regions. This contrasts with the households who experienced no/light and moderate damage as the majority of them lived in rural areas. The share of farmers in no or light and medium damage communities was slightly higher than that of the heavily damaged category. Further to these household characteristics, I also control for information regarding household composition to see if particular types of age groups would influence households' health financing decisions. For example, the presence of dependents such as children, women-child bearing age, or senior members might induce higher spending on health. Unlike other characteristics, questions used to construct household composition as a proportion of household size are based on information acquired in the household roster and not from the previous year before the disaster.

Table 3.3 Section B provides the outcomes of interest 5-17 months after tsunami. In the first row of the panel, the health expenses of households in heavily damaged areas increased by 46% compared to their expenses prior to the tsunami in real prices, significantly higher than the corresponding 12% of spending in the undamaged or lightly damaged areas. Even though OOP expenditures on health by households in medium damaged areas were higher than the no or light damaged household categories, they were statistically insignificant. As expected, the proportion of households in heavily damaged areas reporting at least one member having poorer health was higher at 63% than 41% with no or light damage. Similarly, medium damage communities also had more households recorded with at least one worse health family member at 53%.

In the next section C, I observe that OOP health spending of households in the heavily damaged category fell 2 years after the tsunami. I also do not see any significant mean difference in health spending between households in the no or light damage and heavily damaged locations.

3.4 Estimation Strategy

To estimate the effects of hazard intensity on changes in the OOP health expenditure among households in the affected provinces, I compare the health spending of two different groups of households in two different periods, pre- and post-tsunami. The problem arises when it comes to determining the affected and unaffected households as some households' choices, such as residential locations may be subjective to people's preferences and economic conditions. Despite being destructive, tsunami events rarely happen with the high fatality ones occurring in around hundreds of years (Martin et al., 2019; University of Washington, 2008). Hence, people will not be able to predict when extreme natural hazards will happen and it is unlikely for households to anticipate that their residential areas will be severely, moderately, or lightly damaged. Under this assumption, I choose the control group for the affected households living in medium and heavily damaged regions.

Relying on the exogenous and random nature of tsunami timing occurrence, $E(\varepsilon_{idt}|Tm_i, Th_i, X_{it} = 0)$, the identification strategy is to compare the changes in monthly health expenses of households living in medium and heavily damaged-regions in the short and medium term periods with changes in monthly health-related expenses of households living in no/light damage areas in the short and medium term periods. Hence, based on household variation and information on the damage clusters, the identification comes from selecting a comparison group for the affected households (those who resided in medium and heavily damaged regions), observed through the aforementioned variables and demographic characteristics of the households. The valid control households for those affected households are then those who lived in the areas with no or had light damage.

I specify the model in equation (3.1); adopted from Syukriyah and Himaz (2023) where the method that I use to generate pre-tsunami monthly household health expenses is different from such a paper as explained in Section 3.3 above.[5] I denote year 2004 as the pre-tsunami period,

[5] Syukriyah and Himaz (2023) generates the pre-tsunami household health expenditure by first running a logit

Table 3.3: Pre-tsunami Household Characteristics and Post-tsunami Outcomes

Variable Name	Household Residence Based on Destruction Levels			Means Difference (Std. Error)	
	No/Light (1)	Medium (2)	Heavy (3)	(1)-(2)	(1)-(3)
Section A: Pre-tsunami household characteristics					
Wealth index (quintiles)	2.938	2.927	2.153	0.011	0.784***
				(.045)	(0.055)
Rural	0.762	0.762	0.543	0.0004	0.219***
				(0.013)	(0.018)
Farming	0.452	0.470	0.413	-0.018	0.039**
				(0.016)	(0.020)
Household size	4.404	4.412	3.706	-0.009	0.698***
				(0.066)	(0.080)
Male 0-15	0.163	0.161	0.130	0.002	0.034***
(prop to family size)				(0.006)	(0.007)
Female 0-15	0.150	0.148	0.114	0.002	0.035***
(prop to family size)				(0.006)	(0.007)
Male 16-60	0.286	0.296	0.377	-0.010	-0.091***
(prop to family size)				(0.007)	(0.010)
Female 16-60	0.331	0.320	0.316	0.012	0.016*
(prop to family size)				(0.007)	(0.009)
Male 61- older	0.028	0.031	0.030	-0.003	-0.002
(prop to family size)				(0.003)	(0.004)
Female 61 - older	0.042	0.045	0.033	-0.003	0.008
(prop to family size)				(0.005)	(0.006)
Section B: 5-17 Month Post-tsunami Outcomes					
Change in health cost per capita between 2004 and 2005 (as a % of health expenses in 2004)	0.124	0.157	0.457	-0.033	-0.333***
				(0.065)	(0.095)
Share of households with worse health's family members than pre-tsunami period	0.410	0.525	0.626	-0.114***	-0.215***
				(0.015)	(0.019)
Section C: 18-30 Month Post-tsunami Outcomes					
Change in health cost per capita between 2004 and 2006 (as a % of health expenses in 2004)	0.460	0.330	0.428	0.130	0.032
				(0.116)	(0.146)
Number of observations	1,328	3,582	1,245		

Source: STAR 1 and 2 data, Author calculation.

or **t=0** and **d=1,2** as post-tsunami times where 5-17 months if **d=1** and **d=2** for 18-30 months after the event.

$$\Delta y_{i,t+d} = \alpha + \beta_1 Tm_i + \beta_2 Th_i + \sum_{i=1}^{N} X'_{it}\theta + \varepsilon_{i,t+d} \tag{3.1}$$

for household $i = 1, ..., N$ where:

$\Delta y_{i,t+d}$ denotes the change in household expenditure on health before and after the tsunami for household i living in district and year $t + d$;

Tm_i is a time-invariant indicator of moderate level of damage due to tsunami as a treatment variable;

Th_i is a time-invariant indicator of heavy levels of damage from the tsunami as a treatment variable;

X_{it} is a vector of individual or household baseline characteristics of the household heads from pre-tsunami period plus household demographic composition;

ε_{idt+d} is an error term.

In Table 3.3, I compare the household characteristics of the respondents in medium and heavily damaged areas with those who were located in no or light levels of damage. In this case, I assign households living in no or lightly damaged locations as the control group and those living in medium and heavily damaged areas as the treatment group or the affected group. As seen previously, the pre-tsunami household information were not balanced between heavy, medium, and the comparison households resided in no or lightly damaged areas. The imbalance distribution of pre-tsunami characteristics in the sample could thus cause biased

model of a binary variable that explains whether at least one family member experienced a worse health condition on wealth index and a dummy variable of urban-rural locations of the households. Then, it obtains the predicted probability values that are used to calculate the weights $\frac{1}{prob}$. Subsequently, the paper runs the 2005 household health spending on the same control variables used earlier in the first estimation by applying the inverse weights if households with no family members reported deteriorating health. The fitted values of this estimation are used as predicted pre-tsunami amounts of monthly household health expenses. The paper itself also investigates the indirect effects of the tsunami event on mental/physical well-being and income. Meanwhile, this chapter's result is partly used as an unreported robustness check for the reference paper and extends the analysis to estimate the effect of the tsunami on health costs using expenditures from five health categories outside the consumption module.

results in changes to households' health OOP spending due to other confounding factors that were not attributable to the "treatment". To avoid any potential self-selection bias arising from the imbalanced distribution on the outcome of interest, I need to ensure all observed pre-tsunami characteristics of the sample correspond to their damage intensities, as the treatment assignments are statistically similar. If observed pre-tsunami covariates and damage intensities are overlapped and similar, I can apply balancing weights on the affected households to match with other household groups, which subsequently allows me to compare between two comparable sample groups' outcomes (Rosenbaum and Rubin, 1983).

IPW scheme is suitable to measure the effect of the 2004 tsunami by comparing the outcome of interest between the affected households and those living in no/light-damaged regions and accounting for differences in their observable covariates. This method will adjust unequal covariates in a sample survey using the weights that are proportional to the inverse propensity of actually receiving the treatment (Sugihara, 2010). Once the probabilities of being assigned to the affected households conditional on observed variables or the propensity scores are obtained, the affected households receive a weight equal to $\frac{1}{\hat{Prob}}$ and the control households' weight will be $\frac{1}{1-\hat{Prob}}$. IPW assigns a larger weight to the affected households with a low probability and control households with a high probability of being affected. On the contrary, it will adjust and give a lower weight to affected households with a high probability of being affected and the comparison households with a low weight of being affected. In other words, this method mitigates the confounding factors by giving more weight to observations that are difficult to predict to achieve the covariate balance between the exposed/affected and the comparison groups (Rosenbaum and Rubin, 1985).

First, I need to compute propensity scores and then run a logistic regression model. In this setting, I run a multinomial logit with the tsunami intensity measure as a dependent variable on the relevant pre-tsunami household characteristics; wealth index, type of locations, and farming as matching variables. Subsequently, I set household weights that are proportional to the inverse propensity scores similar to Deryugina et al. (2018) and Kirchberger (2017).

There are some advantages of applying inverse propensity score weighting as opposed to propensity score matching: 1) The propensity score matching produces pairs of the treated and control groups with similar or close propensity scores and discards any observations that lie outside the common support range. IPW on the other hand, will retain all observations since it allows us to improve the covariate balance via inverse probability score weighting procedure and hence, it increases its statistical power (Deryugina et al., 2018), 2) it gives a larger weight to each member of the control group with a higher estimated probability of participation; 3) IPW produces less variance (Handouyahia et al., 2013) and 4) it produces a parsimonious model that is relatively more efficient in terms of variable numbers in the model (Wang and Aban, 2015). The multinomial logit model is given below:

$$\pi_{ir} = Prob\left((D)amage = r|X_{idt}\right) \tag{3.2}$$

where *damage* is a tsunami intensity comprising 3 discrete values representing no or light damage (0), moderate (1) and heavy damage (2). As for X_{idt}, it denotes the wealth index, rural location, and farming that are considered as factors to influence the likelihood of being affected by the tsunami in the baseline year, 2004.

3.5 Results

Following the model specification, I will begin by showing the estimation result from an Ordinary Least Square (OLS) method and subsequently, from the proposed model using a matching model with IPW.

3.5.1 Ordinary Least Squares

As previously explained, I obtain the percentage change of private health expenses from household spending per capita on health between 2004 and 2005 for both the treatment and control groups according to the damage level experienced in their respective residential areas. In this analysis, per capita health costs are in real prices as they are adjusted according to consumer price indices of the corresponding years and cities in Aceh taken from BPS.[6]

[6]Source: Inflation data based on expenditure found at the website: www.bps.go.id

The percentage change in monthly household spending on health becomes a proxy measure of household well-being after the 2004 Tsunami. Table 3.4 column (1)-(3) presents the estimation results with robust standard errors provided in parentheses. In the first column, the result shows that the tsunami had a greater impact on households that were severely affected, compared to those who were unaffected by lesser damage after the event. The coefficient estimate on *heavy* suggests that after this tsunami, households who were facing heavy damage in their areas recorded a 31% increase in health spending. Our results in less parsimonious models in columns (2) and (3) are robust around 25-27% even after controlling for household demographic composition.

A natural concern in running the model with an OLS approach is that some of these baseline characteristics are not balanced and cause the estimated coefficients of the outcome to be biased. To deal with this potential bias arising from any confounding factors to obtain an accurate impact of the tsunami on household welfare, I estimate the model with an IPW.

