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Does Fuel-Switching Improve Health? Evidence from LPG Subsidy Program

(A Preliminary Draft)

Imelda*

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Abstract

Does the adoption of cleaner cooking fuels improve health? This paper provides new evidence on the impact of access to cleaner fuel to health outcomes through a major kerosene to LPG (Liquefied Petroleum Gas) conversion program in Indonesia happened in 2007. The program was deemed success through its significant rise of LPG users to almost five fold within three years and a reduce in household kerosene demand by 80%. This paper is the first that investigates the health benefit of such policy. Instead of using cooking fuel choice which is potentially endogenous, I use the regional and time variation of the program and apply Difference-in-Difference and matching estimation. The key finding suggests that fuel-switching has a significant impact on improving child survival rate by 1.1%-6.7% (about 11 lives from every 1000 births). The poorer households experienced the biggest improvement on child's health such as lower probability of low birth weight and pneumonia symptom. It suggests that switching to cleaner cooking-fuel may indeed have short term health benefits on children.

1 Introduction

As of 2010, an estimated 41 percent of households worldwide still relied on dirty fuel for cooking (Bonjour et al. 2013). Indoor air pollution (IAP) results from the cooking-fuel combustion is deemed to be acute due to its daily exposure and its close proximity to households. It is listed as one of the most serious health problems and estimated to cause around 4.3 million premature deaths each year which happen mostly in developing countries (WHO, 2015). World Health Organization reported about 2 million premature children death in the world was associated with IAP, while for adults, exposure to IAP increases the risk of chronic lung disease such as tuberculosis, asthma and cataracts. In Indonesia, premature death associated with IAP occurs in 19 from 1000 people annually (WHO/UNDP 2009).

*PhD Student in Economics at University of Hawai'i at Manoa and East-West Center Student Affiliate. Email: imelda9@hawaii.edu

Does switching to cleaner cooking fuel improve health? The existing evidence on the relationship between indoor air pollution and health is far from conclusive. Most of the existing evidence is based on associations rather than causal. It is inevitably hard to measure the pollution endpoints as the impact may have long lags. Even though many of public health literatures do indicates a high-exposure levels of indoor air pollution in developing countries has immediate consequences to health outcomes, those literatures significantly suffer from small sample bias. Some Randomized Controlled Trials (RCT) on improved cooking stoves may also suffer with small sample size and the observer effect where respondents change their behavior in response to their awareness of being observed. Duflo et al. (2012) find through their large-scale RCT in Indian villages that improved cook stoves has little effect on health mainly because households did not use them.

This paper contributes to the literature in two ways. First, it adds to the thin literature on cleaner cooking fuel impact on health by addressing endogeneity problem in fuel-switching through plausibly exogenous shifter: LPG conversion program. Major studies are focused more on solid fuel such as wood, while very limited studies conducted on comparing kerosene and LPG. Second, as far to my knowledge, this paper is the first that investigates health outcomes associated with this policy. I use a repeated cross-section data of Indonesian Demographic and Health Surveys (DHS), a nationally representative data on health and population, for the year 2002, 2007, 2012. I investigate the pregnancy problems and child's health outcomes following existing literatures which suggested that pregnant woman and children are likely more responsive to short and medium changes in pollution. Moreover, it is also an especially vulnerable one, and so losses of life expectancy may be large.

For the main analysis, I use Difference-in-Difference (DID) and matching to address the endogeneity in cooking fuel choice. I compare three specifications: DID with binary treatment, DID with continuous treatment and DID with matching. I show with an OLS model that regress fuel-choice on health outcomes could result in a bias estimates. A positive effect from the program is consistently showed in both DID specifications which is lower than the OLS model. It could indicate that OLS model is over estimating the true impact of the fuel-switching on health. I find that switching to a cleaner cooking-fuel leads to an increase in survival rate of child, lower probability of low birth weight and pneumonia symptom. This finding is consistent with previous literature such as Radim J., et al. (2005) and Jayachandra (2009). It suggests that reducing pollution exposure through an adoption of a cleaner cooking-fuel may have short term health benefits on children. The results of this policy analysis can provide a starting point for discussions about the design of policies and intervention that addressing IAP.

