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Three Essays on Health and Education in Indonesia

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ABSTRACT

THREE ESSAYS ON HEALTH AND EDUCATION IN INDONESIA

By

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Improvement in health, education, and reducing child labor are a widely accepted public policy in the developed as well as developing countries. This dissertation consists three essays that examines the impact of health and education policy in Indonesia. The first essay examines the impact of the existence of limited resource hospitals on medical care utilization and household health expenditures. Limited physical access to facility health care is a primary concern that contributes to high health risks and inadequate medical care in developing countries, primarily in poor areas. The Indonesian government built limited-resource hospitals in poor areas. Difference-in-differences and matching-difference-in-differences methodologies were used in exploiting timing implementations of mobile hospital establishments. To do so, I scrape and utilize variables about hospital location and travel distance from many different sources. I find the existence of public hospitals more likely increases outpatient and inpatient in public hospitals, as well as household health expenditures. Also, I find only areas in which new hospitals are located closer than existing hospitals or more transportation alternatives benefit from the intervention. These results suggest that not only broadly expanding facility health centers but also improving infrastructures in poor areas are critical for improving access to health care.

The second essay investigates how dependent coverage changes for civil servants' children impacts medical care utilization for Indonesia universal health insurance (*BPJS*) scheme in 2014. I use a difference-in-differences and triple difference-in-differences methodologies with the third children as a treatment group, and both the first two children and the fourth and afterward children as a control group, by exploiting timing implementation of policy changes in civil servant dependent coverage insurance policy. I employ representative data from Indonesia Family Life Survey (IFLS). I find coverage expansion more likely increases outpatient medical care utilization in public hospitals for eligible children. Also, I separate the impacts of eligibility status and reduction of copayment. Our results are robust to many specifications. These findings suggest that broadly expanding public insurance dependent coverage is beneficial for insurance holders.

The last essay the impacts of compulsory education and free tuition programs in Indonesia on child labor and health outcomes for children. I use difference-in-differences and matching difference-in-differences approaches with 13- to 15-year-old junior high school students as a treatment group and 16- to 18-year-old senior high schoolers as a control group by exploiting timing implementations of compulsory education and free tuition programs. I employ large representative data from Indonesian Household Surveys (*SUSENAS*). I find compulsory education and free tuition programs significantly reduce the probability of child labor and illness symptoms. The results support the notion that free tuition eases household budget constraints to keep children in school and prohibit them from working, thus leading to children becoming healthier. Our results are robust to many specifications. These findings suggest that broadly expanding compulsory education supported by free tuition programs to higher levels of education would benefit society in general.

THREE ESSAYS ON HEALTH AND EDUCATION IN INDONESIA

BY

BONDI ARIFIN

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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DEDICATION

I dedicate this dissertation for my mother, and my father who take care of me from when I was born until today. Thank you for being there for me for all the prays for my healthiness, success and all good deeds. Thank you for your patience and support when I did something wrong and promising me that the God will give a better way. Thank you for being my biggest fan through single stage of my life. I would not achieve everything what I have today without your love. After this big day, I will always be with you. Also, I dedicate this dissertation for my beautiful wife and two beautiful daughters for their love and patience. They always support in every stage of my study. I wish you the strength to face challenges with confidence. I wish you love your journey and may you always remember to help people along the way and remember how much you are loved.

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INTRODUCTION

Improving education, reducing child labor, and increasing health outcomes are widely accepted public policy goals in developed as well as developing countries. However, there always been a debate about which government intervention best for its citizen welfare and how do similar interventions in developed countries create a different impact when they are applied in developing countries. This dissertation purpose seeks to examine the impact of government interventions about health and education in a developing country. In particular, the first two chapters investigate the construction of health facilities and health insurance expansion on medical care utilization; the last chapter focuses on how an education policy affects child labor and health outcomes.

Limited physical access to health care is a major factor contributing to the poor health of populations in developing countries. Furthermore, inequality of development between city and rural areas creates an additional burden for people who live in the countryside. Tough topography or remote regions hamper individuals' access to medical care, and these factors also contribute to lack of health centers. In the first chapter, I examine the impact of limited resource hospitals, namely mobile hospitals, for underdeveloped municipalities on medical care utilization and household health expenditures. Access to the hospital would lower the effective price (regarding time and traveling cost) of medical care utilization and reduce delays in getting medical care. On the other hand, severe topography and lack transportation would hamper individual access to newly-built hospitals.

I applied difference-in-differences (DID) and matching-DID methods with areas that constructed mobile hospitals as a treatment group and municipalities that did not have any hospitals as a control group. Also, variables such as hospital location and travel distance were collected from many different sources, including Google Developers. I find that the establishment of mobile hospitals more likely increases outpatient to more than 1.2 percentage points, corresponding to more than a 40 percent increase from the pre-intervention period. Furthermore, it more likely increases inpatient by 0.2 percentage points, corresponding to more than a 33 percent increase from the pre-intervention period. Interestingly, our results suggest enormous impact for areas that are located in main islands, but I find no evidence for outer islands. Also, only regions with new hospitals located closer than existing hospitals benefit from the intervention. The findings support the notion that healthcare facilities are an essential factor that contributes to access to medical care utilization. Moreover, there may be another policy required in addition to public hospital construction in outer islands, such as infrastructure construction to connect those islands.

In the second chapter, I examines the causal effect of government-provided insurance for children on their medical care utilization by exploiting changes in public insurance coverage for children in Indonesia. Access to health insurance for covered children will lower the effective price of medical care utilization in all public health facilities and member private health facilities, and reduce delays in getting medical care that may translate into better health outcomes. I use difference-in-differences (DID) and triple DID approaches with newly eligible children (third child) because of the policy change as a treatment group and both eligible children already in place (first and second children) or ineligible children (fourth and above) within a household as a control group. I find that eligible children are more likely to have outpatient care in hospitals by 4 percentage points, corresponding to a 210 percent increase from the pre-intervention period. There is a more substantial impact when I count both eligibility and co-payment reduction effects. That is, universal health coverage not only adds the third children to the scheme but also includes co-payment reduction from their initial program.

The last chapter estimates the causal effect of compulsory education together with free school programs on child labor and health outcomes by exploiting changes in compulsory government education and free tuition programs in Indonesia. The Indonesian government has mandated primary nine-year school since 2003, from previous (1993) mandates of only up to six years of education. However, in developing countries, mandates per se may not be optimal to bring children into school and keep them away from working. Additional interventions are required for developing countries because of the nature of developing countries' limited financing ability or limited education facilities to put their children into school.

I apply difference-in-differences (DID) and matching DID approaches with 13- to 15-year-old junior high school students as a treatment group and 16- to 18-year-old senior high school students as a control group. I employ representative large-scale multi-purpose socioeconomic survey data of Indonesian families and individuals (*SUSENAS*) for the years 1997-1999 and 2003-2014. I find compulsory education and free tuition programs likely lead to reductions in child labor and fewer experiences with diarrhea and migraines. The impact is larger for children from low-income families and children from rural areas. It suggests the program eases household budget constraints. Our results suggest the benefit of government expenditures in education on child labor and health outcomes.

CHAPTER 1. THE IMPACT OF PUBLIC HOSPITAL AVAILABILITY IN UNDERDEVELOPED AREAS ON MEDICAL CARE UTILIZATION AND HOUSEHOLD HEALTH EXPENDITURES

1.1. Introduction

Limited physical access to health care is a major factor contributing to the poor health of populations in developing countries (Perry & Gesler, 2000). Furthermore, inequality of development between city and rural areas creates an additional burden for people who live in the countryside. Tough topography or remote regions hamper individuals' access to medical care, and these factors also contribute to a lack of health centers. The Indonesian government has introduced limited resource hospitals, named mobile hospitals, for underdeveloped municipalities, outer islands, and shared state border cities.

A mobile hospital is a hospital with a non-permanent structure (such as combined containers) and limited land area (around 2,500 m^2). However, it provides all medical care required including outpatient, inpatient, midwifery, and emergency. It was a substantial policy intervention because there were neither public nor private hospitals in areas that are far from any other place and lack transportation. The purpose of this paper is to estimate the causal effect of government-provided hospitals on medical care utilization and household health expenditures by exploiting mobile hospital development over time in Indonesia.

This government policy creates a differential impact on families living in one area and families residing in other regions over time. Access to the hospital would lower the effective price (regarding time and traveling cost) of medical care utilization and reduce delays in getting medical care. On the other hand, severe topography and lack transportation would hamper individual access to newly-built hospitals. So, the impact depends on the hospital location, whether it is reachable by the society in an area and relative distance compared to an existing hospital in neighboring cities. Also, it may either increase or decrease household health expenditures. Improving access to health care facilities can enhance medical care utilization, thus increasing household health expenditures. On the other hand, closer health facilities may reduce transportation cost, thus decreasing family health expenses. Substitution or complement effects between health centers may either increase or decrease household health expenditures Therefore, the impact on health expenditures depends on whether the reduction in transportation cost outweighs the increase in medical care cost due to higher medical care utilization, also substitution/complement effect between health center. Furthermore, improvement in access to health care utilization may translate into better health outcomes.

Despite the importance of access to health facilities, there are scant studies in developing countries. Well-designed transportation systems in urban areas may cause inconclusive evidence in developed countries because additional health facilities may not substantially decrease travel time (Carpenter, Morrow, Del Gaudio, & Ritzler, 1981; McGuirk & Porell, 1984; Mooney, Zwanziger, Phibbs, & Schmitt, 2000). Even though medical care utilization significantly correlates with distance in developing countries (Ayeni, Rushton, & McNulty, 1987; Stock, 1983; Tanser, Gijsbertsen, & Herbst, 2006), those areas are mostly covered by land. Indonesia has unique geographic characteristics that differ from countries in previous studies. For example, Indonesia consists of thousands of separate islands, even within the same municipalities. It creates an additional burden to access primary health centers since no ground transportation is available to travel to other islands.

This study contributes a valuable resource for policymakers in assessing the impact of public expenditures for rural development in developing countries. To my knowledge, this is the first study the impact of public hospital availability in Indonesia. Our solution to the problem of lack of health facilities in developing countries is to exploit a quasi-experimental intervention of government spending on public hospitals. I applied difference-in-differences (DID) and matching-DID methods with areas that constructed mobile hospitals as a treatment group and municipalities that did not have any hospitals as a control group. Also, variables such as hospital location and travel distance were collected from many different sources, including Google Developers. This information enables us to understand who benefits and who does not benefit from the intervention within the same municipality by comparing travel distance to new hospitals and existing hospitals.

I compared the evolution of medical care utilization at the individual level between the treatment and control units by policy interventions. I used large representative data from Indonesian Household Surveys (*SUSENAS*) that covers underdeveloped or remote areas. Indonesian government built more than 80 percent of the overall mobile hospitals in Indonesia between 2008 and 2012. I estimated the impact of mobile hospital establishment in 2008 since it was the first large wave in building mobile hospitals.

I find that the establishment of mobile hospitals more likely increases outpatient use by more than 1.2 percentage points, corresponding to more than a 40 percent increase from the pre-intervention period. Furthermore, it more likely increases inpatient by 0.2 percentage points, corresponding to more than a 33 percent increase from the pre-intervention period. Interestingly, our results suggest enormous impact for areas that are located in main islands, but I find no evidence for outer islands. Also, only regions with new hospitals located closer than existing hospitals benefit from the intervention. Our results are robust to many specifications. The findings support the notion that healthcare facilities are an essential factor that contributes to access to medical care utilization. Moreover, there may be another policy required in addition to public hospital construction in outer islands, such as infrastructure construction to connect those islands.

The paper is organized as follows. Section 2 reviews the relevant literature on the impact of health facilities. Sections 3 and 4 describe the history of the mobile hospital in Indonesia and data sources. Section 5 discusses identification strategies. In section 6 I apply those methods to mobile hospital availability, robustness and placebo tests. Section 7 concludes.

1.2. Review of the relevant previous literature

1.2.1. The impact of physical distance of health facilities

Research on the physical distance of human activities and economic outcomes mostly comes from environmental and resource studies, namely distance-decay approaches. It shows how population characteristics or the demand for a particular good may differ when physical distance increases. For instance, biodiversity studies use distance-decay approaches to explain how the similarity between two communities varies with the geographic distance that separates them. Transportation demand studies evaluate the performance of the transportation network and travel patterns and their effects on medical care facilities (Bashshur, Shannon, & Metzner, 1971; Martínez & Viegas, 2013; Morlon et al., 2008).

A basic distance-decay model assumes interaction intensity of population with health facilities as a function of physical distance:

$$I_j = f(d_j) \tag{1}$$

$$d_j = [(x_j - x_i)^2 + (y_j - y_i)^2]^{1/2} \tag{2}$$

where I_j is some measure of interaction intensity, f(.) is monotonically decreasing function of distance, and d_j is some measure of distance measured as direct lines from the coordinate (x_j,y_j) location j of each residence to the coordinate (x_i,y_i) location of medical facility i (Bashshur et al., 1971; Taylor, 1971). Equation (2) of the basic distance-decay model assumes distance as a straight line measured from point A to point B. However, a distance from one point to another point may not be a straight line. For example, the travel distance from house A to hospital B follows roads or rivers instead of straight-line distance. Moreover, people who live in mountainous areas may have to use spiral-shaped streets to reach a hospital that is located down the mountain. It creates a significant difference between straight-line distance and travel distance.

Varieties of this model develop some specifications and control factors that affect both distance and outcomes. Two most-often-used specification developments are an exponential model and a gravity model. Exponential models treat f(.) as the exponential of distance, and gravity models normalize range with all intervening hospital ranges around a neighborhood (De Vries, Nijkamp, & Rietveld, 2004; McGuirk & Porell, 1984; Morlon et al., 2008; Roghmann & Zastowny, 1979; Stock, 1983).

Many factors confounded the impact of physical distance of the hospital. People are more likely to travel to a different level of services, such as a general or a specializing health facility, and larger hospitals are perceived to be higher quality. Socio-demographic characteristics such as income, gender, age, and culture may create a differential impact of distance on utilization. For instance, adults are more likely to travel farther than children. There also may be cultural restrictions in society related to distance. Season and type of illnesses have different utilization patterns. For example, rainy seasons are more likely to generate more flu diseases, and some populations may be inclined to go to a traditional healer for fractured bones. Other important factors affecting both distance and health facility choices include the existence of intervening hospitals and physicians in the neighborhood; more hospitals give more opportunities for medical care utilization (McGuirk & Porell, 1984; Stock, 1983).

1.2.2. The impact on medical care utilization

Improving access to medical care utilization will lower the effective price of health care, thus increasing its use (Dafny & Gruber, 2005). However, empirical evidence shows inconclusive evidence about whether physical access affects health facility utilization choices and medical care utilization. There are two principal directions of empirical research studies that examine the impact of hospital physical distance on medical care utilization, rural and urban areas.

Empirical studies examining the effects of physical access to a hospital for medical care utilization in cities have found inconclusive evidence, whereas one study in a Allegheny county, Pennsylvania found that significant distance and time factors strongly influence hospital choices that vary by service and hospital (McGuirk & Porell, 1984). On the other hand, other studies showed no significant differences in hospital or clinic choice pattern services based on the distance from Rochester, New York and the greater Cleveland area (Bashshur et al., 1971; Carpenter et al., 1981). These instances of mixed evidence may be related to well-developed transportation systems in urban areas. Increasing physical distance in a metropolitan area may only slightly increase travel time due to reliable transportation systems.

Empirical evidence in the countryside has mostly come from developing countries. Empirical studies in Kano State, Nigeria, and Kwa-Zulu Natal, South Africa, found that utilization per capita declined with distance or travel time (Tanser et al., 2006). Another study in rural areas in Nigeria revealed that new facilities have increased the use of maternal and child health centers. However, current location of health facilities could be improved which population could have been more accessible to the centers (Ayeni, Rushton, & McNulty, 1987; Stock, 1983).

I introduce substitution or complementary effect between health facilities. The idea is that reducing the effective price of one provider may reduce utilization of another provider. This substitution effect could create a different impact on health outcomes if there are differences in quality across providers. For example, closer distance to the public hospital might mean that an individual visits a primary-care physician instead of traditional healer, since doctors are more likely to refer the person to a hospital if they need further advanced treatment. A closer distance to the public hospital may substitute similar medical care utilization on the private hospital, and vice versa since they provide similar services. The existence of a health facility could have a complementary impact if nearby facilities have similar objectives and supporting activities. For example, public hospitals in Indonesia use a referral from public health care before someone could visit a hospital, except for some urgent medical care such as an emergency.

Furthermore, increasing the accessibility of medical care may increase *ex-ante* moral hazards by people not taking preventive uses such as immunizations and routine check-up. Also, reducing the effective price of medical care would discourage self-protection because of decreased financial losses associated with illness (Barbaresco et al., 2015; Ehrlich & Becker, 1972). Therefore, hospital availability may increase or decrease the utilization of medical care from different medical care utilization channels.

1.3. History of mobile hospitals in Indonesia

The Indonesian government-provided limited medical facility hospital started in 2005 when a new government regime prioritized developing poor areas and remote islands by issuing Presidential Decree No. 78 about outer islands management. The Ministry of Health spelled out this mandate that requires cooperation between central and local governments to build hospitals, issuing regulations about field and mobile hospitals in underdeveloped municipalities and/or on remote islands. They started to build one field hospital in 2004 and 2005, then established two in 2006. Ten mobile hospitals were constructed in 2008 and nine in 2012. Modern mobile hospitals have better medical facilities than those built years ago. While the field hospital may be built by using tents in the temporary location, the mobile hospital can be constructed using bricks or mixed containers.

The mobile hospital is a hospital in a non-permanent building with limited land area. For example, a mobile hospital can be made using mixed containers covering less than 2,500 m^2. Although it was created with limited resources, it gives all required medical care services, including outpatient, inpatient, midwifery, and emergency. The central government constructed the hospital and covered all operating costs in the first year, reducing its support gradually over time as local authorities started financing this hospital from that point on.

To support a mobile hospital operation, cooperation between central and local governments was necessary to provide at least three general practitioners and two specialists in the hospital. Using another regulation, the Ministry of Health mandated each newly graduated doctor to dedicate their time for a particular period, one or two years, in remote places. They also gave additional monetary incentives for physicians who worked at those places, both for mandated physicians and doctors voluntarily working at those remote sites.

The Ministry of Health together with the local government developed eligibility criteria from the Ministry of Underdeveloped Areas for building mobile hospitals based on geography, accessibility, social, economic, culture, health, and budget priorities. One obvious eligible criterion was that a municipality must not have a single hospital. They defined remote areas as a zone located in inland areas, mountainous regions, small outer islands, and/or a shared international border region. Furthermore, they identified underdeveloped areas as those with less developed sectors nationally in their social, economic, culture, and health conditions. Therefore, we would expect these targeted areas would more likely have high-risk people and less transportation compared to non-targeted areas.

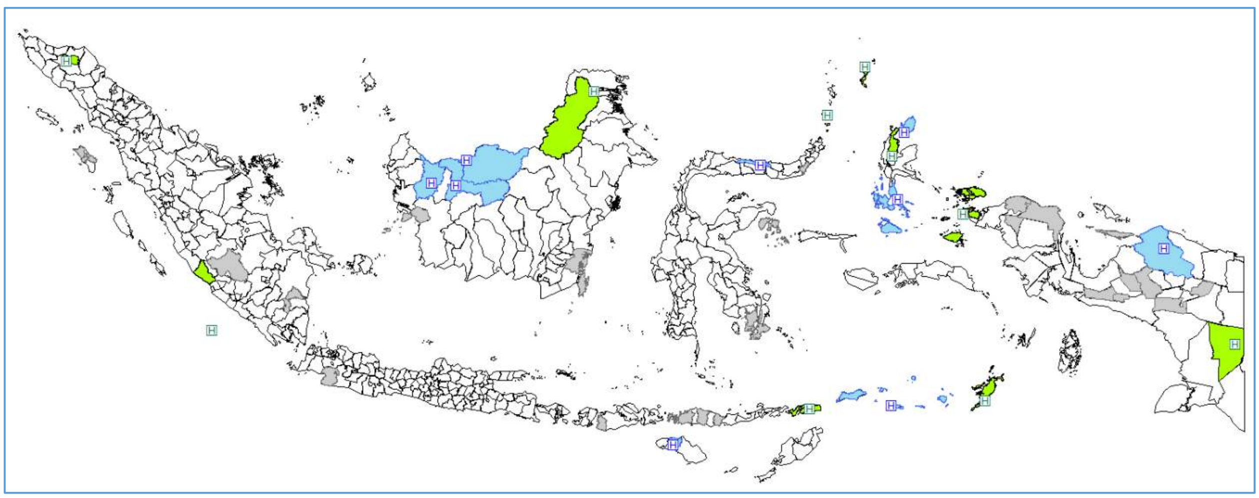


Figure 1.1. Mobile Hospital Map

Figure 1.1 provides the mobile hospital map across Indonesia. The green shaded areas with green "H" signs are municipalities where mobile hospitals were built in 2008. The blue shaded with blue "H" signs are municipalities where mobile hospitals were constructed in 2012. The grey patterns without any "H" signs are municipalities which have no hospital as of 2014. The figure suggests that hospitals have been built both in the west and east regions, but they were not made on Java Island. Hospitals were built not only inside the main five big islands but also in the outer and isolated regions. However, mobile hospitals only reached the east region in 2012. The west region is more developed than the east region in infrastructure and economy on average. For example, the Indonesian capital city, Jakarta, is located on the island of Java (in the western part of Indonesia). So, different level of economic and infrastructure development between those two regions may be one possible reason why mobile hospitals were only built in the east region in 2012.

Different geographical characteristics between the main islands and outer islands are other relevant facts to consider. People who live on the main islands could have more choices of transportation mode compared to people who live on the outer islands. For example, while people on the main islands could either use ground transportation, water transportation or just walk to nearest hospitals, people on the outer islands must use either ferry or private boat to reach hospitals in the neighboring islands, even within the same municipality.

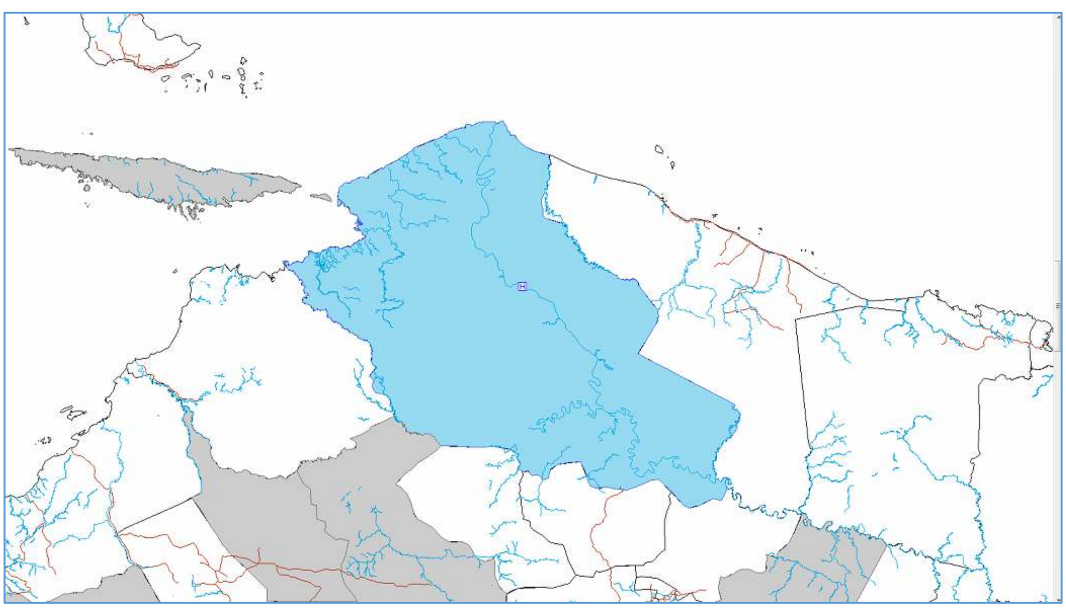


Figure 1.2. A Municipality on a Main Island (Papua Island)

Figures 1.2 and 1.3 provide example areas in main islands and outer islands. The blue shaded area in Figure 1.2 is a municipality on a main island, Mamberamo Raya. Water transportation is the primary transportation mode in this area. People in this area could use either water transportation or ground transportation for limited distance, or simply walk to the nearby hospital.

Figure 1.3. A Municipality on an Outer Island (Alor)

Figure 1.3 shows two islands within the same district, Alor. People on one island must use either a ferry or private boat to reach their nearest hospital on a neighboring island because a sea isolates those islands. In addition, people who live on outer islands could have much longer travel time to reach nearby islands because of using a ferry or other water transportation. For example, travel from Sulawesi Island (main island) to Talaud Islands (outer islands) might take ten hours using a ferry. Additionally, water transportation may not be available all of the time. A ferry transportation may be available only once or twice a week and a private boat only once or twice a day, depending on travel locations. Therefore, people who live on outer islands have more burden to reach both nearby existing hospitals and newly-constructed mobile hospitals.

1.4. Data

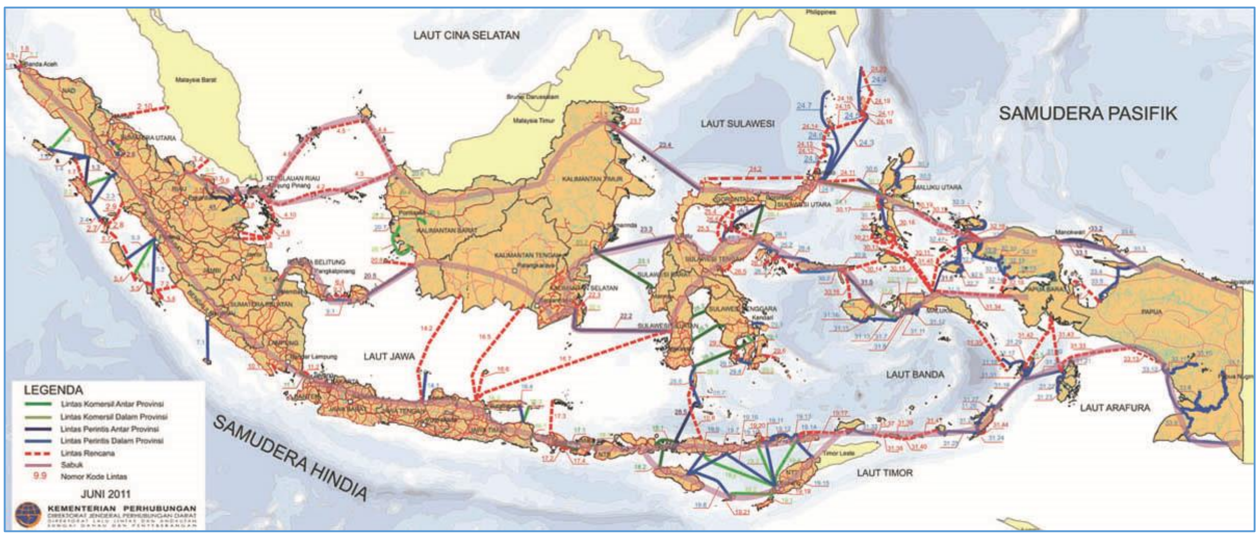
I employed eight waves' repeated cross-section data sets from the Indonesia National Socioeconomic Survey (*SUSENAS*), periods 2004-2007 and 2009-2011. I excluded 2008 because of the mobile hospital regulation effective as of October 2008. Thus, an individual may or may not be treated depending on when they were interviewed during that year. *SUSENAS* removed sub-district identifiers since 2012. Sub-district identifiers are required to merge with travel distance data on our primary analysis. Therefore, I included 2012-2014 for robustness purposes without utilize travel distance.

SUSENAS is a series of restricted large-scale multi-purpose socioeconomic surveys initiated in 1963-1964 and fielded every year or two since then. Since 1993, *SUSENAS* has collected household and individual data across all provinces in Indonesia, including underdeveloped or remote areas. Each survey contains a core questionnaire that consists of roster household characteristic, healthcare and educational attainment, and labor force experience. SUSENAS conducts a quarterly survey that is stacked into yearly data sets; it samples around 75,000 households on average for each study period: March, June, September, and December. Therefore, it typically includes 200,000 to 300,000 families in one-year data sets.

Since *SUSENAS* does not have hospital information, I complemented this dataset by scraping Hospital Information System (SIRS) data from the Indonesian Ministry of Health website. This dataset covers all hospitals in Indonesia and provides detailed hospital characteristics such as the number of beds, number of general practitioners and specialists, hospital equipment, hospital address and municipality, and hospital establishment or extension regulation.

I utilized Google Developers and Facebook to obtain hospital geographic coordinate information from the information provided in SIRS. In particular, I used Google Developers'

Places API to find each hospital address and determine its geographic location. However, not all hospital addresses were found in Google Developers, since I am working on underdeveloped/remote areas. I used Facebook to complement what is missing from Google Developers. For example, when someone “checked in” or created a fan page for a hospital in Indonesia, I could obtain that hospital's coordinates from Facebook. With a similar method, I gathered coordinate locations for each centroid sub-district in our population interest.



Source: Ministry of Transportation Republic of Indonesia *(Republic of Indonesia, 2011)*

Figure 1.4. Water Transportation Routes in Indonesia

Next, I utilized Google Developers' Direction API to obtain travel distance from each sub-district to both existing hospitals in the shared border municipality and a newly-built hospital within district. Figure A.1 provides example information of travel distances from Google Developers’ Direction API using R software. Google gives both origin and destination coordinates, address, polygon (travel routes), boundaries, travel time, travel distance, and travel mode. I used driving travel mode to achieve a similar travel mode for all observations. Figure A.1 also shows a missing value when Google Developers cannot estimate travel distance from point A to point B.

Locations without ground transportation generate those missing values since Google Developers only estimates travel distance when there is ground transportation available between two points.

I manually tracked and estimated travel distances for missing locations in Google Developers using either ArcMap software or Google Maps. The Ministry of Transportation of the Republic of Indonesia provides maps for ferry or other boat routes across all Indonesian regions, as depicted in Figure 1.4. I followed these routes using Google Maps to determine the waterway travel distance from a sub-district to existing municipalities in which boats possibly pass an island in our population of interest. For example, I estimated the travel distance from a local island seaport in a sub-district in the Talaud Islands to a domestic seaport on Sulawesi Island; then I estimated the travel distance from a local seaport to a hospital location using Google Developers' Direction API. Travel distance is the summation of the waterway travel distance between two local seaports and ground transportation travel distance from a local seaport to a hospital. Also, I estimated travel distance when people use river transportation, primarily in areas of main islands which do not have any ground transportation. Figure 1.2 above shows an example of a hospital located on the main river. I tracked and estimated the river distance from a sub-district to a hospital location to obtain the travel distance either using Google Maps or ArcMap software. Finally, I matched *SUSENAS* and all available information at the sub-district level.

1.5. Identification strategy

In this section, I describe identification strategy and estimation methods. I utilized central government criteria for building mobile hospitals based on geographic, accessibility, social, economic, culture, health analysis, and budget priorities. Our control groups are municipalities in Indonesia without hospitals, and they are not located on Java Island since it is the primary criteria to build a mobile hospital in a particular area. Furthermore, the Indonesian government identified underdeveloped regions as areas that have less development than other sectors in their social, economic, culture, and health conditions. Therefore, I expected these targeted areas would more likely have high-risk people and a small number of municipalities that do not have any hospital and meeting all of those criteria. I identified 35 municipalities satisfying the above criteria, in addition to 9 areas in which mobile hospitals were constructed in 2012.

The basic approach is a difference-in-differences (DID) estimation. Our baseline regression is the following:

$$Y_{ikrt} = \alpha_0 + \alpha_1(T_{ikr} * Post_t) + \alpha_2 X`_{ikrt} + \alpha_3 Z`_{krt} + \gamma_k + \mu_{rt} + \epsilon_{ikrt} \qquad (3)$$

where Y_{ikrt} is a binary variable whether an individual has outpatient/inpatient visit at the public/private hospital or household health expenditures per capita for an individual/family i living in region r and municipality k at time t. T_{ikr} is a treatment indicator of whether an individual or a family is residing in a community where a mobile hospital was built. $Post_t$ indicates whether period t is after the implementation of the new policy (2008). $X`_{ikrt}$ is an individual or a household level vector of control variables including gender, age, married, year of education, family size, and whether a person is living in a rural area. Travel distance and nearby municipality hospital characteristics correlate with medical care utilization with community who live on areas under studies. Controlling travel distance and hospital characteristics are essential to capture heterogeneity between medical care utilization because of hospital existence in the neighborhood areas. $Z`_{krt}$ is a sub-district vector of control variables for an indicator of sub-district total travel distance and travel distance using water transportation to the nearest shared border town hospital, number of beds of a nearest hospital, and hospital type (public hospital governed by central government, public hospital run by local government, or private hospital) at time t. I included municipality fixed effect (γ_k) and region year fixed effect (μ_{rt}) to capture unobserved differences for space and time, respectively, and ϵ_{ikrt} is the idiosyncratic error term. I defined nine regions, one for each of the five main large islands, and outer small islands as the last four regions. I clustered by household level to capture unobserved differences between families.

I expanded the standard DID approach above with a matching-DID approach, due to the various demographic criteria developed in building a mobile hospital and compositional characteristics changes over time between the treatment and control group that may confound the impact of the treatment (Hong, 2013). For example, due to infrastructure and economic development in certain areas, one municipality may not be categorized as the countryside over time, and this composition change may confound the impact of the intervention. The effect magnitude is not only from the incidence of the existence of a mobile hospital in the area but also the effect of diffusion of the infrastructures in the areas, although this is less likely to happen due to harsh topography conditions.

To begin matching difference-in-differences, I first estimated multivariate propensity score using standard propensity score matching methods (see, for examples Angrist & Pischke, 2008; Rosenbaum & Rubin, 1983). I estimated propensity scores of being treated separately for each time t, both pre-treatment-year and post-treatment-year following multivariate propensity score propensity score method from Hong (2013), using the following:

$$P(T_{ikrt} = 1 \mid X_{ikrt}, Z`_{krt}) = \phi(X`_{ikrt}\beta_t) \quad (4)$$

where T_{ikrt} , X_{ikrt} , and X_{krt} are as described in equation (3). Each year, propensity score matching is used to balance the sample characteristics for both pre- and post-treatment periods from repeated cross-sectional data.

Suppose I have an estimated propensity score P_{ikrt} for an individual/household i who lives in municipality k at time t. I then impute those propensity scores for all observations as probability weights. I use the matched-sample and apply DID in equation (3), but including probability weight for each matched observation.

1.6. Empirical results

In this section, I provide descriptive statistics, and empirical analysis of limited resource hospital existence. Our analysis includes the average treatment effects of limited hospital existence, heterogeneity between main islands and outer islands, and travel distance analysis regarding to new constructed hospitals.

1.6.1. Descriptive statistics (Mobile hospitals available in 2008)

Table 1.1 shows the means and standard deviations for medical care utilization outcomes and covariates. The outpatient variable is a binary variable of 0 or 1 showing whether an individual went to outpatient care in the last 30 days. Inpatient variable is a binary variable of whether a person received inpatient services in the last year. Nominal household health expenditures are continuous variables for nominal household health expenditures per capita in a given year.

The treatment group has higher outpatient, inpatient, and household health expenditures per capita before the intervention period; it depicts the treatment group as having a higher health risk. However, the treatment group has a more considerable increase in outpatient, inpatient trend, and household health expenditures per capita after the intervention period, implying preliminary evidence of improvement in medical care accessibility. One interesting evidence is similar inpatient and outpatient traffic at private hospitals for both periods between treatment and control groups. It may show evidence of no substitution effect between health facilities.

Table 1.1. Means and Standard Deviations

Variables	Pre-Intervention (2004-2007)		Post-Intervention (2009-2011)	
	Treatment	Control	Treatment	Control
Outcomes				
Inpatient, Public Hospital	0.006(0.080)	0.005(0.067)	0.010(0.099)	0.005(0.099)
Outpatient, Public Hospital	0.031(0.172)	0.020(0.139)	0.042(0.201)	0.016(0.201)
Outpatient, Private Hospital	0.006(0.075)	0.005(0.068)	0.006(0.077)	0.006(0.077)
Inpatient, Private Hospital	0.001(0.028)	0.001(0.032)	0.001(0.032)	0.002(0.032)
Ln(HH Health Expenditures/Capita)	11.459(1.303)	11.184(1.293)	12.675(1.267)	12.545(1.267)
Control				
Male	0.511(0.500)	0.509(0.500)	0.507(0.500)	0.509(0.500)
Married	0.447(0.497)	0.437(0.496)	0.456(0.498)	0.448(0.498)
Age	26.76(18.90)	25.76(18.61)	27.43(19.49)	26.37(19.49)
Year of Education	6.087(4.322)	5.012(4.124)	6.170(4.318)	4.869(4.318)
HH Size	5.055(1.939)	5.093(1.942)	4.184(2.404)	4.202(2.404)
Rural	0.907(0.290)	0.885(0.320)	0.854(0.353)	0.913(0.353)
Travel Distance to Nearest Existing Hospital (km)	188.1(126.9)	125.4(100.4)	170.8(126.9)	117.1(126.9)
Nearby Hospital Beds	80.08(60.22)	77.64(44.35)	79.47(61.02)	77.93(61.02)
Travel Distance to New Hospital (km)	0.000 (0.000)	0.000(0.000)	101.9(124.0)	0.000(0.000)
N	41,968 to 181,022		33,439 to 138,443	

For demographic characteristics, both groups have similar traits except for age and year of education. The treatment group tends to have older people and higher education levels compared to their counterparts. Most of the population lives in rural areas, which capture poor/remote areas. One substantial difference is the travel distance to existing hospitals in the nearest municipality since they have no hospital in their regions. Both treatment and control areas had a travel distance of more than 125 km to shared-border neighborhood hospitals before the intervention, which decreased over time as hospitals opened in nearby municipalities. But the control group has 50 to 60 km shorter distance both before and after the intervention.

New hospitals provide substantial decreases in travel distance for the treatment group. For example, new hospitals constructed in the nearby town reduce travel distance up to 18 km on average from travel distance mean to existing hospitals before 2008, but mobile hospital construction further reduce travel distance up to 88 km on average. Furthermore, our analysis, later on, shows great variation in travel distances between sub-districts located on main islands and outer islands. There are some areas having closer distances to new hospitals, but there are some areas farther distance new hospitals than existing hospitals.

1.6.2. The impact on medical care utilization

The impact of public hospital existence and travel distance varies between main islands and outer islands because of geographic characteristics different such as reliability of transportation alternatives in those islands. For example, communities who live on main islands could either use ground transportation or water transportation to a hospital in nearby municipalities, but water transportation is the only transportation available for those who live on outer islands.

1.6.2.1.All samples

Figure 5 presents the outpatient at public hospital trend for the treatment and control groups for all samples. Figure 1.5 suggests the treatment group has bounced trends before the intervention period, but the treatment group has substantially higher outpatient use at public hospitals after the intervention period. Although mobile hospitals were constructed at the end of the year 2008, the treatment group shows two years' lag before increased outpatient care in the year 2011. In the next section we are able to show smoother outpatient trends when we separate between main islands and outer islands. It indicates different medical care utilization between communities living on main islands versus outer islands.

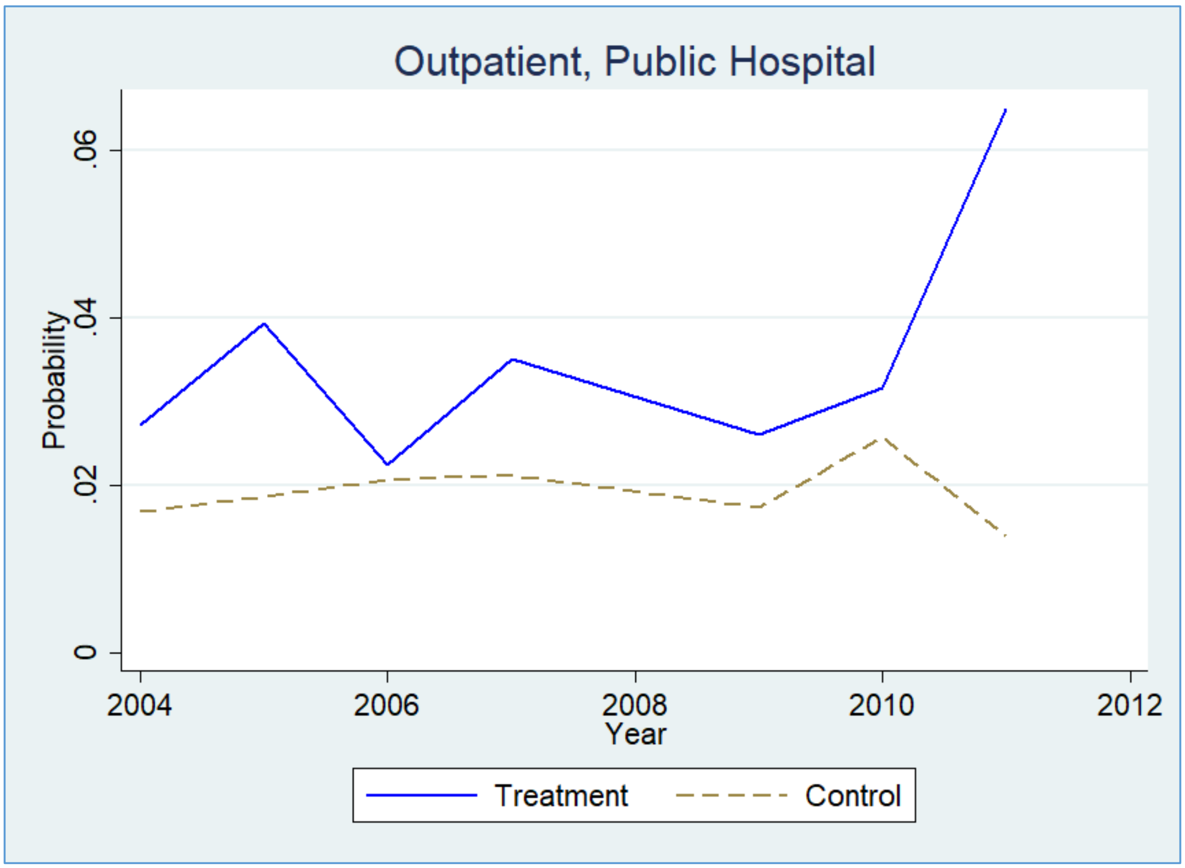


Figure 1.5. Outpatient in Public Hospital

Figure 1.6 provides the inpatient in public hospital trend for the treatment and control groups for all samples. I excluded Malinau municipality from our primary analysis for inpatient care because of unusual patterns over time. Excluding Malinau municipality decreases 3 percent of all inpatient samples. Figure B.1 shows that the Malinau district trends up and down. Figure 1.6 suggests the treatment group has a similar inpatient trend as the control group before the intervention period, but then the treatment group has higher inpatient care use at the public hospital after the intervention period.