3.5.2 Matching with Inverse Propensity Weighting

I report the estimation outcomes using the IPW technique in Table 3.4 columns (4) to (6). The first column of the IPW estimations resulted from the baseline model of 3.1. I find that the effect of the tsunami on health expenses for households living in the locations suffering from heavy damage is higher than for those from regions with no or light damage, with a 38% increase 5-17 months after the tsunami. No changes are seen among households who lived in the regions with medium damage compared to the same counterpart of households living in no or light damage areas. The rural dummy has a negative relationship with the changes in spending suggesting that this spending increase only affected those who were in urban areas. This finding is in line with Salmanidou et al. (2021) that observes urban regions underwent more severe destruction than rural ones and Escobar Carías et al. (2022) that also finds increased medical-related expenditures of households suffering from flooding by 24.6% in the following year after the incident. The results remain robust at 34% in a less simple model when I incorporate shares of household composition (column 6). The majority of farmers lived in rural areas and it is seen that the coefficient on farming indicates farmers were unlikely to spend higher or additional

Table 3.4: Results on Percentage Change of Health Expenses 5-17 Months Post-tsunami

	(1) OLS 1	(2) OLS 2	(3) OLS 3	(4) IPW 1	(5) IPW 2	(6) IPW 3
Medium	0.04	0.04	0.04	0.04	0.04	0.03
	(0.063)	(0.063)	(0.063)	(0.066)	(0.066)	(0.066)
Heavy	0.31***	0.25**	0.27***	0.38***	0.32***	0.34***
	(0.100)	(0.100)	(0.100)	(0.119)	(0.116)	(0.121)
Wealth Index	0.03	0.02	0.02	0.07**	0.05	0.05
	(0.022)	(0.021)	(0.021)	(0.034)	(0.034)	(0.034)
Rural	-0.20**	-0.22***	-0.22***	-0.18	-0.21*	-0.21*
	(0.082)	(0.083)	(0.084)	(0.115)	(0.115)	(0.116)
Farming	-0.15**	-0.12*	-0.12**	-0.24***	-0.19**	-0.20**
	(0.060)	(0.060)	(0.059)	(0.086)	(0.086)	(0.084)
Household Size		-0.06***	-0.03*		-0.07***	-0.03*
		(0.014)	(0.016)		(0.016)	(0.018)
Male 0-15			-0.25			-0.23
			(0.166)			(0.232)
Female 0-15			-0.18			-0.30
			(0.197)			(0.207)
Female 16-60			0.45**			0.54
			(0.188)			(0.330)
Male 61-Older			0.63*			0.50
			(0.333)			(0.404)
Female 61-Older			0.61**			0.93**
			(0.237)			(0.406)
Constant	0.25***	0.56***	0.29**	0.18	0.53***	0.21
	(0.095)	(0.117)	(0.144)	(0.128)	(0.143)	(0.228)
Household Sample	6,155	6,155	6,155	6,155	6,155	6,155

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

expenses on health after the tsunami event. I also analyse the damage level intensities on farmers by interacting between the farming occupational status and both levels of damage and the results suggest are robust. The result is presented in the Appendix Table C1.

Table 3.5: Results on Percentage Change of Health Expenses 18-30 Months Post-tsunami

	(1) OLS 1	(2) OLS 2	(3) OLS 3	(4) IPW 1	(5) IPW 2	(6) IPW 3
Medium	-0.13	-0.12	-0.13	-0.13	-0.13	-0.13
	(0.132)	(0.131)	(0.131)	(0.126)	(0.126)	(0.126)
Heavy	-0.03	-0.08	-0.10	-0.09	-0.14	-0.16
	(0.140)	(0.142)	(0.140)	(0.141)	(0.143)	(0.141)
Wealth Index	-0.01	-0.02	-0.02	0.01	0.00	-0.00
	(0.031)	(0.031)	(0.031)	(0.037)	(0.037)	(0.037)
Rural	0.07	0.05	0.07	-0.04	-0.06	-0.03
	(0.105)	(0.105)	(0.109)	(0.124)	(0.125)	(0.126)
Farming	-0.21**	-0.16	-0.17	-0.13	-0.08	-0.08
	(0.102)	(0.105)	(0.106)	(0.109)	(0.109)	(0.110)
Household Size		-0.07***	-0.04*		-0.06***	-0.04
		(0.022)	(0.024)		(0.023)	(0.025)
Male 0-15			-0.60**			-0.63**
			(0.298)			(0.295)
Female 0-15			-0.56**			-0.46*
			(0.279)			(0.269)
Female 16-60			-0.04			-0.07
			(0.266)			(0.284)
Male 61-Older			-0.20			-0.11
			(0.330)			(0.350)
Female 61-Older			-0.09			-0.20
			(0.259)			(0.269)
Constant	0.51***	0.86***	0.93***	0.50***	0.83***	0.92***
	(0.144)	(0.183)	(0.227)	(0.157)	(0.207)	(0.246)
Household Sample	6,155	6,155	6,155	6,155	6,155	6,155

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

However, the increase in OOP spending on health by the affected households was short-lived. In Table 3.5, we can see that neither households in moderately nor heavily damaged areas had additional expenses on their monthly health expenses between 18-30 months after the disaster. This suggests that the affected households had to bear a higher health cost in the short-term period after the tsunami and recovered to their previous pre-tsunami health spending in the medium term, 1.5-2 years later.

The monthly health expenses that I use in the estimation are obtained from the consumption module of the survey, where household heads or their representatives answered questions on the list of consumption expenditures of all items, including health. In addition to that, wave 1 of the STAR survey also collected information on five health components but not with the subsequent waves 2 and 3. These five elements of health expenses that households had to spend every month included inpatient care, outpatient care, traditional and self-treatment medication as well as other expenses such as health products, pregnancy consultation fees, eye-glasses, dental care, and other healthcare services. The total amounts of these five components are not necessarily the same as the total health expenses from the consumption module, because the questions on these five components were specifically asked for spending on these five items and were listed separately from the consumption module.

Further, I also estimate the effect of the tsunami on percentage changes in monthly health expenses of households by aggregating the total expenditures from the five components. The estimation results are provided in the Appendix Table C2. The results show a similar pattern to the ones presented in Table 3.4, but with different coefficient magnitudes.

Since in wave 1 of the survey, there are health expenses on five components, I estimate another regression on the detailed breakdown of spending on health to investigate which cost components caused monthly spending on health to increase. Table 3.6 the results of the percentage changes in health expenses across five healthcare categories 5-17 months post-tsunami. I find that across five spending items, households in heavily damaged locations appeared to have higher expenses on outpatient care and self-medication. I do not have any further information on what type of self-treatment the households took in this case. However, this result is similar to other studies' findings that also observe that in general self-medication is a common practice (Handayani et al., 2001; Widayanti et al., 2020). The common use of self-medication could be also the reason for underutilisation of public healthcare facilities in Indonesia. In addition, we also see that households suffering from moderate levels of destruction in the residential areas had to pay nearly a third more of their expenses on health products, consultancy, and other healthcare services. Since higher health costs were devoted to outpatient visits and self-treatment, this situation infers that health-related injuries associated with the tsunami were not severe and healed in a relatively short time. This result also confirms our earlier findings that health costs rose in the first 5-17 months after the tsunami only.

Table 3.6: Changes in Health Expenses of Health Components 5-17 Months Post-tsunami

	(1) Inpatient	(2) Outpatient	(3) Traditional	(4) Self-treatment	(5) Health Products
Medium	0.48	0.08	0.34	-0.04	0.27**
	(0.337)	(0.080)	(0.236)	(0.035)	(0.113)
Heavy	0.68	0.27*	0.06	0.10*	0.12
	(0.551)	(0.138)	(0.267)	(0.059)	(0.121)
Wealth Index	0.21	-0.00	-0.22***	-0.01	-0.10***
	(0.163)	(0.034)	(0.058)	(0.014)	(0.033)
Rural	-0.76	-0.26**	-0.46*	0.02	-0.27**
	(0.632)	(0.128)	(0.255)	(0.048)	(0.120)
Farming	-0.12	-0.12	0.16	-0.05	0.11
	(0.333)	(0.089)	(0.185)	(0.044)	(0.082)
Household Size	0.14	-0.02	0.05	-0.05***	0.02
	(0.113)	(0.020)	(0.044)	(0.009)	(0.030)
Male 0-15	-0.20	-0.27	-0.91	-0.19	0.20
	(1.152)	(0.246)	(0.851)	(0.133)	(0.321)
Female 0-15	0.35	-0.10	-1.07	-0.19	0.03
	(1.189)	(0.275)	(0.571)	(0.122)	(0.367)
Female 16-60	3.56**	0.43	-0.19	-0.05	0.10
	(1.540)	(0.293)	(0.441)	(0.106)	(0.163)
Male 61-Older	0.46	0.27	0.94	0.07	-0.69***
	(1.303)	(0.456)	(1.051)	(0.302)	(0.226)
Female 61-Older	2.62	1.24	0.68	0.56	0.09
	(2.685)	(0.882)	(0.685)	(0.539)	(0.196)
Constant	-1.02	0.57**	1.80***	0.31***	0.55***
	(0.874)	(0.228)	(0.466)	(0.108)	(0.179)
Household Sample	6,155	6,155	6,155	6,155	6,155

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.6 Conclusion

Some studies on evaluating the impact of natural disasters focus on the macroeconomic effects and are limited in their capacity to assess household well-being consequences at the household level, particularly from a developing country perspective. This study investigates if the 2004 Indian Ocean Tsunami affected households' welfare in terms of changes in monetary-related health expenditures spent by households living in regions with distinct levels of damage. After controlling for damage intensities, residents' socio-economic status proxied by their wealth index, residential region, farming occupational status, and household demographic composition, the IPW regression results show that households located in heavily damaged regions spent higher health-related expenses by 34% than those in areas with no or light-damage 5-17 months after the tsunami. The increased health spending was short-lived and substantially disappeared after 18-30 months. Even though the tsunami aid earmarked to the health sector was adequate and succeeded in preventing epidemic disease outbreaks, limited and fragmented health insurance coverage might have induced households to pay for their medical services after the disaster. In addition, health facilities were generally sparse pre-tsunami which might require people to also spend on transportation fees if required to visit healthcare facilities. The breakdown spending of analysis further shows that households' higher expenditures were allocated to outpatient care, self-treatment, and health-related products, and other services. This finding suggests that those incurring higher health-related spending did not suffer serious injuries and did not require hospitalisation. The result of increased health expenses on self-treatment and health-related products and services are similar to previous studies reflecting the health-seeking behaviour of the population that preferred to undertake self-medication than visiting formal care.