2 Existing Literature

The existing evidence on the relationship between indoor air pollution (IAP) and health is far from conclusive. Most of the evidence is based on associations rather than causal. Many of public health literatures do indicates a high-exposure levels of indoor air pollution in developing countries has immediate and negative consequences to health outcomes, but they significantly suffer from small sample bias. Ezzati and Kammen (2001) evaluate exposure and response relationship for particulate matters generated from biomass combustion with a real-time monitoring in 55 houses in Kenya. Rinne et al. (2007) examine a lifetime history of infant mortality in 80 households in a small community in Ecuador. Fullerton et al. (2009) measure concentrations of indoor air quality in 62 homes in both rural and urban in southern Malawi. Dionisio et al. (2008) measure IAP concentrations and examine the risk of pneumonia for children in 13 households in the Gambia. Rumchev et al. (2007) monitor levels of IAP in 48 households in a village in Zimbabwe.

Moreover most of studies relied upon the estimates that is observational, i.e. they examined the health conditions of populations with existing differences in exposure patterns. Such studies are always subject to potential bias due to confounders (i.e. low education level, malnutrition, and other factors associated with poverty). Even though those studies have accounted for some related household's characteristics, it is still hard to guarantee that all potential confounders has been taking into account to eliminate the bias. Bruce et al. (2000) provides a recent survey of a large number of papers estimating the health effects of indoor air pollution in developing countries and concludes that the observational nature of most studies and the inadequate control for heterogeneity results in biased estimates of risk.

Some past Randomized Controlled Trials (RCT) experiments suffer with small sample size and potentially *Hawthorne effect*—often known as observer effect where respondents change their behavior in response to their awareness of being observed. While the large-scale RCT maybe expensive to conduct. It is also hard to measure the pollution endpoints as the impact may have long lags. Moreover, in RCT, some behavioral issues might arise, where actually households do not use the improved cook stoves thus made it hard to evaluate the health impact from it. Hanna et al. (2012) find through their large-scale RCT in Indian villages that improved cook stoves has little effect on health mainly because households did not use them.

Many of existing literatures show that the pollution exposure at early ages can have not only short and direct but also long lasting influences on health outcomes and productivity (Behrman and Rosenzweig 2004; Black, Sandra et al., 2007; Oreopoulos et al. 2008; Royer 2009). The economic literatures in health and development have devoted some attention to IAP since early 80's. Dozens of expert groups conducted Comparative Risk Assessments (CRAs) for household air pollution from use of solid fuels for cooking estimated that this risk factor was responsible for 3.54 million premature deaths in 2010 (Smith et al. 2014). It is not surprising that high level of emission from burning the wood will be associated with lower health, but it is unclear what is the lower bound of the emission that can actually harm human. In some contexts, compared to LPG, solid fuel has about 19 times higher of carbon monoxide (CO) and 26 times higher of particulate matter (PM) on average per meal, while kerosene has only about three times higher of CO and 30% higher of PM. This study examines whether a possibly slight improvement in IAP could improve health outcomes.

This study will focus the health outcomes on women and children in households as existing literatures have showed evidence that woman and children suffer respiratory symptoms and illnesses compared with those in households cooking with LPG. 547 women and 845 children in households exclusively cooking with either kerosene or LPG in urban Banglore (Choi et al. 2015). Again, there is limited literatures showed similar result for kerosene and LPG. Some literatures suggest that pollution influence the productivity impacts by reducing work hours (Hanna and Oliva, 2013; Graff Zivin and Neidell, 2012). Some suggest that the marginal effect of pollution on health might be increasing in pollution levels (Jayachandra, 2009; Areco et al, 2012).