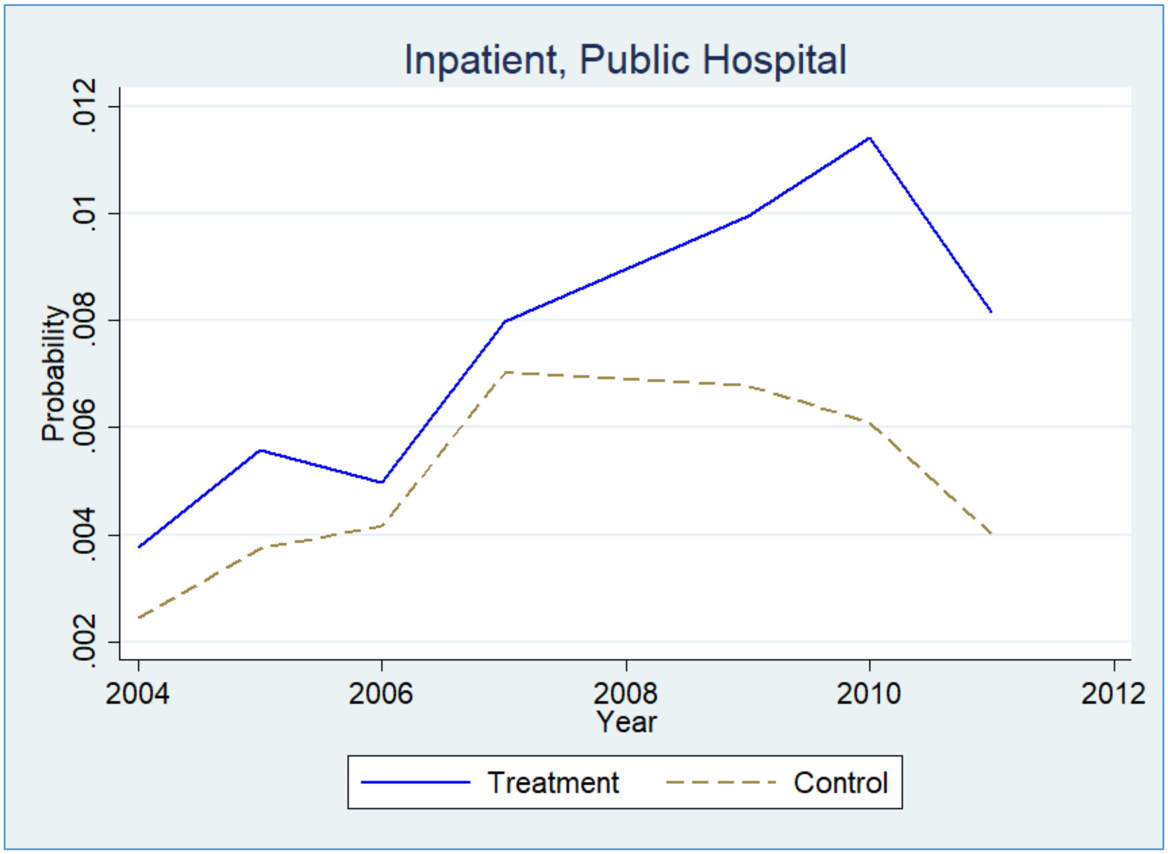


Figure 1.6. Inpatient in Public Hospital

Table 1.2 provides DID and matching-DID probability estimations in outpatient and inpatient at the public hospital for population interest. Column (1) contains the DID approach, and column (2) provides the matching-DID approach for outpatient at government hospitals, similarly applied for inpatient at government hospitals in columns (3) and (4). I imputed a propensity score from the matching process and treated it as a probability weight in the matching-DID computations in columns (2) and (4). Treatment is an indicator of whether an individual lived in a municipality in which a mobile hospital was built in 2008. The dependent variable is an indicator of whether a person experienced outpatient (inpatient) care at a public hospital in the last 30 days (12 months). While inpatient includes all individuals in the community, outpatient only covers individuals who experienced any morbidity symptoms. I included municipality fixed effects and region year fixed effects and clustered the standard error by household level to capture unobserved differences between families.

Table 1.2. The Impact on Medical Care Utilization at Public Hospital (2008)

VARIABLES	Outpatient		Inpatient	
	Public Hospital		Public Hospital	
	DID	Matching DID	DID	Matching DID
	(1)	(2)	(3)	(4)
Treatment*Post	0.0168***	0.0119***	0.0019**	0.0015
	(0.0043)	(0.0046)	(0.0009)	(0.0010)
Travel distance to an existing	0.0015	-0.0021	-0.0009**	-0.0010**
hospital (100 Km)	(0.0016)	(0.0019)	(0.0003)	(0.0004)
Observations	74,401	73,435	303,291	299,193
R-squared	0.0189	0.0242	0.0050	0.0057
Individual and HH Controls*	YES	YES	YES	YES
Sub-District Controls**	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES
Propensity Score***		YES		YES

* Gender, marital status, education, HH Size, and rural
** # beds of existing hospitals, type of existing hospital
*** Imputed propensity scores from matching process

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The matching-DID model shows smaller magnitudes for both outpatient and inpatient medical care although they are not much different. This magnitude difference may be due to the wide variability distribution of travel distances in outer islands compared to main islands. While people who live on main islands travel 150 km to existing hospitals in the nearby municipality on average, people who live on outer islands travel 180 km on average. A matching approach gives a higher weight to the control group, who has similar travel distances as people in the treatment group. It suggests that the matching-DID approach addresses the potential bias in the DID approach that confounds hospital availability and medical care utilization. I address this problem in the next section by showing the smaller difference in magnitudes when I separate main islands from outer islands.

Both models suggest an individual who lives in the treatment municipality is more likely to have both outpatient and inpatient medical care at a public hospital after the intervention period. In particular, a city in which a mobile hospital was opened in the areas is more likely to have public-hospital outpatient services increase more than 1.2 percentage points, corresponding to more than a 40 percent increase from the pre-intervention period outpatient average. Similar for inpatient, municipalities in which mobile hospitals were opened in the areas are more likely to have public-hospital inpatient care increase by 0.2 percentage points, corresponding to a 33 percent increase from the pre-intervention period inpatient average. It supports the notion that primary health facilities are essential factors contributing to access to health care. Harsh topography and lack of transportation hamper individual access to appropriate medical care, and even an existence of limited healthcare facilities may improve their health care access.

The model suggests travel distance to the nearest hospital in a neighboring municipality more likely affects medical care utilization, primarily for inpatient medical services. 100 Km increase travel distance more likely decreases inpatient medical care by 0.1 percentage points. The result indicates people who required intensive medical care utilization through hospitalization more likely have an adverse impact on the farther distance to the nearest hospital. It is very intuitive because people who experience severe health risks less likely to travel farther to obtain medical care.

1.6.2.2.Main islands and outer islands

To further investigate heterogeneity between Indonesian regions, I estimate the impact on main islands, and small outer islands. I define small outer islands as any island which is located outside the five main islands. The main islands and outer islands have different geographic characteristics. For example, municipalities which are located in the outer islands are more likely surrounded by sea that makes them more isolated from other areas, and their island location may result in wide variability in travel distances. It makes them less accessible to existing hospitals in the nearby municipalities because people have to use either ferry, boat, or airplane to reach nearby cities. Also, it is harder for residents on different islands within the same municipalities to reach new hospitals located on another island.

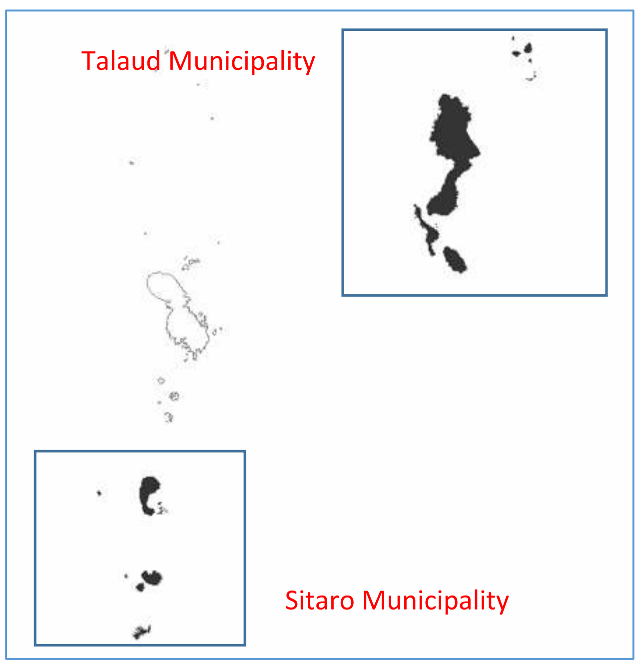


Figure 1.7.Talaud and Sitaro Islands

Figure 1.7 shows Talaud and Sitaro Islands, two sample municipalities which have a mobile hospital. Although there is a mobile hospital on one island, people who live on another island may not be able to go to an island where a mobile hospital is located since the sea isolates them. Therefore, we expect only the fraction of people who live on the same island as a mobile hospital may benefit from newly-constructed health facilities. On one hand, more isolated areas may represent higher marginal utilities of medical care, thus greater impact. On the other hand, separated islands within municipalities would lower access to constructed mobile hospitals, thus lowering treatment effects. Therefore, the net effect depends on whether infrastructure effects outweigh utilities of medical care, or vice versa.

Figures 1.8 and 1.9 provide public-hospital inpatient and outpatient trends for individuals who live in the municipalities located on the main islands of Indonesia, respectively. The main islands include Sumatera, Java, Kalimantan, Sulawesi, and Papua. Table C.1 and C.2 present similar public hospital trends for inpatient and outpatient medical care utilization for outer islands. Outer islands include Nusa Tenggara, Halmahera, Talaud, Sitaro (Siau Tagulandang Biaro), Maluku, and Morotai.

Figure 1.8 suggests the treatment and control groups have similar public-hospital inpatient trends before the intervention period, primarily in 2006 and 2007. Their trends started to diverge in 2009 where mobile hospitals were constructed. The treatment group has higher public-hospital inpatient medical care rates over time after the intervention period. Table C.1 provides similar inpatient medical care information as in Figure 1.8, but for the outer islands. Similarly, table C.1 suggests that both the treatment and control groups have similar trends before the intervention period, but the treatment group are more often likely inpatients at public hospitals after the intervention period, although the trend is not as pronounced as with the main islands. Both treatment and control groups depict a substantial reduction in inpatient care at public hospitals in 2011.

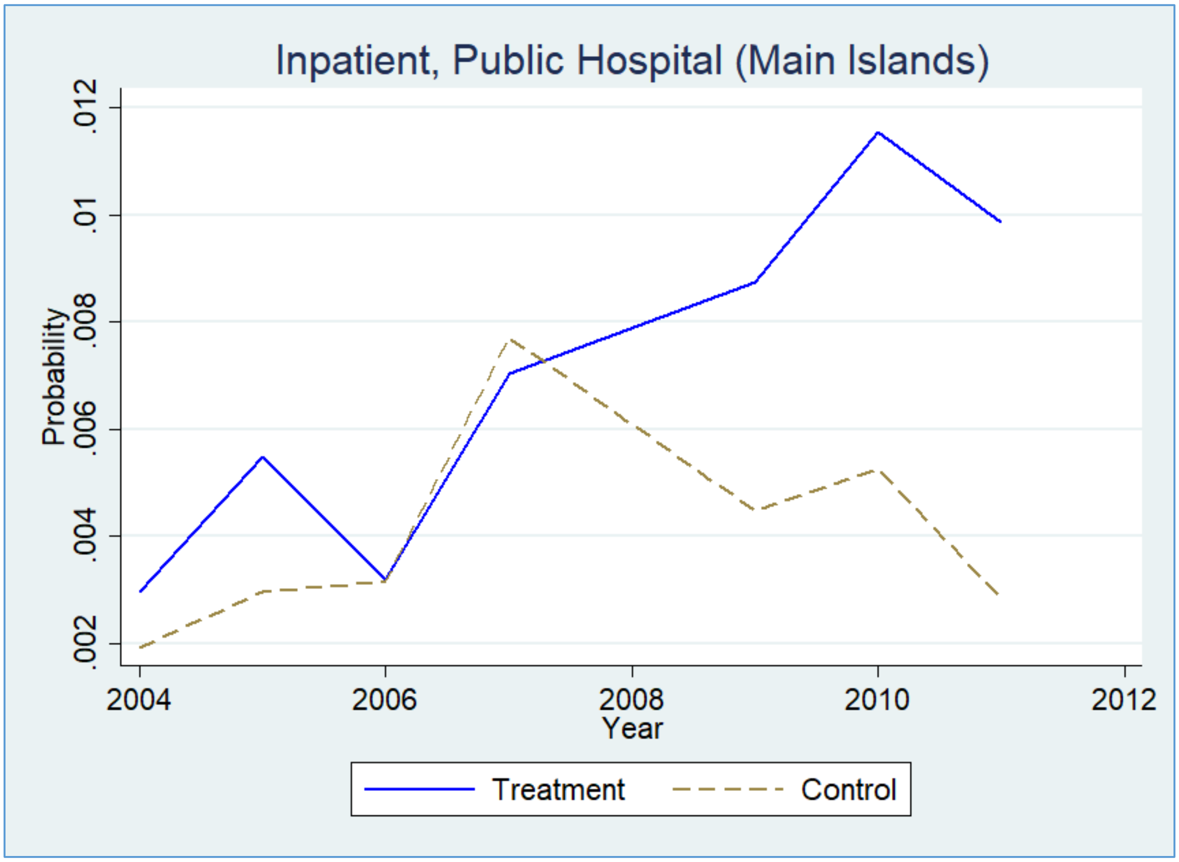


Figure 1.8. Inpatient in Public Hospital: Main Islands

Figure 1.9 suggests similar trends for public-hospital outpatient care utilization on the main islands. Initially, the treatment and control groups have similar patterns before the intervention period, primarily year 2006 and 2007. In particular, the lines cross each other; the treatment group has higher inpatient rates in 2004 and 2005 but then lower in 2006 and 2007. For both groups, three percent of people on average seek public-hospital outpatient care before the intervention period, evidence that harsh topography hampers community access to appropriate medical care. While there is no substantial difference in outpatient rates for the control group after the intervention period, the treatment group has a considerable increase in public-hospital outpatient rates after the intervention period. Table C.2 provides public-hospital outpatient information for the outer islands. The figure suggests no substantial difference after the intervention. Therefore, all figures indicate a consistent increase in the inpatient and outpatient trends over time for the main islands' treatment group but a slight increase for outer islands.

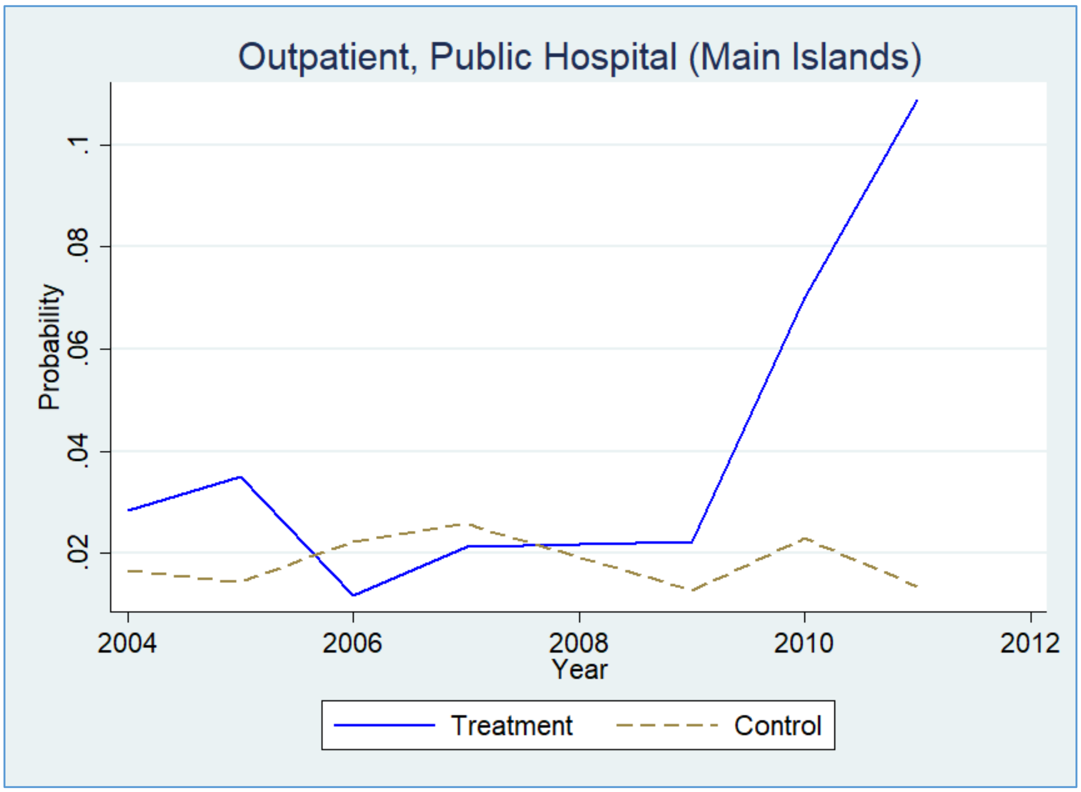


Figure 1.9. Outpatient in Public Hospital: Main Islands

Table 1.3 provides DID and matching-DID estimations for the main islands and outer islands of Indonesia. Panel A is the DID approach, and Panel B is the matching-DID approach. Column (1) is an outpatient estimator for municipalities located on the main islands, column (2) is the analogous estimator for those found on outer islands, column (3) is the inpatient estimator for those discovered in main islands, and column (4) shows the estimator for inpatient in public hospitals on outer islands. All columns use similar specifications as Table 1.2, and Panel B shows matching-DID with imputed propensity scores for weighting. Main islands include Sumatera, Kalimantan, and Papua. Outer islands include Nusa Tenggara, Halmahera, Talaud, Sitaro (Siau Tagulandang Biaro), Maluku, and Morotai.

Table 1.3. The Impact on Utilization at Public Hospital: Main Island, and Outer Island

VARIABLES	Outpatient, Public Hospital		Inpatient, Public Hospital	
	Main Islands	Outer Islands	Main Islands	Outer Islands
	(1)	(2)	(3)	(4)
Panel A (DID)				
Treatment*Post	0.0490***	-0.0016	0.0051***	0.0006
	(0.0078)	(0.0051)	(0.0014)	(0.0011)
Travel distance to an existing	0.0041**	-0.0036	-0.0006	-0.0014**
hospital (100 Km)	(0.0019)	(0.0026)	(0.0004)	(0.0006)
Observations	30,018	44,383	121,486	181,805
R-squared	0.0263	0.0210	0.0045	0.0057
Pre-Intervention Mean	0.021	0.037	0.005	0.006
% Change	186%	-4%	100%	21%
Panel B (Matching DID)* **				
Treatment*Post	0.0359***	-0.0019	0.0051***	0.0002
	(0.0078)	(0.0059)	(0.0015)	(0.0014)
Travel distance to an existing	0.0003	-0.0042	-0.0011**	-0.0009
hospital (100 Km)	(0.0025)	(0.0028)	(0.0005)	(0.0007)
Observations	29,334	44,101	118,422	180,771
R-squared	0.0281	0.0272	0.0046	0.0066
Pre-Intervention Mean	0.021	0.037	0.005	0.006
% Change	170%	-5%	100%	3%
Individual and HH Controls*	YES	YES	YES	YES
Sub-district Controls**	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES

* Gender, marital status, education, HH Size, and rural
** # beds of existing hospitals, type of existing hospital
*** Imputed propensity scores from matching process
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The models suggest the impact of public hospital existence on medical care utilization was driven by a municipality located on the main islands. For outpatient, while there was a slight smaller magnitude for matching-DID, both models suggest substantial increases in public-hospital outpatient care on main islands. Public hospital existence on the main islands more likely increases outpatient rates in public hospitals more than 170 percent from the pre-intervention period. However, I find no evidence of such an increase for municipalities located on outer islands. A substantial outpatient increase on the main islands supports the notion that there are higher marginal utilities of having medical care utilization for communities with fewer health care facilities.

For inpatient, the DID and matching-DID methods have similar magnitude. In particular, mobile hospital availability on the main islands of Indonesia is more likely to increase inpatient medical care at public hospitals by 0.5 percentage points, corresponding to a 100 percent increase from the pre-intervention period inpatient average. I do not find evidence of this for outer regions. It seems counter-intuitive; we expect more isolated areas would have higher marginal utilities of having medical care utilization. However, separated small islands within a municipality may be the reason for this. A mobile hospital is located in one of the various small islands within each district. Less infrastructure, especially roads and less reliable transportation would hamper individuals' hospital visits. For instance, ferry transportation may only run once or twice a week, or private boat only once or twice a day, for people who live on different islands that have no ground transportation, so sick people cannot reach the hospital. It suggests that either more similar hospitals on each different island but within the same cities, or infrastructure to connect those separated islands, is critical for those communities.

Therefore, our findings support the notion that primary health facilities are critical in underdeveloped municipalities. Also, the results suggest that transportation and infrastructures are essential to improving access to health care facilities, in addition to the existence of healthcare facilities.

1.6.2.3.Robustness checks

In this section, I employ some robustness checks and sensitivity analyses to test the primary results. Table D.1-D.4 provide robustness tests for mobile hospital availability estimations with specification variations of equation (1). I use five specifications for primary outcomes both for the DID approach and matching-DID approach. Column (1) is a simple DID. Column (2) includes individual and household controls. Column (3) includes sub-district controls, column (4) includes municipality and year fixed effects, and column (5) is our baseline regression. Table D.5-D.8 reflect a similar robustness test when I include 2012-2014. I removed travel distance because, since 2012, *SUSENAS* has not provided sub-district identifier information. In general, our results are robust to those specifications. Estimation magnitudes slightly decrease when I include travel distance, suggesting the importance of controlling travel distance to hospitals in nearby municipalities.

Table D.9-D.12 provide similar regression information as Table D.1-D.4 for main islands and Table D.13-D.16 for outer islands. Our results are robust to those specifications, and the differences between the DID and matching-DID methods are smaller. I find only one weakly significant (10 percent significant level) value from 20 regressions for outer islands. That estimate was eliminated by either including travel distance to nearby existing hospitals or region-year fixed effects.

To test our estimates' sensitivity from our choices of treatment and control groups, I either exclude municipalities in which mobile hospitals were constructed in 2012 as a control group, or I include those towns as a treatment group. Table D.17 presents DID estimates when I exclude cities in which 2012 mobile hospital construction took place in the control group and expand observations by including the year 2012-2014 for all samples and main islands. Column (1) is outpatient in public hospitals for all samples; Column (2) is outpatient in government hospitals for main islands; Column (3) and (4) have similar specifications as in columns (1) and (2) for inpatient rates. As discussed above, the Indonesian government introduced the second wave of mobile hospital construction in 2012. If our results are sensitive to sample choices, then I may see substantial differences when I exclude those 2012 municipalities. I implement the base specification on equation (3) but without travel distances, since *SUSENAS* does not provide sub-district identifiers for years 2012-2014. In general, the model suggests the estimator slightly increases when I exclude those municipalities and years 2012-2014. These results make sense since more information about new hospitals and their services spreads over time, thus more people visit new hospitals.

Table D.18 presents DID estimates when I include municipalities in which 2012 mobile hospitals were opened as a treatment group. I define 2009-2014 as the post period for mobile hospitals opened in 2008 and 2012-2014 for mobile hospitals constructed in 2012. Table D.18 has similar specifications as in table D.17. The model suggests similar magnitudes as the previous table. It supports the notion that our findings are not sensitive to treatment and control groups' choices.

Table D.19-D.26 provide estimates when I include a morbidity symptom to test sensitivity of our estimates from omitted variables. Health condition is an important factor affecting medical care utilization. Severe health condition lead more medical treatment in hospitals. In general, our preliminary estimates show slight increase when we include health condition. But, it also shows that our findings are not sensitive to omitted variable biases.

1.6.2.4.Falsification tests

The identifying assumption for the DID approach is common parallel trends between treatment and control groups without any intervention. It implies that, without any intervention, both treatment and control groups would have parallel trends over time before the treatment period. I estimate various specification tests for artificial effects during pre-treatment years using the DID and Matching DID approaches. Table E.1-E.4 provide falsification tests for our primary outcomes for all samples and municipalities within the main islands with total 24 regressions.

I use the years 2005, 2006 and 2007 as our artificial effect. Columns (1)-(3) are falsification tests for outpatient and columns (4)-(6) are the same tests for inpatient using the base specification on equation (3). Column (1) and (4) are using 2005 as artificial year, column (2) and (5) are using 2006 and, column (3) and (6) are using 2007. If the intervention drove our results instead of inherent differences between the treatment and control groups, then I would see no impact on the pre-treatment period. In general, the model suggests all but two estimators are not significant and reduce the estimation magnitude substantially. Those two significant estimates were eliminated when I separate between main islands and outer islands. These results support the notion that the actual interventions likely drive the difference in outcomes and importance of separating main islands and outer islands.

1.6.3. Travel distance and transportation infrastructures matter

In this section we explore travel distance and infrastructures heterogeneity to understand the importance of travel distance and transportation infrastructures.

1.6.3.1. Closer distance or farther distance

The wide coverage area of a newly-built hospital within a municipality results in the newly-built hospitals being closer than the existing hospital for some areas, but farther for others. Figure 1.10 provides travel distance comparison between new-construction hospitals and existing hospitals per treated sub-district for people who are living on main islands. The X-axis is travel distance to existing hospitals, and the Y-axis is travel distance to newly-constructed hospitals. Therefore, people who are living in areas that are closer to new hospitals are below the 45-degree line. The figure shows that regions within 200 km of existing hospitals are more likely farther from new hospitals. In contrast, areas located over 200 km from existing hospitals are closer to new hospitals. Figure F.1 shows a similar graph for outer islands, but more areas are now closer to newly-constructed hospitals. We expect only people who are living closer to the new hospitals to benefit from the intervention.

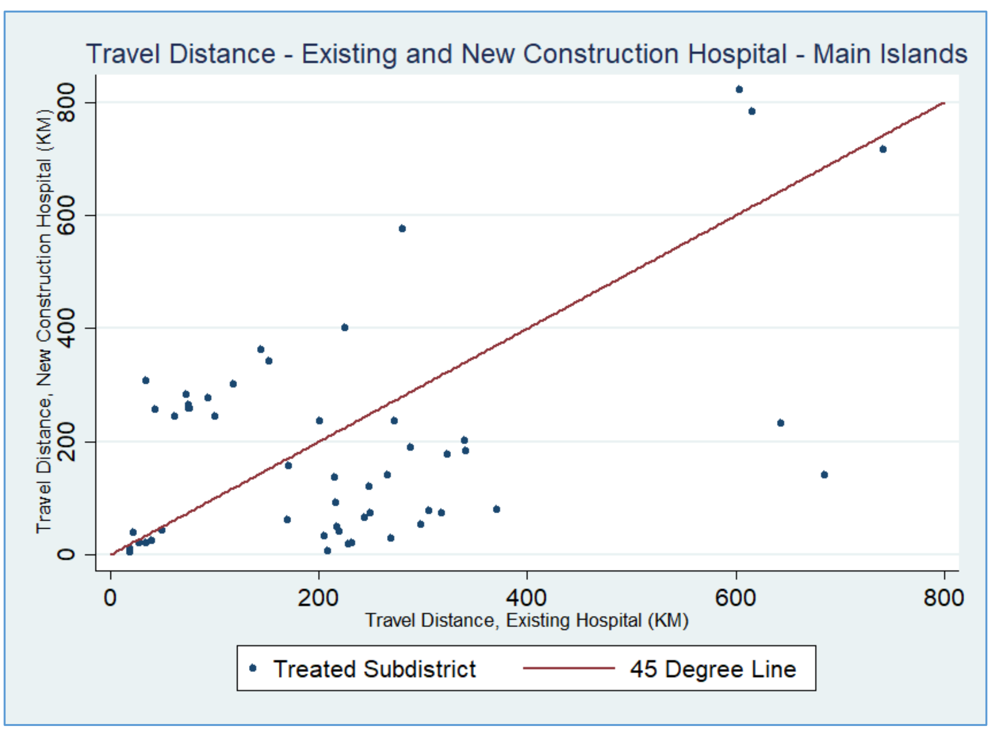


Figure 1.10. Travel Distance Between New and Existing Hospitals – Main Islands

Table 1.4 provides DID and matching-DID estimation for areas that are closer to newly hospitals. It is analogous to the specifications in Table 1.3. As expected, the models suggest more considerable impact for both outpatient and inpatient at public hospitals on main islands when I exclude people who are living farther from new hospitals than existing hospitals. I find no evidence of improvement of access to medical care utilization for people who are living in outer islands.

Table 1.4. The Impact on Utilization at Public Hospital: Closer Distance

	Outpatient, Public Hospital		Inpatient, Public Hospital	
VARIABLES	Main Islands	Outer Islands	Main Islands	Outer Islands
	(1)	(2)	(3)	(4)
Panel A (DID)				
Treatment*Post	0.0720***	-0.0030	0.0078***	0.0005
	(0.0099)	(0.0055)	(0.0017)	(0.0012)
Travel distance to an existing	0.0034	-0.0047*	-0.0004	-0.0019***
hospital (100 Km)	(0.0022)	(0.0027)	(0.0004)	(0.0007)
Observations	27,741	42,728	112,030	174,926
R-squared	0.0300	0.0214	0.0046	0.0057
Panel B (Matching DID)* **				
Treatment*Post	0.0553***	-0.0034	0.0067***	0.0001
	(0.0098)	(0.0062)	(0.0018)	(0.0015)
Travel distance to an existing	-0.0010	-0.0063**	-0.0009*	-0.0018**
hospital (100 Km)	(0.0030)	(0.0029)	(0.0004)	(0.0008)
Observations	27,057	42,446	108,966	173,892
R-squared	0.0316	0.0271	0.0046	0.0067
Individual and HH Controls*	YES	YES	YES	YES
Sub-district Controls**	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES

* Gender, marital status, education, household size, and rural
** # beds of existing hospitals, type of existing hospital
*** Imputed propensity scores from matching process

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.5 provides similar estimators for areas that are farther from new hospitals. Mobile hospitals are limited resource hospitals compared with existing hospitals in nearby municipalities.

People may still visit a new-constructed hospital since it is located in their administrative areas if they have more benefits from local administrative government such as local government subsidy for hospital fees. Otherwise, people tend to visit existing hospitals because those hospitals are not only closer but also better perceived quality.

Table 1.5. The Impact on Utilization in Public Hospital: Farther Distance

VARIABLES	Outpatient, Public Hospital		Inpatient, Public Hospital	
	Main Islands	Outer Islands	Main Islands	Outer Islands
	(1)	(3)	(4)	(6)
Panel A (DID)				
Treatment*Post	0.0014	0.0054	0.0012	-0.0004
	(0.0087)	(0.0086)	(0.0023)	(0.0015)
Travel distance to an existing	0.0055**	-0.0034	-0.0007	-0.0015**
hospital (100 Km)	(0.0022)	(0.0033)	(0.0005)	(0.0007)
Observations	24,362	34,077	108,511	137,127
R-squared	0.0207	0.0172	0.0044	0.0053
Panel B (Matching DID)* **				
Treatment*Post	-0.0004	0.0167	0.0030	-0.0001
	(0.0087)	(0.0115)	(0.0026)	(0.0021)
Travel distance to an existing	0.0049**	0.0025	-0.0014**	0.0001
hospital (100 Km)	(0.0024)	(0.0042)	(0.0006)	(0.0009)
Observations	23,678	33,795	105,447	136,093
R-squared	0.0251	0.0205	0.0043	0.0055
Individual and HH Controls*	YES	YES	YES	YES
Sub-district Controls**	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES

* Gender, Marital Status, Education, HH Size, and Rural
** Travel distance to existing hospital, # beds of existing hospitals, whether public or private hospital
*** Imputed propensity scores from matching process

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If travel distance drives the impact of new hospital construction, we expect either smaller or no impact for people who are farther from new hospitals. In general, the models suggest that no estimators are significant and estimation magnitude is substantially reduced. Inpatient in public hospital estimates reduce more than by 55 percent from areas which closer to newly constructed hospitals and outpatient in public estimates reduce more than 97 percent. These results support the notion that travel distance to newly hospitals likely drives the difference in outcomes.

1.6.3.2.How far people are from newly-built hospitals

A community who lives closer to new hospitals within a municipality may have better access to medical care utilization. I estimate the relationship between travel distance and medical care utilization for the community in the treatment areas. Figure 1.11 provides a relationship between travel distance and outpatient care in public hospitals for treated areas after the intervention period (2009-2011). The X-axis is travel distance to the mobile hospital from a sub-district and Y-axis is the percentage of the population in a sub-district who had outpatient care in the last 30 days. The red line is a local polynomial fitted line to show the relationship between travel distance and outpatient care at the public hospital.

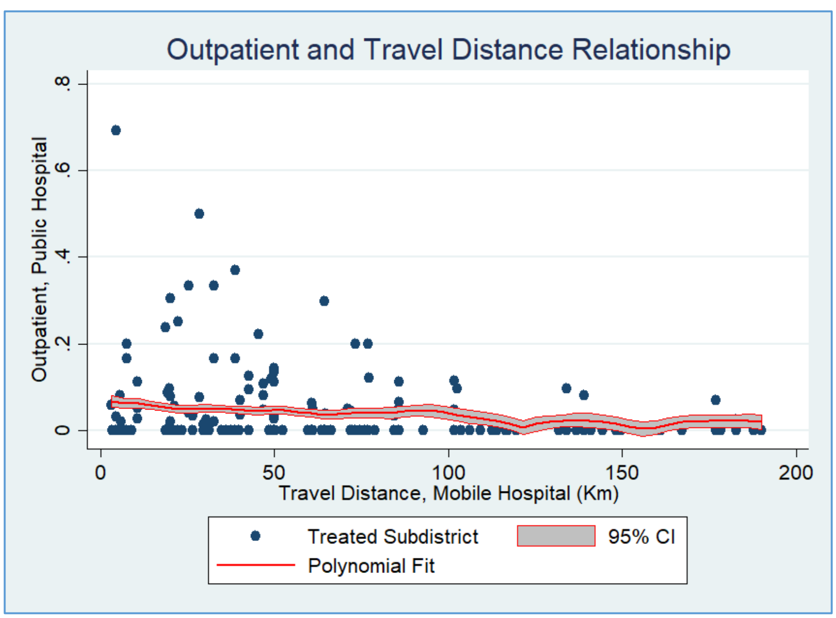


Figure 1.11. Travel Distance and Outpatient, Treated Sub-District

The picture suggests a negative relationship between travel distance and outpatient care; farther areas would have less outpatient access at public hospitals. Furthermore, most people in a community cannot reach new hospitals when they live more than 100 km from new hospitals. Figure G.1 shows a similar trend for the relationship between travel distance and inpatient access at public hospitals.

Transportation alternative is another essential factor affecting medical care besides travel distance. Similar travel distance could end with longer travel time with water transportation compare to ground transportation. An individual has to wait for either a ferry or a boat schedule which often longer waiting time between two available schedules than a bus schedule. Also, a ship runs slower than if a person uses a bus with similar distance. It suggests small increase travel distance to new-constructed hospitals could decrease higher possibility an individual to visit that hospital if people have better transportation alternative to existing hospitals. In another side, small increase travel distance to new-constructed hospitals could only reduce smaller possibility an individual to visit new hospitals if he has worse transportation alternative to existing hospitals.

Table 1.6 provides DID estimates between travel distance to mobile hospitals and medical care utilization by geographic condition both existing hospitals as well as new-constructed hospitals. Panel A is regression estimates for public-hospital outpatient care and Panel B is similar estimates for public-hospital inpatient services. Column (1) is estimators for people who can use a ground transportation both to new hospitals and existing hospitals; column (2) is the analogous estimators for those who can use ground transportation to new hospitals, but they requires water transportation to existing hospitals; column (3) is estimators for those required water transportation to reach new hospitals, but they have a ground transportation access to existing hospitals; column (4) is similar estimators for those need water transportation to new hospitals as well as existing hospitals. I define ground transportation if an individual uses ground transportation more than 50% of their travel distance to a particular hospital. Similarly, water transportation was defined if an individual uses water transportation more than 50% of their travel distance to a hospital.

Table 1.6. Travel Distance and Medical Care Utilization Relationship

VARIABLES	New Hospital: Ground Transportation		New Hospital: Water Transportation	
	Existing: Ground	Existing: Water	Existing: Ground	Existing: Water
Difference-in-differences (DID)	(1)	(2)	(3)	(4)
A. Outpatient in Public Hospital				
Ln(Travel Distance (100 km))	-0.0155***	-0.0051**	-0.0106***	-0.0039
	(0.0028)	(0.0024)	(0.0030)	(0.0028)
Observations	62,570	62,194	56,562	56,596
R-squared	0.0174	0.0198	0.0160	0.0161
B. Inpatient in Public Hospital				
Ln(Travel Distance (100 km))	-0.0013**	-0.0008*	-0.0018***	-0.0015***
	(0.0006)	(0.0004)	(0.0006)	(0.0005)
Observations	252,985	259,059	239,656	239,500
R-squared	0.0046	0.0053	0.0046	0.0044
Individual and HH Controls*	YES	YES	YES	YES
Sub-district Controls**	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES

* Gender, marital status, education, household size, and rural
** Travel distance to existing hospital, # beds of existing hospitals, type of existing hospital

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The model suggests increased travel distance likely reduces medical care utilization and estimates lower for those who have worse transportation alternative to existing hospitals. In particular, increase 1% travel distance more likely decreases outpatient in public hospitals by 0.016 percentage points and decreases inpatient in public hospitals by 0.001 percentage points for those who have access to ground transportation for both new and existing hospitals. However, a similar increase in travel distance only reduces smaller magnitudes for those have just water transportation (worse transportation) to existing hospitals. In contrast, increase 1% travel distance more likely decreases outpatient in public hospitals by 0.004 percentage points and decreases inpatient in public hospitals by 0.002 percentage points for those who have access to water transportation for both new and existing hospitals. A similar increase in travel distance reduces higher magnitudes for those have access to ground transportation (better transportation) to existing hospitals. The model also suggests higher reduction for outpatient in public hospitals when an individual has less transportation mode. Our results support the notion that travel distance would have a more considerable impact if people have better transportation alternative to existing hospitals. Also, our results suggest less severe health condition that requires medical care would have higher reduction if people have choices for transportation alternative. It is intuitive because people with less critical health condition could choose to stay at home instead of going to a hospital as it farther from their house. But people with critical health condition fewer choices because they require urgent medical care.

1.6.4. Substitution between public and private hospital

When mobile hospitals open closer to public hospitals, does this lead to a substitution effect between hospital providers? This occurs primarily in main-island municipalities since they have a substantial increase in public-hospital outpatient and inpatient care. Private hospital openings along shared municipality borders may also lead to substitution between private and public health facilities. If there is substitution between health centers, then the net impact of health facility construction depends on the two magnitudes since they provide similar services.

Table 1.7. The Impact on Medical Care Utilization at Private Hospital, Main Islands

VARIABLES	Outpatient		Inpatient	
	Private Hospital	Private Hospital	Private Hospital	Private Hospital
	DID	Matching DID	DID	Matching DID
	(1)	(2)	(3)	(4)
Treatment*Post	0.0000	0.0010	0.0002	0.0007
	(0.0024)	(0.0024)	(0.0008)	(0.0009)
Observations	29,370	28,695	121,097	118,035
R-squared	0.0104	0.0096	0.0025	0.0034
Individual and HH Controls*	YES	YES	YES	YES
Municipality Controls**	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES
Propensity Score***		YES		YES

* Gender, Marital Status, Education, HH Size, and Rural
** Travel distance to existing hospital, # beds of existing hospitals, type of existing hospital
*** Imputed propensity scores from matching process

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.8 provides DID and matching-DID estimates for private-hospital outpatient and inpatient care for municipalities which are located on main islands. Columns (1) and (3) show DID approaches for outpatient in private hospitals and columns (2) and (4) matching-DID approaches for inpatient in private hospitals. The models suggest no evidence of substitution effect between private and public hospitals because of mobile hospital opening. Incorporated weights do not change the conclusion. Our conclusion does not change with many specifications, as shown in table H.1 to table H.4. These results suggest tough topography and lack of transportation hamper individual access to appropriate outpatient and inpatient medical care, even though many private health facilities are opening along shared municipality borders. Rough ground transportation, limited and expensive sea, river, and air transportation, may obstruct community hospital access in neighboring cities.

1.6.5. The impact on household expenditures

An important feature of the mobile hospital is fulfilling medical care needs in harsh topography and isolated areas. Improving access to health care facilities can enhance medical care utilization, thus increasing household health expenditures. On the other hand, closer health facilities may reduce transportation costs, thus decreasing family health expenses. Substitution or complement effect between health centers may also either increase or decrease household health expenditures. Therefore, the impact depends on whether the reduction in transportation costs outweighs the increase in medical care cost due to higher medical care utilization and also cost differential between health facility. I estimate the impact of mobile hospital availability on yearly household health expenditures per capita. Nominal household health expenditures include preventive cost, curative cost, medicine, and medical devices bought at any medical facility. Figure 1.12 shows trends in household medical expenditures per capita before and after the intervention period for a municipality located on the main islands. The treatment group has slightly higher household health expenditures than the control group in 2004 and 2007, but a similar trend in 2005 and 2006. Although I find almost similar pattern before the intervention period, the treatment group continuously increases in medical spending after the intervention period.

I estimate the impact of mobile hospital availability on household health expenditures. Table 1.9 provides DID and matching-DID results for household health expenditures for municipalities located on the main islands. The dependent variable is yearly household health expenditures per capita. Table 1.9 has similar specifications as Table 1.2. I am using household-level data since household health expenditures are on the household level. I aggregate individual characteristics into the household level to obtain household-level demographics.