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Appendix A: Chapter 1

A.1 Reform's Effects on Insurance Rates, Healthcare Utilisation, and OOP Health Spending

Table A1: Event Study Estimates for Health Insurance Rates

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Poorest	-0.03***	-0.03**	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Poorest: 2011Q2	-0.02***	-0.02	-0.03***	-0.03	-0.03***	-0.03*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2011Q3	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2011Q4	0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2012Q1	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Poorest: 2012Q2	-0.03***	-0.03*	-0.03***	-0.03*	-0.03***	-0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2012Q3	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2012Q4	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2013Q1	0.13***	0.13***	0.13***	0.13***	0.13***	0.13***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2013Q2	0.17***	0.17***	0.17***	0.17***	0.17***	0.17***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2013Q3	0.15***	0.15***	0.14***	0.14***	0.14***	0.14***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2013Q4	0.17***	0.17***	0.16***	0.16***	0.16***	0.16***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor	-0.07***	-0.07***	-0.08***	-0.08***	-0.07***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Poor: 2011Q2	-0.02*	-0.02	-0.02**	-0.02	-0.02***	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Poor: 2011Q3	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Household observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich
(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A1: Event Study Estimates for Health Insurance Rates

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Poor: 2011Q4	0.01*	0.01	0.01	0.01	0.01*	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Poor: 2012Q1	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Poor: 2012Q2	-0.04***	-0.04**	-0.04***	-0.04**	-0.03***	-0.03**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2012Q3	-0.00	-0.00	0.00	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Poor: 2012Q4	-0.00	-0.00	-0.01	-0.01	-0.00	-0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2013Q1	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2013Q2	0.14***	0.14***	0.14***	0.14***	0.14***	0.14***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2013Q3	0.14***	0.14***	0.14***	0.14***	0.13***	0.13***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2013Q4	0.13***	0.13***	0.13***	0.13***	0.13***	0.13***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Middle: 2011Q2	-0.01*	-0.01	-0.01*	-0.01	-0.01*	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Middle: 2011Q3	0.01	0.01	0.01*	0.01	0.01*	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Middle: 2011Q4	0.01*	0.01	0.02*	0.02	0.02**	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Middle: 2012Q1	0.00	0.00	0.01	0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Middle: 2012Q2	-0.01*	-0.01	-0.01*	-0.01	-0.01*	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Middle: 2012Q3	-0.02**	-0.02	-0.01*	-0.01	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Middle: 2012Q4	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Middle: 2013Q1	0.08***	0.08***	0.08***	0.08***	0.08***	0.08***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2013Q2	0.13***	0.13***	0.12***	0.12***	0.13***	0.13***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Middle: 2013Q3	0.08***	0.08***	0.08***	0.08***	0.08***	0.08***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2013Q4	0.09***	0.09***	0.09***	0.09***	0.09***	0.09***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich
(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A1: Event Study Estimates for Health Insurance Rates

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Rich	-0.08***	-0.08***	-0.07***	-0.07***	-0.07***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Rich: 2011Q2	-0.01	-0.01	-0.01**	-0.01	-0.02**	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Rich: 2011Q3	-0.00	-0.00	-0.00	-0.00	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Rich: 2011Q4	0.02***	0.02*	0.02**	0.02	0.02**	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Rich: 2012Q1	0.01	0.01	0.01	0.01	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Rich: 2012Q2	-0.01	-0.01	-0.01*	-0.01	-0.01*	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2012Q3	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Rich: 2012Q4	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Rich: 2013Q1	0.05***	0.05**	0.05***	0.05**	0.05***	0.05***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2013Q2	0.09***	0.09***	0.08***	0.08***	0.09***	0.09***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2013Q3	0.04***	0.04**	0.04***	0.04**	0.04***	0.04**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2013Q4	0.07***	0.07***	0.06***	0.06***	0.06***	0.06***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2011Q2	0.01*	0.01	0.01**	0.01	0.01**	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Richest: 2011Q3	-0.00	-0.00	-0.00	-0.00	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Richest: 2011Q4	-0.01**	-0.01	-0.01**	-0.01	-0.01**	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Richest: 2012Q1	-0.01*	-0.01	-0.01**	-0.01	-0.01*	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich
(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A1: Event Study Estimates for Health Insurance Rates

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Richest: 2012Q2	0.02***	0.02*	0.02***	0.02*	0.02***	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Richest: 2012Q3	0.01**	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Richest: 2012Q4	0.01	0.01	0.01	0.01	0.01	0.01
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Richest: 2013Q1	-0.00	-0.00	-0.00	-0.00	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.01)
Richest: 2013Q2	-0.02***	-0.02	-0.02***	-0.02	-0.03***	-0.03*
	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)
Richest: 2013Q3	-0.00	-0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.02)
Richest: 2013Q4	-0.01**	-0.01	-0.01*	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Individual & HH charac.	No	No	Yes	Yes	Yes	Yes
District Fixed Effects	No	No	No	No	Yes	Yes
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors (SEs) in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich
(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Event Study Estimates for Outpatient Visits

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Poorest	-0.03***	-0.03*	-0.06***	-0.06***	-0.05***	-0.05***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2011Q2	0.03***	0.03	0.04***	0.04*	0.04***	0.04*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2011Q3	0.02**	0.02	0.02**	0.02	0.02**	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2011Q4	0.03***	0.03*	0.04***	0.04*	0.04***	0.04**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2012Q1	0.01	0.01	0.01	0.01	0.01*	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2012Q2	0.02***	0.02	0.02***	0.02	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2012Q3	0.03***	0.03	0.03***	0.03	0.03***	0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2012Q4	0.02*	0.02	0.02**	0.02	0.02**	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2013Q1	0.02*	0.02	0.02**	0.02	0.02**	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2013Q2	0.02**	0.02	0.02***	0.02	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2013Q3	0.03***	0.03	0.03***	0.03	0.03***	0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poorest: 2013Q4	0.03***	0.03	0.03***	0.03	0.03***	0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor	-0.02***	-0.02	-0.04***	-0.04**	-0.03***	-0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2011Q2	0.02***	0.02	0.02***	0.02	0.02**	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2011Q3	0.01	0.01	0.01*	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich

(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Event Study Estimates for Outpatient Visits

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Poor: 2011Q4	0.02**	0.02	0.03***	0.03	0.03***	0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2012Q1	-0.01	-0.01	0.00	0.00	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2012Q2	0.02**	0.02	0.02**	0.02	0.02**	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2012Q3	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2012Q4	0.02**	0.02	0.02***	0.02	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2013Q1	0.00	0.00	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2013Q2	-0.00	-0.00	0.01	0.01	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2013Q3	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Poor: 2013Q4	0.00	0.00	0.01	0.01	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle	-0.02***	-0.02	-0.04***	-0.04**	-0.03***	-0.03*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2011Q2	0.02***	0.02	0.03***	0.03	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2011Q3	0.02**	0.02	0.02***	0.02	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2011Q4	0.02*	0.02	0.02***	0.02	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2012Q1	0.00	0.00	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2012Q2	0.02***	0.02	0.03***	0.03	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2012Q3	0.01	0.01	0.01	0.01	0.01*	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2012Q4	0.02**	0.02	0.02***	0.02	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2013Q1	0.01	0.01	0.01	0.01	0.01*	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2013Q2	0.02***	0.02	0.03***	0.03	0.03***	0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2013Q3	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Middle: 2013Q4	0.02*	0.02	0.02**	0.02	0.02**	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich
(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Event Study Estimates for Outpatient Visits

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Rich	-0.02***	-0.02	-0.03***	-0.03*	-0.03***	-0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2011Q2	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2011Q3	0.02***	0.02	0.02***	0.02	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2011Q4	0.03***	0.03	0.03***	0.03	0.03***	0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2012Q1	0.00	0.00	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2012Q2	0.03***	0.03	0.03***	0.03	0.03***	0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2012Q3	0.02**	0.02	0.02**	0.02	0.02**	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2012Q4	0.02**	0.02	0.02**	0.02	0.02**	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2013Q1	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2013Q2	0.02**	0.02	0.02**	0.02	0.02**	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2013Q3	0.01*	0.01	0.01*	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Rich: 2013Q4	0.02***	0.02	0.02***	0.02	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2011Q2	-0.03***	-0.03	-0.03***	-0.03	-0.03***	-0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2011Q3	-0.03***	-0.03	-0.04***	-0.04*	-0.04***	-0.04*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2011Q4	-0.04***	-0.04**	-0.05***	-0.05**	-0.05***	-0.05***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2012Q1	-0.01**	-0.01	-0.02***	-0.02	-0.02***	-0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich
(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Event Study Estimates for Outpatient Visits

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Richest: 2012Q2	-0.04***	-0.04*	-0.04***	-0.04**	-0.04***	-0.04*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2012Q3	-0.03***	-0.03*	-0.04***	-0.04**	-0.04***	-0.04**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2012Q4	-0.04***	-0.04*	-0.04***	-0.04**	-0.04***	-0.04**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2013Q1	-0.02***	-0.02	-0.02***	-0.02	-0.02***	-0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2013Q2	-0.03***	-0.03	-0.04***	-0.04*	-0.04***	-0.04**
	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)
Richest: 2013Q3	-0.04***	-0.04*	-0.04***	-0.04**	-0.04***	-0.04**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Richest: 2013Q4	-0.03***	-0.03	-0.03***	-0.03	-0.03***	-0.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Individual & HH charac.	No	No	Yes	Yes	Yes	Yes
District Fixed Effects	No	No	No	No	Yes	Yes
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich
(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Event Study Estimates for OOP Health Expenditures

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Poorest	-431.92***	-431.92***	-594.95***	-594.95***	-617.63***	-617.63***
	(16.78)	(29.63)	(16.86)	(32.80)	(16.94)	(31.79)
Poorest: 2011Q2	-33.47	-33.47	-46.85*	-46.85	-50.04**	-50.04
	(24.22)	(36.31)	(24.07)	(35.84)	(24.07)	(35.54)
Poorest: 2011Q3	57.91**	57.91	61.06**	61.06*	58.89**	58.89*
	(24.26)	(36.66)	(24.11)	(34.77)	(24.11)	(35.30)
Poorest: 2011Q4	30.17	30.17	27.15	27.15	19.63	19.63
	(24.57)	(32.60)	(24.42)	(32.02)	(24.42)	(32.37)
Poorest: 2012Q1	-99.39***	-99.39**	-104.45***	-104.45**	-112.29***	-112.29***
	(24.05)	(43.91)	(23.90)	(41.71)	(23.90)	(41.83)
Poorest: 2012Q2	-12.74	-12.74	-29.01	-29.01	-36.04	-36.04
	(24.36)	(37.40)	(24.21)	(36.18)	(24.21)	(35.34)
Poorest: 2012Q3	11.32	11.32	11.25	11.25	4.82	4.82
	(24.18)	(36.90)	(24.03)	(35.72)	(24.03)	(35.44)
Poorest: 2012Q4	-17.39	-17.39	-20.41	-20.41	-28.47	-28.47
	(24.26)	(37.52)	(24.11)	(36.76)	(24.11)	(37.24)
Poorest: 2013Q1	-196.89***	-196.89***	-206.69***	-206.69***	-206.68***	-206.68***
	(24.37)	(48.08)	(24.22)	(46.77)	(24.22)	(46.71)
Poorest: 2013Q2	-92.17***	-92.17**	-110.34***	-110.34***	-111.37***	-111.37***
	(22.31)	(36.02)	(22.17)	(34.74)	(22.18)	(35.17)
Poorest: 2013Q3	-96.11***	-96.11***	-113.13***	-113.13***	-110.66***	-110.66***
	(24.97)	(35.28)	(24.82)	(35.40)	(24.82)	(35.26)
Poorest: 2013Q4	-112.94***	-112.94*	-138.70***	-138.70**	-137.70***	-137.70**
	(25.62)	(64.15)	(25.46)	(62.29)	(25.47)	(63.14)
Poor	-413.15***	-413.15***	-534.59***	-534.59***	-542.28***	-542.28***
	(16.75)	(29.44)	(16.76)	(31.34)	(16.79)	(30.31)
Poor: 2011Q2	-33.94	-33.94	-46.63**	-46.63	-51.52**	-51.52
	(23.82)	(36.76)	(23.67)	(36.50)	(23.67)	(36.04)
Poor: 2011Q3	54.76**	54.76	53.96**	53.96	53.42**	53.42
	(23.72)	(36.45)	(23.57)	(34.68)	(23.57)	(35.20)
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich
(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Event Study Estimates for OOP Health Expenditures