3 The Policy

In 2004, 48 million households out of the estimated 52 million households nationwide depended on kerosene for daily cooking. Government of Indonesia (GOI) has been subsidizing kerosene for decades to make it affordable for citizens. During 2006 and 2007, state's budget for kerosene subsidy took about half of the states total petroleum product subsidy budget (Budya and Arofat, 2011). The rising cost of oil made the subsidies a burden for the government and a large issue in the state budget. This event trigger GOI to provide incentives to lower kerosene demand and to diversify its energy consumption.

LPG was selected by GOI as the conversion fuel with several reasons. First, based on the end-use calorific value of energy delivered for cooking, and the subsidy per unit of fuel, the LPG subsidy is significantly lower than that of kerosene. One litre of kerosene equals 0.57 kg of LPG (Budya and Arofat, 2011). Second, LPG is cleaner than kerosene. Many studies worldwide have analyzed advantages and disadvantages of various household cooking fuels, e.g., Siyanbola et al. (2004), and Smith et al., 1993, 2000. In terms of health benefit, in some context, kerosene has approximately three times more carbon monoxide (CO) and 30% more particulate matter (PM) than LPG per meal (Smith, Rogers, and Cowlin 2005). Third, the infrastructure for LPG is the most readily implemented infrastructure compared to other alternatives such as coal and natural gas. Fourth, Subsidized LPG programs have been successfully implemented in neighboring countries such as Malaysia and Thailand.

Kerosene is a relatively cleaner cooking fuel compared to wood, dung, and coal while LPG, a cleaner, faster and arguably the more convenient fuel compared to kerosene. Many of existing literatures in developing countires have been focusing more on dirty cooking fuels but not so much on cleaner fuel. Indeed health impact from dirtier fuel might be stronger and more extreme. In some contexts, compared to LPG, solid fuel has about 19 times higher of carbon monoxide (CO) and 26 times higher of particulate matter (PM) on average per meal, while kerosene has only about three times higher of CO and 30% higher of PM (Smith, Uma et al. 2000).

In 2007 the government of Indonesia introduced a massive energy program to encourage kerosene users to switch to LPG. The purpose of this program is mainly reduce kerosene subsidies while other benefits such as efficiency, health and environmental benefit may come along. Before 2007, households mainly use kerosene and solid fuel (i.e. wood) for daily cooking. Other smaller portion of kerosene is used as lighting fuel by households, fishermen, and small industries. Before the program, the availability of LPG was limited in the big cities, relatively more expensive and thus only being used by middle-high income households. By offering subsidized gas cylinders and stoves, the government effectively increased the supply of LPG to rural areas. The fuel-switching did happen and it was reflected by a significant rise of LPG users to almost five fold within three years (Figure 6).

Distribution of initial conversion packages started in May 2007. The first figure showed total LPG distributed to household was peaked during 2008 and 2009 which accounts for more than 70% of total planned unit distribution. The later figure showed that total kerosene demand was significantly drop in 2012, nearly 89% from total kerosene demand in 2007. From this figure, we can be assured that the fuel-switching did happen after the policy. Note that before the program, kerosene was subsidized and LPG was not. The program supplied a new size of LPG (3 kg) which was the only type that is being subsidized while the other size was still not being subsidized. Household who have used the LPG before the program were mostly the richest household and represent about 10% of the sample (Figure 4). The figure 3 shows the treated region (23 regions) along with approximate year of intervention and the grey color indicated untreated regions (10 regions). Post 2012, GOI was planning to expand the distribution to these untreated region as the program was deemed to be successful and thus will be extended.