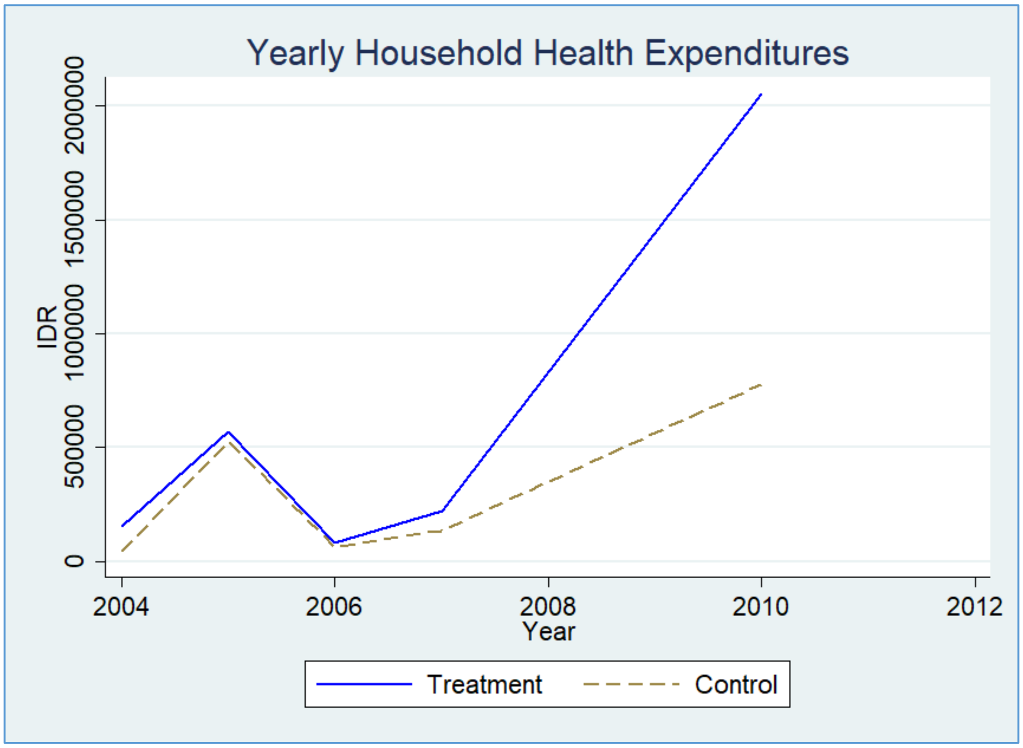


Figure 1.12. Household Health Expenditures, Main Islands

Despite a small different in magnitude estimates between the two approaches, they offer the same general conclusion: that people living in treatment areas are more likely to increase household health expenditures per capita by IDR 2 million (US $153), assumes USD 1 equal to IDR 13,000. Household yearly income (household head and spouse income) in the treatment areas from 2004 to 2011 are around IDR 9.5 million (US $730), thus corresponding to 20 percent of household income. Large increase in household health expenditures per capita may due to high differential out of pocket cost between outpatient and inpatient medical care services. Inpatient medical care services could cost much larger than outpatient medical care services because it includes room fees, and it may include intensive treatment fees. Our finding supports the notion that people in the community would spend more on medical care utilization when they have a hospital in their neighborhood.

Table 1.8. The Impact on Household Health Expenditures

VARIABLES	DID Household Health Expenditures/Capita (IDR)	Matching DID Household Health Expenditures/Capita (IDR)
	(1)	(2)
Treatment*Post	1,957,518.680***	2,027,835.166**
	(735,385.273)	(844,003.322)
Observations	17,485	16,976
R-squared	0.029	0.049
Individual and HH Controls*	YES	YES
Sub-District Controls**	YES	YES
Municipality FE	YES	YES
Region*Year FE	YES	YES
Propensity Score***		YES

* Gender, Marital Status, Education, HH Size, and Rural
** Travel distance to existing hospital, # beds of existing hospitals, whether public or private hospital
*** Imputed propensity scores from matching process

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.1 provides falsification tests for household health expenditures per capita. Table I.1 shows DID and matching-DID approach when we use three artificial years: 2005, 2006, and 2007. If our results were driven by differences in pre-treatment trends, then we might see a significant impact before the intervention period. In general, the models suggest no estimators are significant and estimation magnitude is substantially reduced. It implies that the actual intervention, instead of spurious regressions, likely drive the difference in outcomes.

1.7. Discussion and conclusion

The existence of facility health centers in underdeveloped and remote areas in developing countries is a major factor in improving access to medical care utilization. However, difficult topography also creates a burden on those attempting to visit newly-built hospitals. I examined the impact of mobile hospital availability in underdeveloped and remote regions on medical care utilization using difference-in-differences and matching difference-in-differences approaches.

I found evidence that mobile hospital existence likely increases inpatient and outpatient utilization at public hospitals for municipalities which are located on main islands without any substitution effect for medical care utilization in private hospitals. I did not find evidence of increased public-hospital utilization for municipalities located on outer islands when a mobile hospital is located in one of the various small islands within districts. It suggests either the building of similar hospitals on each different island within the same cities or creating infrastructure to connect those separated islands. I have suggested that travel distance matters. I found that only areas in which new hospitals are closer than existing hospitals benefit from the intervention. Also, locations farther from newly-built hospitals are less likely to have inpatient and outpatient at public hospitals. Larger reduction for those who have better transportation mode to an alternative hospital. Households spend more on health when new hospitals appear. It suggests a family would spend more money and visit hospitals to get access to medical care when there is a hospital available in their neighborhood area.

Our study contributes to facility health center planning in underdeveloped and remote areas in Indonesia and provides information to policymakers in developing countries. Our study suggests not only facility health center existence in remote areas, but also transportation infrastructure, in general, are both critical to improving medical care utilization. Policymakers may even consider growing limited facilities within hospitals because of medical care utilization growth over time.

CHAPTER 2. THE IMPACT OF PUBLIC INSURANCE'S DEPENDENT COVERAGE ON MEDICAL CARE UTILIZATION

2.1. Introduction

Indonesia introduced public insurance for civil servants (*Askes*) in 1968 that covered parents and all of their children. They reformed this insurance scheme by both dropping and adding eligibility for some children within a household during the last three decades. A universal health coverage scheme (*Badan Penyelenggara Jaminan Sosial / BPJS*) started on January 1, 2014, reducing cost sharing and covering three children but not the fourth and afterward children, while the previous insurance plan only covered two children but not the third and afterward children of a civil servant family. This study examines the causal effect of government-provided insurance for children on their medical care utilization by exploiting changes in public insurance coverage for third children in Indonesia.

This government policy creates differential insurance coverage among eligible children and ineligible children within a household. Reduction in cost sharing and access to health insurance for covered children will lower the effective price of medical care utilization in all public health facilities and member private health facilities, and reduce delays in getting medical care that may translate into better health outcomes. Also, better health outcomes could help children to invest in education, and improve their future labor market outcomes.

I use difference-in-differences (DID) and triple different approaches (DDD) with newly eligible children (third child) because of the policy change as a treatment group and both eligible children already in place (first and second children) or ineligible children (fourth and above) within a household as a control group. The change in government policy over the last three decades provides an opportunity to examine the impact of public insurance for children who have gained eligibility. Also, I employ nationally representative survey data of Indonesian families and individuals to discuss the impact of the public insurance program on a variety of outcomes. I find that eligible children are 4 percentage points more likely to have an outpatient care in hospitals, corresponding to a 210 percent increase from the pre-intervention period. There is a more substantial impact when I count both eligibility and co-payment reduction effects. That is, universal health coverage not only adds the third children to the scheme but also includes co-payment reductions from their initial program.

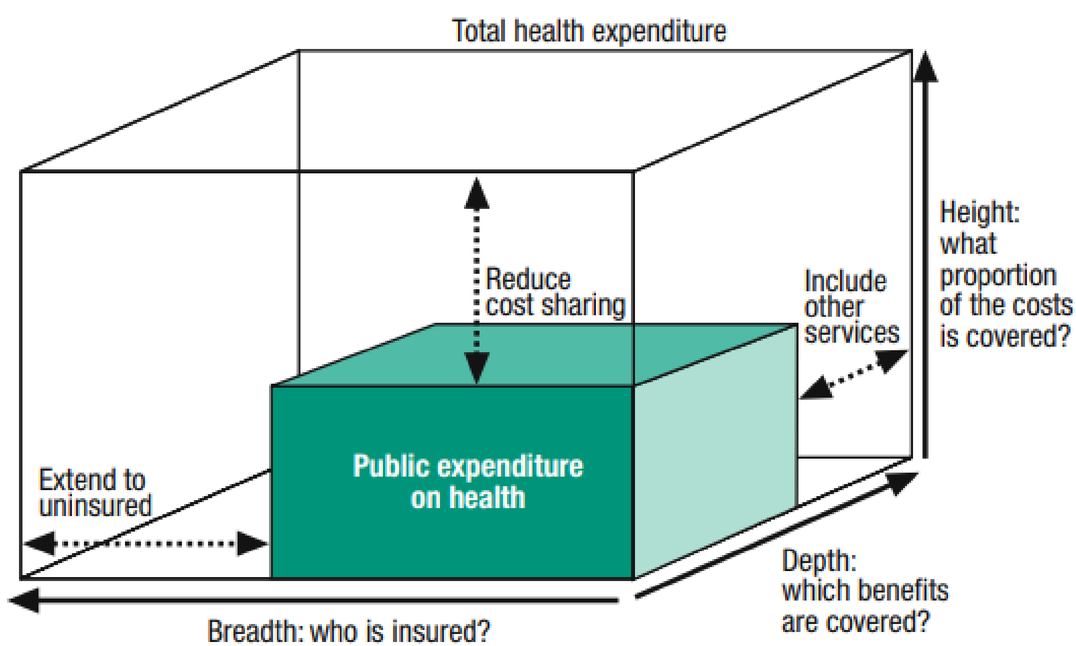
This study contributes a valuable resource for policy-makers in assessing the impact of public insurance for children in developing countries by exploiting quasi-experimental intervention of government intervention in public insurance. The rest of the paper is organized as follows. Section 2 reviews the relevant literature on the impact of insurance. Sections 3 and 4 describe the history of public insurance in Indonesia and data sources. Section 5 discusses the identification strategy. In Section 6, I apply those methods on public insurance. Section 7 employs robustness and placebo tests, and section 8 concludes.

2.2. Review of the relevant previous literature

2.2.1. The universal health insurance program

Many countries had legislation mandating health insurance; 75 out of 192 countries studied had a bill about universal health care (Stuckler, Feigl, Basu, & McKee, 2010). Social health insurance development started when Germany introduced The Sickness Insurance Law in 1883 and The Insurance Consolidation Act in 1911 (Bärnighausen & Sauerborn, 2002; Dawson, 1913). The insurance was compulsory, irrespective of age and no wages limit (Dawson, 1913). In 1953, United States (US) spent 0.4 cents out of each dollar government spending to a social security program that provided 18% of the income of the typical elderly household and continuously increases to 19 cents out of each dollar government spending in 2003. This program is labeled social insurance programs, government interventions to protect against adverse events, including unemployment insurance, disability insurance, workers' compensation, and Medicare (Gruber, 2007).

Universal health insurance definition varies in several ways, including potential recipients, costs sharing, the range of services, and quality of care. World Health Organization (2008) proposes three ways moving towards universal coverage as depicted in figure 2.1: the breadth of coverage, the depth of coverage, and the height of coverage.



Source: World Health Organization (2008)

Figure 2.1. Three Ways of Moving Towards Universal Coverage

The breadth of coverage asks how much population covered by the insurance scheme and whether it covers the poorest and most vulnerable population groups; how profound benefit of essential services covered that are necessary to address people's health; and a system has a greater height when it has higher public spending so that individuals spend lower out-of-pocket costs (Stuckler et al., 2010; World Health Organization, 2008).

There are many reasons for potential government interventions in public insurance programs. A classic rationale for government intervention in the insurance market is the negative externalities imposed on others through underinsurance. Individuals are concerned with the health of others, and each participant derives satisfaction from the contributions of all because the lack of insurance can be a cause of illness for the uninsured person, thereby exerting a negative physical externality to the society (Arrow, 1963; Gruber, 2007). Another negative externality rationale comes from pooling health insurance premium that may not exist in the private insurance market. Health insurance coverage systematically shields those covered from the full costs of illnesses. Since high-risk individual consumes significantly more medical resources than the low-risk one but pays the same health insurance premiums, they impose a negative externality on healthy individuals in their insurance pool (Bhattacharya & Sood, 2006; Rothschild & Stiglitz, 1992).

Another reason is an adverse selection that one party has more information than another side of the transaction, and it appears whenever an individual is independent to choose the amount and plan of health insurance. On the one hand, there is a tendency of the sick to choose differently the most generous plan (Cutler & Zeckhauser, 2000). On the contrary, the insurance company may pick out only the healthy individuals. Thus, no insurance market existence may appear at any given price (Akerlof, 1970; Rothschild & Stiglitz, 1992). In fact, this is one argument for a favorable

Medicare program, because the elderly want to buy insurance but no insurance company is willing to sell the insurance plan because it will attract too many "lemons" (Akerlof, 1970). Universal coverage limits this to happen.

2.2.2. The impact on utilization of medical care

The literature generally concludes that there is a positive association between health insurance and medical care utilization. But the extent to which those results could be generalizable is unclear. Furthermore, the association does not imply causation. People with higher demand of medical care utilization because of their health condition may choose to have health insurance; on another hand, healthier people may choose not to have an insurance plan.

Research study findings in developed countries about insurance on medical care utilization might depend on the type of coverage and the population of interest. Medicaid expansion increases primary care, preventive services, and hospitalization, as well as emergency use (Baicker et al., 2013; Currie & Gruber, 1995; Finkelstein et al., 2012; Taubman, Allen, Wright, Baicker, & Finkelstein, 2014). Massachusetts Health Reform suggests health insurance increases utilization for some preventive services, but decreases in inpatient, hospitalizations and emergency services (Kolstad & Kowalski, 2012; Miller, 2012a, 2012b). The Affordable Care Act (ACA) in 2010 increases utilization of inpatient care for both emergency and non-emergency sources of admissions, with increases in having a primary care doctor (Antwi, Moriya, & Simon, 2013; Barbaresco, Courtemanche, & Qi, 2015a). While the Affordable Care Act and Massachusetts Health Reform are universal for all in a population, Medicaid is a program designed for low-income families and the disabled. The previous studies above suggest the effect of health insurance varies by context. Type of health insurance, insurance benefits offered, and a population that received health coverage could result in different health insurance impact on medical care in developed countries.

Stuckler et al. (2010) randomly pick 100 papers from the most relevant international Universal Health Coverage literature to understand the different implementation of universal health insurance in developed and developing countries. They find the term Universal Health Care has most frequently been used in describing policies for care in high-income countries, while Universal Health "Coverage" has most often been applied to low- and middle-income countries; hence, the fact that population coverage may not guarantee sufficient breadth of care services in developing countries.

Many research studies in developing countries focus on sub-population instead of universal coverage. There is recognition that one source of the problem is the weak capacity of health systems in developing countries (Stuckler et al., 2010). Limited health budget may also another problem faced by developing countries. In Rwanda, The Global Fund Against AIDS, Tuberculosis, and Malaria (GFAMT) project in 2007 enhanced financial access to health care by subsidizing health insurance to the poor. The project improved health service utilization for those income groups (from 0.4 health center visits per person and year in 2005 to 0.5 visits in 2007), including better control of AIDS, tuberculosis, and malaria (Kalk, Groos, Karasi, & Girrbach, 2010). Another study examines nine developing countries in Africa and Asia to understand the extent of universal health coverage implementation in those countries. They reported moving towards universal health coverage increases enrollment in government health insurance, expands benefit package, and decreasing out-of-pocket spending accompanied by increasing government share of spending on health (Lagomarsino, Garabrant, Adyas, Muga, & Otoo, 2012). However, the available evidences in those studies were based on descriptive methodology. Further research studies with better methodologies may be necessary to complement those studies on universal health coverage implementation in developing countries.

In Indonesia, a research study utilizing the Indonesia Family Life Survey (IFLS) 1997 and using logistic regression sampled 19- to 60-year-old citizens across a variety of occupations. Their results suggested that government-provided insurance scheme likely increases outpatient care in public health facilities (Hidayat, Thabrany, Dong, & Sauerborn, 2004). Another study, using IV and GMM methods, revealed that the same insurance scheme likely increased public outpatient care by 63% (Hidayat & Pokhrel, 2009). However, the former study could have a potential endogeneity problem between occupation and choices of insurance. For example, sick people may choose to be civil servants. Even though civil servant insurance scheme (*Askes*) is mandatory for government employees, participation to be a civil servant is voluntary. In fact, our results using the same household survey datasets, utilizing four waves, reveal that government employee families are more likely to visit public hospitals than private employee families in any given year. The later research attempts to address a potential endogeneity issue with instrumental variable methodologies. They use occupation and spouse as selected instruments. However, occupation was the initial problem; if a person or his/her family is more likely to have health problems, then the more likely it is for him/her to take a government job in order to gain eligibility for public insurance.

Previous research studies explain multiple channels by which health insurance may affect medical care utilization. The access effect is a distinct channel of health insurance impact on medical care utilization; health insurance will lower the effective price of health care, thus likely increasing its use (Dafny & Gruber, 2005). However, public insurance reimbursement payments may differ from private ones (Baicker et al., 2013). For example, Indonesia's universal insurance scheme up to the year 2014 only covered 20 percent of private health facilities (Kompas, 2016). The lower level of reimbursement compared to private insurance level may be one apparent reason for those low private health facilities' participation.

Insurance benefits may lead to a substitution across different types of services (the efficiency effect). For instance, an increase in preventive services such as general check-ups could decrease inpatient and emergency services (Antwi et al., 2013; Barbaresco, Courtemanche, & Qi, 2015b; Kolstad & Kowalski, 2012). Also, health insurance plans may lead to a substitution effect across different types of healthcare facilities. That is when public insurance creates differential prices between the various kinds of healthcare facilities. For example, public insurance would increase utilization of public health care facilities, but it could decrease usage of private healthcare facilities.

Accessibility of medical care may increase *ex-post* and *ex-ante* moral hazard. *Ex-ante* moral hazard by people not taking preventive utilization such as receiving immunizations. Also, reducing the effective price of medical care would discourage self-protection because of decreased financial losses associated with illness. *Ex-post* moral hazard when health insurance increases medical care demanded in any given technology because the insurer would not purchase additional medical care if they had to pay its full cost. (Barbaresco et al., 2015b; Ehrlich & Becker, 1972; Manning & Marquis, 1996; Zweifel & Manning, 2000). Therefore, insurance may increase or decrease utilization of medical care from different medical care utilization channels.

2.3. History of public insurance in Indonesia

The Indonesian government-provided insurance health reform started in 1968 when the government issued Presidential Decree 230 concerning government employee and retirees' health benefits (Indonesia, 1968). This policy mandated that each government employee have public insurance and pay the insurance premium, around five percent of their salary. The insurance scheme, *Askes*, covered parents and all children within a household. *Askes* provides insurance holder outpatient and inpatient benefits to the particular doctors and public health facilities.

Dependent insurance coverage is one characteristic of interest in a government-provided insurance system for civil servants. Dependent insurance coverage has changed several times in the last three decades. In 1981, the insurance plan limited the number of children covered and imposed age limitations. On April, 1981, the government-provided insurance scheme covered all children born before that date, and otherwise only 3 children per family. New employee only had up to 3 children covered. Also, children would lose their coverage after their 21st birthday and are not in school, or at 25 years old if they are still in college. In 1994, the insurance scheme further limited the number of dependent coverage from three to only two children. Therefore, either their parents were working after March 22, 1994, or the third, fourth, and afterward children who were born after March 22, 1994, would not be covered by the insurance policy. The 1981 and 1994 insurance schemes had grandfathered features. If the old rule covered a child and the newer law was applied, then he/she was still covered by the following insurance scheme.

The Indonesian government expanded public insurance for private employees as well. The coverage was called *Jamsostek (Jaminan Sosial Tenaga Kerja)*. It has a different scheme from civil servant insurance. Law 3/1992 regarding the Social Security Act (SSA) mandates each private employer who has at least ten employees or at least pays IDR 1 million per month to have health insurance. However, the health benefit is compulsory but optional. If a private employer already provides private insurance for their employees, then they are not required to provide public insurance managed by *Jamsostek*, a state-owned company, to their employees. In practice, *Jamsostek* covered less than 1.5% of the population in 2001 (Thabrany, 2008). *Jamsostek* covers employees' spouses and up to three children under 21 years of age. Premiums, which are capped at 3 percent of basic salary for unmarried and 6 percent for married employees, are paid solely by employers (Hidayat & Pokhrel, 2009). While *Jamsostek* benefits include outpatient and inpatient care in public health centers, private insurance may consist of outpatient and inpatient services in private health centers. Therefore, provider choice depends on citizens' employer-provided health insurance; private employees could have more health provider choices if their employers provide them with private insurance.

In 2014, Indonesia introduced universal health coverage (*BPJS*) through law number 24/2011 and government regulation number 111/2013 that mandated each Indonesian citizen to join the national government health insurance starting January 1, 2014 (Indonesia, 2011, 2013). There are two health insurance coverage changes applied for civil servant children: reduction in cost sharing and restore eligibility for the third child. Previous civil servant health insurance scheme (*Askes*) requires cost sharing when services fall outside basic benefits package (Achadi, Achadi, Pambudi, & Marzoeki, 2014). Minister of Health regulation number 138/2009 and Minister of Home Affair regulation number 12/2009 states that cost sharing could be applied for outpatient, inpatient, emergency, midwifery and any medical care outside the basic package. In contrast, the national health insurance scheme does not require co-payments (Lagomarsino et al., 2012). To achieve this objective, *BPJS* issued series of regulations about reimbursement payment system. *BPJS* health regulation number 1/2014 article (77) states that primary health care facilities which cooperate with *BPJS* do not allow to charge additional fees. Also, Minister of Health regulation number 69/2013 regulates standard reimbursement fees for both primary and more advanced medical care facilities. Although most medical care services are covered, there are some medical care services that are not covered by the new insurance scheme, including health services for aesthetic purposes; service to overcome infertility; orthodontics; health problems or diseases caused by drug or alcohol dependence; interference health from deliberately hurting oneself, and traditional medicine (*Badan Penyelenggara Jaminan Sosial*, 2014). Therefore, two children from government employee families that are covered by previous scheme benefit from co-payment reduction in the new insurance scheme.

Additional to cost-sharing reduction, the universal health insurance scheme restores the third-child eligibility but not for the fourth and afterward children. Government regulation number 111/2013 indicates that the new insurance scheme covers a household head, a spouse, and maximum three children. So, the new insurance scheme covered the third child who previously does not covered in *Askes*. Also, the new insurance scheme allows a household to cover their ineligible children by paying an extra insurance premium. While there were many changes in the dependent coverage for the insurance for government employees, there was no substantial change in the government-provided insurance for other professional workers.

Public health centers (*Puskesmas*) and public hospitals were mandated to join the new insurance scheme. For private clinics and private hospitals, however, it is voluntary to join the new insurance scheme. Although some private clinics and hospitals may join their network, only a few of them enter the system, either because of lower reimbursement levels or other administrative reasons. Up to 2016, about 1,800 of the 2,500 hospitals have joined the network. However, only 20% of those hospitals are private hospitals (Kompas, 2016). Public health centers serve most of the government-provided health programs such as insurance for needy families (*Askeskin*) and health financial assistance; thus, we expect that more people will visit public health centers.

2.4. Data

I employ four waves' of datasets (1997, 2000, 2007, and 2014) from the Indonesian Family Life Survey (IFLS). The IFLS is household and individual longitudinal data which represents 83 percent of the Indonesian population living in 13 out of 33 provinces in Indonesia. IFLS sampling scheme involved stratification into provinces, then a random sampling of 321 enumeration areas (EA) within provinces using the 1993 National Socioeconomic Survey (*SUSENAS*) sampling frame designed by the Indonesian Central Bureau of Statistics (BPS). It used oversampling of urban EAs and EAs in smaller provinces to facilitate urban-rural and Javanese-nonJavanese comparisons. Next, it randomly selected households within enumeration areas and then interviewed selected respondents within the household who knew household-level demographic and economic conditions. Finally, it randomly selected household members to provide individual-level information.

Recently, IFLS surveys have consisted of five waves: IFLS 1 (1993), IFLS 2 (1997), IFLS 3 (2000), IFLS 4 (2007), and IFLS 5 (2014). Originally, IFLS data consisted of 57,072 households year (IFLS 1 [1993]: 7,224, IFLS 2 and 2+ [1998]: 8,347, IFLS 3 [2000]: 10,574; IFLS 4 [2007]: 13,996; and IFLS 5[2014]: 16,931) . IFLS 5 interviewed 58,337 individuals, which included 6,131 infants, 11,146 children (5-14 Years Old), and 41,06 adults. I use IFLS 2, 3, 4, and 5 to avoid an impact of treatment in 1981 and 1994. Moreover, I use government families and private employee families for my study. I use children age 0-20 years old because age 21 and above coverage depends on their education status. I exclude households that have twin sibling children because I don't know who is the third child and which sibling is older or younger, and I exclude household with missing values of key variables. My final samples consist of 4,980 government employee children and 13,695 private employee children for our baseline regressions.

2.5. Identification strategy

In this section, we describe the identification strategy and estimation methods. I utilize government criteria for treatment selection. Our treatment group is the third child of a government employee's family. Our control groups are the first two children, and the fourth children and afterward. The first two children represent eligible children already in place. This group gains benefits from the new universal health scheme from co-payment reduction. For example, while they had to pay the difference between the insurance coverage rate and medical care charges for having surgery, the new scheme is free of co-payment charges. The difference between the treatment group and this control group represents an eligibility effect since they are in the same plan after the intervention period.

The fourth and afterward children represent ineligible children. They do not gain any benefits from the new insurance scheme. Those children could voluntarily join the new insurance scheme by paying an extra premium for each additional child. The difference between the treatment group and this control group represents both an eligibility effect and reduction in co-payment effect. Therefore, I can estimate the reduction in copayment effect by subtracting the latter from the former estimates. The basic approach is a difference-in-differences estimation. Our baseline regression is the following:

$$Y_{ibmt} = \alpha_0 + \alpha_1(T_{ibm} * Post_t) + \alpha_2 X`_{ibmt} + \delta_b + \gamma_m + \mu_t + \epsilon_{ibmt} \quad (1)$$

where Y_{ibmt} is the probability of having medical care utilization for individual i at birth order b living in municipality m at time t. T_{ibm} is equal to one if the child is the third child of government employee children (one is the number of children beyond the two covered). $Post_t$ indicates whether period t is after the implementation of the 2014 policy. $X`_{ibmt}$ is an individual, or a household, level vector of control variables including educational attainment, gender, age fixed effect, whether a child is working, children's income, parents' income, whether a child was born after March 1994 to capture the 1994 policy change, hhsize, religion fixed effect and whether a child is living in rural areas. I include a birth order fixed effect (δ_b) to capture unobserved invariance of birth order. Also, I include a municipality fixed effect (γ_m) and year fixed effect (μ_t) to capture unobserved differences in space and time, respectively; and ϵ_{ibmt} is the idiosyncratic error term. I cluster by household level to capture the unobserved differences between families. The coefficient interest is α_1, the effect of dependent insurance coverage, which captures the difference between the change in third child medical care utilization from the "before" to the "after" period and the change in the control group from the "before" to the "after" period and difference between those two groups; in other words, the "difference in differences".

I expand the difference-in-differences approach with a triple difference approach, including private employees as an additional control group, to understand different trends between government-employee children and private-employee children over time for the same birth order. Private employees have been required to have either private or public insurance (*Jamsostek*) since 1992. Different from *Askes*, *Jamsostek* covers up to three children 20 years old or under. So, I expect there to be no substantial difference regarding dependent coverage for private employee's insurance schemes after the new insurance scheme implementation. Our triple difference-in-differences regression is the following:

$$\mathrm{Y_{ibmt}} = \beta_0 + \beta_1(\mathrm{T_{ibm}} * \mathrm{Post_t} * G_{ibmt}) + \beta_2(\mathrm{T_{ibm}} * \mathrm{Post_t}) + \beta_3(G_{ibmt} * \mathrm{Post_t}) + \beta_4(\mathrm{T_{ibm}} * G_{ibmt}) + \beta_5 \mathrm{G_{ibmt}} + \beta_6 \mathrm{X`_{ibmt}} + \delta_b + \gamma_\mathrm{m} + \mu_\mathrm{t} + \varepsilon_\mathrm{ikrt} \quad (2)$$

where G_{ibmt} is an indicator whether a child is a government employee dependent i at birth order b living in municipality m at time t. Other symbols specified are analogous to the specifications in equation (1). The coefficient interest is β_1, which capture the different between the difference between the change in third child medical care utilization from the "before" to the "after" period and the change in the control group from the "before" to the "after"; the change in government-employee children medical care utilization from the "before" to the "after" period and the change in private-employee medical care utilization from the "before" to the "after" period; the change in third child medical care utilization for government-employee families and the change in third child medical care utilization for private-employee families; and the change of those groups. For example, additional effects include differences between third child and first two children within government-employee families; the triple difference-in-differences equation would capture different implications between a third child of government-employee families and third child of private-employee families on medical care utilization. Additionally, I can gather information about different medical utilization patterns between those two occupations.

2.6. Empirical results

I provide analysis changes of public insurance dependent coverage on medical care utilization for children in this section. I employ both difference-in-differences and triple difference approach.

2.6.1. Descriptive statistics

Table 2.1 shows means and standard deviations for medical care utilization outcomes and covariates. The outpatient variable would be a binary variable equal to one if a child sought outpatient care in the previous four weeks. The inpatient variable would be a binary variable equal to one if a person received inpatient services during the last 12 months. I break down outpatient services into four types of health centers: public hospitals, private hospitals, public health centers (clinic / *Puskesmas*), and private clinics.

In general, the treatment group has a slightly higher outpatient but smaller inpatient utilization level compared to the control group before the intervention period, but then the treatment group has more both outpatient and inpatient care after the new insurance scheme. For hospital outpatient care, the treatment group uses both public and private hospitals less frequently than the control group. It is as expected, as a control group includes the first two children who were already eligible for previous insurance schemes. In contrast, the treatment group has higher outpatient care use both in public and private hospitals after the intervention period. It implies preliminary evidence that insurance gives access to eligible children. Table 2.1 shows a reduction in public-health-center outpatient care but an increase in private-clinic outpatient service use. It suggests a substitution effect between health facilities. One potential reason is more private clinics join the new insurance scheme. There is a slightly larger inpatient increase after the intervention period for the treatment group.

Table 2.1. Means and Standard Deviations

Description	Pre-Intervention (1997,2000,2007)		Post-Intervention (2014)	
	Treatment	Control (Gov)	Treatment	Control (Gov)
(1)	(2)	(3)	(4)	(5)
Outcomes				
Outpatient	0.181(0.386)	0.167(0.370)	0.233(0.424)	0.191(0.394)
Outpatient, Hospital	0.019(0.137)	0.025(0.157)	0.074(0.262)	0.036(0.186)
Outpatient, Public Hospital	0.013(0.112)	0.017(0.130)	0.049(0.217)	0.014(0.117)
Outpatient, Private Hospital	0.008(0.089)	0.008(0.090)	0.031(0.173)	0.022(0.146)
Outpatient, Clinic	0.137(0.344)	0.114(0.317)	0.123(0.329)	0.111(0.315)
Outpatient, Public Health Care	0.068(0.253)	0.051(0.221)	0.049(0.217)	0.042(0.200)
Outpatient, Private Clinic	0.070(0.255)	0.065(0.246)	0.080 (0.272)	0.070(0.256)
Inpatient	0.022(0.148)	0.031(0.174)	0.074(0.262)	0.052(0.223)
Control				
Year of Education	3.422(3.853)	4.201(4.240)	1.724(2.604)	3.026(3.806)
Male	0.539(0.499)	0.527(0.499)	0.558(0.498)	0.524(0.500)
Age	8.458(5.403)	9.453(5.662)	6.252(4.291)	7.947(5.276)
Working Children	0.016(0.125)	0.024(0.153)	0.000(0.000)	0.011(0.106)
Children's Income (in thousands)	26.64(314.4)	70.55(1119.9)	0.000(0.000)	89.1(1177.5)
Parents' Income (in millions)	23.12 (23.99)	24.34(31.67)	96.05(133.2)	89.73(127.1)
Rural	0.334(0.472)	0.352(0.478)	0.252(0.435)	0.296(0.457)
Religion	1.328(0.858)	1.305(0.830)	1.276(0.803)	1.247(0.763)
Birth Order	3.000(0.000)	1.873(1.253)	3.000(0.000)	1.528(0.709)
N	3,702		1,312	

The control group has higher education levels and is more likely to work since they are also older siblings than the treatment group. Both the treatment and control group have similar gender and religion distributions before and after the intervention period. They also are more likely to live in urban areas. Indonesia GDP per capita in 2007 was around IDR 19 million (USD 1,860) and in 2014 approximately IDR 36 million (USD 3,499). Our sample parents' income is higher than the GDP per capita both before and after the intervention period. It suggests that our sample comes from more middle-income families and higher-income families than the average Indonesian population. One possible reason for the large increase in parents' income after the intervention period is bureaucratic reform in the middle of 2007. Indonesia's Ministry of Finance initiated bureaucratic reform in 2007, gradually followed by the implementation of another ministry which substantially increased government employee salary over time.

2.6.2. The impact on outpatient care utilization

Figure 2.2 provides the trend in outpatient care at hospitals (public and private) for the treatment and the control group for both government and private employee families' children under 21 years old of age. Blue and green lines are a third child (birth order equal 3); red and orange lines are first child and second child (birth order 1,2,4 and afterward). Blue and red lines represent government employee family children; green and orange lines are private employee family children. The figure suggests third children, both from government-employee and private-employee families, have lower outpatient care use in public hospitals before the new insurance scheme. In 1997, the third child of a government employee had similar outpatient care in the hospital. One possible reason is many third children who were born before 1994. Insurance would cover the third child if she/he was born before March 22, 1994, and their parent's works before that date. While the third children of private employees remain lower in receiving outpatient care from public hospitals, the treatment group (3^{rd} children of government-employee families) has much higher outpatient care use at public hospitals after the intervention period.

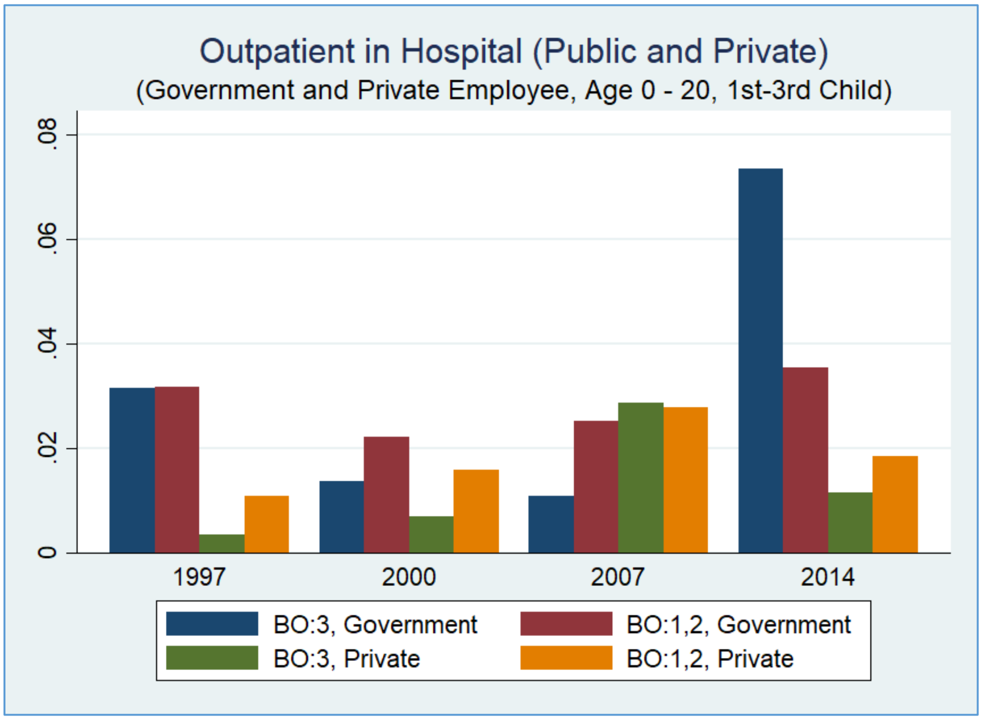


Figure 2.2. Outpatient Care in Hospitals (1st, 2nd, 3rd Children)

Figure J.1 and J.2 show similar figures for outpatient utilization in public hospitals and private hospitals, respectively. The outpatient in public hospital trend is analogous to figure 2.1. Third children have a lower outpatient care before the intervention period, but higher outpatient care after the intervention period for the third children of government employee families. In contrast, both the first two children and the third children of government employee families have an increasing trend in private hospital utilization, primarily in 2014. One potential reason is the participation of private hospitals into the new insurance scheme. If more private hospitals join the new insurance network, insurance holders have more hospital choices. If this is the case, then it suggests the participation of private health facilities in the new insurance scheme could benefit the insurance holder and reduce public hospitals' patient load. Furthermore, private employee families have a higher outpatient care in private hospitals while they have a lower outpatient care in public hospitals. It indicates private employees have more access to private hospitals than government-employee children. It is as expected because some private employee families may have private insurance from their employer instead of public insurance (*Jamsostek*).

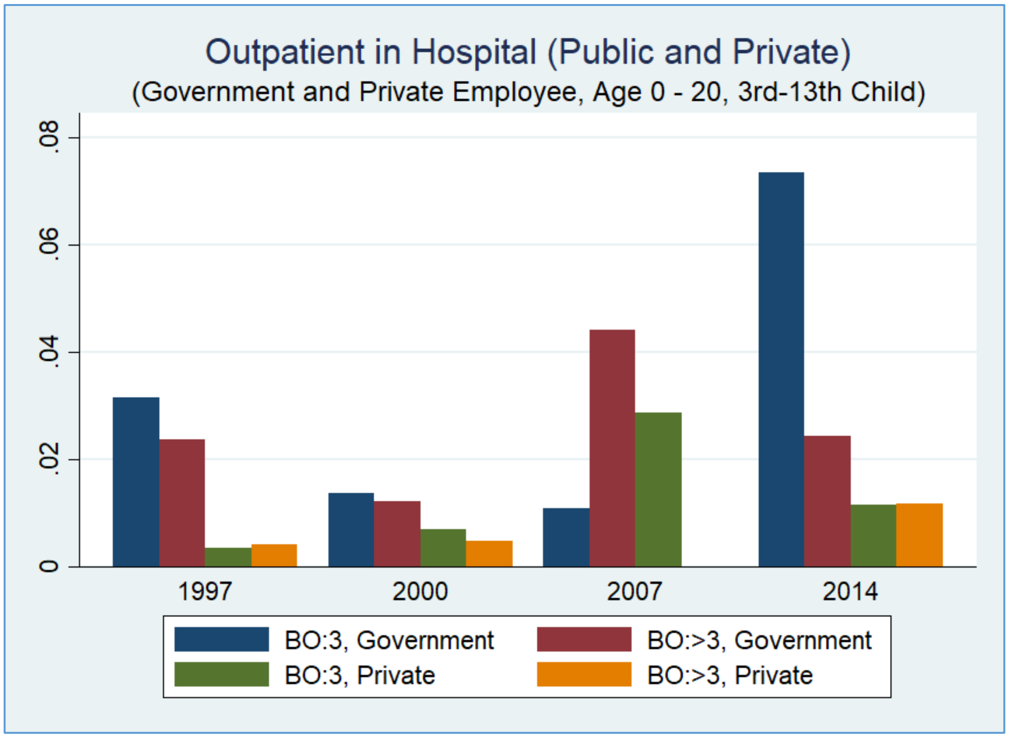


Figure 2.3. Outpatient Care in Hospitals (3rd and afterward children)

Figure 2.3 shows outpatient care in hospitals for 3rd children, 4th children, and their younger siblings. Despite they voluntary join the new insurance scheme, 4th and afterward children do not benefit from the new intervention period. Contrary to figure 2.2, the third children have a higher outpatient care before the intervention period. Figure 2.2 and 2.3 indicate younger sibling have less medical care utilization. It is intuitive because younger sibling more likely healthier thus less likely have outpatient care for medication. However, they may not necessarily have lower preventive care. The third children of government employee families have much higher outpatient care than their younger sibling after the intervention period. The medical care utilization gaps are larger than depicted in figure 2.2. It indicates the more substantial impact on medical care utilization when we account both eligibility effects and reduction in cost sharing.

Figure J.3 and J.4 provide outpatient care in public and private hospitals for third children and afterward. Figure J.3 shows ineligible children (4^{th} and later children) of government employee families in our samples have increasing outpatient in public hospitals before the intervention period but decrease substantially after the intervention period. Figure J.4 depicts those younger siblings more likely have outpatient in private hospitals after the intervention period. All 4^{th} and afterward children of private employee families visit private hospitals instead of public hospitals both before and after the insurance scheme period; slightly larger outpatient in private hospitals after the intervention period. These evidence indicate substitution effect between public and private medical care facilities. An individual choose private hospitals instead of the public hospital when more people go to public hospitals.

Table 2.2 provides difference-in-difference estimators and triple difference estimators for the probability in the outpatient populations of interest. Columns (1) and (3) are estimators for the difference-in-difference approach; columns (2) and (4) are estimators for the triple difference methodology. R-squared are populated in one field for outpatient, outpatient in public and outpatient in private. I separate public hospitals, private hospitals, public health centers, and private clinics. Treatment is an indicator whether an individual is the third child of government-employee families. Control is an indicator whether a child is either older siblings (1^{st}, 2^{nd} children) or younger siblings (4^{th} and afterward children). The dependent variable is an indicator whether a person experienced outpatient services in the last four weeks. I include birth order fixed effect, age fixed effect, religion fixed effect, municipality fixed effect, and year fixed effect, clustering the standard error by household level to capture the unobserved differences between families.