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Poor: 2011Q4	25.33	25.33	22.13	22.13	17.25	17.25
	(23.74)	(32.38)	(23.59)	(31.74)	(23.59)	(31.99)
Poor: 2012Q1	-99.49***	-99.49**	-98.97***	-98.97**	-105.40***	-105.40**
	(23.86)	(43.41)	(23.71)	(41.41)	(23.71)	(41.19)
Poor: 2012Q2	-12.95	-12.95	-27.70	-27.70	-32.86	-32.86
	(24.02)	(37.28)	(23.87)	(36.63)	(23.86)	(36.14)
Poor: 2012Q3	10.79	10.79	13.14	13.14	5.09	5.09
	(23.48)	(36.88)	(23.34)	(36.18)	(23.33)	(35.86)
Poor: 2012Q4	-18.53	-18.53	-23.46	-23.46	-30.04	-30.04
	(23.55)	(37.63)	(23.41)	(36.48)	(23.41)	(36.81)
Poor: 2013Q1	-192.16***	-192.16***	-200.02***	-200.02***	-199.60***	-199.60***
	(24.36)	(48.21)	(24.21)	(46.75)	(24.20)	(46.90)
Poor: 2013Q2	-96.53***	-96.53***	-112.21***	-112.21***	-113.64***	-113.64***
	(22.23)	(36.00)	(22.09)	(34.26)	(22.10)	(34.69)
Poor: 2013Q3	-98.00***	-98.00***	-112.32***	-112.32***	-111.52***	-111.52***
	(24.03)	(35.27)	(23.88)	(34.96)	(23.88)	(34.87)
Poor: 2013Q4	-113.17***	-113.17*	-140.08***	-140.08**	-137.64***	-137.64**
	(24.48)	(63.41)	(24.33)	(61.40)	(24.33)	(62.22)
Middle	-384.56***	-384.56***	-482.16***	-482.16***	-484.70***	-484.70***
	(16.50)	(28.93)	(16.48)	(30.11)	(16.50)	(29.24)
Middle: 2011Q2	-35.29	-35.29	-42.48*	-42.48	-46.12**	-46.12
	(23.32)	(36.68)	(23.17)	(35.82)	(23.16)	(35.36)
Middle: 2011Q3	45.26*	45.26	52.93**	52.93	53.58**	53.58
	(23.20)	(36.14)	(23.05)	(34.11)	(23.05)	(34.53)
Middle: 2011Q4	19.06	19.06	24.12	24.12	19.94	19.94
	(23.17)	(32.50)	(23.02)	(31.67)	(23.02)	(32.12)
Middle: 2012Q1	-103.73***	-103.73**	-98.35***	-98.35**	-104.58***	-104.58**
	(23.46)	(43.67)	(23.31)	(41.96)	(23.31)	(42.13)
Middle: 2012Q2	-14.99	-14.99	-21.16	-21.16	-26.90	-26.90
	(23.32)	(38.01)	(23.18)	(37.42)	(23.17)	(37.04)
Middle: 2012Q3	5.46	5.46	12.22	12.22	5.24	5.24
	(23.11)	(36.42)	(22.97)	(35.97)	(22.96)	(35.77)
Middle: 2012Q4	-23.95	-23.95	-18.04	-18.04	-24.99	-24.99
	(23.08)	(37.11)	(22.94)	(36.45)	(22.93)	(36.97)
Middle: 2013Q1	-183.61***	-183.61***	-183.42***	-183.42***	-183.02***	-183.02***
	(24.00)	(48.02)	(23.85)	(46.38)	(23.85)	(46.28)
Middle: 2013Q2	-88.92***	-88.92**	-96.40***	-96.40***	-97.97***	-97.97***
	(21.84)	(35.47)	(21.71)	(33.77)	(21.71)	(33.82)
Middle: 2013Q3	-97.93***	-97.93***	-110.73***	-110.73***	-111.78***	-111.78***
	(23.45)	(34.86)	(23.30)	(34.97)	(23.30)	(34.90)
Middle: 2013Q4	-115.75***	-115.75*	-130.44***	-130.44**	-126.75***	-126.75**
	(23.75)	(63.81)	(23.60)	(62.24)	(23.60)	(62.89)
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Event Study Estimates for OOP Health Expenditures

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Rich	-344.27***	-344.27***	-404.53***	-404.53***	-401.89***	-401.89***
	(15.99)	(28.53)	(15.93)	(29.07)	(15.94)	(28.20)
Rich: 2011Q2	-19.64	-19.64	-24.59	-24.59	-27.89	-27.89
	(22.71)	(36.56)	(22.56)	(36.07)	(22.56)	(35.80)
Rich: 2011Q3	51.05**	51.05	49.25**	49.25	50.11**	50.11
	(22.34)	(36.91)	(22.20)	(34.88)	(22.20)	(35.29)
Rich: 2011Q4	28.27	28.27	27.46	27.46	28.10	28.10
	(22.68)	(32.36)	(22.54)	(31.42)	(22.54)	(31.81)
Rich: 2012Q1	-79.15***	-79.15*	-77.20***	-77.20*	-81.85***	-81.85*
	(22.76)	(43.99)	(22.62)	(42.11)	(22.62)	(42.01)
Rich: 2012Q2	-2.82	-2.82	-9.75	-9.75	-12.37	-12.37
	(22.79)	(38.04)	(22.65)	(37.16)	(22.64)	(36.55)
Rich: 2012Q3	7.97	7.97	10.47	10.47	8.34	8.34
	(22.45)	(36.98)	(22.31)	(36.24)	(22.30)	(36.08)
Rich: 2012Q4	-14.23	-14.23	-17.31	-17.31	-21.47	-21.47
	(22.18)	(37.91)	(22.04)	(37.52)	(22.04)	(37.78)
Rich: 2013Q1	-148.51***	-148.51***	-155.35***	-155.35***	-150.12***	-150.12***
	(23.46)	(48.54)	(23.32)	(47.39)	(23.31)	(47.09)
Rich: 2013Q2	-74.08***	-74.08**	-87.43***	-87.43***	-87.36***	-87.36***
	(21.04)	(34.85)	(20.91)	(33.34)	(20.91)	(33.69)
Rich: 2013Q3	-81.47***	-81.47**	-99.79***	-99.79***	-96.91***	-96.91***
	(22.82)	(35.24)	(22.68)	(35.86)	(22.67)	(35.78)
Rich: 2013Q4	-94.80***	-94.80	-110.21***	-110.21*	-105.30***	-105.30*
	(23.03)	(63.22)	(22.89)	(62.48)	(22.88)	(62.75)
Richest: 2011Q2	31.48**	31.48	40.09***	40.09	42.87***	42.87
	(15.29)	(36.45)	(15.19)	(35.98)	(15.19)	(35.77)
Richest: 2011Q3	-66.32***	-66.32*	-72.48***	-72.48**	-74.00***	-74.00**
	(14.82)	(36.49)	(14.73)	(34.59)	(14.73)	(35.26)
Richest: 2011Q4	-34.20**	-34.20	-36.25**	-36.25	-32.68**	-32.68
	(15.28)	(32.52)	(15.18)	(31.60)	(15.18)	(31.95)
Richest: 2012Q1	96.20***	96.20**	92.03***	92.03**	96.66***	96.66**
	(15.31)	(43.83)	(15.22)	(41.84)	(15.22)	(41.86)
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich

(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Event Study Estimates for OOP Health Expenditures

	Baseline		Indiv & HH Char.		District FE	
	Non-clust	Clustered	Non-clust	Clustered	Non-clust	Clustered
Richest: 2012Q2	11.38	11.38	18.84	18.84	22.42	22.42
	(15.64)	(37.44)	(15.54)	(36.93)	(15.54)	(36.50)
Richest: 2012Q3	-18.66	-18.66	-25.90*	-25.90	-21.55	-21.55
	(14.80)	(37.01)	(14.70)	(36.33)	(14.71)	(36.22)
Richest: 2012Q4	16.26	16.26	11.45	11.45	15.39	15.39
	(14.57)	(37.61)	(14.48)	(36.75)	(14.49)	(37.10)
Richest: 2013Q1	204.10***	204.10***	207.11***	207.11***	203.33***	203.33***
	(15.45)	(48.11)	(15.36)	(46.63)	(15.36)	(46.74)
Richest: 2013Q2	95.40***	95.40***	99.49***	99.49***	102.26***	102.26***
	(13.96)	(35.92)	(13.88)	(34.21)	(13.89)	(34.74)
Richest: 2013Q3	94.52***	94.52***	102.29***	102.29***	97.91***	97.91***
	(15.09)	(35.30)	(15.00)	(35.04)	(15.00)	(34.90)
Richest: 2013Q4	118.14***	118.14*	130.15***	130.15**	123.89***	123.89**
	(15.61)	(64.20)	(15.51)	(62.17)	(15.51)	(62.93)
Individual & HH charac.	No	No	Yes	Yes	Yes	Yes
District Fixed Effects	No	No	No	No	Yes	Yes
Household Observations	849,028	849,028	849,028	849,028	849,028	849,028

Notes: (1) Standard errors in parentheses. (2) P20: Poorest, P40: Poor, P60: Middle, P80: Rich
(3) Non-clust: SEs are not clustered, Clustered: SEs clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.2 Robustness Check for Healthcare Utilisation

As a robustness check for our result on the healthcare utilisation effect of the reform, we run two things:

1. We convert our dependent variable of the number of outpatient visits from a count variable into a binary indicator and employ the same event study model.

2. We employ an instrumental variable to capture the effects on the healthcare access from being insured by *Jamkesmas*. We measure our outcome changes among the poor from the ownership of health insurance and try to isolate that the effects are solely from the poverty reform in 2013.

Both results deliver the same results as in section 5.2 where no improvements were seen in the number of outpatient visits after the reform was implemented.

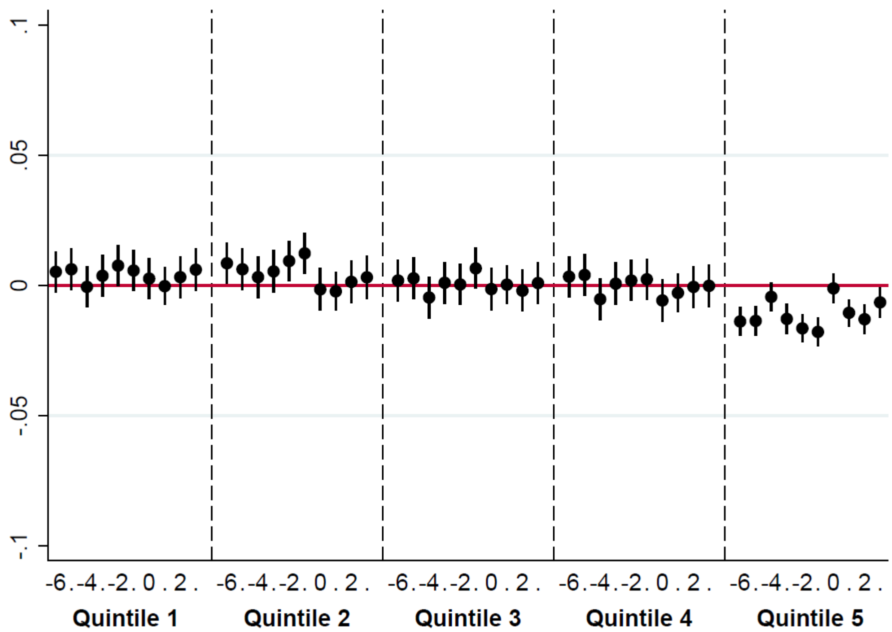

Figure A.1: Reform's Effects on the Outpatient Visits in the districts
Source: Q1.2011-Q4.2013 Susenas, Author calculation

Appendix B: Chapter 2

B.1 Construction of The Household Wealth Index

In generating factor solutions using a factor analysis method, I employ 14 variables of household assets and housing quality from house and land ownership, livestock, vehicles, hard stem plants (coconut, coffee, rubber, and cloves plants), possession of durable goods, savings, the type of house's wall, floor, roof, number of rooms, and the floor size of the house. Household wealth index construction starts by generating a correlation matrix table from the 14 household assets and housing quality variables by running a polychoric correlation matrix command (UCLA: Statistical Consulting Group, n.d.). The generated correlation matrices across all variables describe a mutual relationship between one variable to another. For example, a house with concrete walls tended to be highly correlated with having a good type of floor but a low correlation with house ownership. Based on the correlation matrix table B1, a lot of variables had an adequate correlation among them even though some had a low weak relationship between variables. I will only report my FA calculation from the 2014 wave here but a similar approach is done for the 2007 data.