4 Data

I use a repeated cross-section data of Indonesian Demographic and Health Surveys (DHS), a nationally representative data on health and population, for the year 2002, 2007, 2012. With total sample of 17,595 households and 51,048 unit observations. It includes data about pregnancy problems and extensive health data for children for the last five year preceding the survey. I investigate the pregnancy problems and early-life health outcomes following existing literatures which suggested that pregnant woman and children are likely more responsive to short and medium changes in pollution. Moreover, the first year of life is an especially vulnerable one, and so losses of life expectancy may be large. The survey elicited information on health status, activities, nutritional intake, housing, including the location of the kitchen (outside or not) as well as roof and wall material which are important mediation for the dispersion of indoor smoke. Table 1 presents summary statistics for the sample. From the table we can see that household characteristics and health outcomes before and after the program are not significantly different. Figure **??** shows household main cooking fuel pre and post the policy where there is a clear significant increase of LPG users after the policy.

Table 1: Summary Statistics

Variable	Before Program Obs	Mean	Std. Dev.	Min	Max	After Program Obs	Mean	Std. Dev.	Min	Max
Household characteristics										
Cooking-Fuel										
LPG	33,716	0.10	0.30	0	1	17,332	0.43	0.50	0	1
kerosene	33,716	0.38	0.49	0	1	17,332	0.16	0.37	0	1
wood	33,716	0.51	0.50	0	1	17,332	0.41	0.49	0	1
Location										
urban	33,716	0.39	0.49	0	1	17,332	0.45	0.50	0	1
rural	33,716	0.61	0.49	0	1	17,332	0.55	0.50	0	1
wealth	33,716	-0.09	1.02	-2.41	2.68	17,332	-0.06	1.04	-2.75	3.16
livingchild	33,716	2.52	1.57	0	13	17,332	2.37	1.50	0	13
working	33,628	0.45	0.50	0	1	17,324	0.49	0.50	0	1
HH member	33,716	5.56	2.19	1	20	17,332	5.54	2.28	1	31
mother age	33,716	29.48	6.36	15	49	17,332	30.02	6.44	15	49
years of school	33,716	1.55	0.69	0	9	17,332	1.76	0.72	0	3
smoke last 24hr	33,702	0.07	0.80	0	32	17,283	0.14	1.40	0	48
Child characteristics										
child born alive in last 5yr	33,716	0.96	0.20	0	1	17,332	0.96	0.19	0	1
babies born										
singleton	33,716	0.98	0.12	0	1	17,332	0.98	0.13	0	1
twins	33,716	0.01	0.09	0	1	17,332	0.01	0.09	0	1
triplets	33,716	0.00	0.01	0	1	17,332	0.00	0.01	0	1
gender										
male	33,716	0.52	0.50	0	1	17,332	0.52	0.50	0	1
female	33,716	0.48	0.50	0	1	17,332	0.48	0.50	0	1
living with										
parents	32,306	0.99	0.11	0	1	16,704	0.98	0.13	0	1
somewhere	32,306	0.01	0.11	0	1	16,704	0.02	0.13	0	1
prefered waiting time for another child										
<12 months	14,525	0.09	0.28	0	1	7,399	0.10	0.29	0	1
1 yr	14,525	0.06	0.23	0	1	7,399	0.06	0.24	0	1
2 yr	14,525	0.15	0.35	0	1	7,399	0.14	0.35	0	1
3 yr	14,525	0.19	0.39	0	1	7,399	0.17	0.38	0	1
4 yr	14,525	0.12	0.32	0	1	7,399	0.11	0.32	0	1
5 yr	14,525	0.26	0.44	0	1	7,399	0.24	0.42	0	1
6 yr	14,525	0.14	0.35	0	1	7,399	0.17	0.38	0	1
birth size	31,757	2.82	0.84	1	5	16,638	2.80	0.78	1	5
birth weight	24,899	3.17	0.58	0.5	6	14,545	3.16	0.57	0.5	8
cough	33,716	0.30	0.46	0	1	17,332	0.33	0.47	0	1
pneumonia symp	33,716	0.10	0.30	0	1	17,332	0.11	0.31	0	1
stillbirth	33,716	0.21	0.95	0	9	17,332	0.22	0.95	0	9
diare	33,716	0.12	0.32	0	1	17,332	0.14	0.35	0	1
antenatal	27,427	6.70	3.68	0	30	14,548	7.33	3.75	0	36