Table 2.2. The Impact on Outpatient Care for Third Child

VARIABLES	Outpatient at Hospital		Outpatient at Clinic	
	DID	Triple DID	DID	Triple DID
	(1)	(2)	(3)	(4)
Outpatient	0.041*	0.044**	-0.011	-0.022
	(0.021)	(0.022)	(0.031)	(0.035)
Outpatient, Public	0.039**	0.039**	-0.005	-0.015
	(0.017)	(0.018)	(0.021)	(0.024)
Outpatient, Private	0.006	0.010	0.000	-0.004
	(0.014)	0.010	(0.025)	(0.028)
Observations	4,980	18,675	4,980	18,675
R-squared	0.074; 0.063; 0.070	0.032; 0.025; 0.026	0.077; 0.088; 0.071	0.050; 0.039; 0.044
Controls*	YES	YES	YES	YES
Birth Order FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Religion FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

* Gender, education level, whether a child is working, child's income, parents' income, rural residency

Robust standard errors in parentheses

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

The difference-in-differences and triple DID models suggest similar results for outpatient care utilization in hospitals. These results suggest eligible children for universal health public insurance scheme are more likely to have an outpatient medical care in hospitals after the intervention period by four percentage points or corresponding to a 210 percent increase from the pre-intervention period outpatient in hospital average. Also, both models suggest the result is driven by an increase in public hospitals. These results are very intuitive. Public hospitals are mandated to join the public insurance scheme. Therefore public hospitals must accept public insurance holders, and people visit public hospitals when they are eligible for public insurance. The mandatory participation of public hospitals also creates less of an endogeneity issue.

I find a slight increase in outpatient care use in private hospitals, although it is not statistically significant. There are two possible reasons for this finding. Private hospitals may voluntarily join the insurance scheme, and limited private hospitals accept the insurance plan. Voluntary participation may create an endogeneity participation problem on the supply side. For example, a hospital which has very few public insurance holders in the area chooses to join the insurance scheme. Also, only 20 percent private hospital from all hospital network in the insurance system implies a limited private hospital supply. It makes insurance holders have limited choices for private hospitals; that is, they cannot go to the private hospital with their insurance just because limited hospitals accept the insurance. Figure J.3 and J.4 indicate the last reason more likely happened. Both the treatment and control groups increase outpatient utilization in private hospitals over time. If this increase because of more private hospitals joins the insurance network, then it supports the notion that not only insurance but also health facility availability is an essential factor contributing to access to health care.

I find a slight reduction of outpatient utilization in public healthcare, although it is not statistically significant. While the explanations for this are somewhat similar to those of the private clinics, there are two possible reasons why people are less likely to visit public health care after the new insurance: the negligible price differential between insured and uninsured outpatient care in public health centers, and different medical technology between public hospitals and public health centers. Outpatient care in public health centers is highly subsidized both by central and local governments, making it affordable for all citizens with very low prices for most utilization services. For instance, Figure B.1 provides a summary of outpatient and inpatient utilization fees in public health centers in Jakarta based on Governor Regulation 68/2012 regarding public health center fees. Twenty-five percent outpatient medical care utilization in public health care costs less than IDR 5,000 or corresponding to less than 0.5 USD, and 85 percent costs less than IDR 50,000 or corresponding to less than 5 USD.

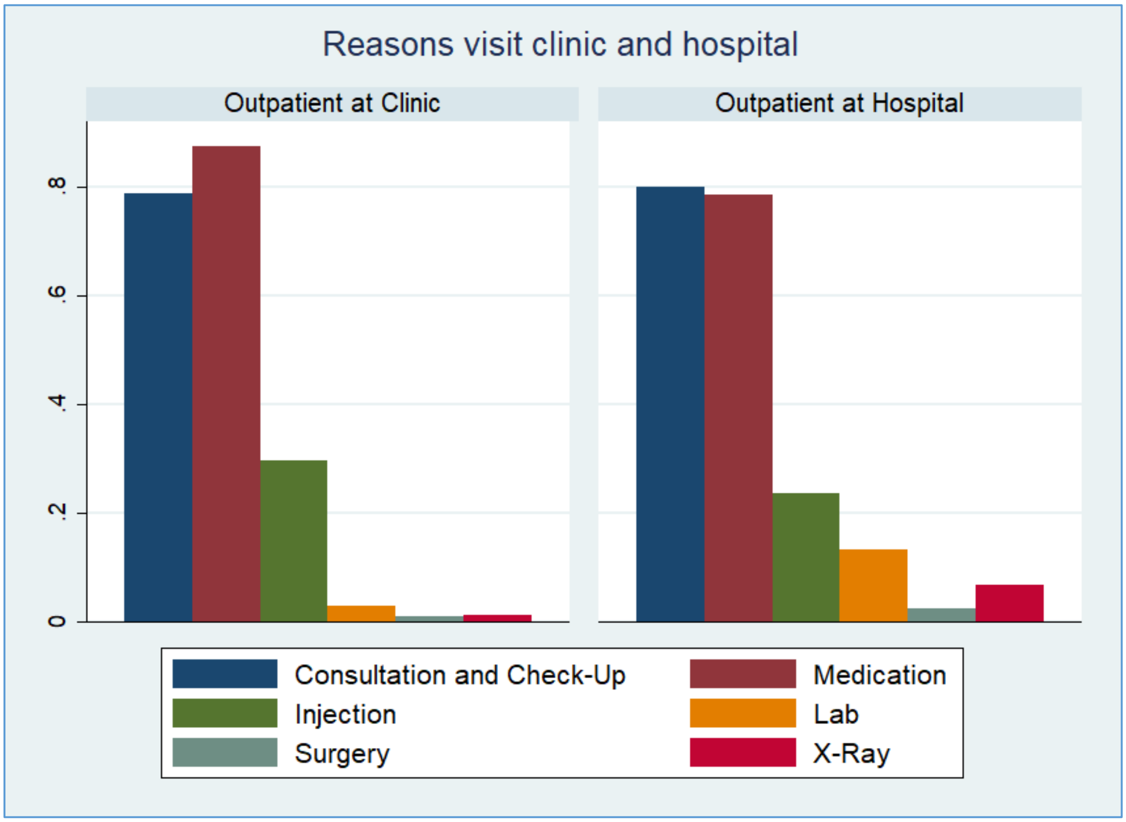


Figure 2.4. Reasons Visit Clinic and Hospital

Figure 2.4 shows six doctor treatments (consultation and check-up, injection, surgery, medication, x-ray, and laboratory services) on average when children under 21 years of age went to hospitals and clinics. We sought to understand why children went to those two places. The graph shows around 80% children visit hospitals and clinics for medication, also consultation and check-up. It indicates children mostly visit clinics and hospitals because they want to have medication and check-ups at the same time. The medication reason is more prominent when they are going to clinics, but hospital visits for consultations and check-ups are slightly higher than those for medication. Another important finding is they are more likely to have advanced medical care treatment, indicated by higher amounts of lab and x-ray procedures when they visit hospitals. It suggests parents visit a hospital when they need advanced medical technology for their children, either for preventive or curative reasons.

2.6.2.1.Eligibility and co-payment

Two essential features in the new universal health coverage scheme are to add eligibility for the third child and cost-sharing reduction for most medical care utilization. The first two kids represent eligible children already in place. This group benefits from the new universal health scheme from co-payment reduction. For example, while policyholders had to pay the difference between insurance coverage rate and the medical care charge for having surgery, the new scheme is free of co-payment charges. The difference between the third child and the first two children represents an eligibility effect since they are in the same plan after the intervention period.

The fourth and afterward children represent ineligible children. They do not gain any benefit from the new insurance scheme if they do not voluntarily join the new insurance scheme. The difference between the treatment group and this control group represents both an eligibility effect and reduction in co-payment effect. Therefore, I can estimate the co-payment reduction effect by subtracting the latter from the former estimates.

Table 2.3 provides difference-in-differences and triple difference estimators for the probability of outpatient care utilization in public hospitals for the two different groups. Columns (1) and (3) contain the difference-in-difference approach for the first three children; columns (2) and (4) correspond to the third and afterward. The Table 2.3 specifications are analogous to those in Table 2.2. Treatment is an indicator whether an individual is the third child of government employee families. The control group in columns (1) and (3) is the first two children, and the control group in columns (2) and (4) reflects the fourth and afterward children. The dependent variable is an indicator whether a person experienced outpatient care in public hospitals in the prior four weeks. I only use outpatient care at a government hospital in this section, following our previous finding that public hospitals drive different outpatient medical care utilization patterns.

Table 2.3. Eligibility and Co-payment

VARIABLES	DID		Triple DID	
	Birth Order	Birth Order	Birth Order	Birth Order
	1,2,3	3,4-13	1,2,3	3,4-13
	(1)	(2)	(3)	(4)
Outpatient, Public	0.037**	0.065***	0.037**	0.054***
Hospital	(0.018)	(0.022)	(0.018)	(0.019)
Observations	4,542	1,223	17,116	4,161
R-squared	0.070	0.149	0.026	0.073
Controls*	YES	YES	YES	YES
Birth Order FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Religion FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

* Gender, education level, whether a child is working, child's income, parents' income, rural residency

Robust standard errors in parentheses

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

All columns point to the same general conclusion that the new insurance scheme more likely increases the probability of outpatient care utilization in public hospitals. The triple difference estimators do not change much from the difference-in-differences estimators. However, triple differences approach shows smaller R-squared. It suggests triple differences approach explained less variation in government and private employee children outpatient care. As expected, both models suggest a larger estimate of magnitude when I use the fourth to tenth children as a control group, which represents the impact of eligibility status of dependent insurance and lower co-payment. In particular, being an eligible child (eligibility effect) in the new insurance scheme more likely increases outpatient care utilization in public hospitals by 3.7 percentage. Furthermore, being an eligible dependent and having a co-payment reduction with the new insurance scheme more likely increases outpatient utilization in public hospitals by more than 5.4 percentage points. Subtracting the former and the latter provides the effect of lower co-payment effect; that is, lower co-payment in the new insurance scheme more likely increases outpatient utilization in public hospitals by more than 1.7 percentage points (5.4 percentage points - 3.7 percentage points).

2.6.3. The impact on inpatient care utilization

Figure 2.5 provides the trend in inpatient care use at public hospitals for the treatment and control groups over time. Control group is the first and second children both government employee families and private employee families. The figure suggests an increase in inpatient care at hospitals over time for both third children and other children for government- and private-employee families. The trend for inpatient care at public hospitals for third children for government-employee families is similar over time to that of outpatient care above. That is, the third children are less likely have inpatient medical care in a hospital in any given year. It indicates younger siblings more likely healthier thus less likely have inpatient care for medication. The third children of government-employee families are more likely to have more frequent use of inpatient care after the new insurance scheme than the control group. It indicates improvement in access to inpatient medical care.

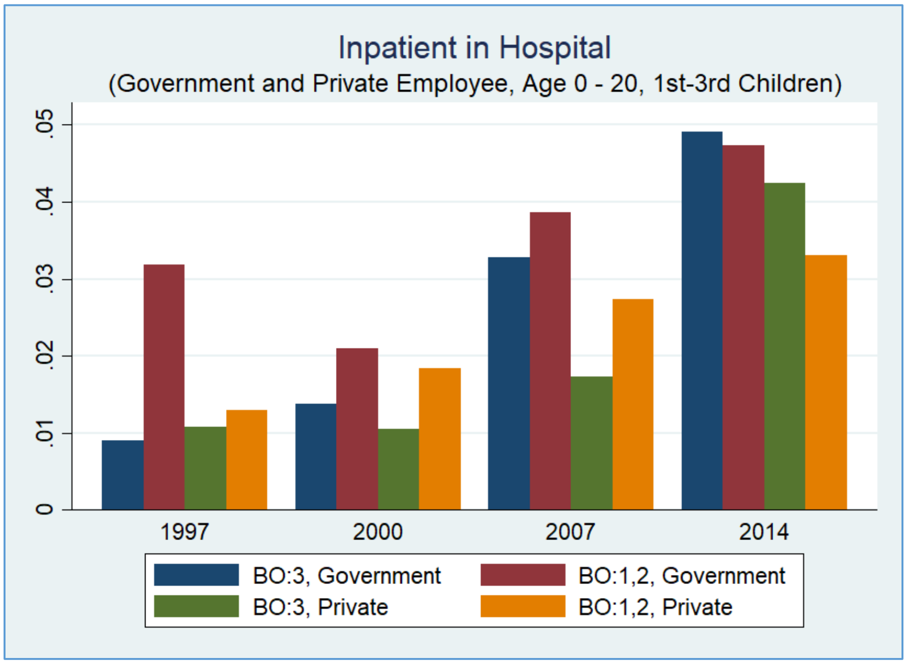


Figure 2.5. Inpatient Care in Hospitals (1st, 2nd, 3rd Children)

Figure J.5 and J.6 show trends between the two groups for inpatient care in private hospitals and all hospitals. The third child of government families has lower inpatient care in public hospitals but higher inpatient utilization in private hospitals before the new insurance scheme. While the third child has slight larger inpatient care in public hospitals after the new intervention period, she/he has lower inpatient gap in a private hospital after the intervention period compares to pre-intervention period. Similarly, the third child of private-employee families more likely has higher inpatient care use in private hospitals after the introduction of the new insurance scheme. These suggest indication of substitution for both civil servant' and private employee's family on hospital usage. In particular, the third children of government families visit public hospitals and limited private hospitals which joins the new insurance scheme when they are eligible for the new insurance scheme. On the other hand, private-employee families who have more access to private hospitals more likely visit private hospitals when more people visit public hospitals because of the new insurance scheme.

Figure 2.6 provides inpatient in hospitals for the third children and afterward. Figure 2.6 has similar specification as previous tables. 4th and afterward children had higher inpatient in 1997, but the third children have higher in 2007. In general, the third children have higher inpatient at a public hospital in general because they are an older than their siblings. There is no substantial difference between the treatment group and the control group after the intervention period.

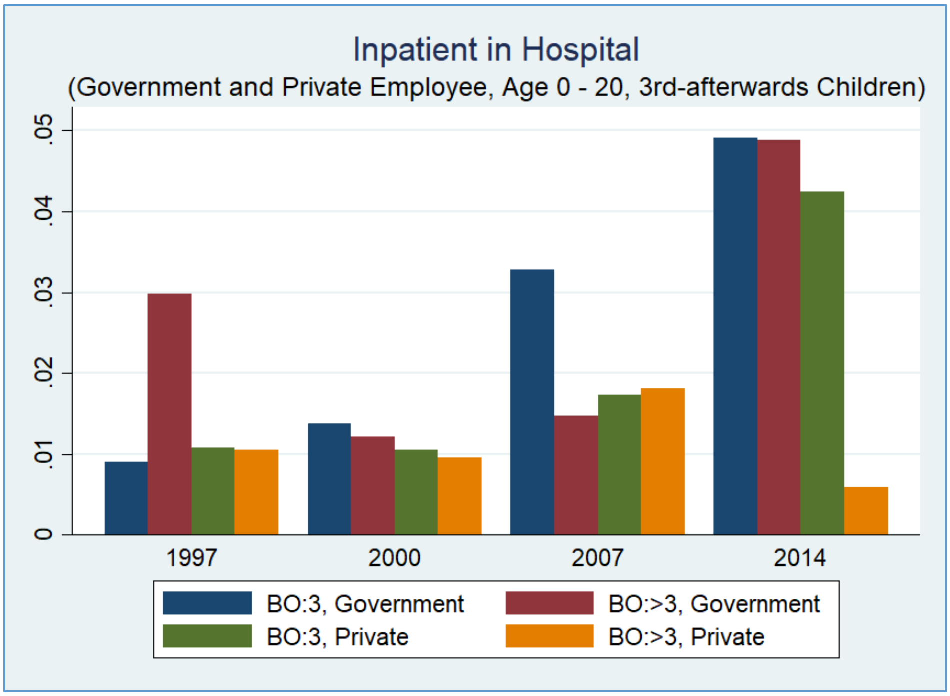


Figure 2.6. Inpatient Care in Hospitals (3rd and afterward children)

Figure J.7 and J.8 provide inpatient in public hospitals and private hospitals for the same groups as in figure 2.6. In general, both figures indicate government employee families more likely visit public hospital for inpatient care, but private employee families more likely visit the private hospital for having inpatient. The similar indication with the outpatient care that private employee families choose to have medical care utilization in private hospitals because some of them have private insurance which allows them having more hospital alternatives.

Table 2.4. The Impact on Inpatient Care

VARIABLES	Inpatient at Hospital		Inpatient at Clinic	
	DID	Triple DID	DID	Triple DID
	(1)	(2)	(3)	(4)
Inpatient	0.008	-0.004	0.018	0.024*
	(0.019)	(0.021)	(0.013)	(0.013)
Inpatient, Public	0.008	0.007	0.009	0.013
	(0.016)	(0.017)	(0.009)	(0.009)
Inpatient, Private	-0.002	-0.013	0.009	0.011
	(0.012)	(0.014)	(0.009)	(0.009)
Observations	4,980	18,679	4,980	18,679
R-squared	0.049; 0.042; 0.053	0.030; 0.019; 0.026	0.053; 0.054; 0.049	0.023; 0.020; 0.017
Controls*	YES	YES	YES	YES
Birth Order FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Religion FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

* Gender, education level, whether a child is working, child's income, parents' income, rural residency

Robust standard errors in parentheses

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

Table 2.4 provides difference-in-difference and triple difference estimators for the probability in the inpatient populations of interest. Columns (1) and (3) give the difference-in-difference approach; columns (2) and (4) show triple difference-in-difference. I use similar specifications as table 2.2. Treatment is an indicator whether an individual is the third child of government-employee families. The dependent variable is an indicator whether a person experienced inpatient services in the last 12 months. I include birth order fixed effect, age fixed effect, religion fixed effect, municipality fixed effect, and year fixed effect, clustering the standard error by household level to capture the unobserved differences between families.

Two models suggest eligible children for universal health public insurance are more likely to visit public hospitals and clinics but less likely to visit private hospitals, although only inpatient utilization in clinics for triple difference-in-difference is statistically significant. There is a more substantial impact reduction when I include private-employee families because of their increased visits to private hospitals for inpatient care after the intervention period, as depicted in figure J.6 and A.8. Therefore, our results indicate parents reoptimize their utility when the new insurance takes effect. Families who are eligible for public insurance more likely visit public hospitals and limited private hospitals member of the new insurance scheme, and families who have more access to private hospitals more likely visit private hospitals when more people visit public hospitals.

2.6.3.1.Eligibility and cost-sharing reduction

Table 2.5 provides difference-in-differences and triple differences methodologies for an inpatient in public hospitals for two birth order groups to investigate whether universal health insurance program affects inpatient in public hospitals differently between children who benefit cost-sharing reduction and children who do not benefit from the new insurance scheme. Table 2.5 has analogous specification as table 2.3. Birth order 1 and 2 benefits from cost-sharing reduction, but birth order 4 and afterward do not benefit from the new insurance scheme. Therefore, the difference between the third children and their older siblings capture eligibility impact since they are in the same new insurance plan. The difference between the third children and their young siblings capture both eligibility effects and cost-sharing reduction. The dependent variable is an indicator variable whether a child had inpatient in public hospitals in the last 12 months.

Table 2.5.Eligibility and Co-payment

VARIABLES	DID		Triple DID	
	Birth Order 1,2,3	Birth Order 3,4-13	Birth Order 1,2,3	Birth Order 3,4-13
	(1)	(2)	(3)	(4)
Inpatient, Public Hospital	0.008	0.011	0.008	0.004
	(0.016)	(0.030)	(0.017)	(0.030)
Observations	4,484	1,216	17,120	4,161
R-squared	0.043	0.129	0.019	0.056
Controls*	YES	YES	YES	YES
Birth Order FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Religion FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

* Gender, education level, whether a child is working, child's income, parents' income, rural residency

Robust standard errors in parentheses

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

The models suggest the third children more likely visit public hospitals for inpatient care after the new insurance scheme period although they are not statistically significant. DID shows larger impact when we account for eligibility impact and cost-sharing reduction impact on inpatient care. The triple different approach shows similar magnitude for the first and second children from DID, but smaller magnitudes for the third and afterward children. Substantial inpatient reduction for the 4^{th} and afterward private employee children after the new insurance scheme, as depicted in figure J.8., could drive the different. Similar as an outpatient, R-squared for triple differences methodologies shows smaller than difference-in-differences approach. It suggests triple differences approach explained less variation in government and private employee children inpatient care.

2.7. Robustness checks and falsification tests

I provide robustness checks, and falsification tests to test sensitivity of our estimates from omitted variable biases, sample chosen and difference-in-differences identifying assumption.

2.7.1. Robustness checks

In this section, I employ robustness checks and sensitivity analyses to test the robustness of our primary result. Table L.1-L.8 provide robustness tests for the public insurance dependent coverage specification variations of equation (1). I use five specifications for primary outcomes (hospital, public hospital, and private hospital) both for outpatient and inpatient. Column (1) is a simple difference-in-difference model without any control. Column (2) includes age fixed effects. Column (3) provides education, column (4) consists of all controls, and column (5) is the baseline regression provided in our primary results. Our results are robust to those specifications. Our estimation is smaller when I include municipality fixed effects, specifically in the private hospital regression. It suggests different cities may have different private hospital availability that correlates with hospital outpatient care. For example, families with only two children live in towns where there is no private hospital which joined the new insurance scheme, but families with three children live in cities with a private hospital which has joined the new insurance scheme.

To check our sample sensitivity, I either strike or relax our sample restriction. I relax our sample restriction by including twin siblings except those family having birth order 2nd and 3rd twin children since I am not able to determine which sibling is treatment or control. To do so, I adjust the birth order for twin siblings. For example, I use birth order equal to one for both siblings if they are either first or second twins since I don't know which one is an older or younger sibling. Table L.9-L.14 provide our main regression when I relax our sample restrictions. Table L.9-L.14 have similar specifications as previous tables. Our results do not change with this alteration of the sample. It suggests our results are not sensitive to sample choices.

One concern is whether a family with only one or two children may have a different preference with a family who has three children or more. To answer this problem, Table L.15-L.17 provide our principal regression when I use the only family with at least three children. It gives treatment impact within the family, that is, the only family which the treatment group is the third child and the control group is their siblings. Table L.15-L.17 are analogous specifications as previous tables. Our results do not change much with this sample choices; It suggests our result are robust to sample options.

In 1994, the government-provided scheme made dependent coverage changes that covered only two children after initially covering three children. On March 22, 1994, government insurance scheme covered three children born before that date, and otherwise only two children per family. New government employee only had up to two children covered. To test the sensitivity of our sample to that policy, I restricted our samples to only children who were born after March 1994. Table L.18-L.20 provide our primary results for children who were born after March 1994. I apply five different specifications analogous to previous tables. The results indicate that hospital utilization slightly increases from our primary findings. In particular, hospital outpatient care increases from 4.1 percentage points to 4.4 percentage points and public-hospital outpatient care increases from 3.9 percentage points to 4.8 percentage points. It might suggest that some children were the third child, born before March 1994 with their parents working before that date, who received public insurance coverage benefits before the universal health coverage scheme. However, it also suggests that issue may not change our primary estimates substantively.

2.7.2. Falsification tests

The identifying assumption for the difference-in-differences approach is common parallel trends between treatment and control groups without any intervention. It implies without any interference, both treatment and control groups would have parallel trends over time before the treatment period. To check this assumption, I estimate various specification tests for artificial effect during pre-treatment years. Table M.1-M.10 provide falsification tests for our primary outcomes. I use the years 2000 and 2007 as our artificial effects, and I implement five different specifications analogous to previous tables. If the intervention drove our results instead of inherent differences between the treatment and control groups, then I would see no impact on the artificial treatment period. In general, the model suggests no estimators are statistically significant (except four estimators in private hospitals from 50 regressions which disappear when I include municipality fixed effect) and reduce the estimation magnitude. These results support the notion that the actual interventions likely drive the difference in outcomes.

2.8. Discussion and conclusion

Improving access to medical care is one primary public policy objective both in developed and developing countries. Indonesia first introduced its universal insurance scheme in 2014. Two interesting features are reduction in cost-sharing and expansion dependent coverage from only the first two children to three children. A unique dependent coverage scheme for government-provided insurance allows us to analyze the impact of public insurance on medical care utilization.

Our results are more substantial than previous studies in Indonesia even though we achieve a similar conclusion. I account differential occupation medical care usage by using different triple methodology. I find that eligible children are more likely to go to public hospitals for outpatient utilization. There is a more considerable impact when I include both eligibility and co-payment reduction effects. That is, universal health coverage not only adds the third children to the scheme but also consists of a co-payment reduction from their initial program (*Askes*). I find a slight reduction in clinic outpatient care although they are not statistically significant. The negligible price differential between insured and uninsured children in the public health center (*Puskesmas*) and different medical technological equipment between clinics and hospitals may be two reasons why there is a slight reduction on public health centers.

My empirical results should be of interest to policymakers for their public insurance improvement programs. My findings suggest public insurance benefits insurance holders on having access to medical care, primarily in public health centers. Also, the expansion of public insurance health facility networks to all private health centers may advantage public insurance holders because it reduces the public health center patient load. Minimizing the number of physicians' patient load per day could result in an adequate treatment time per patient.

CHAPTER 3. THE IMPACT OF COMPULSORY AND FREE SCHOOL PROGRAMS ON CHILD LABOR AND HEALTH OUTCOMES

3.1. Introduction

Improving education, reducing child labor, and increasing health outcomes are widely accepted public policy goals in developed as well as developing countries. Although a strong empirical correlation between education, labor, and health is now well established, the debate among economists currently lies in possible mechanisms explaining that correlation (Albouy & Lequien, 2009). Correlation doesn't imply causation; as poor health may inhibit people investing in education (reverse causality). Many factors affect both education and health outcomes (omitted variable bias). This study estimates the causal effect of compulsory education together with free school programs on child labor and health outcomes by exploiting changes in compulsory government education and free tuition programs in Indonesia.

The Indonesian government has mandated primary nine-year school since 2003, from previous (1993) mandates of only up to six years of education. However, in developing countries, mandates per se may not be optimal to bring children into school and keep them away from working. Additional interventions are required in developing countries because of the nature of developing countries' limited financing ability or limited education facilities to put their children into school.

Previous literature accords with this idea. For developed countries, such as the United Kingdom and the United States, raising the minimum dropout age from 14 to 15 years old in the United Kingdom or changes in compulsory state schooling in the United States from 1915 to 1930 increased future labor earning and health outcomes, and reduced the mortality rate (Lleras-Muney, 2005; Oreopoulos, 2006).

However, evidence shows additional interventions are required in developing countries. In addition to extending compulsory education from six to nine years, the Taiwanese government opened over 150 new junior high schools in 1968; uses school opening as an instrument for mother's or father's schooling, they find that parent's schooling reduce infant mortality (Chou, Liu, Grossman, & Joyce, 2007). Indonesia's education reform which constructed over 61,000 primary schools between 1973 and 1978 led to an increase in education and future labor earnings (Duflo, 2000). In contrast, even after reforms to decentralize education and introduce basic free education in Indonesia in the 1990s, such policies often fail to increase access and quality of education, household expenditures on child education are high and increasing, and extensive social and geographical disparities exist (Kristiansen, 2006; Rosser & Joshi, 2013).

To address this problem, in 2005, through the School Operational Grant Program *(Bantuan Operasional Sekolah / BOS*), the government supported nine-year compulsory education with free tuition for all Indonesian citizens. The government spent more than IDR 15 trillion (1.5 billion USD) each year to finance primary and junior high schools in Indonesia to support compulsory education and free tuition programs. Access to a free school for eligible children may lower the effective price of schooling, enabling children to invest in education. Also, schooling could decrease child labor. Increasing schooling opportunities and decreasing child labor would improve health behavior and health outcomes.

I apply difference-in-differences (DID) and matching DID approaches with 13- to 15-year-old junior high school students as a treatment group and 16- to 18-year-old senior high school students as a control group. I employ representative large-scale multi-purpose socioeconomic survey data of Indonesian families and individuals (*SUSENAS*) for the years 1997-1999 and 2003-2014. The *SUSENAS* is household and individual data which covers the Indonesian population living in all provinces in Indonesia. Each survey contains a core questionnaire which consists of roster household characteristics, health care, and educational attainment.

I find compulsory education and free tuition programs likely lead to reductions in child labor and fewer experiences with diarrhea and migraines. It suggests the program eases household budget constraints. For children who come from lower-income family or children who live in rural areas, the impact is larger on the probability of working. It supports the notion the loss in utility from sending the child to school is inversely related to the level of parental income, and school subsidy for the cost of going to school would decrease the disutility of household consumption, primarily in rural areas which less likely have access to the credit market. Our results are robust to many specifications. Our results suggest the benefit of government expenditures in education on child labor and health outcomes.

This study contributes a valuable resource for policy-makers and research studies in assessing the impact of public expenditures in developing countries. Our solution to the problem of compulsory education in developing countries, by exploiting additional quasi-experimental intervention of government expenditures in education to give free tuition programs reduces child labor and improves health outcomes.

3.2. Review of the relevant previous literature: Theory and empirics

I provide both theoretical and empirical research studies regarding school and child labor to understand mechanism of school subsidy could affect child labor.

3.2.1. Education and child labor: Basic model

A conceptual framework of education and labor market outcomes assumes individuals face a market opportunity that gives the level of earnings associated with alternative schooling choice and reaches an optimal schooling decision by balancing the benefits of higher schooling against the cost (Card, 1999). Particularly for children, there is a trade-off between child labor and the accumulation of human capital, and it is socially inefficient when it has a sufficiently adverse effect on ability. Child labor exists because of family hardship, working children as a substitute for negative bequest (to transfer income from children to parents), and a substitute of borrowing because of limited access to credit (Baland & Robinson, 2000; Beegle, Dehejia, & Gatti, 2004).

In constructing an economic model of child labor, I develop a model of child labor from Ranjan (1999) by including the cost of going to school because the cost of schooling is one important variable that affects child labor. Parents think that the cost of education when deciding to enroll their children in school because it reduced household consumption. In this economy, there are three types of labor: child labor, adult unskilled labor, and skilled adult labor. Skilled labor is more productive than unskilled labor ($r_s/r_u > 1$), and child labor is less productive than unskilled labor ($r_c/r_u < 1$), where r_s, r_u, and r_c are adult skilled wages, adult unskilled wages, and child wages, respectively.

Each household consists of parents and a child who live in two periods. Parents have income in both periods (Y_{p1}, Y_{p2}), which we may conceptualize as parent salary and retirement. If a child is working in the first period, they will have child wages in the first period and adult unskilled wages in the second period, otherwise they will have no child wages in the first period and skilled wages in the second period. Parents also have to pay child's school tuition and any other associated school cost (C_s) when their children attend school.

3.2.1.1.No credit constraint case

The no credit constraint case assumes each household has access to credit market at the market interest rate (r). Parents maximize household utilities to choose whether to put their children to school or work, modeled using the following maximization problem:

$$Max \frac{C_1^{(1-\theta)}-1}{(1-\theta)} + \beta \frac{C_2^{(1-\theta)}-1}{(1-\theta)} \qquad (1)$$

subject to

$$C_1 + C_s.(1 - \mathbf{1}(W_c)) \leq Y_{p1} + r_c.\mathbf{1}(Wc) - S$$

$$C_2 \leq (1+r)S + Y_{p2} + r_u.\mathbf{1}(Wc) + r_s.(1 - \mathbf{1}(Wc))$$

where C_1 *and* C_2 are household consumption in first and second period, $\mathbf{1}(Wc)$ is an indicator whether a child is working, S is savings, θ is the constant intertemporal elasticity of substitution, and β is the time discount factor.

Considering the household utility maximization for a household who sends children to work ($\mathbf{1}(Wc) = 1$), the maximization on equation (1) becomes:

$$Max \frac{C_1^{(1-\theta)}-1}{(1-\theta)} + \beta \frac{C_2^{(1-\theta)}-1}{(1-\theta)} \qquad (2)$$

subject to

$$C_1 \leq Y_{p1} + r_c - S$$

$$C_2 \leq (1+r)S + Y_{p2} + r_u$$

This maximization problem yields:

$$S_u = \frac{Y_{p1} + r_c + \beta^*(Y_{p2} + r_u)}{(1 + \beta^*(1+r))} \quad (3)$$

$$C_{1u} = \frac{\beta^*(1+r)\left(Y_{p1} + r_c\right) + \beta^*(Y_{p2} + r_u)}{(1 + \beta^*(1+r))} \quad (4)$$

$$C_{2u} = \frac{(1+r)\left(Y_{p1} + r_c\right) + (Y_{p2} + r_u)}{(1 + \beta^*(1+r))} \quad (5)$$

$$\beta^* = (\beta(1+r))^{-\frac{1}{\theta}} \quad (6)$$

The two-period household utility for a household who sends children to work has the following indirect utility function:

$$U_u = \frac{\left[\frac{\beta^*(1+r)(Y_{p1} + r_c) + \beta^*(Y_{p2} + r_u)}{(1 + \beta^*(1+r))}\right]^{(1-\theta)} - 1}{(1-\theta)} + \beta \frac{\left[\frac{(1+r)(Y_{p1} + r_c) + (Y_{p2} + r_u)}{(1 + \beta^*(1+r))}\right]^{(1-\theta)} - 1}{(1-\theta)} \quad (7)$$

Alternatively, if parents send their children to school ($\mathbf{1}(Wc) = 0$), their household utility function becomes:

$$Max \frac{C_1^{(1-\theta)} - 1}{(1-\theta)} + \beta \frac{C_2^{(1-\theta)} - 1}{(1-\theta)} \quad (8)$$

subject to

$$C_1 + C_s \leq Y_{p1} - S$$

$$C_2 \leq (1+r)S + Y_{p2} + r_s$$

The maximization problem results in:

$$S_s \leq \frac{(Y_{p1} - C_S) + \beta^*(Y_{p2} + r_s)}{(1 + \beta^*(1+r))} \tag{9}$$

$$C_{1s} \leq \frac{\beta^*(1+r)(Y_{p1} - C_S) + \beta^*(Y_{p2} + r_s)}{(1 + \beta^*(1+r))} \tag{10}$$

$$C_{2s} \leq \frac{(1+r)(Y_{p1} - C_S) + (Y_{p2} + r_S)}{(1 + \beta^*(1+r))} \tag{11}$$

The lifetime household utility for a household who sends children to school has the following indirect utility function:

$$U_s = \frac{\left[\frac{\beta^*(1+r)(Y_{p1} - C_S) + \beta^*(Y_{p2} + r_s)}{(1 + \beta^*(1+r))}\right]^{(1-\theta)} - 1}{(1-\theta)} + \beta \frac{\left[\frac{(1+r)(Y_{p1} - C_S) + (Y_{p2} + r_S)}{(1 + \beta^*(1+r))}\right]^{(1-\theta)} - 1}{(1-\theta)} \tag{12}$$

Parents would send their children to school if utility from attending school (U_s) is preferred to the utility from sending children to work (U_u). Comparing equation (7) and equation (12), parents will send their children to school if and only if the first term in equation (12) satisfies $r_s > (1 + r)(r_c + C_s) + r_u$; that is, their future skilled child wages are larger than the future value of the current child wage, cost of going to school and future unskilled wages. Rearranged, we could also consider the rate of education with the following equation:

$$\frac{r_s - r_u}{r_c + C_s} \geq (1 + r) \tag{13}$$

Therefore, as long as the rate of education is larger than the interest rate, parents would always send their children to school. Equation (13) also shows that as the cost of going to school (C_s) is smaller, then larger is the net return of education. However, there are still children who are not in school in the real world. These important results provide the importance of access to credit and cost of education. For example, urban areas such as a capital city may have a better credit market than a rural area since cities have better financial infrastructure such as banks.

3.2.1.2.Credit constraint case

An alternative condition is provided next. Assume each household does not have access to the credit market. I also assume each household cannot save or borrow. These assumptions are more probable for a family with child labor since they usually come from a low-income family that cannot save and may not have access to the credit market. The household maximization problem could be represented by the following equation:

$$Max \frac{C_1^{(1-\theta)}-1}{(1-\theta)} + \beta \frac{C_2^{(1-\theta)}-1}{(1-\theta)} \tag{14}$$

subject to

$$C_1 + C_s(1-\mathbf{1}(W_c)) \leq Y_{p1} + r_c\mathbf{1}(Wc)$$

$$C_2 \leq Y_{p2} + r_u\mathbf{1}(Wc) + r_s(1-\mathbf{1}(Wc))$$

After substituting the budget constraints into household utility maximization for having working children ($\mathbf{1}(Wc) = 1$), the maximization on equation (14) becomes:

$$U_u = \frac{(Y_{p1}+r_c)^{(1-\theta)}-1}{(1-\theta)} + \beta \frac{(Y_{p2}+r_u)^{(1-\theta)}-1}{(1-\theta)} \tag{15}$$

Similarly, the household maximization problem for a household who sends children to school is ($\mathbf{1}(Wc) = 0$):

$$U_s = \frac{(Y_{p1}-C_s)^{(1-\theta)}-1}{(1-\theta)} + \beta \frac{(Y_{p2}+r_s)^{(1-\theta)}-1}{(1-\theta)} \tag{16}$$

Comparing equations (15) and (16), there exists a threshold level of parental income $I_{p1}*$ $= (Y_{p1}* - C_s*)$ such that:

$$U_s(I_{p1}) \geq U_u(I_{p1}) \qquad \text{for all} \quad I_{p1} \geq I_{p1}*$$

and

$$U_s(I_{p1}) \leq U_u(I_{p1}) \qquad \text{for all} \quad I_{p1} \leq I_{p1}*$$

where $Y_{p1}*$, C_s*, and $I_{p1}*$ are threshold of parent income in first period, threshold of cost of education, and threshold of parent net income after cost of education that creates indifferent utility between schooling and working, respectively.

There are two important intuitions. The loss in utility from sending the child to school is inversely related to the level of parental income and very high for low-income families due to diminishing marginal utility. Thus, extreme low-income families are forced to send their children to work (Ranjan, 1999). Various combinations of parental income and educational costs would determine parents' decision to send their children to school. Increases in subsidies for the cost of schooling would increase parents' utility for sending their children to school. However, even the full subsidy may not eliminate school dropouts and child labor.

In general form, the household maximization problem would be the following equation:

$$Max\, U(C_1) + \beta\, U(C_2) \tag{17}$$

subject to

$$C_1 + C_s(1 - W_c) \leq Y_{p1} + r_c(Wc)$$

$$C_2 \leq Y_{p2} + r_u + r_s(1 - Wc)$$

After substituting the budget constraint into the objective function, the maximization yields the optimal schooling condition:

$$U'_{c2}(Y_{p2}, r_u, r_s).r_s \geq \frac{1}{\beta} U'_{C1}(Y_{p1}, C_s, r_c)(C_s + r_c) \tag{18}$$

The marginal benefits of schooling because of higher second-period consumption due to higher wage from their skilled children are equal to the disutility of foregone first-period consumption because of the higher costs of education and foregone child labor wages. A larger subsidy for the cost of going to school would decrease the disutility of first-period consumption, thus increasing the likelihood of parents sending their children to school. However, the higher child labor wage (r_c) would cause a higher disutility of foregone first-period consumption; hence, higher child wages would decrease the probability of parents sending children to school. Therefore, the net impact depends on how successfully the subsidy eases household budget constraints and how important the child wages are for household consumption.

3.2.2. Education and child labor: Empirics

Developed and developing countries have different integration levels in implementing one particular policy. It may drive different conclusions for these two country groups. While citizens' compulsory education is supported by other pro-education policies in developed countries, developing countries often mandate their citizens to go to school and support that policy later rather than preparing it before the main policy being implemented. This differential policy implementation calls for different empirical strategies to estimate the impact of compulsory education on education and child labor outcomes between developed and developing countries.

One developed country, the United Kingdom, changed its compulsory schooling laws in the second half of the twentieth century, increasing the minimum dropout age from 14 to 15 years old. Those policies had a powerful impact on redirecting almost half the population of 14-year-olds in the mid-twentieth century to stay in school for one more year (Oreopoulos, 2006; Silles, 2009). Similar evidence also found that, in the United States, there were at least 30 states that implemented compulsory schooling from 1915 to 1930. The enforcement of compulsory schooling increased educational attainment by 5% a year (Lleras-Muney, 2005). Developed countries are more likely than developing countries to enforce child labor regulations, which may drive less research on how education affects child labor.

However, conclusive evidence may not be reached in developing countries. Extending compulsory education from 6 to 9 years in Taiwan increased junior high school enrollment in 1968 (Chou et al., 2007). In contrast, even after the decentralization of education, with the 1990s reform, such policies often fail to increase access to and quality of education. Additionally, household expenditures for children's education are high and increasing, and huge social and geographical disparities exist in Indonesia (Kristiansen, 2006; Rosser & Joshi, 2013). Related to labor outcomes in Indonesia, the construction of primary schools led to an increase in education, and the increase has translated into an increase in future wages more than 1.5 percent (Duflo, 2000).

Additional pro-education intervention policies to support main education policies and demographic differences may drive these different findings between developed and developing countries. Before developed countries implemented compulsory education, they provided other education policies to support the main education policies. For instance, the United Kingdom's compulsory education in the second half of the twentieth century was supported by the 1944 Education Act (the Butler Act), which provided free universal secondary education for all pupils (Silles, 2009). Taiwan compulsory education in 1968 was supported by opening 150 junior high schools at a differential rate among regions (Chou et al., 2007). Indonesian primary school construction provides an access to education, especially in rural areas which are less likely to have high-quality school infrastructures and more likely to have rough geographic conditions.

Also, developed and developing countries have different demographics, governance levels, and political will. For instance, people in developing countries simply have less income than people in developed countries. Moreover, developing countries' corruption level may be higher than that of developed countries. The different local governments may also have differing levels of corruption or political will. Kristiansen and Pratikno (2006) find the administration of education services is without transparency and accountability in Indonesia, even after decentralization of education. Many parents in Indonesia also paid illegal fees to principals or teachers for various reasons (Rosser & Joshi, 2013).