Table B1: Correlation Matrices of Household Asset and Housing Quality Variables

	Own House	Own Land	Livestock	Plants	Vehicles	Appliances	TV
Own House	1						
Own Land	0.07	1					
Livestock	0.08	0.08	1				
Plants	0.35	0.19	0.40	1			
Vehicles	0.16	0.14	0.11	0.12	1		
Appliances	0.16	0.16	0.06	0.05	0.62	1	
TV	0.31	0.17	0.06	0.12	0.49	0.83	1
Concrete Walls	-0.004	0.07	-0.02	0.11	0.26	0.23	0.30
Floor	-0.02	0.11	-0.02	0.07	0.23	0.31	0.32
Roof	-0.07	0.03	-0.01	-0.04	-0.01	0.08	-0.01
Savings	-0.06	0.26	-0.03	0.05	0.27	0.29	0.19
Jewelry	0.06	0.21	0.10	0.11	0.28	0.30	0.35
No. Room	0.37	0.19	0.05	0.15	0.30	0.37	0.56
Floor Size	0.23	0.12	0.02	0.11	0.19	0.20	0.35

Source: 2014 IFLS, Author's calculation.

The next step is to choose the number of factors that summarise the data structure. The

Table B1: Correlation Matrices of Household Asset and Housing Quality Variables (Contd.)

	Concr. Walls	Floor	Roof	Savings	Jewelry	No. Room	Floor Size
Concrete Walls	1						
Floor	0.79	1					
Roof	-0.21	-0.16	1				
Savings	0.21	0.26	0.025	1			
Jewelry	0.18	0.22	0.65	0.44	1		
No. Room	0.45	0.37	-0.04	0.22	0.26	1	
Floor Size	0.15	0.16	0.01	0.14	0.15	0.41	1

Source: 2014 IFLS, Author's calculation.

correlations from Table B1 were then used as our input to extract factor solutions by running an exploratory FA. To determine the number of factors that I need to retain, I will use the eigenvalue criterion or Kaiser's criterion. This method will sort eigenvalues and show us how many factors are greater than 1 (Kaiser, 1960). I also use a scree-test by observing the number of factors that can be found after a kink in the graph. Based on these two criteria, I choose 2 factors that explain cumulatively 80-88% of the variance (Table B2 and Figure B.1).[7]

Table B2: Eigenvalues of the Correlation Matrix from 2014 Data

	Eigenvalues	Difference	Proportion	Cumulative
Factor 1	3.48	2.30	0.59	0.59
Factor 2	1.19	0.33	0.21	0.80
Factor 3	0.86	0.23	0.15	0.94
Factor 4	0.63	0.21	0.11	1.05
Factor 5	0.42	0.32	0.07	1.12
Factor 6	0.10	0.06	0.02	1.14
Factor 7	0.04	0.04	0.01	1.14
Factor 8	0.01	0.03	0.00	1.14
Factor 9	-0.03	0.04	-0.00	1.14
Factor 10	-0.06	0.05	-0.01	1.13
Factor 11	-0.11	0.04	-0.02	1.11
Factor 12	-0.15	0.06	-0.03	1.09
Factor 13	-0.21	0.09	-0.04	1.05
Factor 14	-0.30	.	-0.05	1.00
No of observations	5,745			

Source: 2014 IFLS, Author's calculation.

In the third stage, I apply an orthogonal rotation method to simplify and clarify the data structure to ease the interpretability of the factors. I use the common method of varimax rotation

[7]The selected two factors explain 88% and 80% in 2007 and 2014 respectively.

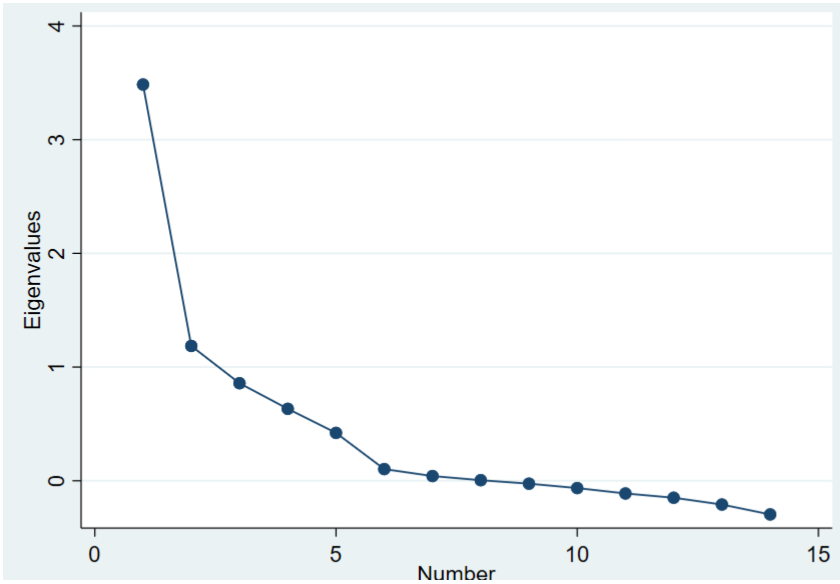

Figure B.1: Scree plot from Eigenvalues from 2014 Data
Source: 2014 IFLS, Author's calculation

that analytically ensures that in each factor, certain variables appear as high as possible, and the others come up as low as possible on each column of the loading matrix. In this case, varimax rotation is an orthogonal rotation that produces factors that are uncorrelated to each other. To note, in the loading tables for 2 factors, I only keep those loadings above 0.30 as they are best to show the pattern of the data structure (Costello and Osborne, 2019; Osborne, 2014). Table B3 below lists the original variables such as house ownership, vehicles, house appliances, TV, savings, jewelry, number of rooms, floor size that load on component 1 and concrete walls, type of flooring, and number of rooms load on the second component. I also plot these loading scores into a graph to see the pattern or commonality of data structure (unreported).

After the varimax rotation, I predict the two-factor solutions or two variables generated from the last step and label these two household wealth proxies according to the observed data structure. Instead of 14 variables, these 2 variables now summarise a considerable amount of information from our data.

The last step of this household wealth index construction is to run Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy if data were suitable for factor analysis and Cronbach's Alpha to check the reliability of the factor solutions. The KMO measure from the 2007 and

Table B3: Factor Loadings after Orthogonal Rotation from the 2014 Data

Variable	Factor 1	Factor 2	Uniqueness
Own House	0.41		0.82
Own Land			0.92
Livestock			0.95
Plants			0.93
Vehicles	0.59		0.62
Appliances	0.80		0.33
TV	0.85		0.24
Concrete Walls		0.84	0.26
Floor		0.82	0.29
Roof			0.96
Savings	0.30		0.83
Jewelry	0.41		0.79
No. Room	0.56	0.36	0.56
Floor Size	0.38		0.84

Source: 2014 IFLS, Author's calculation.

2014 data are 0.75 and 0.66 respectively and both are above the cut-off point of 0.5, it is suitable to conduct the FA for generating the household wealth index using this method. Subsequently, the results of Cronbach's Alpha values in 2007 and 2014 are 64 and 0.62, closer to the sufficient reliability measure of 0.7.

Based on the FA calculation using a polychoric correlation matrix, I rename my household wealth proxies as house ownership and house appliances.

B.2 Common Support

In performing multiple null hypothesis tests simultaneously, it is important to avoid the chance of falling into a type I error or the probability of rejecting one or more null hypotheses when they are true. This result often happens when one uses a standard-multiple hypothesis method and the probability of falsely rejecting true null hypotheses tends to be higher as the number of hypotheses grows. The Romano-Wolf multiple hypothesis technique can correct this error or, particularly, the family-wise error rate (FWER) asymptotically using a bootstrap resampling procedure (Clarke et al., 2020). In this paper, Romano-Wolf multiple hypotheses testing is conducted to examine if, in the baseline year, the observed variables significantly affect four variables of PAMSIMAS' expected outcomes. If the adjusted p-values from the Romano-Wolf tests are statistically not significant, it means that the treatment and comparison groups are balanced. Table B4 presents the result where the adjusted p-values are not significant for three variables, while the *access to water* variable is significant. This result matches to our single t-test outcomes and infer imbalance baseline covariates.

Table B4: Romano-Wolf Multiple Hypotheses Testing

Variables	Model p-value	Resample p-value	Romano-Wolf p-value
Access to Water	0.0001	0.0020	0.0040
In-house Water Supply	0.5287	0.5564	0.7652
Distance to Water	0.1693	0.2078	0.4466
Open Defecation	0.4972	0.4985	0.7652

Source: IFLS, Author's calculation.
Note: Running on entire and same covariates in Table 5.

Lechner (2008) suggests that a visual graph depicting the density of propensity scores distribution is adequate to confirm a large enough common support between treatment and control groups. A similar procedure can be done to examine all variables in the treatment and non-treatment groups by observing the graphical diagnostics of covariates balance in the form of the scatter plots of all covariates, side-by-side box plots and non-parametric density plots between the treatment and control groups. The graphical results illustrate that all covariates look balanced and convergence in all graphs.

To verify achieving balance apart from numerical computation, I perform graphical testing for important outcome variables, such as the share of households' access to water and the distance to water. In addition, Austin (2009) argues that balance is often obtained with the sample theory, so instead, an imbalance will be expected to be present for some covariates even in the randomised control trial experiments. Indeed, all variables in this study are balanced, assuming that both treatment and comparison groups are statistically similar in their pre-treatment conditions. Figure B.4 and Figure B.5 show that for the two outcome variables significantly different in pre-treatment programme period, both numerical and graphical diagnostics confirm no divergence between groups.

B.3 Robustness Check

Aside from running a 1:1 nearest neighbour matching with replacement, I also run the same primary model without replacement. The coefficient estimates are robust to the findings, as seen in Table B5 and Table B6 below.

To verify the results, I also employ other matching algorithms: kernel and local linear matching models. These models show similar results of the nearest-neighbour model. However, among all methods, the 1:1 nearest neighbour is the only model that shows balance post-matching for all covariates with single neighbour. Kernel and LLM require me to trim data by 4% to obtain a balance between the treated and control households. The last two are balanced according to Rubin's standardised bias estimator and pseudo-R-squared but not on the distance to fetch water for Kernel and in-house water provision for the LLM.

Table B5: Results of One-to-one Nearest Matching Without Replacement

	U/M Sample	***Treated***	***Control***	***Diff (ATT)***	***S.E***	***t-val***
Access to Water	U	0.08	0.00	0.08	0.01	7.34
	M	0.09	0.02	0.07***	0.02	3.88
Inside House Supply	U	0.20	0.09	0.11	0.01	9.18
	M	0.16	0.10	0.06***	0.02	2.62
Distance to Water	U	-0.72	-0.28	-0.44	0.09	-4.81
	M	-0.60	-0.33	-0.26	0.20	-1.50
Open Defecation	U	-0.06	-0.06	-0.00	0.00	-0.14
	M	-0.05	-0.07	0.01	0.01	1.49
Observations (N)	4,027					

Note: U/M Sample refers to the Unmatched or Matched sample of households. **Treated (Control)** column shows the estimated mean difference between the 2014 and 2007 outcomes of interest among households in the treated (non-treated) communities. The **Diff (ATT)** column refers to the estimated effect of PAMSIMAS on the outcome interest (e.g. access to water) between the treated and non-treated communities (double difference).

Source: IFLS, Author calculation

Table B6: Results of Matching with a Kernel Function

	U/M Sample	***Treated***	***Control***	***Diff (ATT)***	***S.E***	***t-val***
Access to Water	Unmatched	0.08	0.00	0.08	0.01	7.34
	ATT	0.08	0.02	0.06***	0.01	5.02
Inside House Supply	Unmatched	0.20	0.09	0.11	0.01	9.18
	ATT	0.18	0.12	0.06***	0.01	5.12
Distance to Water	Unmatched	-0.72	-0.28	-0.44	0.09	-4.81
	ATT	-0.67	-0.52	-0.16	0.11	-1.39
Open Defecation	Unmatched	-0.06	-0.06	-0.00	0.00	-0.14
	ATT	-0.06	-0.06	0.00	0.01	0.12
Observations (N)	4,027					

Note: (1) **U/M Sample** refers to the Unmatched or Matched sample of households. **Treated (Control)** column shows the estimated mean difference between the 2014 and 2007 outcomes of interest among households in the treated (non-treated) communities. The **Diff (ATT)** column refers to the estimated effect of PAMSIMAS on the outcome interest (e.g. access to water) between the treated and non-treated communities (double difference).
(2) Trimming set at a value of 10% to achieve balancedness.
Source: IFLS, Author calculation.