5 Empirical Analysis

In this section, I first show the evidence of fuel-switching induced by the program. Next, I outline the model setup and present the Difference-in-Difference regression results to show if there is any causal effect from the program and then exploit nearest neighbour matching to measure the average treatment effect on the treated. At the end of this section, I examine heterogeneous impact on subgroups.

5.1 Evidence of fuel-switching

I firstly show whether the fuel-switching induced by the program is actually happen. I adopt a non-parametric approach to estimate relationship between the program and the household main cooking fuel observed in 2012. Note that the data are not informative about the exact time when the fuel-switching happened and whether household use more than one cooking fuel. Thus, I focus on this intent-to-treat (ITT) effect because the data are not informative about whether and when a household switch fuel due to the program. Despite the fact that the program was targeted to reduce kerosene demand, there is no stated restriction that prevent wood users to also switch to LPG. Thus in evaluating the overall policy impact, I include all three major cooking fuel used (LPG, kerosene and wood). I exclude other types of cooking fuel such as electricity and coal as those are relatively very small in the sample.

If household uses the more than one cooking fuel, I could fail to identify the relationship between fuel choice and the health outcomes. I would argue that fuel stacking (use more than one type of cooking-fuel) would be less likely to happen in this setting. Firstly, for kerosene users, when LPG was fully penetrated in certain region, government would remove the subsidy on kerosene thus there will be scarcity in the supply and the price will likely increase. Budya and Arofat (2011) had shown that the price of kerosene increased 150- 200% during the period of distribution. Thus, households who are living in the penetrated region would unlikely to use both LPG and kerosene. Secondly, while we might think that households who use wood would be likely to use both LPG and wood, while the data shows small change in number of household using woods. This is as expected since the program was not targeted to wood users thus fuel stacking in wood users should not be a major concern in this study.

Cooking fuel j will be selected by household i that resides in r region at time t if:

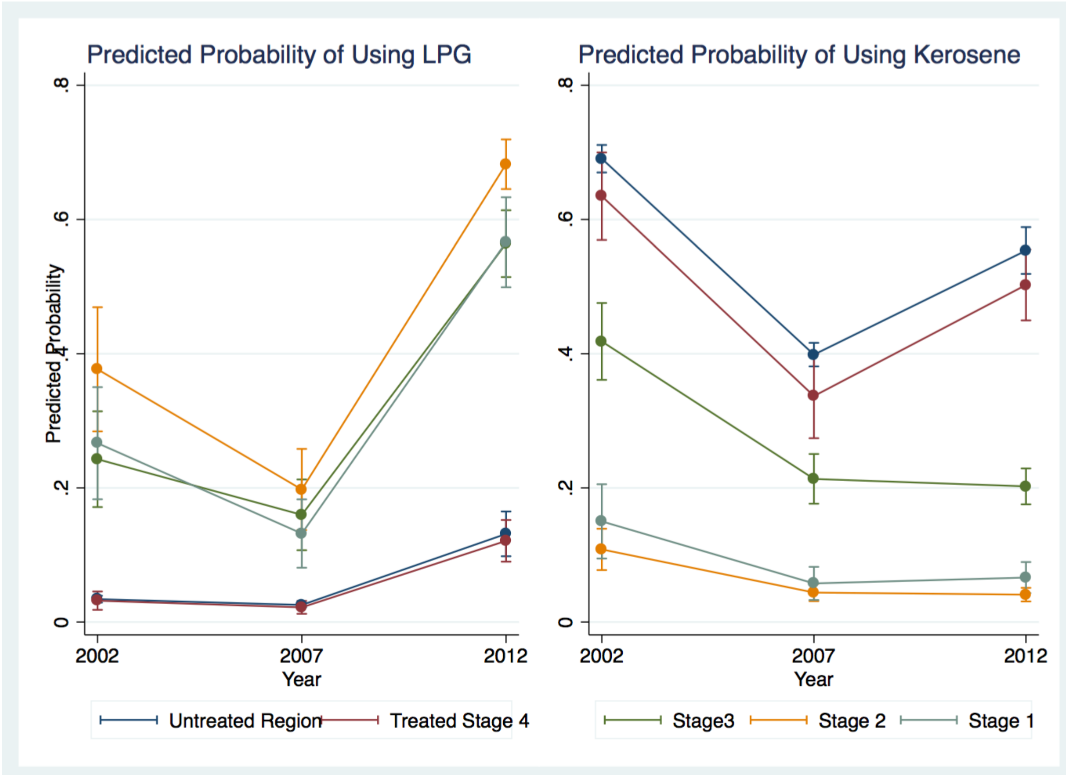
$$Prob_{irt}(j) = Prob(U_{irtj} \geqslant U_{irtk}, \text{for all } k \neq j) \tag{1}$$