3.2.3. Health: General model

A natural extension from the child labor model above is assuming each household cares about their children's health (H). Child health may be modeled as a function of child consumption (C_c), child education $(1 - W_c)$, and given previous child health (H_0). The general form of parents' maximization problem is:

$$Max\ U(C_{p1}, C_{c1}, H_1(C_{c1}, (1 - W_c), H_0)) + \beta\ U(C_{p2}, C_{c2}, H_2\big(C_{c2}, H_1(C_{c1}, (1 - W_c), H_0)\big)\big) \quad (19)$$

subject to

$$C_{p1} + C_{c1} + C_s(1 - W_c) \leq Y_{p1} + r_c(Wc)$$

$$C_{p2} + C_{c2} \leq Y_{p2} + r_u + r_s(1 - Wc)$$

This maximization yields the following optimal health:

$$U'_{H1}\left(H^{`}_{1Sc} - H^{`}_{1Cc1}(C_s + r_c)\right) + \beta\left(U'_{Cc2}.U'_{H2}.H^{`}_{2Cc2}.r_s + U'_{H2}.H^{`}_{2H1}\left(H^{`}_{1Sc} - H^{`}_{1Cc1}(C_s + r_c)\right)\right) \leq U'_{Cc1}(C_s + r_c) \quad (20)$$

The marginal benefit of child health as a function of the price of schooling and child wages. The marginal utility of first-period child health depends on the direct impact of child health on schooling (not working) and the foregone consumption because of the higher price of schooling and household income reduction from foregone child wage. In theory, this sign is ambiguous depending on the sign of the impact of the school on health, the sign of the impact of foregone consumption on health, and which one has a larger impact on health if they both have a common sign.

The marginal utility of the second period is ambiguous as well. It depends on the impact of future child consumption on future child health because of higher skilled wages, and how first-period health may affect second-period child health.

3.2.4. Health: Empirics

Theoretically, there are many channels by which education can affect health outcomes. Education improves the rate of conversion of inputs into health (*productive efficiency*) and improves health behavior because education increases someone's knowledge about healthy behaviors (*allocative efficiency*) (Grossman, 1972). A growing number of studies find education improves health outcomes through improvements in self-reported health, preventing illness, and reducing mortality (Chou et al., 2007; Lleras-Muney, 2005; Oreopoulos, 2006; Silles, 2009).

However, efficiency theory may be less demanding for children since young people are less likely to understand that they should care about their health status and health behavior.

School food may also affect children's health either positively or negatively. Healthy school breakfasts or lunches may have a beneficial impact on child health. However, unhealthy school snacks may have a deleterious impact on child health. One study found reduced-price lunches contributed to childhood obesity (Schanzenbach, 2009). However, other studies argued that the receipt of reduced-price breakfasts or lunches improves the health of children, or were a valuable tool for reducing childhood obesity (Bhattacharya, Currie, & Haider, 2006; Gundersen, Kreider, & Pepper, 2012; Millimet, Tchernis, & Husain, 2010). Those research studies are related with developing countries, primarily when we concern about school snacks sold by school cafeteria or street vendors.

Education may also affect health outcomes from other channels including improvement of labor earnings and less physically demanding labor. Beegle et al. (2004) found child labor in Vietnam led to substantially higher earnings than their friends who do not work, however, the majority of children were working as unpaid family workers in agriculture or non-agriculture businesses run by the household. Improvement in labor earnings for children implies higher household income and higher consumption levels. It may increase health outcomes if they consume healthy foods. However, it may harm health outcomes if children use their earnings for fast food, snacks, or other unhealthy food. Children in developing countries often work long hours, sometimes in physically-demanding areas such as agricultural settings, street work, or garbage scavenging (Beegle et al., 2004; USDOL, 2015). Going to school implies less time allocation for children, so less physically demanding labor may have a beneficial impact on children.

There are various reasons for this inconclusive evidence. The production of health is a complex process. Health depends not only on education or medical care but also a host of other factors such as stress, income, health behaviors, and genetic predisposition to disease (Levy & Meltzer, 2004).

3.3. Compulsory education and free tuition program in Indonesia

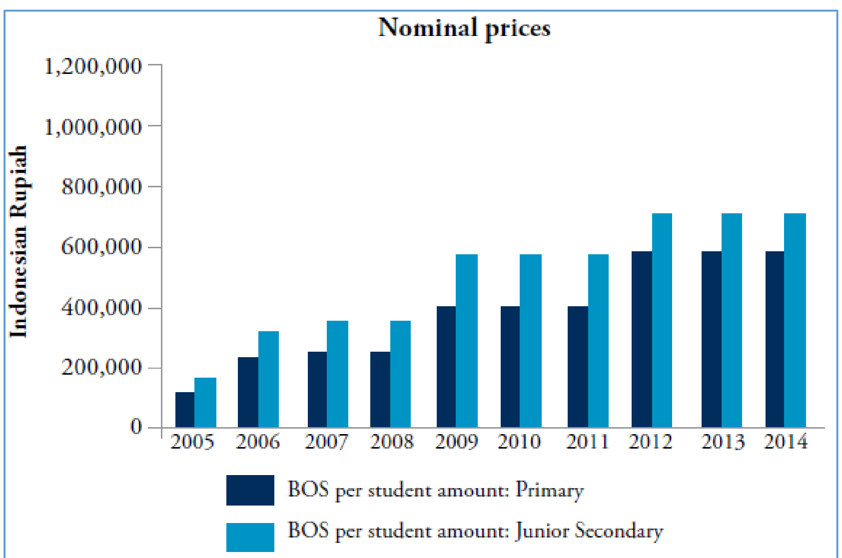
Indonesian government mandated six-year primary education for all Indonesian citizens in 1993. In 2003, Law 20/2013 regarding the National Education System was issued, which expanded the mandates up to nine-year primary education, elementary school, and junior high school. Article (6) mandated each Indonesian citizen who is seven to fifteen years old to have a nine-year primary education.

However, mandates per se may not be a strong incentive to put children into school if there is no other incentive to alleviate budget constraints for a household in putting their children into school. To address this problem, the Indonesian government, through the School Grant Operational Program (*BOS*), provided all Indonesian citizens with free tuition for a primary education starting in July 2005, the enrollment period for the 2005/2006 school year.

The government allocates more than IDR 15 trillion (1.5 billion USD) in 2005/2006 and always increases its contribution each year. In 2012, they provided IDR 24 trillion (2.4 billion USD) for this program. The funding was allocated based on the number of pupils in a school; it covers new student registration, textbooks, teaching and learning activities, teacher development, and other school operations and maintenance (SMERU, 2006; The World Bank, 2015). Figure 3.1

shows BOS funding per pupil from 2005 to 2014 for both elementary and junior high schools. The program provides general education subsidies for each student in a school, and the nominal magnitudes keep growing over time. During the 2005/2006 school year, the program provided IDR 235,000 per year for each elementary student and IDR 324,500 per year for each junior high school student. The education subsidy per pupil increased to IDR 580,000 per year for elementary schools and IDR 720,000 per year for junior high schools in the 2012/2013 school year.

Although legal tuition fees are supposed to be eliminated, a significant challenge concerned the receipt of illegal fees paid to some principals and teachers in the first few years of program implementation (Rosser & Joshi, 2013; SMERU, 2006; The World Bank, 2015). However, the government continued strengthening their program by issuing presidential decree 14/2008 for Compulsory Education in 2008. Article (9) states that both central and local governments should ensure the implementation of compulsory education without tuition fees for students. Furthermore, the Ministry of Culture and Education issued regulation 60/2011 that prohibited schools levying any investment or operational fees against their students.



Source: The World Bank (2015)

Figure 3.1. The School Operational Program (BOS) Amount Per Pupil

In 2003, household education expenditures were around IDR 570 thousand per elementary student and IDR 1.47 million per junior high school student (The World Bank, 2015). School fees and school materials contributed the biggest shares of household spending. The funding amount in 2005/2006 suggests the program subsidized around 41% of household education expenditures for elementary school students and 22% of household education expenditures for junior high schoolers.

Despite law 20/2013 mandating tuition assistance only for children who were seven to fifteen years old, the free tuition program was applied for all children who were still in primary or junior high school, regardless of their age at that time. Therefore, we expect the compulsory education and free tuition program will impact not only seven- to fifteen-year-old children but also all other children who are still in primary and junior high school.

3.4. Data

I use representative survey data of Indonesian families and individuals (*SUSENAS*) for the years 1997 to 2014 but with gaps. It is a series of large-scale multi-purpose socioeconomic surveys initiated in 1963-1964 and fielded every year or two since then. Since 1993, the SUSENAS has contained household and individual data which covers the Indonesian population living in all provinces in Indonesia. *SUSENAS* is not a freely available source; the author does not have the years 2000, 2001, and 2002. I also exclude 1997, 2005, and 2009 from the main analysis since they do not provide some important variables such as labor data and household member income.

Each survey contains a core questionnaire which consists of roster household characteristics, labor, health care, and educational attainment. SUSENAS conducted a quarterly survey stacked into yearly data sets; it sampling around 75,000 households on average for each survey period: March, June, September, and December. Therefore, it is typically composed of 200,000 to 300,000 households in one-year data sets.

For our research purposes, I use only children who are still in junior high school and senior high school, age groups between 13 and 18 years old. Our final sample consists of 418,207 observations, corresponding to 63% of total junior high school and senior high school students. For sensitivity check purposes, I include the years 1997, 2005 and 2009 in our analysis. To include these years, I exclude parent income data since they are not available, but I still have main health outcome variables.

3.5. Empirical method

Because the program was implemented at a national level, there is no obvious comparable control group available. Also, the program was implemented not only based on age but also on school level; that is, elementary and junior high school. Thus, some students in particular age groups who are supposed to be in the next school level may be still eligible if they are in either elementary or junior high school. For example, in Indonesia, the normal school age for junior high school students is from 13 to 15 years old. However, older children are still eligible if they are in junior high school.

Many factors confounded the impact of compulsory education and free tuition programs. Our economic model shows that higher parent income is more likely to increase the indirect utility of schooling, and students in urban areas are more likely to go to school because of more school facilities available lead to lower cost of schooling in term of transportation costs. Economic conditions, specifically countrywide hardships due to the recession and monetary crisis, could decrease schooling and force children to work. Increased medical care prices due to inflation could also reduce investment in child health care if increase household income less than increase in inflation. Thus, it may deteriorate child health. It complicates measuring the impact without any control group.

To address those problems, I construct 13- to 15-year-old children in junior high school as a treatment group and children 16- to 18-years-old in senior high school as a control group. Although eligible children are all elementary and junior high school students, I restricted the junior high group to 13-15 years and senior high group to 16-18 years because those are normal age groups in those school levels and mandated age to be at junior high school by the regulation. For example, 16- to 18-year-old students in senior high schools today were in junior high schools two to three years ago; thus, they might have similar ability as 13- to 15-year-old junior high school students today. But 16- to 18-year-olds who may be in junior high schools represent either children with less ability or children with household financing problems resulting in lower school performance. Also, I exclude elementary school students to avoid the impact of the 1993 elementary school mandates, which may confound our result, and to avoid too far of an age gap between the treatment and control groups.

The basic approach is a difference-in-differences (DID) estimation. Our baseline regression is of the form:

$$Y_{ist} = \alpha_0 + \alpha_1 T_{is} + \alpha_2 Post_t + \alpha_3 (T_{is} * Post_t) + \alpha_4 X`_{ist} + \gamma_s + \mu_t + \epsilon_{it} \quad (21)$$

where Y_{it} is an indicator variable of working, and health-related outcomes for individual i living in municipality s at time t. T_{is}, a treatment variable, is an indicator whether an individual is 13-15 years old and in junior high school, while the control group is 16-18 years old and in senior high school. $Post_t$ indicates whether period t is after the implementation of the new policy (2005 or later). $X`_{ist}$ is a vector of control variables for sex, age fixed effect, year of education, parent income, household size, and whether an individual life in a rural area. Control variables include the 1997-1998 Asian economic crisis, the 2008-2009 US recession, and the 2012-2014 worldwide recession. I separate the impact of the economic crisis/recession for the treatment and control groups to capture the different impacts of economic turmoil on those groups. I include municipality fixed effect (γ_s) and year fixed effect (μ_t) to capture unobserved differences in space and time, respectively; and ϵ_{ist} is the idiosyncratic error term. I cluster by household level to capture unobserved similarities among families.

I expand the standard DID approach above with a matching DID approach. Because of different age and school level between the treatment and control groups, some characteristics between those two groups may differ. Moreover, those compositional characteristics of the treatment and control groups may change over time since I observe different people over time using repeated cross-sectional data (Hong, 2013). For example, senior high school students are more likely to be married; thus, they are more likely to be out of school and instead working. Senior high school students are more likely than junior high school students to live in urban areas because of senior high school facility limitations in rural areas. However, due to senior high school construction, senior high schools become more common in rural areas over time, and this composition change may confound the impact of compulsory and free tuition programs. The impact magnitude is affected not only by the impact of compulsory and free tuition programs, but also the impact of the diffusion of schools opening.

To begin matching difference-in-differences, I first estimate multivariate propensity scores using standard propensity score matching methods (see, for examples Angrist & Pischke, 2008; Rosenbaum & Rubin, 1983). I thus estimate propensity scores treated separately for each year, both pre-treatment-year and post-treatment-year, following multivariate propensity score propensity score method from Hong (2013) using the following:

$$P(T_{ist} = 1 \mid Z_{ist}) = \phi(Z'_{ist}\beta) \tag{22}$$

where T_{ist} is a treatment indicator as described in equation (21), and Z_{ist} is a vector of covariates for gender, marital status, a log of parent income, household size, and whether a child is living in rural areas. I include the municipality in which children live in order to make sure that I matched children within the same municipality. Each year propensity score matching is used to balance the sample characteristics for both pre- and post-treatment periods from repeated cross-sectional data.

Suppose I have an estimated propensity score P_{ist} for an individual i who lives in municipality s at time t. I then impute those propensity scores for all observations as probability weights. I use the matched-sample and apply DID in equation (21), but including the probability weight for each matched observation.

3.6. Empirical results

In this section, I provide descriptive and our regression analysis for child labor and health outcomes. Robustness checks and falsifications are provided to tests sensitivity of our estimates.

3.6.1. Trends and descriptive statistics

Table 3.1 shows means and standard deviations for child labor and health outcomes. Work is a binary variable whether a child was working last week, or he is working but he was off last week. Illnesses outcomes are binary variables whether a child experienced either diarrhea, asthma, or migraine symptoms last month. Upper row for each variable is treatment group means and standard deviations, lower row for each variable is control group means and standard deviations. Column (1), (3), and (5) are means without matching procedures, column (2), (4), and (6) are means after matching process. I separate after intervention period into two groups, compulsory per-se (2003-2004) which compulsory education was implemented without any free tuition, and compulsory and free tuition period implemented.

Table 3.1. Means and Standard Deviations, Outcomes

Variables		Pre-Reform (<2003)		Compulsory (2003-2004)		+Free Tuition (>=2005)	
		w/o Matching	Matching	w/o Matching	Matching	w/o Matching	Matching
		(1)	(2)	(3)	(4)	(5)	(6)
Child Labor:							
Treatment		0.045(0.206)	0.045(0.085)	0.017(0.129)	0.016(0.032)	0.063(0.242)	0.063(0.117)
Control		0.062(0.241)	0.071(0.131)	0.040(0.195)	0.040(0.077)	0.132(0.242)	0.139(0.239)
Health Outcomes:							
Illness	(T)	0.038(0.190)	0.038(0.072)	0.031(0.174)	0.032(0.061)	0.034(0.182)	0.034(0.066)
	(C)	0.037(0.188)	0.038(0.073)	0.032(0.176)	0.030(0.059)	0.038(0.182)	0.040(0.077)
Diarrhea	(T)	0.004(0.066)	0.006(0.011)	0.008(0.092)	0.008(0.017)	0.007(0.086)	0.007(0.015)
	(C)	0.001(0.0008)	0.005(0.010)	0.006(0.076)	0.005(0.009)	0.007(0.086)	0.008(0.015)
Asthma	(T)	0.005(0.074)	0.005(0.011)	0.004(0.064)	0.004(0.008)	0.005(0.072)	0.005(0.010)
	(C)	0.004(0.066)	0.005(0.010)	0.004(0.065)	0.004(0.008)	0.006(0.072)	0.006(0.012)
Migraine	(T)	0.028(0.164)	0.028(0.054)	0.021(0.144)	0.021(0.042)	0.025(0.155)	0.024(0.048)
	(C)	0.029(0.168)	0.029(0.056)	0.024(0.152)	0.023(0.045)	0.028(0.155)	0.030(0.057)
N		31,328	25,625	23,805	19,287	325,381	267,484

For child labor, 4.5 percent of junior high schoolers were working, and 7 percent of senior high schoolers were working before the intervention period. Figure 3.2 provides the trend for child labor. Although both groups have a higher probability of working over time, the treatment group has a less steep trend of working after the intervention period. It supports the notion that there is a trade-off between time for schooling and time for working.

Table 3.1 suggests both groups have similar illness symptoms before the intervention period, but less likely experience illnesses symptoms after free tuition period were implemented. The treatment group less likely experience diarrhea, asthma and migraine symptoms after the free tuition period even though they either had a higher likelihood of diarrhea and asthma symptoms and similar migraine symptom before the intervention period. It indicates preliminary evidence of health outcomes improvement for the treatment group.

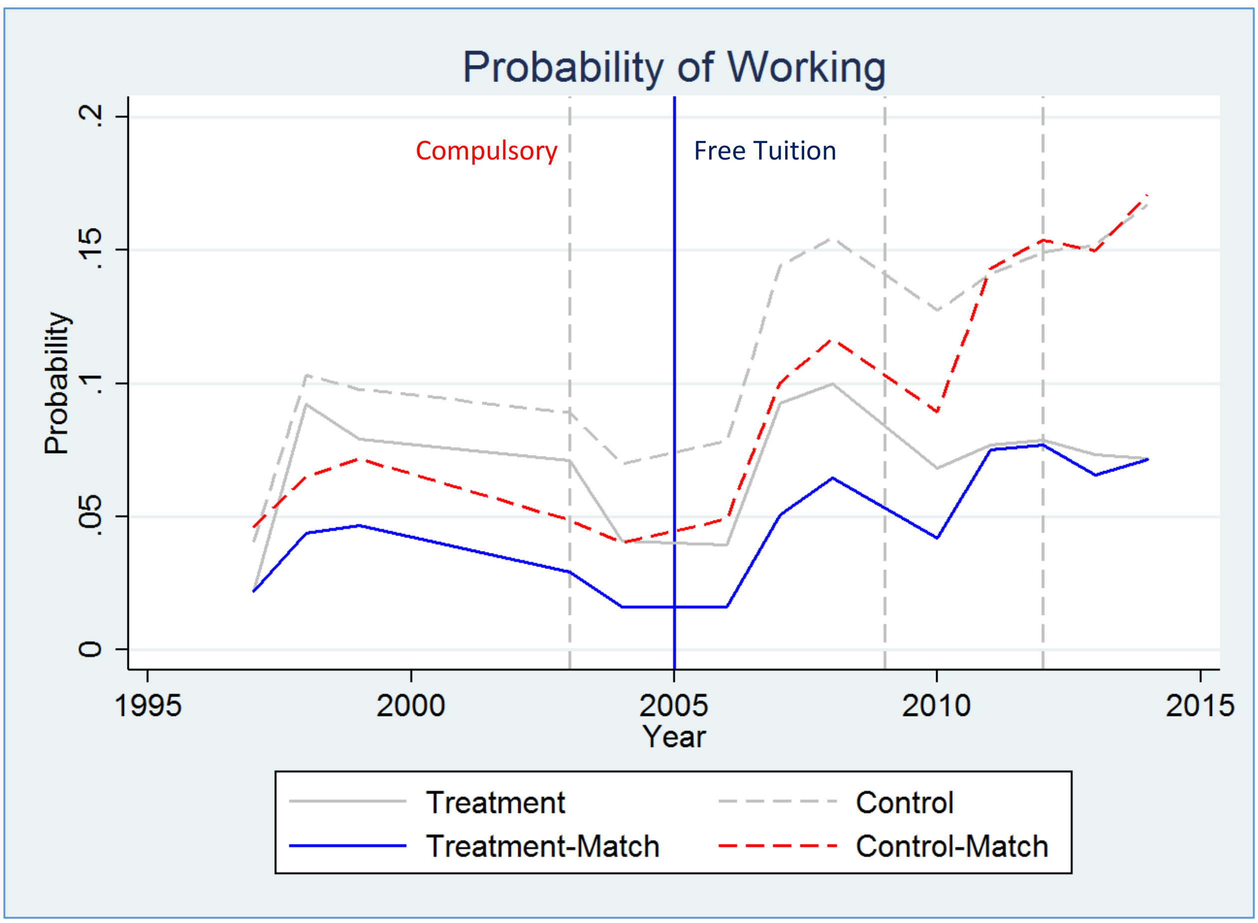


Figure 3.2. Probability of Working

Figure 3.3 provides the trend of children experiencing diarrhea, asthma, or migraine symptoms. The trend suggests economic crisis and turmoil in 1998 increased the gap between the two groups. It also suggests the probability of experiencing illnesses is lower for the treatment group after the intervention period.

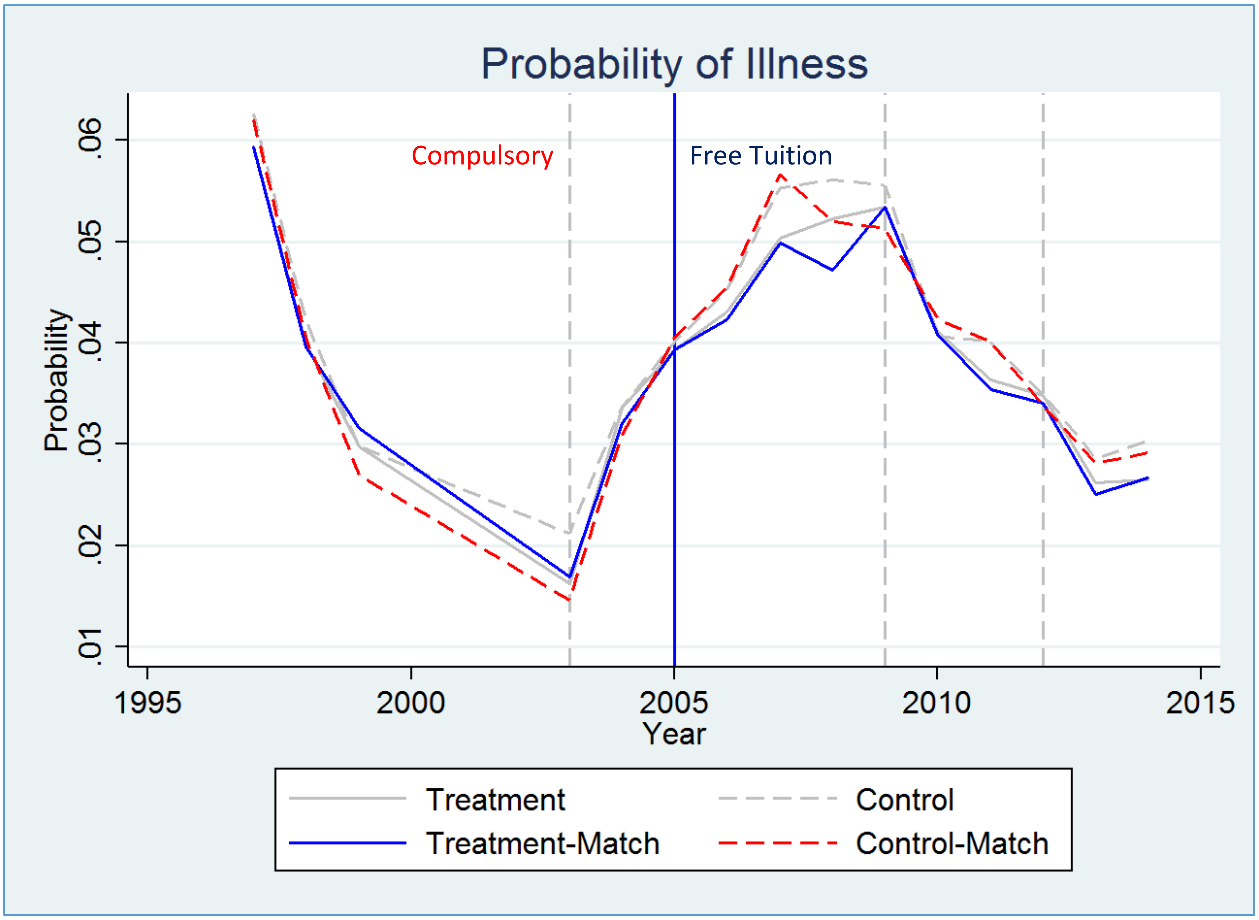


Figure 3.3.Probability of Experiencing Diarrhea, Asthma, Migraine

Table 3.2 provides control variables, means, and standard deviations. Even though outcome variables are similar between the two groups, sample demographics in columns (1), (3), and (5) suggest the control group is more likely to be married, have higher parental income, and reside in urban areas. I don't find any substantial difference in gender and household size between two groups. Columns (2), (4), and (6) provide demographics for the two groups after using propensity score matching. Propensity score matching balances marital status, parental income, and the household location, as previously shown in pre-matching. Also, propensity matching also balances geographic location between the two groups by eliminates control group from different municipalities (not shown), ensuring that the treatment and control groups are coming from the same municipalities.

Table 3.2. Means and Standard Deviations, Controls

Variables		Pre-Reform (<2003)		Compulsory (2003-2004)		+Free Tuition (>=2005)	
		w/o Matching	Matching	w/o Matching	Matching	w/o Matching	Matching
		(1)	(2)	(3)	(4)	(5)	(6)
Control							
Male	(T)	0.501(0.500)	0.502(0.500)	0.513(0.500)	0.512(0.500)	0.507(0.499)	0.507(0.500)
	(C)	0.501(0.500)	0.511(0.500)	0.509(0.500)	0.510(0.500)	0.509(0.499)	0.513(0.500)
Married	(T)	0.001(0.030)	0.001(0.002)	0.002(0.049)	0.002(0.005)	0.004(0.060)	0.004(0.007)
	(C)	0.004(0.065)	0.001(0.001)	0.006(0.079)	0.002(0.005)	0.015(0.060)	0.004(0.007)
Age	(T)	14.00(0.783)	14.00(0.475)	13.93(0.786)	13.93(0.480)	13.90(0.787)	13.90(0.483)
	(C)	17.00(0.785)	17.00(0.463)	17.00(0.789)	17.00(0.481)	16.92(0.787)	16.92(0.486)
Education	(T)	7.438(0.626)	7.437(0.369)	8.076(0.773)	8.077(0.464)	8.113(0.775)	8.113(0.463)
	(C)	10.547(0.645)	10.55(0.390)	11.20(0.778)	11.19(0.474)	11.219(0.775)	11.20(0.475)
Ln(Parent Inc)	(T)	15.176(0.815)	15.18(0.056)	16.30(0.777)	16.302(0.068)	16.683(0.920)	16.68(0.075)
	(C)	15.326(0.742)	15.20(0.056)	16.41(0.734)	16.320(0.069)	16.794(0.920)	16.68(0.078)
HH Size	(T)	5.637(1.685)	5.637(0.501)	5.374(1.557)	5.376(0.482)	5.136(1.652)	5.135(0.488)
	(C)	5.739(1.809)	5.671(0.496)	5.410(1.636)	5.435(0.484)	5.165(1.652)	5.180(0.490)
Rural	(T)	0.424(0.494)	0.424(0.488)	0.362(0.481)	0.361(0.461)	0.548(0.498)	0.548(0.495)
	(C)	0.298(0.458)	0.423(0.488)	0.276(0.447)	0.353(0.457)	0.466(0.498)	0.547(0.496)
N		31,328	25,625	23,805	19,287	325,381	267,484

Table 3.2 also shows substantial compositional changes between the two groups over time. Both groups are more likely to be married, have larger parent income, have a smaller household size, and be spread more evenly between rural and urban areas over time. It is common that widespread school opening in rural areas over time would increase the probability of schooling in

those rural areas. Also, previous research studies find that school openings significantly increases the probability of schooling (Chou et al., 2007; Duflo, 2000). It could cause positive bias because the effect estimated consists of not only the impact of compulsory education and free tuition but also differential impact for junior high school and senior high school opening in the rural areas.

People may be less likely to go to school and more likely to work when they are married. Therefore, there may be a positive effect estimated from the standard DID approach which may reflect this covariate difference. Similarly, parents with higher income are more likely to send their children to school and less likely to send their children to work. The treatment group consists of lower-income families; therefore, there may exist negative bias since the estimation includes the impact of being in a lower-income family. Propensity score matching, both pre- and post-intervention period, controls for those observable sources of bias, balancing their differences between two groups over time.

3.6.2. The impact on child labor

Table 3.3 provides DID and matching DID estimators for the probability of child labor for the populations of interest. Column (1) provides an estimator for standard DID, and column (2) shows the same child labor estimator for the matching DID approach. The dependent variable is an indicator equal to 1 if a child is working last week, or she/he usually works but is currently off this week. The questionnaire defines working as regular activities to earn income or profit for at least one hour per week.

Treatment is an indicator whether an individual is 13-15 years old and in junior high school, while the control group is 16-18 years old and in senior high school. In these regressions, there are five age dummy variables corresponding to age fixed effect for each age group, and interactions between the treatment variable and crisis/recession (the Asian economic crisis (1997-1998), the US recession (2008-2009), the global recession (2012-2014)) to capture the different impact between two groups. I include municipality fixed effect and year fixed effect and cluster the standard error by household level to capture unobserved differences among families.

Table 3.3. The Impact on Child Labor

VARIABLES	Standard DID	Matching DID
	Compulsory and Free Tuition	Compulsory and Free Tuition
	Work	Work
	(1)	(2)
Treatment*Post	-0.037***	-0.035***
	(0.002)	(0.003)
Observations	418,206	343,291
R-squared	0.115	0.118
Age FE	YES	YES
Controls*	YES	YES
Crisis and Recession**	YES	YES
Municipality FE	YES	YES
Year FE	YES	YES

* Controls include Gender, Marital Status, Education, HH Size, Parent Income and Rural
** Crisis and Recession include crisis/recession and interaction between crisis/recession and treatment

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Both models suggest similar results for the impact of compulsory education and free tuition on child labor. It implies bias from covariate imbalance does not greatly affect the estimated result. Both models suggest compulsory education and free tuition programs likely decrease working children more than 3.5 percentage points; it corresponds to more than 77-percent reduction from the pre-intervention period. It suggests free tuition more likely relaxes household budget constraints, and there is a trade-off between child labor and the accumulation of human capital for children. When children are more likely to stay in school, they are less likely to work in the labor market.

Although I find a substantial reduction in child labor, I find a partial instead of full trade-off between schooling and child labor. There are many children who both stay in school and are working. Our economic model suggests that the net impact of child labor depends not only on how important the reduction of cost of education is to easing household budget constraints, but also on how important child wages are to household consumption. One possible reason for this partial trade-off is there are some children who earn substantial wages for their household, probably children from very low-income families. Thus, they are forced to allocate their time between school and working.

3.6.3. Heterogeneity and the impact on child labor

I investigate whether the magnitude of compulsory and free tuition program impacts on child labor vary systematically by parental income, geographic location, and gender.

3.6.3.1.Parent income

My model predicts the loss in utility from sending the child to school is inversely related to the level of parental income, and this loss is very high for low-income families due to diminishing marginal utility. Low income families have less choice to put their children into school since they need their children's help in either household production, farms or labor market. If this is the case, then we would see a larger impact for low-income families than their counterparts.

Table 3.4. Heterogeneity Impact by Parent Income

	Heterogeneity Impact by Parent Income	
	Parent Income <50%	Parent Income >50%
VARIABLES	Work	Work
	(1)	(2)
Panel A: DID		
Treatment*Post	-0.046***	-0.027***
	(0.004)	(0.003)
Observations	213,617	204,266
R-squared	0.136	0.087
Panel B: Matching DID		
Treatment*Post	-0.044***	-0.026***
	(0.005)	(0.004)
Observations	180,356	162,935
R-squared	0.128	0.085
Controls* **	YES	YES
Municipality FE	YES	YES
Year FE	YES	YES

* Controls include Gender, Marital Status, Education, HH Size, Parent Income and Rural
** Crisis and Recession include crisis/recession and interaction between crisis/recession and treatment
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4 provides DID and matching DID estimators. Column (1) is the impact on child labor for parents with income in less than the 50% quartile, and column (2) is parent income from over the 50% quartile, for the population of interest. Panel A shows the DID method while panel B shows the matching DID model results. In line with our theoretical predictions, the results suggest compulsory education and free tuition programs relax household budget constraints and have higher impacts for lower-income families. Incorporates weight in matching DID models do not change our estimates.

3.6.3.2.Geographic location

Urban and rural areas could create different impacts on child labor in at least three ways: My theory predicts parents more likely send their children to school when return on education investment is larger than interest rates. If rural areas have more restrictive credit institutions, then I expect school subsidy would have a larger impact for households with credit constraints. On the other hand, rural areas have fewer school facilities, which hampers individuals attending school. Also, child labor in rural areas is a more common phenomenon due to cultural norms and farming or fishing occupations of the parents, thus resulting in less impact in education investment for rural communities.

Table 3.5. Heterogeneity Impact by Geographic Location

	Heterogeneity Impact by Rural/Urban	
	Urban	Rural
VARIABLES	Work	Work
	(1)	(2)
Standard DID		
Treatment*Post	-0.034***	-0.039***
	(0.003)	(0.005)
Observations	212,312	205,571
R-squared	0.083	0.134
Matching DID		
Treatment*Post	-0.029***	-0.043***
	(0.004)	(0.006)
Observations	166,661	176,630
R-squared	0.077	0.123
Control* **	YES	YES
Municipality FE	YES	YES
Year FE	YES	YES

* Controls include Gender, Marital Status, Education, HH Size, Parent Income and Rural
** Crisis and Recession include crisis/recession and interaction between crisis/recession and treatment

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5 provides similar regressions as Table 3.4 for urban and rural areas. The model suggests compulsory education and free tuition programs more likely reduce child labor for children in rural areas than children in urban areas. Therefore, the results support the notion that subsidies help lower-income families with more credit constraints.

3.6.3.3.Gender

It is a common phenomenon in developing countries that males more likely work in the farm or labor market, while females more likely work in household production. If compulsory education and free tuition programs reduce the probability of children who are working to earn income or profit for their families, then we would expect a larger impact for male than female children.

Table 3.6. Heterogeneity Impact by Gender

	Heterogeneity Impact by Gender	
	Female	Male
VARIABLES	Work	Work
	(1)	(2)
Standard DID		
Treatment*Post	-0.033***	-0.039***
	(0.003)	(0.004)
Observations	205,543	212,340
R-squared	0.103	0.136
Matching DID		
Treatment*Post	-0.028***	-0.042***
	(0.004)	(0.005)
Observations	168,621	174,670
R-squared	0.102	0.127
Municipality FE	YES	YES
Year FE	YES	YES

* Controls include Gender, Marital Status, Education, HH Size, Parent Income and Rural
** Crisis and Recession include crisis/recession and interaction between crisis/recession and treatment
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6 provides estimators for male and female children. Table 3.6 has specifications analogous to Tables 3.4 and 3.5. All columns point to the general conclusion that the compulsory education supported by free tuition programs more likely decreases the probability of working. It shows the impact on child labor is higher for males than females. It supports the notion that boys are more likely to work in the labor market than girls. Thus, free tuition decreases the chance of children working in the labor market earning income and profit for their parents.

3.6.4. The impact on health outcomes

3.6.4.1.Diarrhea, asthma or migraine

Table 3.7 provides the estimated results for the probability of illness. Morbidity is a binary variable equal to 1 if a child experienced either diarrhea, asthma, or a migraine last month. Column (1) presents the standard DID approach while column (2) is the matching DID approach. Similar to previous schooling and working outcomes, both include controls for gender, marital status, age fixed effect, year of education, household size, a log of parent income, and whether a child is living in rural or urban areas. I also include crisis/recession period, municipality fixed effect and year fixed effects.

Both models suggest similar results on the impact of compulsory education and free tuition on morbidity symptoms, larger for the matching DID than for the standard DID approach. It suggests bias from covariate imbalance does not vastly affect the estimated result. Both models suggest compulsory education and free tuition program are more likely to decrease experiences of morbidity symptoms more than 0.5 percentage points; it corresponds to more than a 15-percent reduction from the pre-intervention period. It supports the notion that compulsory education and free tuition significantly increase schooling and decrease child labor, making children healthier.

Table 3.7. The Impact on Illnesses' Symptoms

VARIABLES	Standard DID	Matching DID
	Compulsory and Free Tuition	Compulsory and Free Tuition
	Illnesses Symptoms	Illnesses Symptoms
	(1)	(2)
Treatment*Post	-0.005**	-0.007***
	(0.002)	(0.003)
Observations	418,207	343,292
R-squared	0.014	0.015
Age FE	YES	YES
Controls*	YES	YES
Crisis and Recession**	YES	YES
Municipality FE	YES	YES
Year FE	YES	YES

* Controls include Gender, Marital Status, Education, HH Size, Parent Income and Rural
** Crisis and Recession include crisis/recession and interaction between crisis/recession and treatment
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.6.4.2.By type of morbidity group

I provide standard DID and matching DID estimates for three different morbidity groups in Table 3.8. Column (1) provides diarrhea symptoms, column (2) shows asthma symptoms, and column (3) shows migraine symptoms. Table 3.8 has specifications analogous to previous tables. The models suggest compulsory education and free tuition programs more likely reduce the probability of experiencing diarrhea symptoms by more than 0.2 percentage points, or more than a 25-percent reduction from the pre-free-tuition period. The intervention policy also more likely reduces migraine-symptom probability by more than 0.3 percentage points, or more than a 14-percent reduction from the pre-free-tuition period. I find negative sign, although not significant, for asthma symptoms.

Table 3.8. The Impact on Diarrhea, Asthma, or Migraine

VARIABLES	Standard and Matching DID		
	Compulsory and Free Tuition		
	Diarrhea	Asthma	Migraine
	(1)	(2)	(3)
Standard Difference-in-Difference			
Treatment*Post	-0.002*	-0.000	-0.003*
	(0.001)	(0.001)	(0.002)
Observations	418,207	418,207	418,207
R-squared	0.004	0.003	0.014
Matching Difference-in-Difference			
Treatment*Post	-0.003**	-0.001	-0.004*
	(0.001)	(0.001)	(0.002)
Observations	343,292	343,292	343,292
R-squared	0.005	0.003	0.015
Age FE	YES	YES	YES
Controls*	YES	YES	YES
Crisis and Recession**	YES	YES	YES
Municipality FE	YES	YES	YES
Year FE	YES	YES	YES

* Controls include Gender, Marital Status, Education, HH Size, Parent Income and Rural
** Crisis and Recession include crisis/recession and interaction between crisis/recession and treatment

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Diarrhea may occur because of bacterial infection, parasites, or food poisoning. It is a morbidity symptom that causes the highest inpatient medical care in hospitals in Indonesia (Ministry of Health, Republic of Indonesia, 2011). Stress may cause migraine symptoms. Physically-demanding labor and long work hours for children may cause child stress. Asthma is a chronic inflammation disorder of the airways that leads to recurrent episodes of wheezing, breathlessness, chess tightness, and coughing (World Health Organization, 2003). Half cases of asthma are due to heredity and half result of environmental factors, including air pollutants (Oryszczyn et al., 2000; World Health Organization, 2003). These findings support the notion that increasing schooling and lowering child labor for children may have a beneficial health impact on children. They have more leisure playing with their friends at school. They are also less exposed to unhealthy environments because of a reduced chance of working long hours in physically-demanding and/or unhealthy jobs such as garbage scavenging, food sales, or newspaper delivery.

3.7. Impact of compulsory education per se

The timing difference between the implementation of compulsory education per se and supporting free tuition creates an opportunity to investigate the impact of compulsory education per se without any other supporting education policy such as free tuition. Table 3.9 provides DID and matching DID estimators for child labor, and morbidity symptoms. The specifications in Table 3.9 columns (1) and (2) are analogous to previous tables. The compulsory education period was the years 2003 and 2004 before free tuition was implemented. Column (1) is the impact on child labor, and column (2) is the impact on diarrhea, asthma, or migraine symptoms.

The model suggests compulsory education per se does not significantly affect child labor and illness symptoms. Even though they are not significant, the matching DID model suggests compulsory education per se may increase the probability of child labor. However, smaller sample size might also cause insignificant results. It supports the economic model that compulsory education per se may increase household financial burdens, because families need to raise more money to pay school tuition and any other associated costs, when previously they had not needed to send their children to school. Raising the household burden may force children to work harder.

Table 3.9. The Impact of Compulsory Education

VARIABLES	Compulsory Education Year <=2004	
	Work	Illness
	(1)	(2)
Standard DID		
Treatment*Post	-0.002	-0.005
	(0.006)	(0.004)
Observations	55,133	55,133
R-squared	0.060	0.019
Matching DID		
Treatment*Post	0.004	-0.002
	(0.007)	(0.005)
Observations	44,913	44,913
R-squared	0.067	0.022
Age FE	YES	YES
Controls*	YES	YES
Crisis and Recession**	YES	YES
Municipality FE	YES	YES
Year FE	YES	YES

* Controls include Gender, Marital Status, Education, HH Size, Parent Income and Rural
** Crisis and Recession include crisis/recession and interaction between crisis/recession and treatment

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.8. Robustness checks and falsification tests

I employ robustness checks and falsification of our regression estimates to tests sensitivity of our estimates to omitted variable biases and difference-in-differences identifying assumption.

3.8.1. Robustness checks

In this section, I employ robustness checks to test the robustness of our primary results. I estimate variations of equation (21) both for compulsory education and free tuition and compulsory education per se as robustness checks. Table N.1 provides robustness test results for compulsory and free tuition intervention. I use four specifications for each primary outcome both for standard DID and matching DID approaches. Column (1) is a baseline regression provided in our primary results. Column (2) excludes municipality fixed effect and time effects. If the particular local government was decreasing or increasing their budget allocation to the school, then I would expect substantial impacts on the program. Our results are robust to those specifications. Column (3) excludes years 2012-2014, and column (4) excludes 2009-2014, as the government substantially increased the amount of school funding per student in 2009 and 2012. I find periods with larger funding leads to a larger reduction in the probability of child labor.

3.8.2. Falsification tests

The identifying assumption for the DID approach is common parallel trends between treatment and control groups without any intervention. It implies that, without any intervention, both treatment and control groups would have parallel trends over time before the treatment period. I estimate various specification tests for artificial effects during the pre-treatment years. Table O.1 provides falsification tests for our three primary outcomes. I use the year 1999 as our artificial intervention since 1997, 1998 and 1999 are our pre-treatment years.