B.4 Heterogeneity Analysis: Access to Water Coverage

I am also interested to disaggregating the data based on access to water coverage. First, I obtain the median value of the share of households with access to safe water in the baseline year and divide my treated and not-yet-treated households according to this median percentage value. Combining both types of households, I find that the median statistic of the aforementioned indicator is 83.9%, and those with low access to water coverage accounts for 2,040 households. Table B7 presents the results of the water indicators among households in the programme districts under the new category of low coverage of access to water. The following Table B8 displays the results from households with high coverage of access to water with a sample of 1,987 households.

Looking at the estimations of the two tables, the share of access to safe water sources significantly much larger in the low coverage category with a 9 percentage point increase, approximately 3 percentage points more than the other household group. Households with low access coverage also benefitted from the improved in-house water supply by 4 percentage points.

However, I do not see any improvement among the counterpart households with higher access coverage. These findings provide insight that PAMSIMAS effectively delivered positive effects among households with low access coverage where households benefited from the rise in access to safe water and piped-water sources in their houses.

Table B7: Estimation Results of Low Access to Water Coverage

	U/M Sample	***Treated***	***Control***	***Diff (ATT)***	***S.E***	***t-val***
Access to Water	U	0.20	0.07	0.13	0.02	7.89
	M	0.23	0.14	0.09***	0.02	3.93
In-house Water Supply	U	0.21	0.03	0.19	0.01	11.06
	M	0.14	0.10	0.04*	0.02	1.83
Distance to Water	U	-0.72	-0.22	-0.49	0.14	-3.69
	M	-0.50	-0.75	0.25	0.20	1.23
Open Defecation	U	-0.08	-0.08	-0.00	0.01	-0.47
	M	-0.08	-0.07	-0.00	0.01	-0.39
Observations (N)	2,040					

Note: U/M Sample refers to the Unmatched or Matched sample of households. **Treated (Control)** column shows the estimated mean difference between the 2014 and 2007 outcomes of interest among households in the treated (non-treated) communities. The **Diff (ATT)** column refers to the estimated effect of PAMSIMAS on the outcome interest (e.g. access to water) between the treated and non-treated communities (double difference).

Source: IFLS, Author's calculation

B.5 Heterogeneity Analysis: Household Welfare Status

In this section, I further examine if the impact of PAMSIMAS is homogeneous. To compare benefits accrued to households living in programme districts with different welfare status, I establish two subgroups of households based on wealth quintiles based on per capita expenditures. In Section 5.1 above, I use monthly household expenditures in a logarithmic form; *household expenditures*. Even though the programme districts were selected based on poverty and remoteness along with other selection criteria, it is important to observe if, among households, the effects of receiving the PAMSIMAS project varied according to socioeconomic characteristics. In particular, I use the per capita consumption expenditure in nominal values to divide house-

Table B8: Estimation Results of High Access to Water Coverage

	U/M Sample	*Treated*	*Control*	*Diff (ATT)*	*S.E*	*t-val*
Access to Water	U	-0.03	-0.07	0.04	0.01	4.16
	M	-0.03	-0.09	0.06***	0.02	3.10
In-house Water Supply	U	0.18	0.16	0.02	0.02	1.36
	M	0.17	0.18	-0.01	0.02	-0.37
Distance to Water	U	-0.71	-0.35	-0.37	0.12	-2.99
	M	-0.70	-0.33	-0.36*	0.19	-1.95
Open Defecation	U	-0.04	-0.04	-0.00	0.01	-0.49
	M	-0.05	-0.04	-0.01	0.01	-1.21
Observations (N)	1,987					

Note: U/M Sample refers to the Unmatched or Matched sample of households. **Treated (Control)** column shows the estimated mean difference between the 2014 and 2007 outcomes of interest among households in the treated (non-treated) communities. The **Diff (ATT)** column refers to the estimated effect of PAMSIMAS on the outcome interest (e.g. access to water) between the treated and non-treated communities (double difference).

Source: IFLS, Author's calculation

holds into five wealth quintiles and arrange them into two big household categories [8], with the first three bottom quintiles belonging to lower-and middle-income households and the two top quintiles containing the wealthier household group.

From the total sample of 4,027 households, households in the first group are 2,507 households, whereas the programme and comparison households are 1,442 and 1,104 observations, respectively. Meanwhile, those households in the wealthier sub-group are smaller, with a sample size of 1,481 observations, with the treated and control groups of 840 and 640, respectively. After matching, I find that both groups are balanced by assigning different callipers and neighbours.

In conducting the sub-group analysis outcomes, I treat them as two datasets separately. Hence, these two dataset will generate new propensity scores for each category. Then, I calculate the causal effects of the PAMSIMAS programme on three outcomes based on them. As a result, the outcome will reflect the impact of each measure within its sub-group.

Table B9 and Table B10 present the estimation results of both subgroups. Overall, the

[8] constructing quintiles using logarithmic values of the consumption expenditure does not alter the result

two main DID-matching estimates are significant. The share of access to safe drinking water increased by 6 percentage points among wealthier households, relatively higher than that obtained from the low-middle-income ones at 4 percentage points. As for in-house water provision, both groups show that households living in the programme districts improved by 4 to 5 percentage points, 2 to 3 percentage points lower than the main analysis. Given different socio-economic characteristics, the wealthier households slightly reaped a larger reduction than those in the first bottom quintiles. This result suggests that better-off households possibly invested more in piped-water house connections or switched from purchasing water bottles as their drinking water sources could be far from their houses. Similar to the primary outcomes in Section 5.1, the DID-matching estimate for open defecation practices is not statistically significant, meaning that the Phase I PAMSIMAS did not contribute to lessening open defecation practices in the programme districts.

Table B9: Estimation Results of Lower-and Middle-Income Households

	U/M Sample	***Treated***	***Control***	***Diff (ATT)***	***S.E***	***t-val***
Access to Water	U	0.08	-0.02	0.1	0.01	7.18
	M	0.08	0.05	0.04*	0.02	1.86
In-house Water Supply	U	0.22	0.11	0.11	0.01	7.49
	M	0.17	0.13	0.04**	0.02	2.35
Distance to Water	U	-0.79	-0.38	-0.41	0.11	-3.74
	M	-0.69	-0.50	-0.19	0.15	-1.26
Open Defecation	U	-0.08	-0.07	-0.01	0.01	-0.85
	M	-0.07	-0.06	-0.01	0.01	0.20
Observations (N)	2,546					

Note: U/M Sample refers to the Unmatched or Matched sample of households. **Treated (Control)** column shows the estimated mean difference between the 2014 and 2007 outcomes of interest among households in the treated (non-treated) communities. The **Diff (ATT)** column refers to the estimated effect of PAMSIMAS on the outcome interest (e.g. access to water) between the treated and non-treated communities (double difference).

Source: IFLS, Author's calculation

Table B10: Estimation Results of Wealthier Households

	U/M Sample	***Treated***	***Control***	***Diff (ATT)***	***S.E***	***t-val***
Access to Water	U	0.08	0.04	0.04	0.02	2.50
	M	0.08	0.02	0.06***	0.02	2.97
In-house Water Supply	U	0.16	0.05	0.11	0.02	5.38
	M	0.15	0.10	0.05*	0.03	1.97
Distance to Water	U	-0.58	-0.10	-0.48	0.16	-0.43
	M	-0.56	-0.29	-0.27	0.20	-1.32
Open Defecation	U	-0.03	-0.04	0.01	0.01	1.17
	M	-0.03	-0.04	0.01	0.01	0.80
Observations (N)	1,481					

Note: U/M Sample refers to the Unmatched or Matched sample of households. **Treated (Control)** column shows the estimated mean difference between the 2014 and 2007 outcomes of interest among households in the treated (non-treated) communities. The **Diff (ATT)** column refers to the estimated effect of PAMSIMAS on the outcome interest (e.g. access to water) between the treated and non-treated communities (double difference).

Source: IFLS, Author's calculation

B.6 The Hausman Test Results of Sub-sample Panel Data of Children

The Hausman test has been extensively discussed and used in the literature. The Hausman test is designed to identify which better model fits between the Fixed Effects and Random Effects estimations according to the relationship between the error term and explanatory variables. Under the null hypothesis of such a test, the conditional mean of the error term is orthogonal or uncorrelated to the regressors and if the Hausman test does not reject this claim at 5% level of significance, the RE estimator is appropriate and reported (Baltagi, 2010).

In evaluating PAMSIMAS effect, there are 4,677 children born between 2002 to 2007 who were observed from pre-programme period in 2007 until the first phase of PAMSIMAS completed in 2014. I employ this sub-sample panel data of children to ensure that the results of Table 2.10 are robust. Following a model specification in Equation 2.7, I estimate an individual-level effects model of two health indicators: 1) days missed from primary activities and 2) days of staying in bed due to sickness. For each indicator, I run fixed effects and random effects estimations and perform the Hausman test to compare which model is suitable to exploit the PAMSIMAS effect on that health indicator.

In Equation 2.7, the PAMSIMAS effect on a child's health outcome is demonstrated by $\hat{\delta}$ by interacting a binary variable *(CHILD)* and the post-PAMSIMAS programme *(POST)*. First, I estimate the effect of PAMSIMAS among these children on the number of days that they missed from primary activities, such as attending school. As seen in Table B11, both FE and RE estimates suggest that PAMSIMAS affected the children's activities by reducing the number of days to undertake primary activities by around 10% to 14% less.

From our estimation results, the Hausman diagnostic test shows that under the null hypothesis, the Chi-square statistics is 23 and p-value is 0.114 at 5% level of confidence. It means, the Hausman test does not reject the null hypothesis and suggests that RE estimator of 10% reduction in the number of days missed from doing primary activities among children is more appropriate.

Table B11: The Hausman Test Result of PAMSIMAS Effect on the Number of Days Missed Primary Activities

	Fixed Effects	Random Effects	Difference
CHILD	0.205	0.107**	0.098
	(0.259)	(0.042)	(0.255)
POST	−0.261	−0.059	−0.202
	(0.472)	(0.076)	(0.466)
POST × CHILD	−0.139**	−0.104*	−0.036
	(0.065)	(0.058)	(0.031)
Individual & Household Characteristics	Yes	Yes	
Observations (N)	4,677	4,677	
H0:	Random Effects is efficient		
$\tilde{\chi}^2(16)$	23.00		
P-value	0.114		

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Similarly, I carry out the Hausman test to compare estimation results between the FE and RE models for evaluating the impact of PAMSIMAS among the same cohort of children on the number of days gone due to staying in bed. The result of the diagnostic test presented at Table B12 identifies that the null hypothesis is rejected at 95% confidence level and thus, the FE estimator is selected over the RE one. Yet, neither of these estimators is statistically significant, meaning that PAMSIMAS did not influence the number of days gone due to staying in bed among these children. Overall, our results from children observed in both panel waves are similar to our estimations in Table 2.10.