I use a multinomial logit to estimate the probabilities of each alternative chosen.

$$Prob_{irt}(j) = \frac{e^{\beta_{irtj} X_{irt}}}{\sum_{k=0}^{2} e^{\beta_{irtk} X_{irt}}} \tag{2}$$

where X_{irt} consists of covariates such as household i characteristics (wealth, education), region fixed effects, rural dummy, time and the program dummy variable. While k and j are the cooking fuel alternatives (LPG, kerosene, wood). Figure 1 shows the predicted probability of household switching. Dummy treated region is constructed based on the time of the distribution (0 for untreated region; 1 for treated region in the early phase/ stage 1 which is in 2007-2008; 2 for treated region in stage 2 which is in 2009; 3 for treated region in stage 3 which is in 2010; 4 for treated region in stage 4 which is in 2011 ; the detail list of the region is in appendix). The result indicates that the probability of household using LPG is increase significantly after the program, since the program increase the availability of LPG through out the treated region. Although households in untreated region were also shifted Households who switched to LPG seems to be dominated by richer household and household living in urban (see Figure 5 and Figure 6 in appendix).

Figure 1: Predicted Probability of each cooking fuel choice compare to wood as baseline



5.2 Econometrics Specification

This paper explore Difference-in-Differences (DID) and matching method. Treatment group are households living in the treated region. The treated regions were picked by GOI, generally based on region's LPG infrastructure readiness, and the region's level of kerosene consumption. The program was divided into several stages. Bigger cities and urban area was targeted first due to easiness in distribution. The correlation between dummy kerosene users and dummy treated region is 0.13 before 2012, thus it is plausible to assume that government decision on the treated region is exogenous to the cooking fuel choice before 2012 in household level.

First, I start with a simple DID model with binary treatment.

$$Y_{irt} = fe_r + fe_t + \beta_1 Region_{rt} + \beta_2 Prog_{rt} + \beta_3 Region_{irt} * Prog_{rt} + \beta_4 X_{irt} + \epsilon_{irt} \quad (3)$$

where $_i$ represents child in every household, r represents region, t represent years. fe_r and fe_t are fixed effects for region and years. X_{irt} represents relevant child's controls (i.e. wealth index, education, household size, drink source, toilet facilities, number of cigarettes in the last 24 hours, rural/urban, mother's age, antenatal visits). This model also captures region, cohort fixed effects with error term clustered by region. The *Prog* is dummy program following the year of LPG distributed to the region. It takes value of 1 if the child was born after the intervention and 0 if the child was born before. Dummy *Region* takes value 0-4 based on intervention stages. The survey's sample weight is included in the regression.