I implement four different specifications for each outcome. In column (1), I exclude log of parent income since income data were not available in 1997. It gives us a two-year pre-artificial-intervention (1997-1998) and one post-artificial-intervention period (1999). I include a log of parent income in column (2), thus excluding 1998 in our regression. Columns (3) and (4) follow similar specifications as columns (1) and (2), respectively. But I include both compulsory effects, compulsory and free tuition effect in the regression to capture any impact that comes from those interventions. These specifications give us three treatment*post and post variables, one for artificial intervention and the rest for the actual intervention periods. In general, the model suggests that no estimators are significant and substantial reduced estimation magnitude. This result supports the notion that difference in outcomes is likely driven by the actual interventions.

3.9. Conclusion

It is widely accepted, in both developed and developing countries, that improvements in education, reduction in child labor, and increases in positive health outcomes are important public policies. The Indonesian government mandated all elementary and junior high schoolers to have a nine-year education, and they also supported the program with free tuition for these children as a natural experiment allowing us to analyze the impacts of compulsory education and free tuition programs on child labor and health outcomes. Overall, I find that children affected by compulsory and free tuition programs are less likely to provide child labor and have improved health outcomes. Larger impacts occur for low-income families, children in rural areas, and males. These imply free tuition eases their household budget constraints to keep their children in school and away from working.

Our empirical results should be of interest to researchers and policymakers for designing and assessing compulsory education programs in developing countries. Our model implies compulsory education per se may not be effective to put children into school if the government does not give additional incentives for relaxing families' household budget constraints.

CONCLUSION REMARKS

This dissertation examines three government policies about health and education in Indonesia and how their implication to the society. The first chapter examines the impact of mobile hospital availability in underdeveloped and remote regions on medical care utilization using difference-in-differences and matching difference-in-differences approaches. I found evidence that mobile hospital existence likely increases inpatient and outpatient utilization at public hospitals for municipalities which are located on main islands without any substitution effect for medical care utilization in private hospitals. I did not find evidence of increased public-hospital utilization for municipalities located on outer islands. A mobile hospital is located in one of the various small islands within districts. I have suggested that travel distance matters. I found that only areas in which new hospitals are closer than existing hospitals benefit from the intervention. Also, locations farther from newly-built hospitals are less likely to have inpatient and outpatient at public hospitals. Household more likely spends more on health when new hospitals appear. Our study suggests not only facility health center existence in remote areas, but also infrastructure, in general, are both critical to improving medical care utilization.

Indonesia first introduced its universal insurance scheme in 2014. One interesting feature is expansion dependent coverage from only the first two children to three children. A unique dependent coverage scheme for government-provided insurance allows us to analyze the impact of public insurance on medical care utilization in this second chapter. I find that eligible children are more likely to go to public hospitals for outpatient utilization. There is a more considerable impact when I include both eligibility and co-payment reduction effects. That is, universal health coverage not only adds the third children to the scheme but also includes a co-payment reduction from their initial program (*Askes*). I do not find evidence of increases in outpatient care in clinics, though there is a slight reduction in clinic outpatient care. The negligible price differential between insured and uninsured children in the public health center (*Puskesmas*) and different medical technological equipment between clinics and hospitals may be two reasons why there is slight reduction on public health centers.

The Indonesian government mandated all elementary and junior high schoolers to have a nine-year education, and they also supported the program with free tuition for these children as a natural experiment allowing us to analyze the impacts of compulsory education and free tuition programs on child labor and health outcomes in our last chapter. Overall, I find that children affected by compulsory and free tuition programs are less likely to seek child labor and have improved health outcomes. Larger impacts occur for low-income families, children in rural areas, and males. These imply free tuition eases their household budget constraints to keep their children in school and away from working.

Our empirical results should be of interest to researchers and policymakers for designing and assessing health and education policies in developing countries. On the whole, government policies understudies here are essential to the society in general. Deepen understanding population and geographic characteristics for those implemented systems such as household income, household occupation, rural/urban areas and a municipality archipelago could improve policy targeting. Furthermore, comparing how similar policy works in developed and developing countries may understand to promote those systems.

APPENDICES

Appendix A: Travel Distance Information From Google Developer

origin_lat	origin_lon	origin_address	destination_lat	destination_lon	destination_address	overview_polyline
4.8812885	96.77144	Pintu Rime Gayo, Bener Meriah Regency, Aceh, Indon…	4.6963269	96.8607181	Serule Kayu, Bukit, Bener Meriah Regency, Aceh 245…	akx\otsmQzCoHVsDj@kDnA_@fEh@jCw@r@xCjLvBb…
4.6502384	97.13594		4.69584	96.86008		
4.7256780	96.99524	Mesidah, Bener Meriah Regency, Aceh, Indonesia	4.6963269	96.8607181	Serule Kayu, Bukit, Bener Meriah Regency, Aceh 245…	o~y[gk_oQeBvBgAnCa@pBEn@K`EN~GEhAKdAuBrG}…
4.7641173	96.78254	Timang Gajah, Bener Meriah Regency, Aceh, Indonesia	4.6963269	96.8607181	Serule Kayu, Bukit, Bener Meriah Regency, Aceh 245…	wna\{yumQTXTXh@fA^dAHt@Ej@KN[LMF?NHRT^DRB…
4.8140840	96.93441	Permata, Bener Meriah Regency, Aceh, Indonesia	4.6963269	96.8607181	Serule Kayu, Bukit, Bener Meriah Regency, Aceh 245…	_gk\aosnQfB_GzDoNn@eBdBoBxMyLfUyT~@e@fA_…
4.7044804	96.95552	Bandar, Bener Meriah Regency, Aceh, Indonesia	4.6963269	96.8607181	Serule Kayu, Bukit, Bener Meriah Regency, Aceh 245…	_zu[_swnQqOnFkKzGmEzFoGxE}IxEcGfGeFfHsCzF_B…
4.8071185	96.75974	Gajah Putih, Bener Meriah Regency, Aceh, Indonesia	4.6963269	96.8607181	Serule Kayu, Bukit, Bener Meriah Regency, Aceh 245…	o{i\kkqmQgAvCuAhCs@`Cq@|HOv@y@rDMlF}@lB}Bf…
4.7259694	96.80298	Wih Pesam, Bener Meriah Regency, Aceh, Indonesia	4.6963269	96.8607181	Serule Kayu, Bukit, Bener Meriah Regency, Aceh 245…	i`z[syymQ?UEWQUa@]o@c@KMEUBW`@g@n@u@d@…
4.7750335	96.91715	Bener Kelipah, Bener Meriah Regency, Aceh, Indonesia	4.6963269	96.8607181	Serule Kayu, Bukit, Bener Meriah Regency, Aceh 245…	}rc\ecpnQBYAYISQMy@_@mAi@w@W{MsDiH}ANgCJs…
4.7254345	96.86768	Bukit, Bener Meriah Regency, Aceh, Indonesia	4.6963269	96.8607181	Serule Kayu, Bukit, Bener Meriah Regency, Aceh 245…	}|y[_nfnQFe@R{@Pg@dAqCh@yAPa@~@b@`Ab@rB`A…

bound_sw_lat	bound_sw_lon	bound_ne_lat	bound_ne_lon	totalduration_seconds	totalduration_text	totaldistance_meter	totaldistance_text	travelmode
4.6955107	96.73171	4.8812885	96.86334	4233	1 hour 11 mins	42645	42.6 km	DRIVING
NA	NA	NA	NA	NA		NA		
4.6954853	96.85920	4.7554485	96.99524	3238	54 mins	21408	21.4 km	DRIVING
4.6954853	96.76644	4.7641173	96.86339	2080	35 mins	19873	19.9 km	DRIVING
4.6954853	96.85920	4.8140840	96.94529	2275	38 mins	20135	20.1 km	DRIVING
4.6954853	96.85920	4.7554485	96.95552	3920	1 hour 5 mins	25405	25.4 km	DRIVING
4.6954853	96.73172	4.8170107	96.86339	3116	52 mins	31196	31.2 km	DRIVING
4.6954853	96.80298	4.7294291	96.86339	1102	18 mins	10809	10.8 km	DRIVING
4.6954853	96.85920	4.7799889	96.92337	1842	31 mins	15225	15.2 km	DRIVING
4.6954853	96.85920	4.7254345	96.87205	511	9 mins	4533	4.5 km	DRIVING

Figure A. 1. Travel Distance Information Obtained from Google Developer using R

Appendix B: Include Malinau Municipality

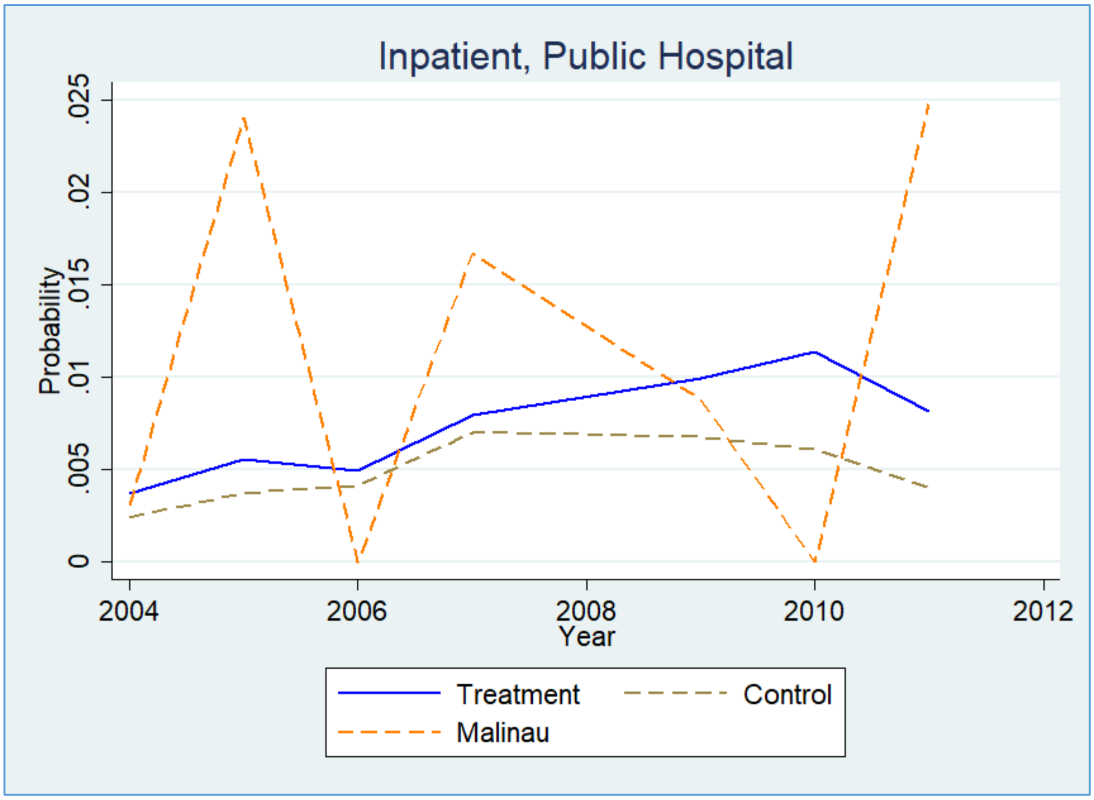


Figure B. 1. Inpatient in Public Hospital (Include Malinau Municipality)

Appendix C: Medical Care Utilization, Outer Islands

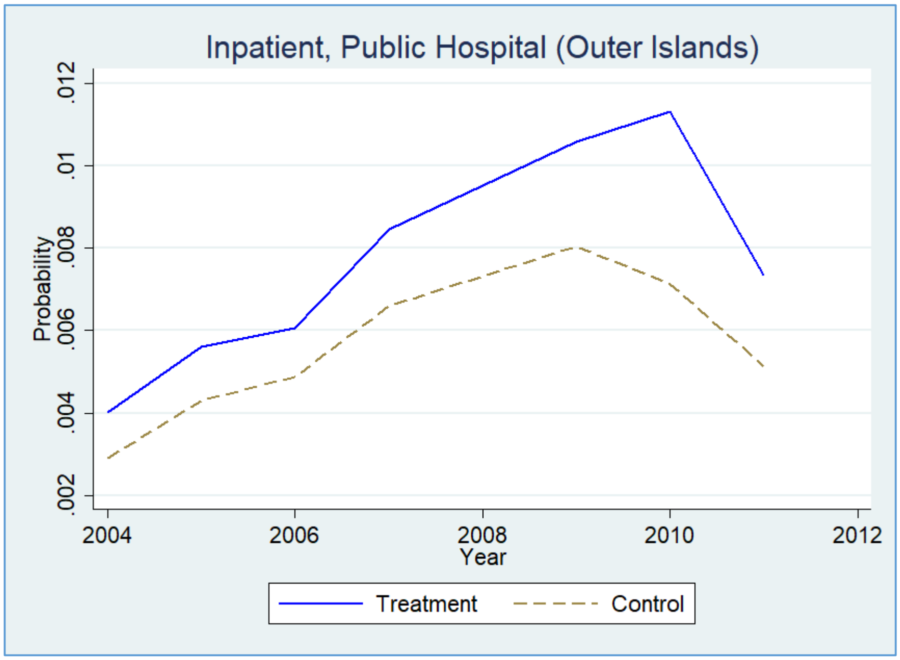


Figure C. 1. Inpatient in Public Hospital: Outer Islands

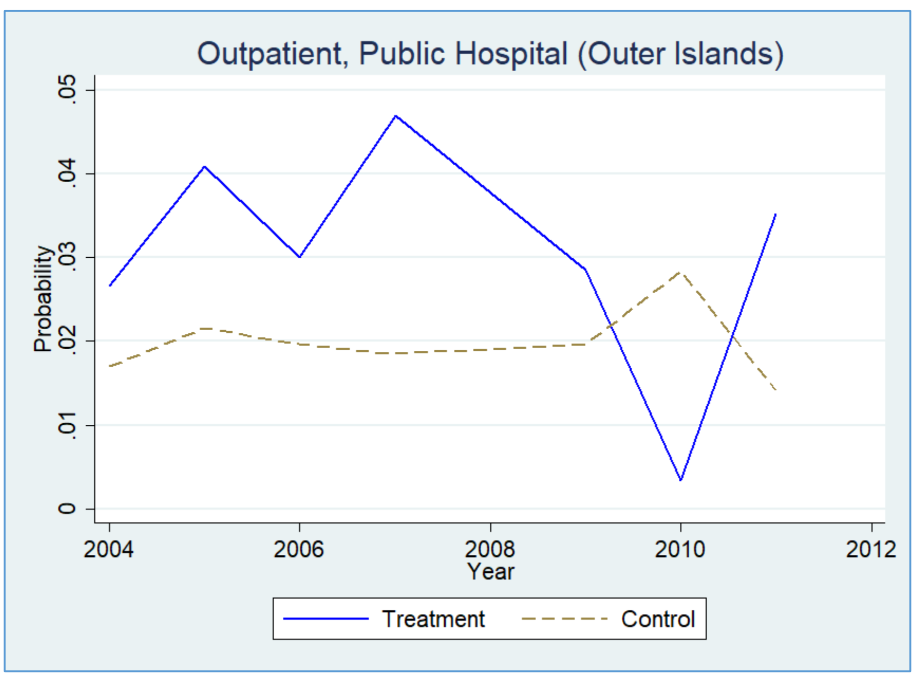


Figure C. 2. Outpatient in Public Hospital: Outer Islands

Appendix D: Robustness Checks, Primary Outcomes

Table D. 1. Robustness Checks: The Impact on Inpatient in Public Hospital (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0026***	0.0019**	0.0020**	0.0023***	0.0019**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)
Treatment	0.0013***	0.0011**	0.0009*		
	(0.0005)	(0.0005)	(0.0005)		
Post	0.0007**	0.0008***	0.0008**		
	(0.0003)	(0.0003)	(0.0003)		
Male		-0.0005*	-0.0005*	-0.0004	-0.0004
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0003	0.0003	0.0007*	0.0007*
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Education		0.0001***	0.0001***	0.0001**	0.0001**
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rural		-0.0084***	-0.0082***	-0.0073***	-0.0074***
		(0.0007)	(0.0007)	(0.0007)	(0.0007)
HH Size		-0.0000	-0.0000	0.0000	0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			0.0018**	-0.0005	-0.0005
(Central Gov)			(0.0008)	(0.0014)	(0.0014)
Public Hospital			-0.0007**	0.0001	0.0002
(Local Gov)			(0.0003)	(0.0006)	(0.0006)
Travel Distance			-0.0009***	-0.0009**	-0.0009**
(Total (100 Km))			(0.0002)	(0.0003)	(0.0003)
Travel Distance			0.0010***	0.0025***	0.0026***
(Water (100 Km))			(0.0002)	(0.0004)	(0.0004)
# of Beds/1000			-0.0002	-0.0007*	-0.0009**
population			(0.0002)	(0.0004)	(0.0004)
Constant	0.0046***	0.0087***	0.0097***	0.0039***	0.0109***
	(0.0002)	(0.0009)	(0.0009)	(0.0013)	(0.0019)
Observations	308,968	307,279	303,291	303,291	303,291
R-squared	0.0003	0.0028	0.0029	0.0048	0.0050
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 2. Robustness Checks: The Impact on Inpatient in Public Hospital (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0014	0.0008	0.0009	0.0013	0.0015
	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0010)
Treatment	0.0022***	0.0017***	0.0016***		
	(0.0005)	(0.0005)	(0.0006)		
Post	0.0010**	0.0008*	0.0010**		
	(0.0004)	(0.0004)	(0.0005)		
Male		-0.0003	-0.0003	-0.0002	-0.0002
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0006	0.0006	0.0009	0.0009
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
Education		0.0001**	0.0001**	0.0001**	0.0001**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0081***	-0.0079***	-0.0068***	-0.0069***
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
HH Size		0.0000	-0.0000	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			0.0024	0.0040	0.0038
(Central Gov)			(0.0020)	(0.0047)	(0.0046)
Public Hospital			-0.0014***	0.0000	0.0001
(Local Gov)			(0.0005)	(0.0007)	(0.0008)
Travel Distance			-0.0009***	-0.0010**	-0.0010**
(Total (100 Km))			(0.0003)	(0.0004)	(0.0004)
Travel Distance			0.0010***	0.0029***	0.0032***
(Water (100 Km))			(0.0003)	(0.0005)	(0.0005)
# of Beds/1000			-0.0008***	-0.0016***	-0.0018***
population			(0.0002)	(0.0006)	(0.0006)
Constant	0.0045***	0.0030***	0.0052***	0.0050***	0.0099***
	(0.0003)	(0.0011)	(0.0013)	(0.0019)	(0.0022)
Observations	299,193	299,193	299,193	299,193	299,193
R-squared	0.0004	0.0028	0.0030	0.0054	0.0057
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 3. Robustness Checks: The Impact on Outpatient in Public Hospital (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0156***	0.0134***	0.0152***	0.0171***	0.0168***
	(0.0038)	(0.0037)	(0.0038)	(0.0039)	(0.0043)
Treatment	0.0108***	0.0103***	0.0066***		
	(0.0022)	(0.0022)	(0.0022)		
Post	-0.0038***	-0.0023*	-0.0029**		
	(0.0013)	(0.0014)	(0.0014)		
Male		0.0010	0.0008	0.0006	0.0005
		(0.0010)	(0.0011)	(0.0011)	(0.0011)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0008	0.0008	0.0011	0.0011
		(0.0014)	(0.0014)	(0.0014)	(0.0014)
Education		0.0006***	0.0006***	0.0006***	0.0007***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Rural		-0.0335***	-0.0338***	-0.0350***	-0.0350***
		(0.0034)	(0.0034)	(0.0035)	(0.0035)
HH Size		0.0006*	0.0006	-0.0000	0.0001
		(0.0003)	(0.0003)	(0.0004)	(0.0004)
Public Hospital			0.0079**	-0.0040	-0.0019
(Central Gov)			(0.0038)	(0.0048)	(0.0048)
Public Hospital			-0.0009	-0.0014	-0.0010
(Local Gov)			(0.0016)	(0.0023)	(0.0024)
Travel Distance			0.0011	0.0016	0.0015
(Total (100 Km))			(0.0011)	(0.0016)	(0.0016)
Travel Distance			0.0034***	0.0030*	0.0028
(Water (100 Km))			(0.0011)	(0.0018)	(0.0018)
# of Beds/1000			0.0025***	0.0013	-0.0003
population			(0.0009)	(0.0019)	(0.0019)
Constant	0.0197***	0.0392***	0.0359***	0.1001***	0.1227***
	(0.0010)	(0.0040)	(0.0042)	(0.0196)	(0.0206)
Observations	75,407	75,104	74,401	74,401	74,401
R-squared	0.0031	0.0090	0.0103	0.0164	0.0189
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 4. Robustness Checks: The Impact on Outpatient in Public Hospital (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	0.0115***	0.0100**	0.0115***	0.0118**	0.0119***
	(0.0044)	(0.0044)	(0.0044)	(0.0046)	(0.0046)
Treatment	0.0126***	0.0103***	0.0058**		
	(0.0027)	(0.0026)	(0.0025)		
Post	-0.0038**	-0.0045**	-0.0046**		
	(0.0019)	(0.0019)	(0.0019)		
Male		0.0023	0.0020	0.0015	0.0013
		(0.0015)	(0.0015)	(0.0015)	(0.0015)
Age		0.0001***	0.0001***	0.0001**	0.0001**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married		0.0011	0.0010	0.0014	0.0014
		(0.0020)	(0.0020)	(0.0020)	(0.0020)
Education		0.0005**	0.0006***	0.0006***	0.0006***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Rural		-0.0432***	-0.0439***	-0.0465***	-0.0459***
		(0.0052)	(0.0050)	(0.0051)	(0.0050)
HH Size		0.0005	0.0004	0.0001	0.0002
		(0.0005)	(0.0005)	(0.0006)	(0.0006)
Public Hospital			0.0086	-0.0129**	-0.0144**
(Central Gov)			(0.0063)	(0.0058)	(0.0062)
Public Hospital			-0.0021	-0.0056*	-0.0052*
(Local Gov)			(0.0023)	(0.0030)	(0.0031)
Travel Distance			-0.0003	-0.0018	-0.0021
(Total (100 Km))			(0.0013)	(0.0019)	(0.0019)
Travel Distance			0.0053***	0.0046**	0.0050**
(Water (100 Km))			(0.0013)	(0.0021)	(0.0022)
# of Beds/1000			0.0026**	0.0015	-0.0014
population			(0.0011)	(0.0027)	(0.0025)
Constant	0.0210***	0.0494***	0.0464***	0.1392***	0.1570***
	(0.0013)	(0.0059)	(0.0064)	(0.0264)	(0.0280)
Observations	73,435	73,435	73,435	73,435	73,435
R-squared	0.0030	0.0114	0.0137	0.0197	0.0242
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 5. Robustness Checks: The Impact on Inpatient in Public Hospital (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0021***	0.0020***	0.0025***	0.0034***	0.0023***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)
Treatment	0.0013***	0.0008*	0.0003		
	(0.0004)	(0.0004)	(0.0004)		
Post	0.0021***	0.0020***	0.0007**		
	(0.0002)	(0.0002)	(0.0003)		
Morbidity		0.0122***	0.0122***	0.0118***	0.0118***
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Male		-0.0007***	-0.0007***	-0.0006***	-0.0006***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		-0.0001	-0.0001	0.0002	0.0002
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Education		0.0003***	0.0003***	0.0003***	0.0003***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rural		-0.0077***	-0.0075***	-0.0068***	-0.0069***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
HH Size		0.0002***	0.0001**	0.0002**	0.0002**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Inaccessible			-0.0004	0.0012**	0.0015**
Nearby			(0.0003)	(0.0006)	(0.0006)
Public Hospital			0.0005***	0.0003**	0.0007***
Nearby			(0.0001)	(0.0001)	(0.0002)
Ln(GRDP/Cap)			0.0001	-0.0018***	-0.0022***
			(0.0002)	(0.0006)	(0.0006)
Ln(Population)			-0.0009***	-0.0009***	-0.0005
			(0.0002)	(0.0003)	(0.0004)
Constant	0.0044***	0.0017**	0.0112***	0.0219***	0.0181**
	(0.0002)	(0.0007)	(0.0029)	(0.0062)	(0.0073)
Observations	555,286	547,536	547,536	547,536	547,536
R-squared	0.0004	0.0084	0.0086	0.0102	0.0105
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 6. Robustness Checks: The Impact on Inpatient in Public Hospital (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0024***	0.0021***	0.0026***	0.0036***	0.0025***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Treatment	0.0011**	0.0004	-0.0001		
	(0.0005)	(0.0005)	(0.0005)		
Post	0.0015***	0.0018***	0.0009***		
	(0.0003)	(0.0003)	(0.0003)		
Morbidity		0.0129***	0.0130***	0.0126***	0.0126***
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Male		-0.0007***	-0.0008***	-0.0007***	-0.0007***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0002	0.0002	0.0005	0.0004
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Education		0.0004***	0.0004***	0.0003***	0.0003***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rural		-0.0073***	-0.0072***	-0.0065***	-0.0066***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
HH Size		0.0002***	0.0001**	0.0001**	0.0002**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Inaccessible			0.0001	0.0012**	0.0015**
Nearby			(0.0003)	(0.0006)	(0.0006)
Public Hospital			0.0006***	0.0002*	0.0007***
Nearby			(0.0001)	(0.0001)	(0.0002)
Ln(GRDP/Cap)			-0.0001	-0.0014**	-0.0017**
			(0.0002)	(0.0007)	(0.0007)
Ln(Population)			-0.0008***	-0.0008**	-0.0004
			(0.0002)	(0.0004)	(0.0004)
Constant	0.0049***	0.0010	0.0116***	0.0174***	0.0123
	(0.0002)	(0.0007)	(0.0031)	(0.0067)	(0.0079)
Observations	547,536	547,536	547,536	547,536	547,536
R-squared	0.0004	0.0088	0.0089	0.0104	0.0107
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 7. Robustness Checks: The Impact on Outpatient in Public Hospital (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	0.0208***	0.0188***	0.0230***	0.0223***	0.0217***
	(0.0033)	(0.0033)	(0.0033)	(0.0034)	(0.0036)
Treatment	0.0108***	0.0097***	0.0037		
	(0.0022)	(0.0022)	(0.0023)		
Post	0.0012	0.0008	-0.0050***		
	(0.0012)	(0.0012)	(0.0014)		
Male		0.0015*	0.0011	0.0012	0.0010
		(0.0009)	(0.0009)	(0.0009)	(0.0009)
Age		0.0002***	0.0002***	0.0002***	0.0002***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		-0.0000	-0.0007	0.0003	0.0004
		(0.0011)	(0.0012)	(0.0012)	(0.0012)
Education		0.0009***	0.0010***	0.0009***	0.0009***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0336***	-0.0337***	-0.0333***	-0.0335***
		(0.0026)	(0.0027)	(0.0026)	(0.0026)
HH Size		0.0013***	0.0011***	0.0004	0.0005*
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Inaccessible			0.0042***	0.0094***	0.0101***
Nearby			(0.0014)	(0.0025)	(0.0027)
Public Hospital			0.0027***	0.0026***	-0.0001
Nearby			(0.0004)	(0.0006)	(0.0010)
Ln(GRDP/Cap)			-0.0015**	0.0042	0.0038
			(0.0007)	(0.0029)	(0.0030)
Ln(Population)			-0.0083***	-0.0012	0.0026
			(0.0009)	(0.0015)	(0.0021)
Constant	0.0198***	0.0343***	0.1474***	0.0306	-0.0006
	(0.0009)	(0.0033)	(0.0141)	(0.0320)	(0.0377)
Observations	120,939	117,259	117,259	117,259	117,259
R-squared	0.0043	0.0109	0.0131	0.0193	0.0213
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 8. Robustness Checks: The Impact on Outpatient in Public Hospital (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	0.0212***	0.0187***	0.0226***	0.0218***	0.0214***
	(0.0034)	(0.0034)	(0.0035)	(0.0035)	(0.0036)
Treatment	0.0085***	0.0069***	0.0005		
	(0.0021)	(0.0021)	(0.0023)		
Post	0.0020	-0.0000	-0.0044***		
	(0.0013)	(0.0013)	(0.0015)		
Male		0.0018*	0.0014	0.0014	0.0012
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
Age		0.0002***	0.0002***	0.0002***	0.0002***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0001	-0.0003	0.0004	0.0004
		(0.0013)	(0.0013)	(0.0013)	(0.0013)
Education		0.0010***	0.0011***	0.0010***	0.0011***
		(0.0001)	(0.0001)	(0.0002)	(0.0002)
Rural		-0.0347***	-0.0353***	-0.0337***	-0.0341***
		(0.0027)	(0.0028)	(0.0027)	(0.0027)
HH Size		0.0013***	0.0010***	0.0004	0.0005
		(0.0003)	(0.0003)	(0.0004)	(0.0004)
Inaccessible			0.0050***	0.0090***	0.0086***
Nearby			(0.0015)	(0.0027)	(0.0029)
Public Hospital			0.0030***	0.0023***	-0.0012
Nearby			(0.0005)	(0.0007)	(0.0011)
Ln(GRDP/Cap)			-0.0030***	0.0037	0.0040
			(0.0007)	(0.0031)	(0.0032)
Ln(Population)			-0.0085***	-0.0013	0.0031
			(0.0009)	(0.0016)	(0.0024)
Constant	0.0205***	0.0337***	0.1629***	0.0381	-0.0034
	(0.0010)	(0.0033)	(0.0156)	(0.0350)	(0.0417)
Observations	117,259	117,259	117,259	117,259	117,259
R-squared	0.0036	0.0116	0.0138	0.0193	0.0214
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 9. Robustness Checks: Inpatient in Public Hospital, Main Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0053***	0.0049***	0.0048***	0.0053***	0.0051***
	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0014)
Treatment	0.0007	0.0003	0.0002		
	(0.0007)	(0.0007)	(0.0008)		
Post	-0.0006	-0.0003	-0.0004		
	(0.0004)	(0.0004)	(0.0004)		
Male		-0.0005	-0.0004	-0.0004	-0.0004
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		-0.0006	-0.0006	-0.0003	-0.0003
		(0.0006)	(0.0006)	(0.0006)	(0.0006)
Education		0.0002***	0.0002***	0.0001**	0.0001**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0049***	-0.0047***	-0.0046***	-0.0044***
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
HH Size		0.0001	0.0001	0.0001	0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			0.0019**	-0.0009	-0.0008
(Central Gov)			(0.0009)	(0.0014)	(0.0014)
Public Hospital			0.0015***	0.0003	0.0003
(Local Gov)			(0.0004)	(0.0008)	(0.0008)
Travel Distance			-0.0007***	-0.0005	-0.0006
(Total (100 Km))			(0.0002)	(0.0004)	(0.0004)
Travel Distance			0.0003	0.0003	0.0000
(Water (100 Km))			(0.0003)	(0.0005)	(0.0005)
# of Beds/1000			0.0000	-0.0002	-0.0004
population			(0.0002)	(0.0004)	(0.0005)
Constant	0.0041***	0.0042***	0.0037***	0.0013	0.0107***
	(0.0003)	(0.0012)	(0.0012)	(0.0016)	(0.0024)
Observations	123,957	123,249	121,486	121,486	121,486
R-squared	0.0006	0.0026	0.0028	0.0043	0.0045
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 10. Robustness Checks: Inpatient in Public Hospital, Main Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0049***	0.0046***	0.0050***	0.0054***	0.0051***
	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0015)
Treatment	0.0010	0.0006	-0.0003		
	(0.0008)	(0.0008)	(0.0008)		
Post	-0.0003	-0.0003	-0.0004		
	(0.0005)	(0.0005)	(0.0006)		
Male		-0.0000	0.0000	0.0001	0.0001
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
Age		0.0002***	0.0002***	0.0002***	0.0002***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		-0.0003	-0.0003	-0.0002	-0.0002
		(0.0008)	(0.0008)	(0.0008)	(0.0008)
Education		0.0001**	0.0001*	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0045***	-0.0045***	-0.0045***	-0.0043***
		(0.0012)	(0.0012)	(0.0012)	(0.0012)
HH Size		0.0002	0.0002	0.0002	0.0002
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Public Hospital			0.0054*	0.0038	0.0050
(Central Gov)			(0.0029)	(0.0046)	(0.0048)
Public Hospital			0.0025***	0.0002	0.0004
(Local Gov)			(0.0005)	(0.0009)	(0.0009)
Travel Distance			-0.0008***	-0.0009*	-0.0011**
(Total (100 Km))			(0.0003)	(0.0005)	(0.0005)
Travel Distance			0.0004	0.0003	0.0001
(Water (100 Km))			(0.0003)	(0.0006)	(0.0006)
# of Beds/1000			-0.0001	-0.0011	-0.0012
population			(0.0003)	(0.0008)	(0.0008)
Constant	0.0040***	0.0027*	0.0022	0.0019	0.0082***
	(0.0004)	(0.0016)	(0.0016)	(0.0022)	(0.0024)
Observations	118,422	118,422	118,422	118,422	118,422
R-squared	0.0008	0.0028	0.0031	0.0043	0.0046
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 11. Robustness Checks: Outpatient in Public Hospital, Main Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	0.0459***	0.0444***	0.0465***	0.0510***	0.0490***
	(0.0064)	(0.0065)	(0.0069)	(0.0073)	(0.0078)
Treatment	0.0004	-0.0016	-0.0045		
	(0.0029)	(0.0029)	(0.0033)		
Post	-0.0065***	-0.0026	-0.0036		
	(0.0020)	(0.0022)	(0.0022)		
Male		0.0039**	0.0040**	0.0037**	0.0037**
		(0.0016)	(0.0017)	(0.0017)	(0.0017)
Age		0.0003***	0.0003***	0.0004***	0.0004***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married		-0.0019	-0.0015	-0.0024	-0.0023
		(0.0024)	(0.0024)	(0.0024)	(0.0024)
Education		0.0008***	0.0008***	0.0010***	0.0010***
		(0.0002)	(0.0003)	(0.0003)	(0.0003)
Rural		-0.0275***	-0.0279***	-0.0270***	-0.0256***
		(0.0059)	(0.0060)	(0.0061)	(0.0062)
HH Size		0.0029***	0.0027***	0.0013*	0.0014*
		(0.0007)	(0.0007)	(0.0008)	(0.0008)
Public Hospital			0.0019	-0.0033	-0.0040
(Central Gov)			(0.0037)	(0.0053)	(0.0053)
Public Hospital			0.0074***	-0.0029	-0.0006
(Local Gov)			(0.0025)	(0.0034)	(0.0035)
Travel Distance				0.0041**	0.0041**
(Total (100 Km))				(0.0020)	(0.0019)
Travel Distance				-0.0058**	-0.0074***
(Water (100 Km))				(0.0024)	(0.0024)
# of Beds/1000				0.0017	0.0015
population				(0.0023)	(0.0021)
Constant	0.0203***	0.0174**	0.0102	0.0851***	0.1055***
	(0.0016)	(0.0068)	(0.0069)	(0.0199)	(0.0218)
Observations	30,385	30,243	30,018	30,018	30,018
R-squared	0.0082	0.0146	0.0159	0.0223	0.0263
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 12. Robustness Checks: Outpatient in Public Hospital, Main Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	0.0373***	0.0372***	0.0368***	0.0406***	0.0359***
	(0.0066)	(0.0066)	(0.0068)	(0.0073)	(0.0078)
Treatment	-0.0009	-0.0035	-0.0052		
	(0.0030)	(0.0030)	(0.0036)		
Post	-0.0067***	-0.0021	-0.0027		
	(0.0025)	(0.0028)	(0.0030)		
Male		0.0059***	0.0058***	0.0052**	0.0052**
		(0.0022)	(0.0022)	(0.0022)	(0.0022)
Age		0.0005***	0.0005***	0.0005***	0.0004***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married		-0.0010	-0.0009	-0.0016	-0.0013
		(0.0033)	(0.0033)	(0.0033)	(0.0033)
Education		0.0006**	0.0007**	0.0008**	0.0007**
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Rural		-0.0332***	-0.0340***	-0.0315***	-0.0289***
		(0.0080)	(0.0081)	(0.0079)	(0.0080)
HH Size		0.0045***	0.0044***	0.0026**	0.0028**
		(0.0013)	(0.0013)	(0.0012)	(0.0012)
Public Hospital			-0.0001	-0.0144**	-0.0131*
(Central Gov)			(0.0059)	(0.0063)	(0.0067)
Public Hospital			0.0062	-0.0079*	-0.0051
(Local Gov)			(0.0039)	(0.0043)	(0.0046)
Travel Distance				0.0016	0.0003
(Total (Km))				(0.0025)	(0.0025)
Travel Distance				-0.0030	-0.0047
(Water (Km))				(0.0030)	(0.0033)
# of Beds				0.0017	-0.0015
				(0.0032)	(0.0031)
Constant	0.0203***	0.0114	0.0051	0.1135***	0.1324***
	(0.0018)	(0.0090)	(0.0093)	(0.0273)	(0.0303)
Observations	29,334	29,334	29,334	29,334	29,334
R-squared	0.0065	0.0174	0.0179	0.0256	0.0281
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 13. Robustness Checks: Inpatient in Public Hospital, Outer Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0010	0.0000	0.0005	0.0007	0.0006
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0011)
Treatment	0.0014**	0.0015**	0.0008		
	(0.0006)	(0.0006)	(0.0006)		
Post	0.0016***	0.0017***	0.0017***		
	(0.0005)	(0.0005)	(0.0005)		
Male		-0.0004	-0.0005	-0.0005	-0.0005
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0011**	0.0012**	0.0014***	0.0014**
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
Education		0.0000	0.0000	0.0000	0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0103***	-0.0100***	-0.0087***	-0.0088***
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
HH Size		-0.0001	-0.0001	-0.0000	-0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			0.0019	-0.0010	-0.0015
(Central Gov)			(0.0015)	(0.0091)	(0.0092)
Public Hospital			-0.0020***	-0.0017	-0.0018
(Local Gov)			(0.0005)	(0.0011)	(0.0011)
Travel Distance			-0.0010***	-0.0014**	-0.0014**
(Total (Km))			(0.0004)	(0.0006)	(0.0006)
Travel Distance			0.0014***	0.0042***	0.0043***
(Water (Km))			(0.0004)	(0.0006)	(0.0006)
# of Beds			-0.0003	-0.0014*	-0.0009
			(0.0003)	(0.0008)	(0.0009)
Constant	0.0049***	0.0115***	0.0131***	0.0070***	0.0060***
	(0.0003)	(0.0012)	(0.0013)	(0.0018)	(0.0015)
Observations	185,011	184,030	181,805	181,805	181,805
R-squared	0.0003	0.0031	0.0034	0.0053	0.0057
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 14. Robustness Checks: Inpatient at Public Hospital, Outer Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	-0.0004	-0.0010	-0.0003	-0.0008	0.0002
	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0014)
Treatment	0.0026***	0.0022***	0.0013*		
	(0.0007)	(0.0007)	(0.0007)		
Post	0.0019***	0.0015**	0.0015**		
	(0.0006)	(0.0006)	(0.0006)		
Male		-0.0004	-0.0004	-0.0004	-0.0004
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0011*	0.0012*	0.0014**	0.0014**
		(0.0007)	(0.0007)	(0.0007)	(0.0007)
Education		0.0001	0.0001*	0.0001*	0.0001*
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0098***	-0.0092***	-0.0077***	-0.0078***
		(0.0013)	(0.0013)	(0.0013)	(0.0013)
HH Size		-0.0001	-0.0002	0.0000	0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			0.0005	-0.0051	-0.0085
(Central Gov)			(0.0021)	(0.0063)	(0.0066)
Public Hospital			-0.0037***	-0.0031**	-0.0026*
(Local Gov)			(0.0007)	(0.0013)	(0.0015)
Travel Distance			-0.0005	-0.0008	-0.0009
(Total (Km))			(0.0005)	(0.0007)	(0.0007)
Travel Distance			0.0011**	0.0042***	0.0044***
(Water (Km))			(0.0005)	(0.0008)	(0.0008)
# of Beds			-0.0014***	-0.0025***	-0.0022*
			(0.0004)	(0.0009)	(0.0011)
Constant	0.0047***	0.0105***	0.0135***	0.0058**	0.0048***
	(0.0004)	(0.0015)	(0.0018)	(0.0025)	(0.0018)
Observations	180,771	180,771	180,771	180,771	180,771
R-squared	0.0003	0.0029	0.0037	0.0063	0.0066
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 15. Robustness Checks: Outpatient in Public Hospital, Outer Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	-0.0055	-0.0079*	-0.0058	-0.0038	-0.0016
	(0.0044)	(0.0044)	(0.0043)	(0.0045)	(0.0051)
Treatment	0.0178***	0.0187***	0.0100***		
	(0.0032)	(0.0032)	(0.0029)		
Post	-0.0019	-0.0014	-0.0010		
	(0.0018)	(0.0018)	(0.0018)		
Male		-0.0016	-0.0019	-0.0020	-0.0019
		(0.0014)	(0.0014)	(0.0014)	(0.0014)
Age		0.0000	-0.0000	-0.0000	-0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0019	0.0024	0.0027	0.0026
		(0.0017)	(0.0017)	(0.0017)	(0.0017)
Education		0.0005**	0.0004*	0.0004**	0.0005**
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Rural		-0.0364***	-0.0353***	-0.0374***	-0.0366***
		(0.0042)	(0.0041)	(0.0042)	(0.0042)
HH Size		-0.0003	-0.0004	-0.0007*	-0.0007
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Public Hospital			0.0101	-0.0257***	-0.0206***
(Central Gov)			(0.0070)	(0.0046)	(0.0056)
Public Hospital			-0.0065***	-0.0019	-0.0033
(Local Gov)			(0.0021)	(0.0032)	(0.0033)
Travel Distance				-0.0050**	-0.0036
(Total (Km))				(0.0025)	(0.0026)
Travel Distance				0.0154***	0.0148***
(Water (Km))				(0.0025)	(0.0025)
# of Beds				-0.0005	0.0004
				(0.0038)	(0.0043)
Constant	0.0193***	0.0499***	0.0511***	0.0471***	0.0397***
	(0.0013)	(0.0049)	(0.0055)	(0.0075)	(0.0066)
Observations	45,022	44,861	44,383	44,383	44,383
R-squared	0.0024	0.0095	0.0133	0.0188	0.0210
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 16. Robustness Checks: Outpatient in Public Hospital, Outer Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	-0.0041	-0.0064	-0.0033	-0.0060	-0.0019
	(0.0057)	(0.0057)	(0.0056)	(0.0059)	(0.0059)
Treatment	0.0204***	0.0189***	0.0086**		
	(0.0038)	(0.0038)	(0.0034)		
Post	-0.0020	-0.0050*	-0.0039		
	(0.0026)	(0.0026)	(0.0026)		
Male		-0.0008	-0.0010	-0.0013	-0.0013
		(0.0021)	(0.0021)	(0.0020)	(0.0020)
Age		-0.0000	-0.0000	-0.0000	-0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married		0.0021	0.0023	0.0021	0.0024
		(0.0026)	(0.0026)	(0.0026)	(0.0026)
Education		0.0005*	0.0004	0.0005	0.0005
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Rural		-0.0480***	-0.0488***	-0.0527***	-0.0516***
		(0.0065)	(0.0062)	(0.0063)	(0.0062)
HH Size		-0.0012**	-0.0010*	-0.0010*	-0.0009
		(0.0006)	(0.0006)	(0.0006)	(0.0006)
Public Hospital			0.0170	-0.0196***	-0.0218***
(Central Gov)			(0.0132)	(0.0055)	(0.0069)
Public Hospital			-0.0062**	-0.0062*	-0.0062*
(Local Gov)			(0.0029)	(0.0036)	(0.0034)
Travel Distance				-0.0050*	-0.0042
(Total (Km))				(0.0028)	(0.0028)
Travel Distance				0.0125***	0.0128***
(Water (Km))				(0.0029)	(0.0030)
# of Beds				0.0008	-0.0035
				(0.0042)	(0.0047)
Constant	0.0213***	0.0675***	0.0677***	0.0658***	0.0588***
	(0.0018)	(0.0076)	(0.0083)	(0.0107)	(0.0094)
Observations	44,101	44,101	44,101	44,101	44,101
R-squared	0.0034	0.0130	0.0174	0.0233	0.0272
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 17. Medical Care Utilization, Excluding Municipality with 2012 Opening as Control Group