Table B12: The Hausman Test Result of PAMSIMAS Effect on the Number of Days Staying in Bed

	Fixed Effects	Random Effects	Difference
CHILD	0.005	0.034	−0.029
	(0.153)	(0.025)	(0.152)
POST	0.364	−0.004	0.369
	(0.280)	(0.045)	(0.276)
POST × CHILD	−0.008	−0.025	0.017
	(0.039)	(0.034)	(0.018)
Individual & Household Characteristics	Yes	Yes	
Observations (N)	4,677	4,677	
H0:	Random Effects is efficient		
$\tilde{\chi}^2(16)$	33.01		
P-value	0.007		

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

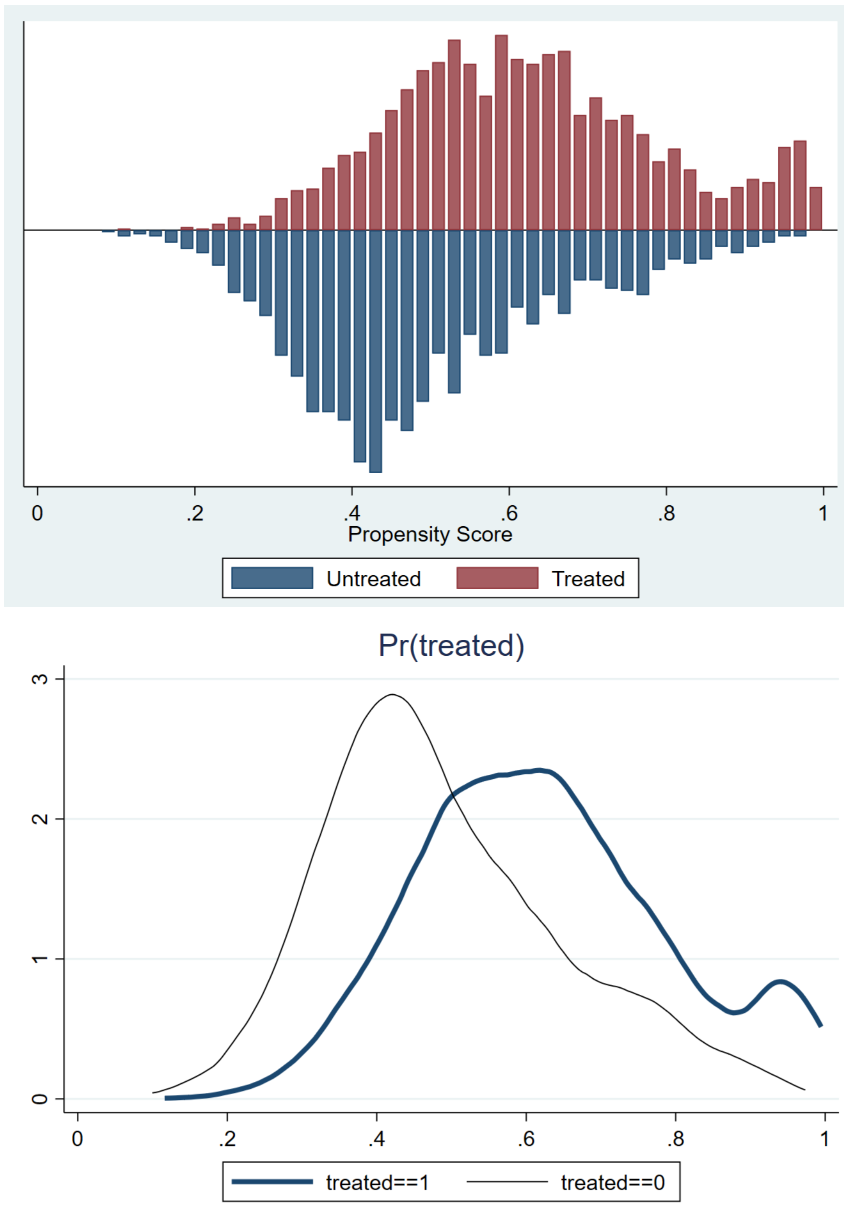

Figure B.2: Common Support Regions
Source: IFLS, Author's calculation

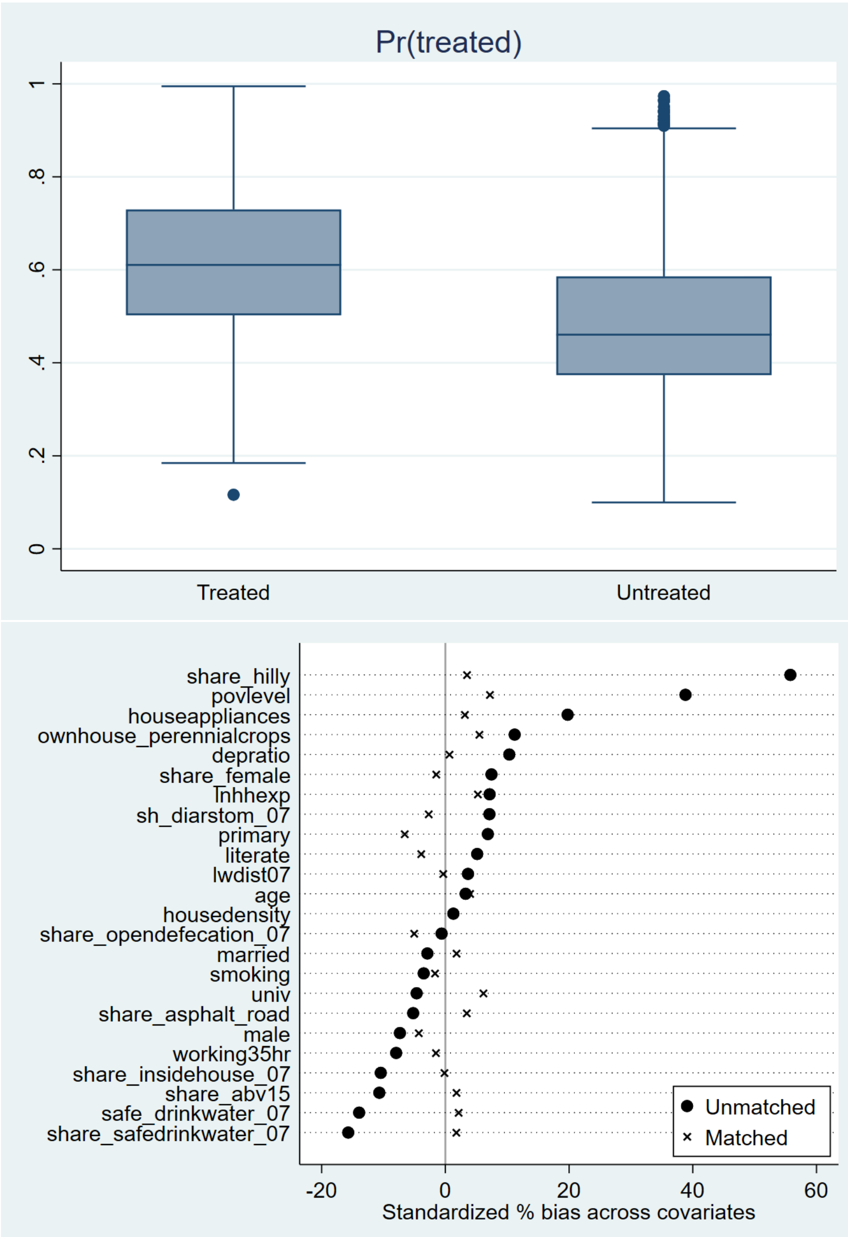

Figure B.3: Common Support Regions
Source: IFLS, Author calculation

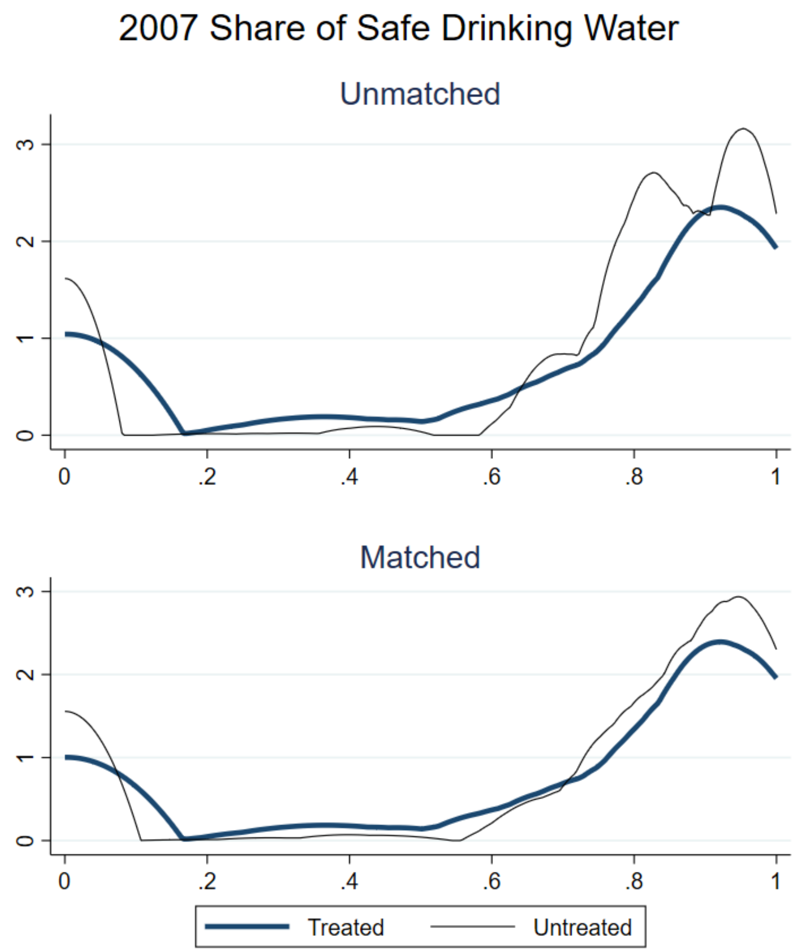

Figure B.4: Shares of access to safe drinking water in 2007
Source: IFLS, Author calculation

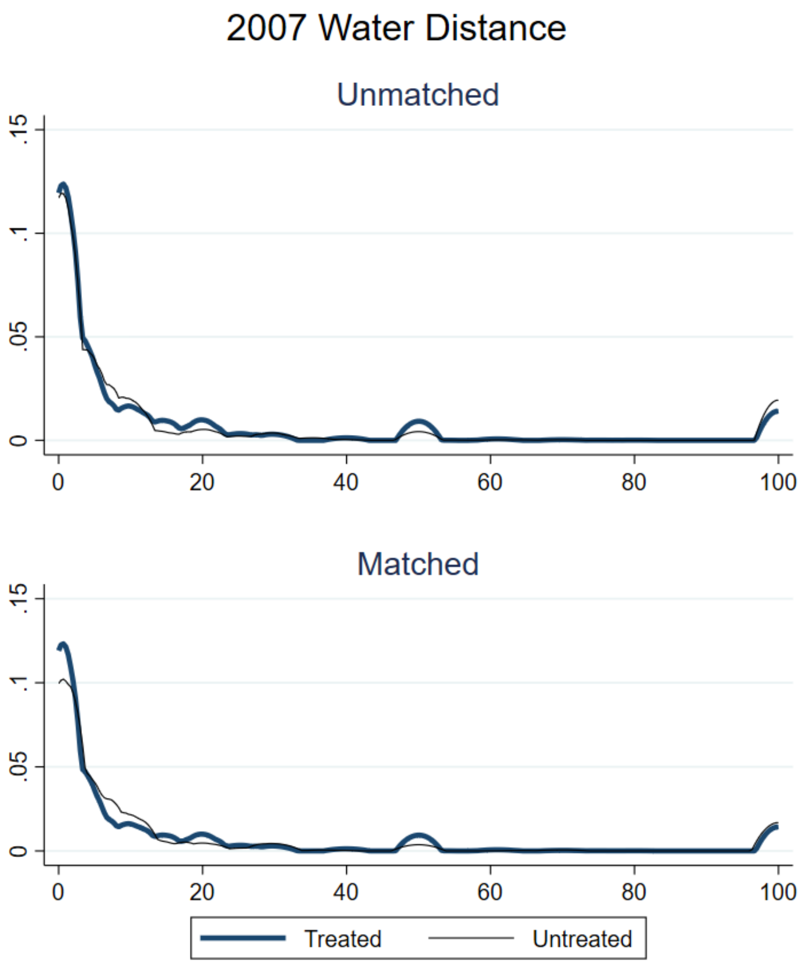

Figure B.5: Journey distance to collect water in 2007
Source: IFLS, Author calculation

Appendix C: Chapter 3

C.1 Regression Results of Interaction Term Analysis

I interact between damage intensity levels experienced in the affected regions with the farming occupational status of the respondents to find if farmers had to spend higher health costs post-tsunami. Our results are presented in Table C1 suggest that farmers in either level of damage were not affected and did not spend higher health expenditures.