	(1)	(2)	(3)	(4)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
	All Samples	Main Islands	All Samples	Main Islands
Treatment*Post	0.0229***	0.0607***	0.0029***	0.0064***
	(0.0037)	(0.0075)	(0.0007)	(0.0013)
Morbidity			0.0122***	0.0142***
			(0.0004)	(0.0006)
Male	0.0005	0.0038**	-0.0007***	-0.0001
	(0.0010)	(0.0018)	(0.0002)	(0.0004)
Age	0.0001***	0.0004***	0.0001***	0.0002***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Married	-0.0004	-0.0067***	0.0005	-0.0006
	(0.0013)	(0.0025)	(0.0004)	(0.0007)
Education	0.0008***	0.0010***	0.0003***	0.0002***
	(0.0002)	(0.0003)	(0.0000)	(0.0001)
Rural	-0.0332***	-0.0234***	-0.0073***	-0.0045***
	(0.0029)	(0.0055)	(0.0006)	(0.0010)
HH Size	0.0005	0.0028***	0.0002***	0.0003**
	(0.0004)	(0.0009)	(0.0001)	(0.0001)
Inaccessible	0.0084**	0.0190***	0.0030***	0.0009
Nearby	(0.0033)	(0.0064)	(0.0008)	(0.0011)
Public Hospital	-0.0007	-0.0105***	0.0010***	-0.0003
Nearby	(0.0013)	(0.0025)	(0.0002)	(0.0004)
Ln(GRDP/Cap)	0.0047	-0.0322***	-0.0030***	-0.0016
	(0.0033)	(0.0093)	(0.0007)	(0.0014)
Ln(Population)	0.0047**	0.0127**	-0.0010**	0.0019**
	(0.0024)	(0.0050)	(0.0005)	(0.0009)
Constant	0.0284***	0.0462	0.0284***	-0.0101
	(0.0081)	(0.0972)	(0.0081)	(0.0162)
Observations	93,903	32,442	431,882	168,775
R-squared	0.0240	0.0454	0.0110	0.0150
Municipality FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES
Year	2004-2014	2004-2014	2004-2014	2004-2014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 18. Medical Care Utilization Including Municipality with 2012 Opening as Treatment Group

	(1)	(2)	(3)	(4)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
	All Samples	Main Islands	All Samples	Main Islands
Treatment*Post	0.0171***	0.0417***	0.0021***	0.0067***
	(0.0035)	(0.0080)	(0.0005)	(0.0012)
Morbidity			0.0118***	0.0114***
			(0.0003)	(0.0005)
Male	0.0010	0.0045***	-0.0006***	-0.0006**
	(0.0009)	(0.0014)	(0.0002)	(0.0003)
Age	0.0002***	0.0004***	0.0001***	0.0001***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Married	0.0004	-0.0034*	0.0002	-0.0010**
	(0.0012)	(0.0020)	(0.0003)	(0.0005)
Education	0.0009***	0.0012***	0.0003***	0.0003***
	(0.0001)	(0.0002)	(0.0000)	(0.0000)
Rural	-0.0340***	-0.0313***	-0.0069***	-0.0047***
	(0.0026)	(0.0044)	(0.0005)	(0.0008)
HH Size	0.0006*	0.0021***	0.0002**	0.0002
	(0.0003)	(0.0007)	(0.0001)	(0.0001)
Inaccessible	0.0114***	-0.0023*	0.0016***	0.0013*
Nearby	(0.0028)	(0.0013)	(0.0006)	(0.0007)
Public Hospital	0.0006	-0.0085	0.0008***	0.0003
Nearby	(0.0010)	(0.0079)	(0.0002)	(0.0002)
Ln(GRDP/Cap)	0.0016	-0.0003	-0.0026***	-0.0015
	(0.0031)	(0.0045)	(0.0007)	(0.0012)
Ln(Population)	0.0032	0.0812	-0.0006	-0.0008
	(0.0021)	(0.0763)	(0.0004)	(0.0007)
Constant	0.0055	-0.0023*	0.0294***	0.0238*
	(0.0385)	(0.0013)	(0.0077)	(0.0133)
Observations	117,259	46,877	547,536	226,362
R-squared	0.0211	0.0308	0.0105	0.0108
Municipality FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES
Year	2004-2014	2004-2014	2004-2014	2004-2014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 19. Robustness Checks: Inpatient in Public Hospital, Main Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0053***	0.0050***	0.0050***	0.0056***	0.0055***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0014)
Treatment	0.0007	-0.0003	-0.0029*		
	(0.0007)	(0.0007)	(0.0016)		
Post	-0.0006	-0.0004	-0.0005		
	(0.0004)	(0.0004)	(0.0004)		
Morbidity		0.0088***	0.0088***	0.0087***	0.0088***
		(0.0005)	(0.0006)	(0.0006)	(0.0006)
Male		-0.0003	-0.0003	-0.0002	-0.0002
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		-0.0004	-0.0004	-0.0002	-0.0001
		(0.0006)	(0.0006)	(0.0006)	(0.0006)
Education		0.0003***	0.0003***	0.0003***	0.0003***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0048***	-0.0048***	-0.0044***	-0.0041***
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
HH Size		0.0001	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			0.0017*	-0.0001	-0.0000
(Central Gov)			(0.0009)	(0.0016)	(0.0016)
Public Hospital			0.0012**	-0.0002	-0.0000
(Local Gov)			(0.0005)	(0.0009)	(0.0009)
Travel Distance			-0.0000**	-0.0000	-0.0000
(Total (Km))			(0.0000)	(0.0000)	(0.0000)
Travel Distance			0.0000	0.0000	0.0000
(Water (Km))			(0.0000)	(0.0000)	(0.0000)
# of Beds			-0.0000	-0.0000	-0.0000
			(0.0000)	(0.0000)	(0.0000)
Constant	0.0041***	0.0012	0.0016	0.0011	0.0101***
	(0.0003)	(0.0012)	(0.0013)	(0.0018)	(0.0026)
Observations	123,957	123,249	121,486	121,486	121,486
R-squared	0.0006	0.0063	0.0066	0.0079	0.0082
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 20. Robustness Checks: Inpatient in Public Hospital, Main Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0058***	0.0059***	0.0062***	0.0066***	0.0056***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0017)
Treatment	0.0013	0.0001	-0.0027		
	(0.0009)	(0.0009)	(0.0024)		
Post	-0.0003	-0.0005	-0.0005		
	(0.0007)	(0.0007)	(0.0007)		
Morbidity		0.0100***	0.0102***	0.0100***	0.0100***
		(0.0009)	(0.0009)	(0.0009)	(0.0009)
Male		0.0009	0.0009	0.0009	0.0009
		(0.0007)	(0.0007)	(0.0007)	(0.0007)
Age		0.0002***	0.0002***	0.0002***	0.0002***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		-0.0018	-0.0018	-0.0016	-0.0016
		(0.0011)	(0.0011)	(0.0011)	(0.0011)
Education		0.0001	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0044***	-0.0045***	-0.0042***	-0.0042***
		(0.0015)	(0.0015)	(0.0015)	(0.0015)
HH Size		0.0000	0.0000	-0.0000	-0.0000
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Public Hospital			0.0055	0.0063	0.0074
(Central Gov)			(0.0038)	(0.0062)	(0.0062)
Public Hospital			0.0016**	-0.0009	-0.0006
(Local Gov)			(0.0007)	(0.0010)	(0.0011)
Travel Distance			-0.0000	0.0000	0.0000
(Total (Km))			(0.0000)	(0.0000)	(0.0000)
Travel Distance			0.0000	-0.0000	-0.0000
(Water (Km))			(0.0000)	(0.0000)	(0.0000)
# of Beds			-0.0000	-0.0000	-0.0000
			(0.0000)	(0.0000)	(0.0000)
Constant	0.0040***	-0.0002	-0.0008	0.0003	0.0043
	(0.0004)	(0.0018)	(0.0020)	(0.0025)	(0.0028)
Observations	106,331	106,331	106,331	106,331	106,331
R-squared	0.0012	0.0074	0.0078	0.0085	0.0087
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 21. Robustness Checks: Outpatient in Public Hospital, Main Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	0.0459***	0.0444***	0.0481***	0.0520***	0.0504***
	(0.0064)	(0.0065)	(0.0071)	(0.0075)	(0.0081)
Treatment	0.0004	-0.0016	0.0065		
	(0.0029)	(0.0029)	(0.0066)		
Post	-0.0065***	-0.0026	-0.0031		
	(0.0020)	(0.0022)	(0.0022)		
Male		0.0039**	0.0041**	0.0038**	0.0038**
		(0.0016)	(0.0017)	(0.0017)	(0.0017)
Age		0.0003***	0.0004***	0.0004***	0.0004***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married		-0.0019	-0.0017	-0.0024	-0.0023
		(0.0024)	(0.0024)	(0.0024)	(0.0024)
Education		0.0008***	0.0009***	0.0010***	0.0010***
		(0.0002)	(0.0003)	(0.0003)	(0.0003)
Rural		-0.0275***	-0.0274***	-0.0264***	-0.0253***
		(0.0059)	(0.0060)	(0.0060)	(0.0061)
HH Size		0.0029***	0.0027***	0.0012	0.0013*
		(0.0007)	(0.0007)	(0.0007)	(0.0008)
Public Hospital			0.0057	-0.0036	-0.0039
(Central Gov)			(0.0038)	(0.0056)	(0.0057)
Public Hospital			0.0131***	-0.0001	0.0017
(Local Gov)			(0.0031)	(0.0031)	(0.0033)
Travel Distance			0.0000	0.0001***	0.0001***
(Total (Km))			(0.0000)	(0.0000)	(0.0000)
Travel Distance			-0.0000*	-0.0000*	-0.0001**
(Water (Km))			(0.0000)	(0.0000)	(0.0000)
# of Beds			-0.0001***	0.0000	-0.0000
			(0.0000)	(0.0000)	(0.0000)
Constant	0.0203***	0.0174**	0.0139*	0.0819***	0.1031***
	(0.0016)	(0.0068)	(0.0073)	(0.0203)	(0.0221)
Observations	30,385	30,243	30,018	30,018	30,018
R-squared	0.0082	0.0146	0.0170	0.0229	0.0267
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 22. Robustness Checks: Outpatient in Public Hospital, Main Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	0.0498***	0.0491***	0.0474***	0.0489***	0.0471***
	(0.0072)	(0.0073)	(0.0074)	(0.0080)	(0.0081)
Treatment	-0.0047	-0.0070**	0.0013		
	(0.0033)	(0.0034)	(0.0074)		
Post	-0.0098***	-0.0048	-0.0045		
	(0.0032)	(0.0035)	(0.0036)		
Male		0.0069***	0.0067**	0.0060**	0.0059**
		(0.0026)	(0.0026)	(0.0026)	(0.0026)
Age		0.0006***	0.0006***	0.0006***	0.0006***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married		-0.0046	-0.0045	-0.0055	-0.0052
		(0.0039)	(0.0039)	(0.0039)	(0.0039)
Education		0.0006*	0.0007**	0.0007*	0.0007*
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Rural		-0.0283***	-0.0283***	-0.0227**	-0.0222**
		(0.0089)	(0.0088)	(0.0089)	(0.0090)
HH Size		0.0052***	0.0052***	0.0024**	0.0027**
		(0.0012)	(0.0012)	(0.0012)	(0.0012)
Public Hospital			-0.0040	-0.0230**	-0.0263**
(Central Gov)			(0.0066)	(0.0103)	(0.0119)
Public Hospital			0.0089**	-0.0110**	-0.0115**
(Local Gov)			(0.0045)	(0.0051)	(0.0055)
Travel Distance			0.0000**	0.0001**	0.0001**
(Total (Km))			(0.0000)	(0.0000)	(0.0000)
Travel Distance			-0.0000**	-0.0000	-0.0000
(Water (Km))			(0.0000)	(0.0000)	(0.0000)
# of Beds			0.0000	0.0001*	0.0001*
			(0.0001)	(0.0001)	(0.0001)
Constant	0.0235***	0.0034	-0.0122	0.0702***	0.0656***
	(0.0023)	(0.0104)	(0.0117)	(0.0243)	(0.0253)
Observations	26,756	26,756	26,756	26,756	26,756
R-squared	0.0102	0.0209	0.0222	0.0323	0.0343
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 23. Robustness Checks: Inpatient at Public Hospital, Outer Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	0.0010	0.0008	0.0016	0.0015	0.0013
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0012)
Treatment	0.0014**	0.0015***	0.0018		
	(0.0006)	(0.0006)	(0.0011)		
Post	0.0016***	0.0013***	0.0012**		
	(0.0005)	(0.0005)	(0.0005)		
Morbidity		0.0114***	0.0115***	0.0112***	0.0112***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
Male		-0.0003	-0.0003	-0.0003	-0.0003
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Age		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0012**	0.0012**	0.0014***	0.0014**
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
Education		0.0002***	0.0002***	0.0002***	0.0002***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0100***	-0.0095***	-0.0083***	-0.0083***
		(0.0010)	(0.0010)	(0.0010)	(0.0009)
HH Size		0.0000	-0.0000	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			0.0020	-0.0040	-0.0042
(Central Gov)			(0.0015)	(0.0092)	(0.0092)
Public Hospital			-0.0026***	0.0017	0.0019
(Local Gov)			(0.0005)	(0.0015)	(0.0015)
Travel Distance			-0.0000**	-0.0000**	-0.0000**
(Total (Km))			(0.0000)	(0.0000)	(0.0000)
Travel Distance			0.0000***	0.0000***	0.0000***
(Water (Km))			(0.0000)	(0.0000)	(0.0000)
# of Beds			0.0000	-0.0000***	-0.0000***
			(0.0000)	(0.0000)	(0.0000)
Constant	0.0049***	0.0067***	0.0079***	0.0050***	0.0050***
	(0.0003)	(0.0011)	(0.0013)	(0.0018)	(0.0015)
Observations	185,011	184,030	181,805	181,805	181,805
R-squared	0.0003	0.0078	0.0083	0.0098	0.0102
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses

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

Table D. 24. Robustness Checks: Inpatient at Public Hospital, Outer Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
Treatment*Post	-0.0020	-0.0016	0.0000	-0.0001	0.0003
	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0013)
Treatment	0.0037***	0.0028***	0.0028**		
	(0.0008)	(0.0007)	(0.0012)		
Post	0.0032***	0.0026***	0.0026***		
	(0.0007)	(0.0007)	(0.0007)		
Morbidity		0.0145***	0.0140***	0.0137***	0.0137***
		(0.0009)	(0.0008)	(0.0008)	(0.0008)
Male		-0.0001	-0.0002	-0.0002	-0.0002
		(0.0006)	(0.0006)	(0.0006)	(0.0006)
Age		0.0001**	0.0001**	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0012	0.0013*	0.0013*	0.0013*
		(0.0008)	(0.0008)	(0.0008)	(0.0008)
Education		0.0003***	0.0003***	0.0003***	0.0003***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0116***	-0.0104***	-0.0076***	-0.0076***
		(0.0016)	(0.0016)	(0.0016)	(0.0016)
HH Size		-0.0000	-0.0000	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			0.0029	-0.0062	-0.0080
(Central Gov)			(0.0043)	(0.0059)	(0.0062)
Public Hospital			-0.0053***	-0.0004	0.0005
(Local Gov)			(0.0008)	(0.0015)	(0.0015)
Travel Distance			0.0000	0.0000	0.0000
(Total (Km))			(0.0000)	(0.0000)	(0.0000)
Travel Distance			0.0000	0.0000***	0.0000***
(Water (Km))			(0.0000)	(0.0000)	(0.0000)
# of Beds			-0.0000	-0.0003***	-0.0003***
			(0.0000)	(0.0000)	(0.0000)
Constant	0.0044***	0.0073***	0.0085***	0.0063***	0.0069***
	(0.0003)	(0.0016)	(0.0018)	(0.0024)	(0.0019)
Observations	143,899	143,899	143,899	143,899	143,899
R-squared	0.0005	0.0100	0.0109	0.0132	0.0134
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 25. Robustness Checks: Outpatient in Public Hospital, Outer Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	-0.0055	-0.0079*	-0.0048	-0.0022	0.0003
	(0.0044)	(0.0044)	(0.0044)	(0.0045)	(0.0052)
Treatment	0.0178***	0.0187***	0.0166***		
	(0.0032)	(0.0032)	(0.0049)		
Post	-0.0019	-0.0014	-0.0007		
	(0.0018)	(0.0018)	(0.0018)		
Male		-0.0016	-0.0018	-0.0021	-0.0019
		(0.0014)	(0.0014)	(0.0014)	(0.0014)
Age		0.0000	-0.0000	-0.0000	-0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0019	0.0023	0.0026	0.0025
		(0.0017)	(0.0017)	(0.0017)	(0.0017)
Education		0.0005**	0.0004*	0.0004**	0.0005**
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Rural		-0.0364***	-0.0349***	-0.0366***	-0.0358***
		(0.0042)	(0.0041)	(0.0042)	(0.0042)
HH Size		-0.0003	-0.0004	-0.0007*	-0.0007*
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Public Hospital			0.0101	-0.0223***	-0.0175***
(Central Gov)			(0.0070)	(0.0055)	(0.0063)
Public Hospital			-0.0073***	0.0082	0.0064
(Local Gov)			(0.0023)	(0.0057)	(0.0056)
Travel Distance			-0.0001***	-0.0001**	-0.0000*
(Total (Km))			(0.0000)	(0.0000)	(0.0000)
Travel Distance			0.0001***	0.0002***	0.0002***
(Water (Km))			(0.0000)	(0.0000)	(0.0000)
# of Beds			0.0000**	-0.0001**	-0.0001**
			(0.0000)	(0.0001)	(0.0001)
Constant	0.0193***	0.0499***	0.0504***	0.0478***	0.0411***
	(0.0013)	(0.0049)	(0.0055)	(0.0075)	(0.0066)
Observations	45,022	44,861	44,383	44,383	44,383
R-squared	0.0024	0.0095	0.0135	0.0192	0.0215
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D. 26. Robustness Checks: Outpatient in Public Hospital, Outer Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Treatment*Post	-0.0091	-0.0093	-0.0060	-0.0084	-0.0041
	(0.0060)	(0.0059)	(0.0060)	(0.0064)	(0.0061)
Treatment	0.0203***	0.0163***	0.0156***		
	(0.0042)	(0.0040)	(0.0058)		
Post	-0.0008	-0.0049	-0.0025		
	(0.0033)	(0.0032)	(0.0033)		
Male		-0.0007	-0.0009	-0.0014	-0.0015
		(0.0024)	(0.0024)	(0.0024)	(0.0024)
Age		-0.0000	-0.0000	-0.0001	-0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married		0.0023	0.0023	0.0021	0.0023
		(0.0030)	(0.0030)	(0.0030)	(0.0030)
Education		0.0004	0.0003	0.0004	0.0004
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Rural		-0.0657***	-0.0637***	-0.0636***	-0.0626***
		(0.0088)	(0.0084)	(0.0080)	(0.0079)
HH Size		-0.0015**	-0.0012*	-0.0013*	-0.0012*
		(0.0007)	(0.0007)	(0.0007)	(0.0007)
Public Hospital			0.0194	-0.0065	-0.0066
(Central Gov)			(0.0185)	(0.0066)	(0.0088)
Public Hospital			-0.0093**	0.0073	0.0107*
(Local Gov)			(0.0036)	(0.0061)	(0.0061)
Travel Distance			-0.0000	-0.0000	-0.0000
(Total (Km))			(0.0000)	(0.0000)	(0.0000)
Travel Distance			0.0001***	0.0001***	0.0001***
(Water (Km))			(0.0000)	(0.0000)	(0.0000)
# of Beds			0.0001***	-0.0005***	-0.0005***
			(0.0000)	(0.0001)	(0.0001)
Constant	0.0231***	0.0894***	0.0800***	0.1030***	0.1072***
	(0.0022)	(0.0102)	(0.0110)	(0.0227)	(0.0235)
Observations	35,000	35,000	35,000	35,000	35,000
R-squared	0.0028	0.0182	0.0220	0.0294	0.0332
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix E: Falsification Test, Primary Outcomes

Table E. 1. Falsification Test, All Samples (DID)

VARIABLES	Outpatient Public Hospital			Inpatient Public Hospital		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*Post	0.009	0.003	0.011*	-0.000	0.000	0.001
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
Morbidity				0.010***	0.010***	0.010***
				(0.000)	(0.000)	(0.000)
Male	0.001	0.001	0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Age	0.000	0.000	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.001	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Education	0.001***	0.001***	0.001***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural	-0.035***	-0.035***	-0.035***	-0.005***	-0.005***	-0.005***
	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
HH Size	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Public Hospital	-0.004	-0.003	-0.004	0.000	0.000	0.000
(Central Gov)	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
Public Hospital	0.007*	0.007**	0.007*	0.000	0.000	0.000
(Local Gov)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Travel Distance	0.000**	0.000*	0.000**	0.000	0.000	0.000
(Total (Km))	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Travel Distance	0.000**	0.000**	0.000**	0.000***	0.000***	0.000***
(Water (Km))	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of Beds	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.081***	0.035**	0.084***	0.005***	0.001	0.003
	(0.021)	(0.015)	(0.023)	(0.002)	(0.002)	(0.002)
Observations	41,483	41,483	41,483	171,834	171,834	171,834
R-squared	0.021	0.021	0.021	0.009	0.009	0.009
Municipality FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES	YES	YES
Year	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007
Artificial Year	2005	2006	2007	2005	2006	2007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E. 2. Falsification Test, All Samples (Matching DID)

VARIABLES	Outpatient Public Hospital			Inpatient Public Hospital		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*Post	0.010	0.008	0.013**	-0.000	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
Morbidity				0.011***	0.011***	0.011***
				(0.001)	(0.001)	(0.001)
Male	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Age	0.000	0.000	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.001	0.001	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Education	0.000	0.000	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural	-0.053***	-0.054***	-0.054***	-0.005***	-0.005***	-0.005***
	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
HH Size	-0.001	-0.001	-0.001	0.000*	0.000*	0.000*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Public Hospital	-0.017**	-0.017**	-0.018**	0.006	0.006	0.006
(Central Gov)	(0.008)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
Public Hospital	-0.001	-0.001	-0.002	-0.000	-0.000	-0.000
(Local Gov)	(0.004)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Travel Distance	-0.000	-0.000	-0.000	0.000	0.000	0.000
(Total (Km))	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Travel Distance	0.000**	0.000***	0.000***	0.000***	0.000***	0.000***
(Water (Km))	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of Beds	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.147***	0.146***	0.131**	0.007***	0.007***	0.007***
	(0.054)	(0.054)	(0.056)	(0.002)	(0.002)	(0.002)
Observations	41,099	41,099	41,099	170,085	170,085	170,085
R-squared	0.029	0.029	0.029	0.010	0.010	0.010
Municipality FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES	YES	YES
Year	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007
Artificial Year	2005	2006	2007	2005	2006	2007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E. 3. Falsification Test, Main Islands (DID)

VARIABLES	Outpatient Public Hospital			Inpatient Public Hospital		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*Post	-0.003	-0.012	0.005	0.001	0.001	0.001
	(0.009)	(0.008)	(0.008)	(0.002)	(0.002)	(0.002)
Morbidity				0.009***	0.009***	0.009***
				(0.001)	(0.001)	(0.001)
Male	0.005**	0.005**	0.004**	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Age	0.000***	0.000***	0.000***	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Education	0.001***	0.001***	0.001***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural	-0.028***	-0.028***	-0.028***	-0.003***	-0.003***	-0.003***
	(0.008)	(0.008)	(0.008)	(0.001)	(0.001)	(0.001)
HH Size	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Public Hospital	-0.010	-0.010	-0.010	-0.001	-0.001	-0.001
(Central Gov)	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
Public Hospital	0.006	0.006	0.005	-0.001	-0.001	-0.001
(Local Gov)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Travel Distance	0.000***	0.000***	0.000***	0.000	0.000	0.000
(Total (Km))	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Travel Distance	-0.000*	-0.000	-0.000*	-0.000	-0.000	-0.000
(Water (Km))	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of Beds	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.067***	0.013	0.067***	0.002	-0.000	0.003
	(0.024)	(0.017)	(0.026)	(0.002)	(0.002)	(0.002)
Observations	16,549	16,549	16,549	67,183	67,183	67,183
R-squared	0.021	0.021	0.021	0.008	0.008	0.008
Municipality FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES	YES	YES
Year	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007
Artificial Year	2005	2006	2007	2005	2006	2007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E. 4. Falsification Test, Main Islands (Matching DID)

VARIABLES	Outpatient Public Hospital			Inpatient Public Hospital		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*Post	-0.014	-0.016	-0.001	0.002	0.003	0.003
	(0.012)	(0.010)	(0.007)	(0.003)	(0.003)	(0.002)
Morbidity				0.009***	0.009***	0.009***
				(0.001)	(0.001)	(0.001)
Male	0.009***	0.009***	0.009***	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Age	0.000***	0.000***	0.000***	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Education	0.001**	0.001**	0.001**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural	-0.044***	-0.044***	-0.044***	-0.004**	-0.004**	-0.004**
	(0.011)	(0.011)	(0.011)	(0.002)	(0.002)	(0.002)
HH Size	0.001	0.001	0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Public Hospital	-0.030**	-0.030**	-0.031**	0.003	0.003	0.003
(Central Gov)	(0.012)	(0.012)	(0.012)	(0.006)	(0.006)	(0.006)
Public Hospital	-0.005	-0.005	-0.006	-0.003**	-0.003**	-0.003**
(Local Gov)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Travel Distance	0.000**	0.000**	0.000**	0.000	0.000	0.000
(Total (Km))	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Travel Distance	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
(Water (Km))	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of Beds	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.076***	0.076***	0.050	0.004	0.005*	0.005
	(0.028)	(0.028)	(0.031)	(0.003)	(0.003)	(0.004)
Observations	14,810	14,810	14,810	59,109	59,109	59,109
R-squared	0.026	0.026	0.025	0.007	0.007	0.007
Municipality FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Region*Year FE	YES	YES	YES	YES	YES	YES
Year	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007
Artificial Year	2005	2006	2007	2005	2006	2007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix F: Travel Distance Between New Hospital and Existing Hospital, Outer Islands

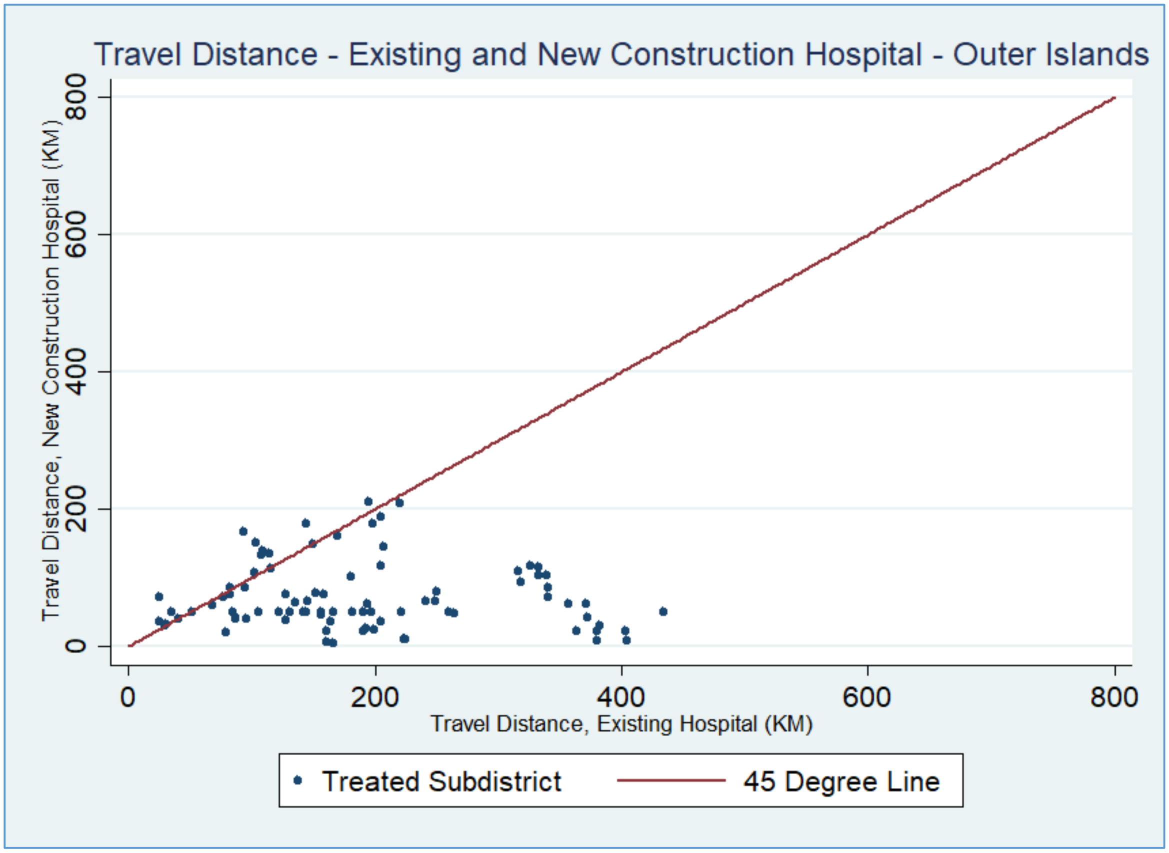


Figure F. 1. Travel Distance Between New Hospital and Existing Hospital, Outer Islands

Appendix G: Travel Distance and Inpatient, Treated Sub-District

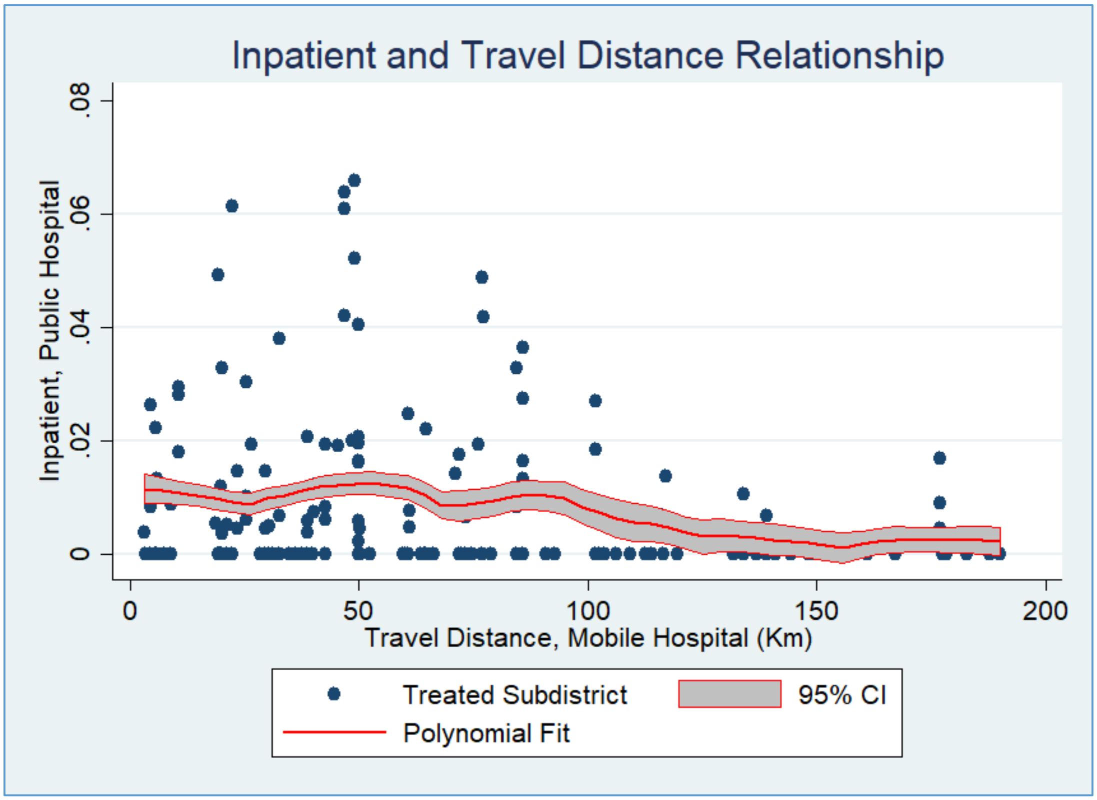


Figure G. 1. Travel Distance and Inpatient, Treated Sub-District

Appendix H: Robustness Checks, Private Hospital, Main Islands

Table H. 1. Robustness Checks: Outpatient in Private Hospital, Main Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital
Treatment*Post	0.0030	0.0021	0.0018	0.0036	0.0000
	(0.0023)	(0.0022)	(0.0023)	(0.0024)	(0.0024)
Treatment	0.0012	0.0010	0.0016		
	(0.0015)	(0.0016)	(0.0017)		
Post	-0.0018*	-0.0019*	-0.0017		
	(0.0010)	(0.0011)	(0.0011)		
Male		0.0019***	0.0020***	0.0018**	0.0018**
		(0.0007)	(0.0007)	(0.0007)	(0.0007)
Age		0.0000	0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0009	0.0010	0.0012	0.0013
		(0.0009)	(0.0009)	(0.0009)	(0.0009)
Education		0.0001	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0047*	-0.0044*	-0.0032	-0.0035
		(0.0024)	(0.0024)	(0.0025)	(0.0025)
HH Size		-0.0002	-0.0002	-0.0003	-0.0003
		(0.0002)	(0.0002)	(0.0003)	(0.0003)
Public Hospital			0.0046*	0.0050	0.0049
(Central Gov)			(0.0027)	(0.0039)	(0.0035)
Public Hospital			0.0032***	0.0004	0.0005
(Local Gov)			(0.0011)	(0.0016)	(0.0015)
Travel Distance			-0.0006	-0.0012	-0.0012
(Total (100 Km))			(0.0005)	(0.0009)	(0.0009)
Travel Distance			0.0004	0.0005	-0.0001
(Water (100 Km))			(0.0007)	(0.0012)	(0.0011)
# of Beds/1000			-0.0011***	0.0001	-0.0000
Population			(0.0003)	(0.0005)	(0.0005)
Constant	0.0048***	0.0075**	0.0059*	0.0011	-0.0023
	(0.0008)	(0.0030)	(0.0030)	(0.0039)	(0.0057)
Observations	29,731	29,593	29,370	29,370	29,370
R-squared	0.0004	0.0014	0.0020	0.0072	0.0104
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table H. 2. Robustness Checks: Inpatient in Private Hospital, Main Islands (DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital
Treatment*Post	0.0009	0.0006	0.0002	0.0009	0.0002
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0008)
Treatment	0.0002	0.0001	0.0003		
	(0.0004)	(0.0004)	(0.0004)		
Post	0.0001	0.0001	0.0003		
	(0.0003)	(0.0003)	(0.0003)		
Male	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age	0.0000*	0.0000	0.0000	0.0000	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married	0.0006**	0.0006**	0.0006**	0.0007**	0.0006**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Education	0.0001**	0.0000*	0.0000	0.0000	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rural	-0.0012**	-0.0011**	-0.0012**	-0.0012**	-0.0012**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
HH Size	-0.0000	0.0000	-0.0001	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			0.0004	0.0006	0.0006
(Central Gov)			(0.0005)	(0.0008)	(0.0008)
Public Hospital			0.0003	-0.0006	-0.0005
(Local Gov)			(0.0003)	(0.0005)	(0.0005)
Travel Distance			-0.0004***	-0.0005**	-0.0005**
(Total (100 Km))			(0.0001)	(0.0002)	(0.0002)
Travel Distance			0.0002*	-0.0007	-0.0008
(Water (100 Km))			(0.0001)	(0.0006)	(0.0007)
# of Beds/1000			-0.0005***	-0.0002	-0.0002
Population			(0.0001)	(0.0001)	(0.0001)
Constant	0.0011***	0.0011*	0.0015**	0.0010	-0.0004
	(0.0002)	(0.0007)	(0.0006)	(0.0009)	(0.0016)
Observations	123,567	122,859	121,097	121,097	121,097
R-squared	0.0001	0.0005	0.0007	0.0020	0.0025
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table H. 3. Robustness Checks: Outpatient in Private Hospital, Main Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital
Treatment*Post	0.0037	0.0034	0.0023	0.0033	0.0010
	(0.0023)	(0.0023)	(0.0023)	(0.0024)	(0.0024)
Treatment	0.0008	0.0004	0.0011		
	(0.0013)	(0.0013)	(0.0013)		
Post	-0.0011	-0.0011	-0.0005		
	(0.0010)	(0.0011)	(0.0011)		
Male		0.0011	0.0011	0.0008	0.0008
		(0.0008)	(0.0008)	(0.0009)	(0.0009)
Age		0.0000	0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0012	0.0013	0.0011	0.0011
		(0.0011)	(0.0011)	(0.0011)	(0.0011)
Education		-0.0000	-0.0000	0.0000	0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural		-0.0073**	-0.0074**	-0.0068**	-0.0066**
		(0.0030)	(0.0030)	(0.0030)	(0.0030)
HH Size		0.0000	0.0001	-0.0002	-0.0001
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Public Hospital			0.0030	-0.0042**	-0.0036*
(Central Gov)			(0.0060)	(0.0021)	(0.0019)
Public Hospital			0.0013	-0.0013	0.0003
(Local Gov)			(0.0011)	(0.0020)	(0.0017)
Travel Distance			0.0006	0.0005	0.0006
(Total (1000 Km))			(0.0006)	(0.0009)	(0.0009)
Travel Distance			-0.0008	-0.0016	-0.0031**
(Water (1000 Km))			(0.0007)	(0.0013)	(0.0013)
# of Beds/1000			-0.0012***	-0.0002	-0.0004
Population			(0.0004)	(0.0007)	(0.0008)
Constant	0.0036***	0.0084**	0.0075**	0.0065	0.0050
	(0.0008)	(0.0035)	(0.0035)	(0.0052)	(0.0044)
Observations	28,695	28,695	28,695	28,695	28,695
R-squared	0.0005	0.0020	0.0025	0.0061	0.0096
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table H. 4. Robustness Checks: Inpatient in Private Hospital, Main Islands (Matching DID)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital
Treatment*Post	0.0009	0.0008	0.0006	0.0010	0.0007
	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0009)
Treatment	0.0001	-0.0001	-0.0000		
	(0.0004)	(0.0004)	(0.0004)		
Post	0.0002	0.0002	0.0004		
	(0.0003)	(0.0003)	(0.0004)		
Male		0.0002	0.0002	0.0002	0.0002
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Age		0.0000*	0.0000*	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married		0.0007**	0.0008**	0.0007**	0.0007**
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Education		0.0001	0.0000	0.0001	0.0001
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rural		-0.0022***	-0.0022***	-0.0023***	-0.0024***
		(0.0008)	(0.0008)	(0.0008)	(0.0008)
HH Size		0.0000	0.0001	-0.0000	-0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public Hospital			-0.0001	-0.0005	-0.0002
(Central Gov)			(0.0007)	(0.0012)	(0.0012)
Public Hospital			0.0001	-0.0009*	-0.0008
(Local Gov)			(0.0003)	(0.0005)	(0.0005)
Travel Distance			-0.0002	-0.0001	-0.0000
(Total (100 Km))			(0.0001)	(0.0002)	(0.0002)
Travel Distance			-0.0001	-0.0011*	-0.0014**
(Water (100 Km))			(0.0001)	(0.0006)	(0.0007)
# of Beds/1000			-0.0006***	-0.0003	-0.0002
population			(0.0001)	(0.0002)	(0.0002)
Constant	0.0011***	0.0016*	0.0021***	0.0020*	0.0007
	(0.0002)	(0.0008)	(0.0008)	(0.0011)	(0.0014)
Observations	118,035	118,035	118,035	118,035	118,035
R-squared	0.0001	0.0009	0.0013	0.0030	0.0034
Municipality FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
Region*Year FE	NO	NO	NO	NO	YES
Year	2004-2011	2004-2011	2004-2011	2004-2011	2004-2011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix I: Falsification Test, Household Health Expenditures

Table I. 1. Falsification Test, Household Health Expenditures, Main Islands (DID and Matching DID)

VARIABLES	Difference in Difference			Matching Difference in Difference		
	(1)	(2)	(3)	(4)	(5)	(6)
	Household Health Expenditures			Household Health Expenditures		
Treatment*Post	-27,486.448	-44,208.012	74,238.718	-25,312.307	28,875.119	93,300.930
	(53,941.841)	(60,764.900)	(100,839.627)	(63,231.799)	(78,189.427)	(115,287.869)
Male	-27,402.072	-27,331.244	-26,649.470	-107,929***	-106,993***	-106,809***
	(49,467.949)	(49,322.461)	(49,297.482)	(39,235)	(38,923.948)	(38,975.582)
Age	3,184.492**	3,178.681**	3,183.030**	2,030.941	2,034.051	2,031.306
	(1,306.388)	(1,310.652)	(1,308.566)	(1,372.147)	(1,384.379)	(1,375.456)
Married	-29,225.423	-29,384.343	-28,308.166	3,188.946	3,992.208	4,232.868
	(46,967.691)	(47,255.762)	(47,082.572)	(67,633.301)	(68,229.465)	(67,890.196)
Education	49,992.859***	50,053.191***	49,865.165***	34,318.918**	34,221.875**	34,205.858**
	(15,291.336)	(15,264.797)	(15,281.679)	(14,356.303)	(14,329.154)	(14,356.582)
Rural	20,087.633	20,095.064	20,090.972	-49,987.554	-50,793.428	-51,856.871
	(98,160.124)	(98,162.528)	(98,170.757)	(36,030.649)	(35,589.490)	(35,244.090)
HH Size	4,345.408	4,298.102	4,393.323	6,740.020	6,806.071	6,759.004
	(4,310.933)	(4,297.845)	(4,313.660)	(4,793.144)	(4,780.208)	(4,810.554)
Public Hospital	-192,789***	-192,846***	-194,417***	-217,832***	-222,207***	-224,104***
(Central Gov)	(67,726.509)	(67,726.798)	(67,734.449)	(67,201)	(67,400.600)	(67,314.557)
Public Hospital	-74,337.674***	-73,097.343***	-76,566.605***	-34,627.063	-38,228.364	-38,706.656
(Local Gov)	(25,838.211)	(26,445.920)	(26,257.777)	(25,474.231)	(28,033.548)	(26,364.114)
Travel Distance	8,002.761	8,728.885	8,191.572	31,154.607	32,004.033	31,159.882
(Total (100 Km))	(15,533.534)	(15,445.355)	(15,442.869)	(24,041.646)	(22,246.016)	(21,978.073)
Travel Distance	-64,109**	-64,049.238**	-65,559.172**	-105,646*	-106,878**	-105,610**
(Water (100 Km))	(29,454.097)	(29,467.474)	(29,420.080)	(56,660.990)	(53,902.845)	(52,860.456)
# of Beds	-188.599	-178.671	-227.339	372.927*	362.752*	337.670*
	(507.489)	(507.442)	(506.828)	(196.500)	(191.495)	(199.230)
Constant	-403,601.086	108,109.486	-480,480.832	18,560.415	27,160.450	-67,641.206
	(394,791.846)	(431,079.595)	(391,911.818)	(71,172.423)	(68,644.921)	(85,790.910)
Observations	16,457	16,457	16,457	14,536	14,536	14,536
R-squared	0.016	0.016	0.016	0.036	0.036	0.037
Subdistrict FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Reg*Year FE	YES	YES	YES	YES	YES	YES
Year	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007
Artificial Year	2005	2006	2007	2005	2006	2007

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

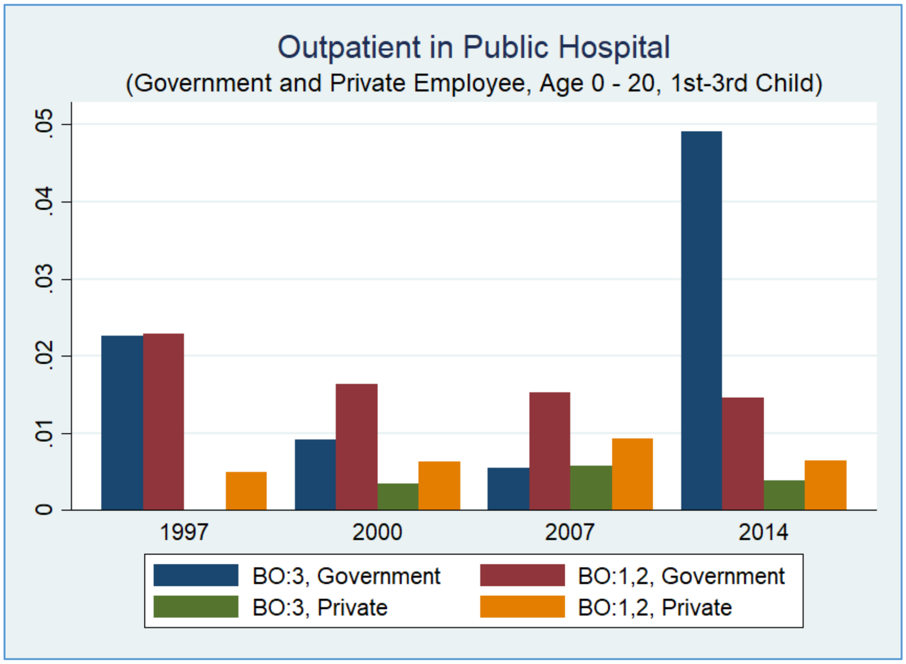


Figure J. 1. Outpatient in Public Hospital (1^{st}, 2^{nd}, 3^{rd} Children)

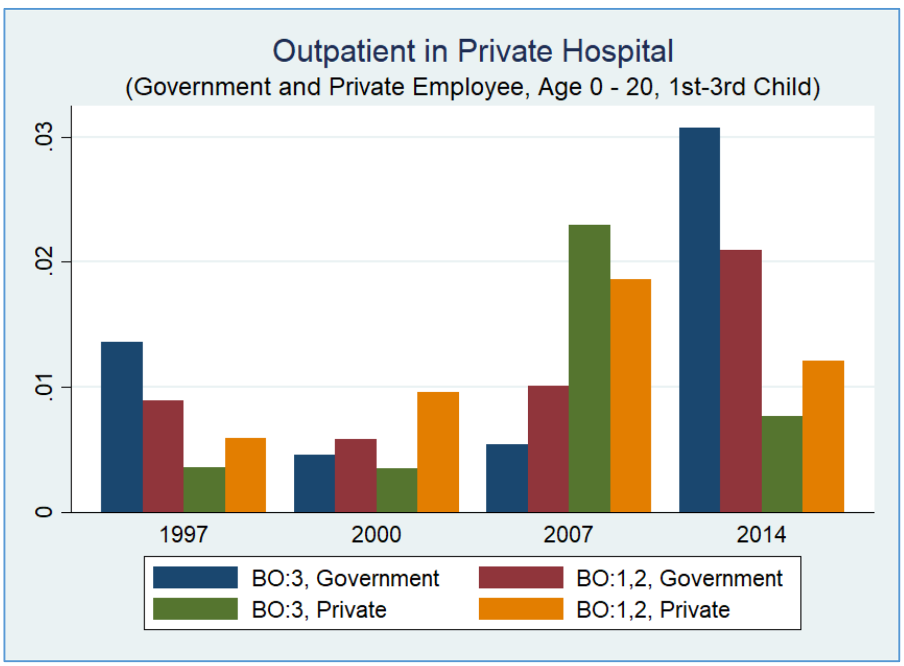


Figure J. 2. Outpatient in Private Hospital (1^{st}, 2^{nd}, 3^{rd} Children)

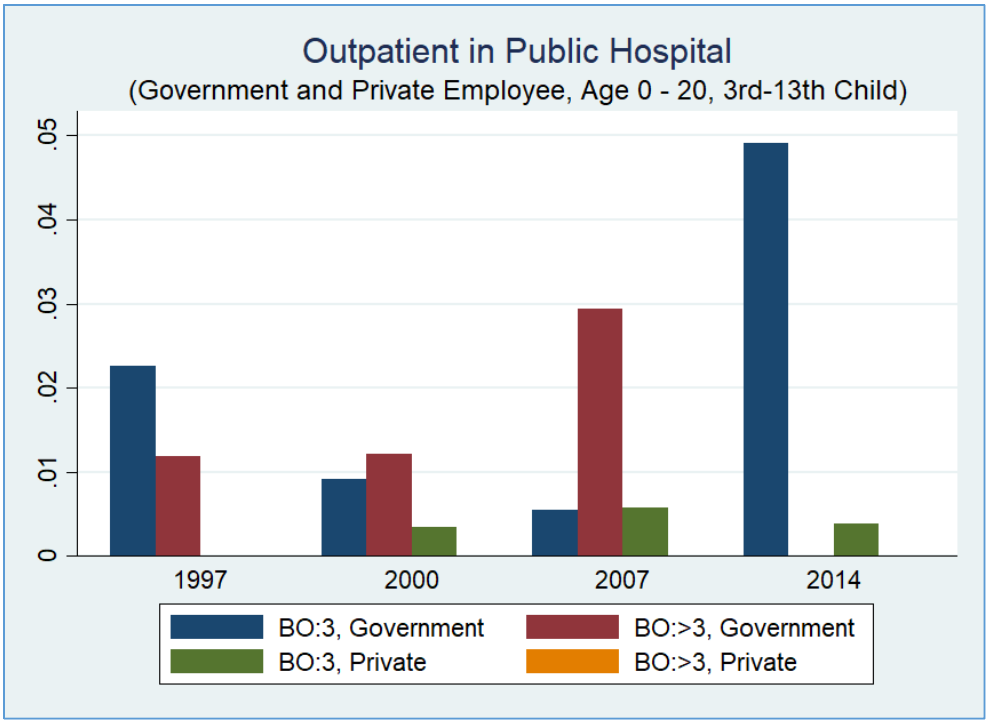


Figure J. 3. Outpatient in Public Hospital (3rd and afterward children)

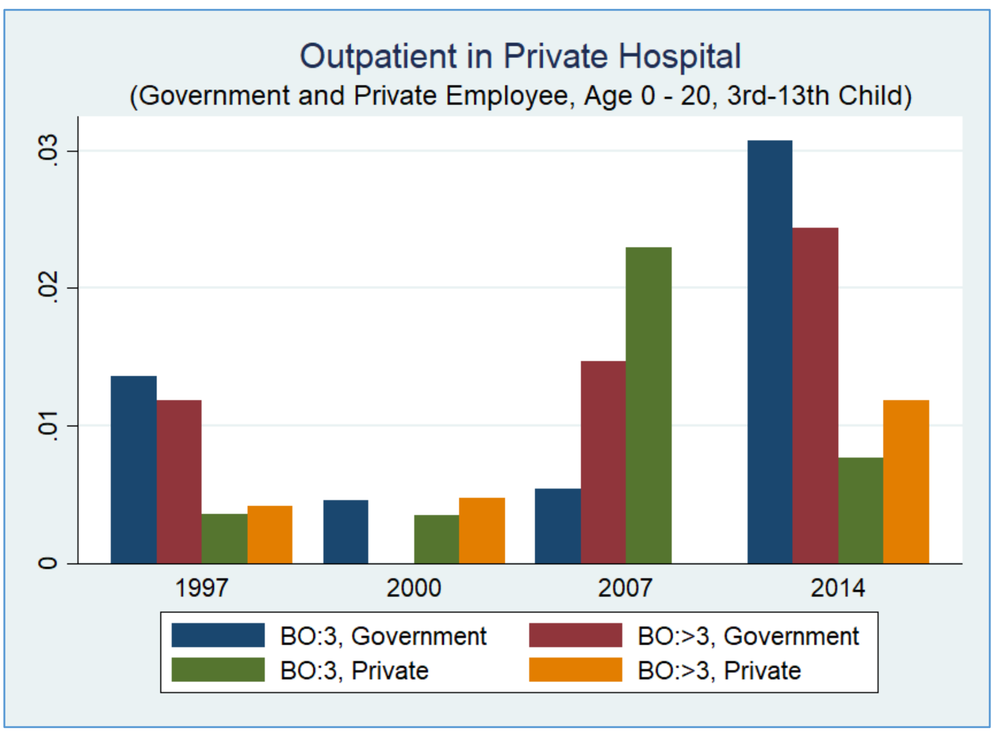


Figure J. 4. Outpatient in Private Hospital (3rd and afterward children)

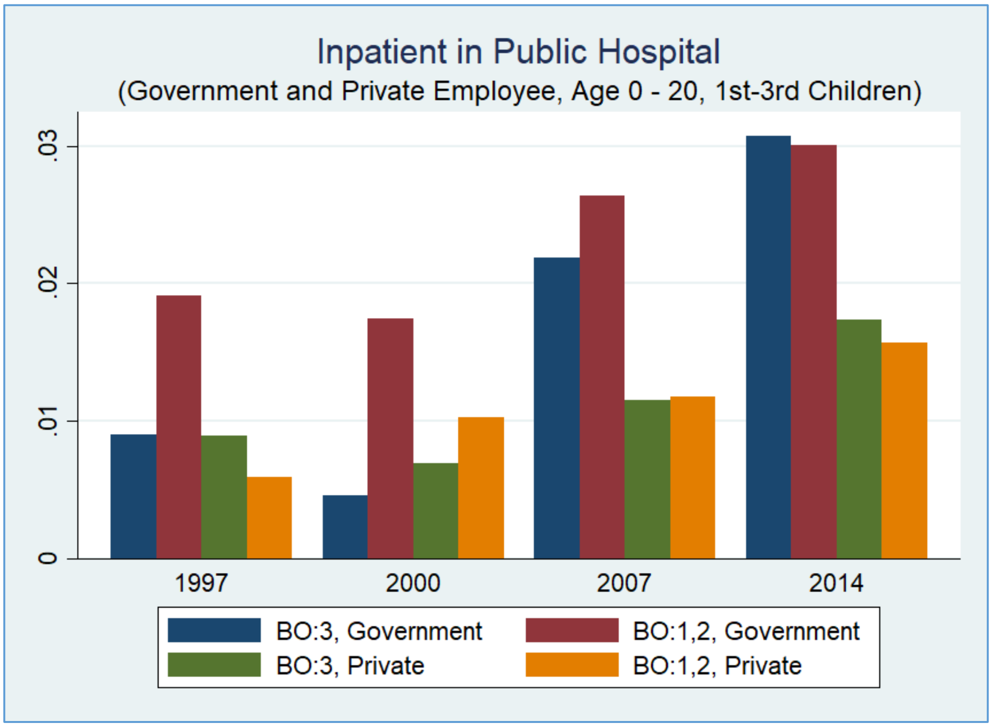


Figure J. 5. Inpatient in Private Hospital (1^{st}, 2^{nd}, 3^{rd} Children)

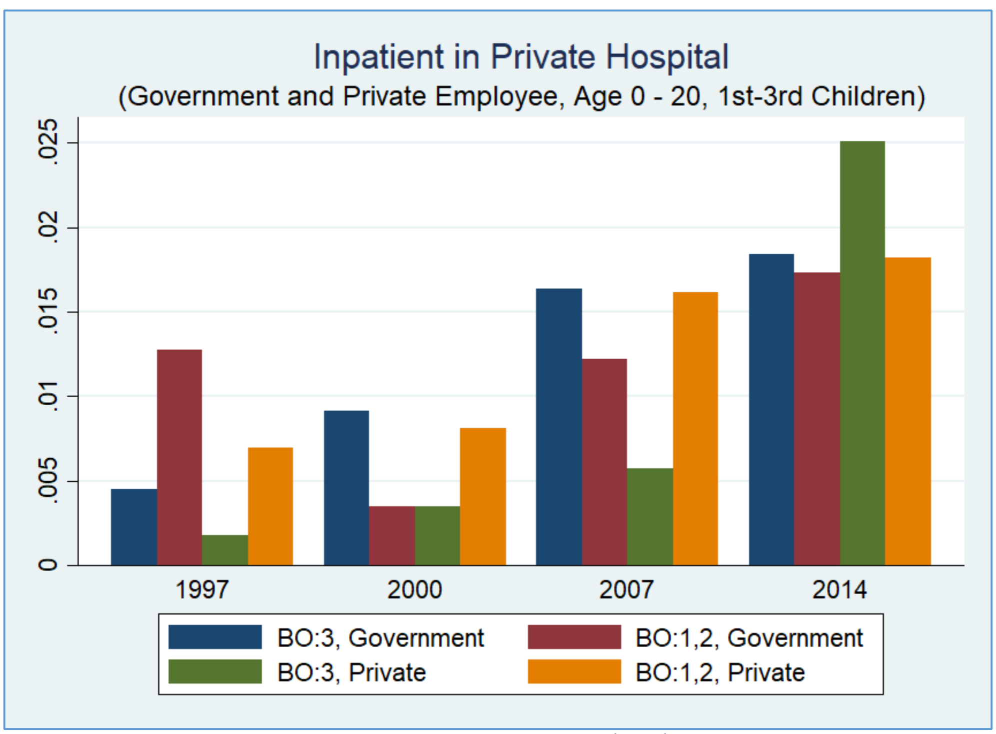


Figure J. 6. Inpatient in Private Hospital (1^{st}, 2^{nd}, 3^{rd} Children)

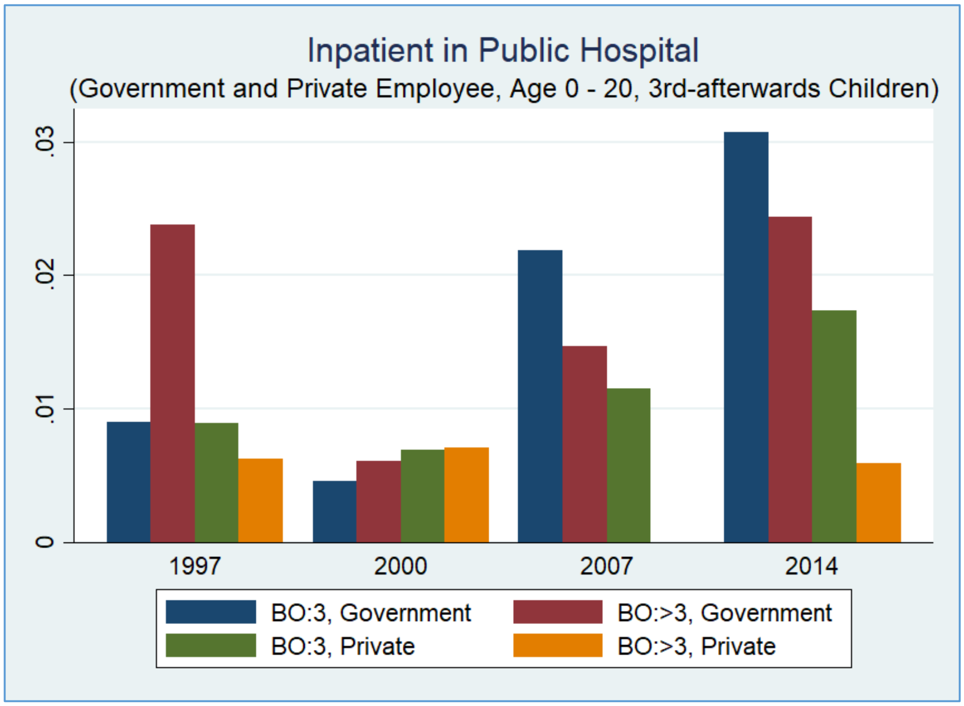


Figure J. 7. Inpatient in Public Hospital (3rd and afterward children)

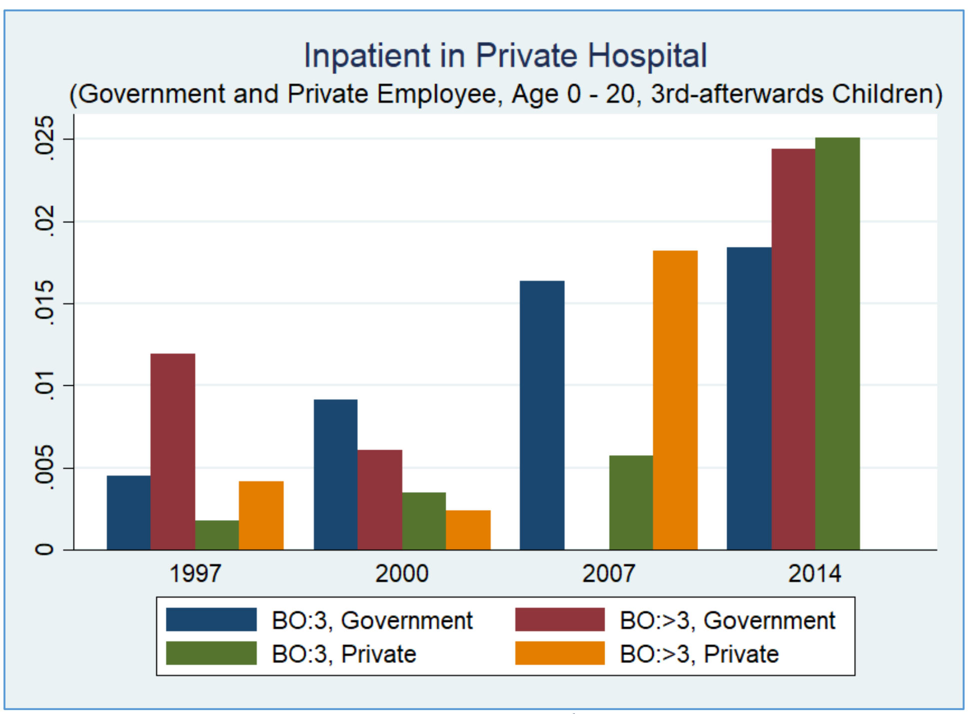


Figure J. 8. Inpatient in Private Hospital (3rd and afterward children)

Appendix K. Public Health Center Medical Care Utilization Service Fees in Jakarta (Jakarta Governor Regulation 68/2012)

Utilization	Fees (IDR)				
	<=5000	5001-10000	10001-50000	50001-100000	>100000
Outpatient (%)	25.28%	17.84%	41.64%	7.43%	7.81%
Services	Policlinic includes lung, skin, dental; laboratory; Emergency	Specialist, Dental; Emergency	Birth control programs, healthy women and children services	ultrasound, laboratory, vasectomy	Surgical operation, tubectomy, prosthesis
Inpatient (%)	6.38%	21.28%	55.32%	6.38%	10.64%
Services	healthy baby/day,	doctor visit	Inpatient room/day, doctor visit, ambulance	Inpatient room/day	Birth delivery

Appendix L: Robustness Checks, Primary Outcomes

Table L. 1. Robustness Checks: Outpatient in Hospital

VARIABLES	Outpatient Hospital	Outpatient Hospital	Outpatient Hospital	Outpatient Hospital	Outpatient Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.045**	0.043**	0.043**	0.042**	0.041*
	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
Observations	5,014	4,995	4,985	4,980	4,980
R-squared	0.005	0.013	0.013	0.022	0.074
Panel B: DDD					
Treatment*Gov*Post	0.044*	0.045**	0.045**	0.044*	0.044**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Observations	18,820	18,761	18,737	18,675	18,675
R-squared	0.004	0.009	0.009	0.014	0.032
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 2.Robustness Checks: Outpatient in Public Hospital

VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.041**	0.039**	0.039**	0.038**	0.039**
	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)
Observations	5,014	4,995	4,985	4,980	4,980
R-squared	0.004	0.008	0.008	0.014	0.063
Panel B: DDD					
Treatment*Gov*Post	0.039**	0.039**	0.039**	0.039**	0.039**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Observations	18,820	18,761	18,737	18,675	18,675
R-squared	0.005	0.008	0.008	0.009	0.025
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 3. Robustness Checks: Outpatient in Private Hospital

VARIABLES	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.009	0.009	0.009	0.008	0.006
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	5,014	4,995	4,985	4,980	4,980
R-squared	0.004	0.011	0.012	0.018	0.070
Panel B: DDD					
Treatment*Gov*Post	0.010	0.011	0.011	0.009	0.010
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Observations	18,820	18,761	18,737	18,675	18,675
R-squared	0.002	0.006	0.006	0.011	0.026
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 4. Robustness Checks: Outpatient in Public Hospital, Birth Order 1st ,2nd , and 3rd

VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.040**	0.038**	0.038**	0.037**	0.037**
	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)
Observations	4,573	4,557	4,547	4,542	4,542
R-squared	0.004	0.009	0.009	0.015	0.070
Panel B: DDD					
Treatment*Gov*Post	0.038**	0.038**	0.038**	0.038**	0.037**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Observations	17,251	17,198	17,176	17,116	17,116
R-squared	0.004	0.007	0.007	0.009	0.026
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 5. Robustness Checks: Outpatient in Public Hospital, Birth Order 3rd , 4th-10th

VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.055***	0.055***	0.055***	0.061***	0.065***
	(0.020)	(0.020)	(0.020)	(0.022)	(0.022)
Observations	1,233	1,224	1,223	1,223	1,223
R-squared	0.010	0.040	0.040	0.047	0.149
Panel B: DDD					
Treatment*Gov*Post	0.050***	0.050***	0.050**	0.050***	0.054***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	4,194	4,173	4,183	4,161	4,161
R-squared	0.016	0.025	0.025	0.027	0.073
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 6. Robustness Checks: Inpatient in Hospital

VARIABLES	Inpatient Hospital	Inpatient Hospital	Inpatient Hospital	Inpatient Hospital	Inpatient Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.013	0.012	0.012	0.011	0.008
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	5,014	4,995	4,985	4,980	4,980
R-squared	0.004	0.017	0.017	0.018	0.049
Panel B: DDD					
Treatment*Gov*Post	-0.004	-0.003	-0.003	-0.004	-0.004
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Observations	18,824	18,765	18,741	18,679	18,679
R-squared	0.005	0.016	0.016	0.018	0.030
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 7. Robustness Checks: Inpatient in Public Hospital

VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.010	0.010	0.010	0.010	0.008
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
Observations	5,014	4,995	4,985	4,980	4,980
R-squared	0.003	0.012	0.012	0.014	0.042
Panel B: DDD					
Treatment*Gov*Post	0.008	0.008	0.008	0.008	0.007
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Observations	18,824	18,765	18,741	18,679	18,679
R-squared	0.003	0.008	0.008	0.009	0.019
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 8. Robustness Checks: Inpatient in Private Hospital

VARIABLES	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Observations	5,014	4,995	4,985	4,980	4,980
R-squared	0.002	0.009	0.009	0.010	0.053
Panel B: DDD					
Treatment*Gov*Post	-0.014	-0.013	-0.014	-0.014	-0.013
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	18,824	18,765	18,741	18,679	18,679
R-squared	0.003	0.010	0.010	0.012	0.026
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 9. Robustness Checks: Outpatient in Hospital (Only Excluding Family Who Has Twins 2nd and 3rd Children)

VARIABLES	Outpatient Hospital (1)	Outpatient Hospital (2)	Outpatient Hospital (3)	Outpatient Hospital (4)	Outpatient Hospital (5)
Panel A: DID					
Treatment*Post	0.045**	0.043**	0.043**	0.041*	0.039*
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Observations	5,110	5,091	5,081	5,076	5,076
R-squared	0.005	0.013	0.013	0.022	0.074
Panel B: DDD					
Treatment*Gov*Post	0.043*	0.045**	0.045**	0.043*	0.044**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Observations	19,073	19,014	18,990	18,928	18,928
R-squared	0.004	0.009	0.009	0.014	0.032
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 10. Robustness Checks: Outpatient in Public Hospital (Only Excluding Family Who Has Twins 2nd and 3rd Children)

VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.040**	0.039**	0.039**	0.038**	0.038**
	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
Observations	5,110	5,091	5,081	5,076	5,076
R-squared	0.004	0.009	0.009	0.014	0.063
Panel B: DDD					
Treatment*Gov*Post	0.038**	0.038**	0.038**	0.038**	0.038**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Observations	19,073	19,014	18,990	18,928	18,928
R-squared	0.005	0.008	0.008	0.010	0.026
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 11. Robustness Checks: Outpatient in Private Hospital (Only Excluding Family Who Has Twins 2nd and 3rd Children)

VARIABLES	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.009	0.008	0.008	0.008	0.006
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	5,110	5,091	5,081	5,076	5,076
R-squared	0.004	0.011	0.012	0.018	0.070
Panel B: DDD					
Treatment*Gov*Post	0.010	0.011	0.011	0.010	0.010
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Observations	19,073	19,014	18,990	18,928	18,928
R-squared	0.002	0.006	0.006	0.011	0.026
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 12. Robustness Checks: Inpatient in Hospital (Only Excluding Family Who Has Twins 2nd and 3rd Children)

VARIABLES	Inpatient Hospital (1)	Inpatient Hospital (2)	Inpatient Hospital (3)	Inpatient Hospital (4)	Inpatient Hospital (5)
Panel A: DID					
Treatment*Post	0.013	0.013	0.013	0.012	0.008
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	5,110	5,091	5,081	5,076	5,076
R-squared	0.005	0.017	0.017	0.019	0.054
Panel B: DDD					
Treatment*Gov*Post	-0.004	-0.004	-0.004	-0.005	-0.004
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Observations	19,077	19,018	18,994	18,932	18,932
R-squared	0.005	0.016	0.016	0.018	0.031
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 13. Robustness Checks: Inpatient in Public Hospital (Only Excluding Family Who Has Twins 2nd and 3rd Children)

VARIABLES	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital	Inpatient Public Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.011	0.011	0.011	0.010	0.008
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Observations	5,110	5,091	5,081	5,076	5,076
R-squared	0.003	0.013	0.013	0.014	0.050
Panel B: DDD					
Treatment*Gov*Post	0.008	0.008	0.008	0.008	0.007
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Observations	19,077	19,018	18,994	18,932	18,932
R-squared	0.003	0.009	0.009	0.010	0.022
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 14. Robustness Checks: Inpatient in Private Hospital (Only Excluding Family Who Has Twins 2nd and 3rd Children)

VARIABLES	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital	Inpatient Private Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Observations	5,110	5,091	5,081	5,076	5,076
R-squared	0.002	0.009	0.009	0.010	0.052
Panel B: DDD					
Treatment*Gov*Post	-0.014	-0.014	-0.014	-0.014	-0.013
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	19,077	19,018	18,994	18,932	18,932
R-squared	0.003	0.010	0.010	0.012	0.026
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 15. Robustness Checks: Outpatient in Hospital (Family with at least 3 children)

VARIABLES	Outpatient Hospital (1)	Outpatient Hospital (2)	Outpatient Hospital (3)	Outpatient Hospital (4)	Outpatient Hospital (5)
Panel A: DID					
Treatment*Post	0.051**	0.045**	0.046**	0.044**	0.044**
	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
Observations	3,145	3,132	3,123	3,119	3,119
R-squared	0.008	0.015	0.016	0.026	0.086
Panel B: DDD					
Treatment*Gov*Post	0.051**	0.051**	0.052**	0.051**	0.051**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Observations	10,584	10,552	10,532	10,478	10,478
R-squared	0.005	0.010	0.010	0.013	0.039
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 16. Robustness Checks: Outpatient in Public Hospital (Family with at least 3 children)

VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.043**	0.037**	0.037**	0.036**	0.036**
	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
Observations	3,145	3,132	3,123	3,119	3,119
R-squared	0.006	0.016	0.016	0.019	0.090
Panel B: DDD					
Treatment*Gov*Post	0.040**	0.040**	0.040**	0.039**	0.040**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Observations	10,584	10,552	10,532	10,478	10,478
R-squared	0.007	0.011	0.011	0.012	0.039
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 17. Robustness Checks: Outpatient in Private Hospital (Family with at least 3 children)

VARIABLES	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.013	0.013	0.013	0.012	0.012
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	3,145	3,132	3,123	3,119	3,119
R-squared	0.004	0.011	0.013	0.028	0.078
Panel B: DDD					
Treatment*Gov*Post	0.016	0.016	0.016	0.016	0.016
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Observations	10,584	10,552	10,532	10,478	10,478
R-squared	0.002	0.005	0.006	0.011	0.035
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 18. Robustness Checks: Outpatient in Hospital, Born after March 1994

VARIABLES	Outpatient Hospital (1)	Outpatient Hospital (2)	Outpatient Hospital (3)	Outpatient Hospital (4)	Outpatient Hospital (5)
Panel A:DID					
Treatment*Post	0.054**	0.053**	0.053**	0.051**	0.044*
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Observations	2,820	2,820	2,820	2,819	2,819
R-squared	0.005	0.013	0.013	0.027	0.102
Panel B:DDD					
Treatment*Gov*Post	0.052**	0.053**	0.053**	0.053**	0.051**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Observations	11,600	11,600	11,599	11,582	11,582
R-squared	0.004	0.009	0.009	0.015	0.040
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 19. Robustness Checks: Outpatient in Public Hospital, Born after March 1994

VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.050***	0.050***	0.050***	0.049***	0.048***
	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
Observations	2,820	2,820	2,820	2,819	2,819
R-squared	0.006	0.010	0.011	0.026	0.080
Panel B: DDD					
Treatment*Gov*Post	0.048**	0.048**	0.048**	0.049**	0.048**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	11,600	11,600	11,599	11,582	11,582
R-squared	0.005	0.007	0.008	0.011	0.030
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table L. 20. Robustness Checks: Outpatient in Private Hospital, Born after March 1994

VARIABLES	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital
	(1)	(2)	(3)	(4)	(5)
Panel A: DID					
Treatment*Post	0.010	0.009	0.010	0.008	0.001
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
Observations	2,820	2,820	2,820	2,819	2,819
R-squared	0.003	0.012	0.012	0.018	0.098
Panel B: DDD					
Treatment*Gov*Post	0.010	0.011	0.011	0.010	0.009
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Observations	11,600	11,600	11,599	11,582	11,582
R-squared	0.002	0.006	0.006	0.011	0.035
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix M: Falsification Tests, Primary Outcomes

Table M. 1. Falsification Test: Outpatient in Hospital (Artificial Treatment Year: 2007)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Hospital	Outpatient Hospital	Outpatient Hospital	Outpatient Hospital	Outpatient hospital
Panel A: DID					
Treatment*Post	-0.012	-0.012	-0.012	-0.012	-0.007
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Observations	3,702	3,702	3,692	3,688	3,688
R-squared	0.003	0.011	0.011	0.020	0.087
Panel B: DDD					
Treatment*Post	-0.022	-0.021	-0.021	-0.023	-0.018
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Observations	12,399	12,399	12,375	12,331	12,331
R-squared	0.004	0.009	0.009	0.016	0.044
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2007	2007	2007	2007	2007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table M. 2. Falsification Test: Outpatient in Public Hospital (Artificial Treatment Year: 2007)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Panel A: DID					
Treatment*Post	-0.007	-0.008	-0.008	-0.008	-0.008
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Observations	3,702	3,702	3,692	3,688	3,688
R-squared	0.003	0.010	0.010	0.014	0.078
Panel B: DDD					
Treatment*Gov*Post	0.007	0.008	0.008	0.008	0.011
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Observations	12,403	12,403	12,379	12,335	12,335
R-squared	0.003	0.009	0.009	0.010	0.023
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2007	2007	2007	2007	2007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table M. 3. Falsification Test: Outpatient in Private Hospital (Artificial Treatment Year: 2007)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital
Panel A: DID					
Treatment*Post	-0.007	-0.006	-0.006	-0.006	-0.001
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Observations	3,702	3,702	3,692	3,688	3,688
R-squared	0.001	0.007	0.008	0.017	0.092
Panel B: DDD					
Treatment*Gov*Post	0.009	0.010	0.010	0.009	0.012
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Observations	12,403	12,403	12,379	12,335	12,335
R-squared	0.002	0.008	0.008	0.011	0.035
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2007	2007	2007	2007	2007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table M. 4. Falsification Test: Outpatient in Hospital (Artificial Treatment Year: 2000)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Hospital	Outpatient Hospital	Outpatient Hospital	Outpatient Hospital	Outpatient Hospital
Panel A: DID					
Treatment*Post	-0.012	-0.012	-0.012	-0.011	-0.008
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	3,702	3,702	3,692	3,688	3,688
R-squared	0.003	0.011	0.011	0.020	0.087
Panel B: DDD					
Treatment*Gov*Post	-0.013	-0.015	-0.015	-0.015	-0.012
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Observations	12,399	12,399	12,375	12,331	12,331
R-squared	0.004	0.009	0.010	0.016	0.044
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2000	2000	2000	2000	2000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table M. 5. Falsification Test: Outpatient in Public Hospital (Artificial Treatment Year: 2000)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Panel A: DID					
Treatment*Post	-0.010	-0.010	-0.010	-0.010	-0.010
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	3,702	3,702	3,692	3,688	3,688
R-squared	0.003	0.010	0.010	0.014	0.079
Panel B: DDD					
Treatment*Gov*Post	0.007	0.006	0.006	0.006	0.008
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	12,403	12,403	12,379	12,335	12,335
R-squared	0.003	0.009	0.009	0.010	0.023
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2000	2000	2000	2000	2000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table M. 6. Falsification Test: Outpatient in Private Hospital (Artificial Treatment Year: 2000)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital	Outpatient Private Hospital
Panel A: DID					
Treatment*Post	-0.007	-0.006	-0.006	-0.005	-0.003
	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Observations	3,702	3,702	3,692	3,688	3,688
R-squared	0.001	0.007	0.008	0.017	0.092
Panel B: DDD					
Treatment*Gov*Post	0.015*	0.013	0.012	0.012	0.013
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	12,403	12,403	12,379	12,335	12,335
R-squared	0.002	0.008	0.008	0.012	0.036
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2000	2000	2000	2000	2000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table M. 7. Falsification Test: Outpatient in Public Hospital (Artificial Treatment Year: 2007; Birth Order: 1st, 2nd, 3rd)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Panel A: DID					
Treatment*Post	-0.006	-0.006	-0.006	-0.006	-0.005
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Observations	3,302	3,302	3,292	3,288	3,288
R-squared	0.003	0.010	0.010	0.015	0.087
Panel B: DDD					
Treatment*Gov*Post	-0.007	-0.006	-0.006	-0.007	-0.005
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Observations	11,040	11,040	11,018	10,976	10,976
R-squared	0.004	0.008	0.008	0.010	0.036
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2007	2007	2007	2007	2007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table M. 8. Falsification Test: Outpatient in Public Hospital (Artificial Treatment Year: 2007; Birth Order: 3rd, 4th – 10th)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Panel A: DID					
Treatment*Post	-0.021	-0.023	-0.023	-0.024	-0.021
	(0.014)	(0.014)	(0.015)	(0.015)	(0.017)
Observations	1,029	1,029	1,028	1,028	1,028
R-squared	0.004	0.024	0.024	0.030	0.157
Panel B: DDD					
Treatment*Gov*Post	-0.031	-0.033	-0.033	-0.034	-0.028
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
Observations	3,302	3,302	3,299	3,291	3,291
R-squared	0.009	0.016	0.016	0.022	0.092
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2007	2007	2007	2007	2007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table M. 9. Falsification Test: Outpatient in Public Hospital (Artificial Treatment Year: 2000; Birth Order: 1st, 2nd, 3rd)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Panel A: DID					
Treatment*Post	-0.008	-0.008	-0.008	-0.008	-0.006
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Observations	3,302	3,302	3,292	3,288	3,288
R-squared	0.003	0.010	0.010	0.015	0.087
Panel B: DDD					
Treatment*Gov*Post	-0.010	-0.010	-0.010	-0.011	-0.009
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Observations	11,040	11,040	11,018	10,976	10,976
R-squared	0.005	0.008	0.008	0.010	0.036
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2000	2000	2000	2000	2000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table M. 10. Falsification Test: Outpatient in Public Hospital (Artificial Treatment Year: 2000; Birth Order: 3rd, 4th – 10th)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital	Outpatient Public Hospital
Panel A: DID					
Treatment*Post	-0.021	-0.023	-0.023	-0.024	-0.021
	(0.014)	(0.014)	(0.015)	(0.015)	(0.017)
Observations	1,029	1,029	1,028	1,028	1,028
R-squared	0.004	0.024	0.024	0.030	0.157
Panel B: DDD					
Treatment*Gov*Post	-0.025*	-0.027*	-0.027*	-0.028*	-0.023
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)
Observations	3,302	3,302	3,299	3,291	3,291
R-squared	0.010	0.017	0.017	0.023	0.093
Controls	NO	NO	YES	YES	YES
Birth Order FE	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES
Religion FE	NO	NO	NO	YES	YES
Municipality FE	NO	NO	NO	NO	YES
Year FE	YES	YES	YES	YES	YES
Artificial Year	2000	2000	2000	2000	2000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix N: Robustness Checks

Table N. 1. Robustness Checks: The Effect of Compulsory and Free Tuition

VARIABLES	Baseline Regression	Without Municipality and Year FE	Exclude Year 2012-2014	Exclude Year 2009-2014
	(1)	(2)	(3)	(4)
Matching-DID				
Work	-0.035***	-0.034***	-0.034***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
Illnesses	-0.007***	-0.006**	-0.007***	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Standard-DID				
Work	-0.037***	-0.035***	-0.036***	-0.022***
	(0.002)	(0.003)	(0.002)	(0.003)
Illnesses	-0.005**	-0.004*	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Age FE	YES	YES	YES	YES
Crisis/Recession**	YES	YES	YES	YES
Controls*	YES	YES	YES	YES
Municipality FE	YES	NO	YES	YES
Year FE	YES	NO	YES	YES

* Controls include Gender, Marital Status, Education, HH Size, Parent Income and Rural
** Crisis and Recession include crisis/recession and interaction between crisis/recession and treatment

Robust standard errors in parentheses

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

Appendix O: Falsification Test

Table O. 1. Falsification Test: The Effect of Compulsory and Free Tuition

OUTCOMES VARIABLES	With Parent Income; 1998-1999***	Without Parent Income; 1997-1999***	Without Parent Income; Include 1997, 2005, 2009	With Parent Income; Exclude 1997, 2005, 2009
	(1)	(2)	(3)	(4)
Matching-DID				
Work	-0.003	-0.002	0.001	0.001
	(0.008)	(0.007)	(0.004)	(0.004)
Illnesses	0.004	0.005	0.003	0.003
	(0.005)	(0.004)	(0.003)	(0.005)
Standard-DID				
Work	0.001	-0.002	-0.002	0.004
	(0.006)	(0.004)	(0.004)	(0.006)
Illnesses	0.005	0.003	0.003	0.005
	(0.005)	(0.003)	(0.003)	(0.005)
Year	1998-1999	1997-1999	1997-2014	1998-2014
Ln(Parent Income)	YES	NO	NO	YES
Controls*	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Crisis/Recession**	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Mun*Year FE	YES	YES	YES	YES

* Controls include Gender, Marital Status, Education, HH Size, and Rural
** Crisis and Recession include crisis/recession and interaction between crisis/recession and treatment
*** Regression before compulsory education without controlling compulsory (2003) and compulsory education and free tuition (2005) intervention variables

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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