Table C1: Results on Percentage Change of Health Expenses 5-17 and 18-30 Months Post-tsunami

	(1) Baseline W1	(2) Long Model W1	(3) Baseline W2	(4) Long Model W2
Medium	0.06	0.05	-0.07	-0.07
	(0.097)	(0.097)	(0.101)	(0.097)
Heavy	0.67***	0.63***	0.18	0.06
	(0.192)	(0.194)	(0.122)	(0.120)
Wealth Index	0.06*	0.05	0.07***	0.05**
	(0.032)	(0.032)	(0.022)	(0.021)
Rural	-0.18	-0.21*	0.02	0.00
	(0.115)	(0.116)	(0.066)	(0.065)
Farming	-0.01	0.02	-0.21*	-0.16
	(0.113)	(0.114)	(0.114)	(0.106)
Medium*Farming	-0.04	-0.03	0.15	0.15
	(0.130)	(0.129)	(0.115)	(0.113)
Heavy*Farming	-0.68***	-0.64***	0.16	0.22
	(0.211)	(0.210)	(0.145)	(0.145)
Household Size		-0.03		-0.08***
		(0.018)		(0.013)
Male 0-15		-0.21		-0.35**
		(0.233)		(0.136)
Female 0-15		-0.26		-0.38***
		(0.208)		(0.135)
Female 16-60		0.55*		-0.00
		(0.330)		(0.249)
Male 61-Older		0.53		-0.18
		(0.403)		(0.185)
Female 61-Older		0.95**		0.00
		(0.402)		(0.192)
Constant	0.10	0.10	-0.35***	0.19
	(0.147)	(0.244)	(0.081)	(0.127)
Household Sample	6,155	6,155	6,155	6,155

Notes: W1, W2 stand for Wave 1 and Wave 2. Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C.2 Regression Results of Percentage Change in Health Expenses from the Total of Five Expenditure Components

The first wave of the STAR survey asked household respondents their expenditures on five items: inpatient care, outpatient care, traditional medication, self-treatment, and health products and services including consultation with health professionals, pregnancy check-ups, eyeglasses, and dentures. The total amounts of expenditures from those components are not necessarily the same as the total health-related expenses spent by households from the consumption module. The households' health-related expenses used in Table 3.4 are taken from the consumption module and include other health items, insurance, and other services that might not be listed in the five spending categories.

The question on monthly health-related expenses for five components is only available in Wave 1 of the survey and not in the subsequent rounds. Hence, I can only observe the estimated percentage changes in health expenses between the affected households and those with no damage in 5 to 17 months after the tsunami. Table C2 presents the results of OLS and IPW estimations following equation 3.1.

Similar to the outcomes in Table 3.4, households living in heavily damaged regions had higher monthly health expenses 5-17 months post-tsunami compared to their counterpart households with no or light damage. Households who resided in medium damage regions, on the other hand, did not face any changes in their monthly health spending on the combination of five spending categories post-tsunami compared to households with no or lesser damage. The magnitudes of percentage changes in health expenditure from the combined five spending components are lower than the estimated changes from the monthly health expenses from the consumption module that are presented in Section 3.5. The size of the increased monthly health expenses borne by households in heavily damaged locations accounts for 62% of that of the consumption module (Please see Table C2 column 4). Controlling for more variables reduces the statistical power of the health spending coefficients but they remain positive in the short run after the tsunami event compared to the unaffected households.

Table C2: Results on Percentage Change of Health Expenses from Detailed Spending 5-17 Months Post-tsunami

	(1) OLS 1	(2) OLS 2	(3) OLS 3	(4) IPW 1	(5) IPW 2	(6) IPW 3
Medium	0.01	0.01	0.01	-0.00	-0.00	-0.00
	(0.065)	(0.065)	(0.066)	(0.069)	(0.069)	(0.069)
Heavy	0.17^{*}	0.12	0.13	0.21^{*}	0.15	0.17
	(0.093)	(0.092)	(0.094)	(0.111)	(0.109)	(0.115)
Wealth Index	-0.03	-0.04^{**}	-0.04^{*}	-0.01	-0.02	-0.02
	(0.019)	(0.019)	(0.019)	(0.031)	(0.031)	(0.031)
Rural	-0.09	-0.11	-0.10	-0.05	-0.07	-0.07
	(0.077)	(0.078)	(0.080)	(0.105)	(0.105)	(0.107)
Farming	-0.13^{**}	-0.09	-0.10	-0.22^{**}	-0.18^{**}	-0.17^{**}
	(0.062)	(0.062)	(0.062)	(0.090)	(0.089)	(0.087)
Household Size		-0.06^{***}	-0.04^{**}		-0.06^{***}	-0.04^{**}
		(0.013)	(0.016)		(0.015)	(0.016)
Male 0-15			-0.27^{*}			-0.20
			(0.159)			(0.210)
Female 0-15			-0.13			-0.23
			(0.199)			(0.199)
Female 16-60			0.46^{**}			0.53^{*}
			(0.194)			(0.313)
Male 61-Older			0.40			0.02
			(0.274)			(0.281)
Female 61-Older			0.09			0.55
			(0.174)			(0.406)
Constant	0.30^{***}	0.60^{***}	0.38^{**}	0.28^{**}	0.60^{***}	0.33
	(0.102)	(0.120)	(0.151)	(0.132)	(0.144)	(0.224)
Household Sample	6,155	6,155	6,155	6,155	6,155	6,155

Notes: Robust standard errors are provided in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Acronyms

Bakornas PBP the National Coordinating Agency for Disaster Management. 97

Askeskin Social Health Insurance for the Poor. 18, 19, 96

ATT average treatment on the treated. 65, 67, 72, 73, 81, 82

BPS Central Office of Statistics. 24, 57, 61, 95, 108

CFR case-fatality ratio. 91

CHC community health centre. 28

CIA conditional independence assumption. 71, 74

DID difference-in-difference. 48, 65–67, 70, 71, 79

EM-DAT Emergency Events Database. 90

FA Factor Analysis. 64, 70

FE fixed effects model. 85

FWER family-wise error rate. 68

GDP gross domestic product. 52, 88, 90

GOARN the Global Outbreak Alert Response Network. 97

GoI the government of Indonesia. 48, 51, 52, 55

HIC health insurance coverage. 27, 30, 32, 34–36, 39, 44, 45

IHS inverse hyperbolic sine function. 58

Indo-Dapoer Indonesia's Database for Policy and Economic Research. 57

IPW inverse-probability weighting. 4, 89, 94, 107–109, 114, 167

LMICs lower-middle-income countries. 21, 47, 50

NGOs non-governmental organisations. 53, 91

OOP out-of-pocket. 17, 27, 30, 32, 38, 40, 41, 45, 99, 103, 104, 107, 111

PCA Principal Component Analysis. 64, 100, 101

PKP-MAK The Center for Health Financing Policy and Health Insurance Management, Faculty of Medicine, University of Gadjah Mada. 2

PODES Village Census Data. 2, 23, 28, 42, 48, 57, 62

PPS probability proportional to size technique. 26

ppts percentage points. 17, 32, 34, 36, 37, 46, 49, 70, 82, 84, 88

PSM propensity score matching. 48, 65–67, 70, 73

RE random effects model. 85

Riskesdas Basic Health Research Survey. 37

Susenas National Socio-Economic Survey. 2, 3, 17, 21–23, 25–30, 33, 35, 37, 39, 43, 57, 99

TNP2K The National Team for the Acceleration of Poverty Reduction. 24

UDB Unified Poverty Database. 17, 22–25, 28–32, 37, 41, 44

WHO World Health Organisation. 58, 91, 97

Glossary

Askes Health insurance for government employees that is mandatory and restricted coverage for civil servants, pensioners, active and retired army personnel including their children with a specific policy. 19, 96

BAPPEDA Badan Perencanaan Pembangunan Daerah or Indonesia's development planning agency at the province or district level. 53

BLT Bantuan Langsung Tunai or Direct Cash Transfer for the poor amounted USD 10 to compensate a partial reduction of fuel price subsidy. 98

BRR Badan Rehabilitasi dan Rekonstruksi or the Indonesia's Agency for Rehabilitation and Reconstruction for Aceh and Nias that operated for 4 years starting from April 2005. The Agency was established to restore livelihoods and empower communities to participate in the reconstruction and rehabilitation effort after the 2004 tsunami. 98

Dinas PU Dinas Pekerjaan Umum or Indonesia's office of public works at the regional level. 53

IDR Indonesian currency called Rupiah or Indonesian Rupiah. 15, 17, 19, 20, 29, 39–41, 45, 54, 62, 94, 98

IFLS The Indonesian Family Life Survey is a longitudinal household survey that is conducted by RAND that collects information on individuals, households, and communities. There have been five waves of surveys since 1993 with the latest one being in 2014 (IFLS5).. 4, 10, 46, 48, 56, 57, 60, 62, 67, 69, 70, 76, 78–80, 82

Jamkesmas Indonesian social health insurance programme. 3, 16–21, 25, 27, 31, 32, 34, 39, 41, 44, 96

Jamsostek A contributory insurance introduced to private sector employees to cover their social security. 19, 96

JPS-BK *Jaringan Pengaman Sosial Bidang Kesehatan* is a social safety net programme for health sector that was introduced by the government of Indonesia in the 1998/1999 fiscal year as a temporary rescue programme after the Asian financial crisis to help the poor families through the provision of free healthcare services, subsidised medicines, immunisation, and other services. 96

PAMSIMAS Penyediaan Air Minum dan Sanitasi Berbasis Masyarakat or Community Based Drinking Water Supply and Sanitation in Indonesia that firstly commenced in 2008 to improve access of households to safe drinking water in the rural, under-served, and low-income regions. 4, 10, 46, 48–50, 52–60, 65–67, 71–75, 80–88

PMD Dinas Pemberdayaan Desa or Village Community Empowerment Unit. 53

PMT A proxy-means testing method is a technique that uses a sophisticated statistical algorithm to proxy income or welfare based on household characteristics. 16, 17, 21–24, 27, 30, 44, 45

PPLS 2011 The data collection for the social protection programme or in the Indonesian language, this data is called Pendataan Program Perlindungan Sosial. This data collection initiative became the source for the Unified Poverty Database (UDB) that was developed in 2011 incorporating the new approach of the poverty mapping method in the process introduced by Elbers et al. (2003). 23, 24

PROGRESA Mexico's national conditional cash transfer programme that was launched in 1997 and targeted poor rural families, conditioning their children to attend schools and the households to visit public health facilities. 21

RAND A research institute and non-profit organisation that serves as a consulting firm and works in research and development (R&D) in multiple areas, such as health, education, and other fields. 2

RCT An evaluation technique that aims to measure the effectiveness or impact of a specific intervention such as a government policy by randomly assigning participants to either an experimental or a control group. 17

RKM Rencana Kerja Masyarakat or Community Work Plan. 54

STAR A survey that collects information about socio-economic well-being, behaviours, and responses of individuals and households as well as information on areas suffering from light, medium, and heavy damage in 13 districts of Aceh and North Sumatra Provinces after the 2004 Tsunami. The survey's sampling frame was the 2004 Susenas with the first round being conducted in May 2005. 2, 4, 89, 93, 99, 100, 102, 112, 167