Child's health outcomes are an appealing measure of the effectiveness of environmental regulations for at least two reasons. First, relative to measures of adult health, infant health is likely to be more responsive to short and medium changes in pollution. Second, the first year of life is an especially vulnerable one, and so losses of life expectancy may be large. Y_{irt} as outcomes variable include survival rate (whether child died divided by total child born within household), stillbirth or pregnancy loss (0 represents no stillbirth, while 1-9 represent the month when the loss happened), low weight birth (dummy of whether child is born with the weight that is below normal weight), cough (dummy of whether child experience cough in the last two weeks proceeding the survey), and pneumonia symptoms (also known as Acute Respiratory Infection (ARI) symptoms which is a dummy variable of whether child has cough with difficult or rapid breathing and chest in-drawing in the last two weeks prior to the survey). Some other non-health measurement, I include leisure time (measured by the frequency of respondent watching TV), and whether respondent is working as the outcomes.

Second, I explore the "fuzzy" design by having continuous treatment variable. The estimation equation is similar with the first model but instead of using binary (0-1) treatment, I use a linear trend for the *Prog* variable. I am interested in estimating the doseresponse function where the treatment might take on a continuum of values. Following Bia, M., and Mattei, A. (2008), I test whether the program exposure that influence the outcome follows a linear trend. effect to the outcomes, which is not captured by binary treatment variable.

Third, to control the observable differences between groups, I use nearest-neighbor matching (NNM) which use a weighted function of the household characteristics for each individual in the household in the regression. Since the model incorporates more than one continuous covariate, the NNM estimator converges to the true value at a rate slower than the parametric rate, which is the square root of the sample size. Thus, I use bias correction suggested by Abadie and Imbens (2006, 2011) as one of ways to correct this problem. Table **??** showed the mean of the difference in outcomes among the treated households known as the Average Treatment Effect on the Treated (ATET). For robustness check, I also provide the placebo test where I change the dummy program to be in 2002.

5.3 Health Impact of the program

Table 2 reports a comparison of different linear models: (1) and (2) show the effect of cooking-fuel (LPG and kerosene) compared to wood using only 2002 and 2007 data while model (3) and (4) use full sample; model (5) and (6) show the first DID model described above with (7) shows its placebo test using data 2002 and 2007 and setting the program dummy to be in 2007 (5 years before the actual program) and ; (8) and (9) show the second DID model with (10) as its placebo test which is similar with (7). The first four models consistenly show that using LPG is lowering the survival rate compared to using wood which is not as expected mechanism even after controlling some observed covariates, while using kerosene is increasing the survival rate compare do using wood which is as expected. These results could be caused by small sample size for LPG users (for model (1) and (2)) and there could be some other unobserved covariates that driving outcomes and the covariates. A positive effect from the program is consistently showed in both DID specification which is lower than the simple OLS model in the first four models. This could indicate that coefficient in OLS model is over estimated.

Table 2: Regression result with survival rate as outcome

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Survival Rate	Exclude 2012		Full sample		DID 1		Placebo	DID 2		Placebo
lpg/natural gas	-0.0132	-0.0208*	-0.0141**	-0.0184**						
	(0.0084)	(0.0090)	(0.0054)	(0.0056)						
kerosene	0.0217***	0.0249***	0.0118**	0.0217***						
	(0.0053)	(0.0056)	(0.0044)	(0.0045)						
Program					0.0155**	0.0110*				
					(0.0053)	(0.0054)				
ProgramPlacebo							0.0103			
							(0.0066)			
ProgramDuration								0.0007***	0.0005*	
								(0.0002)	(0.0002)	
ProgDurPlacebo										0.0003
										(0.0002)
Region					0.0158***	-0.0078	-0.005	0.0156***	-0.0073	-0.0035
					(0.0013)	(0.0081)	(0.0113)	(0.0013)	(0.0081)	(0.0111)
wealth	0.0016	-0.0261***	-0.0077**	-0.0252***	-0.0178***	-0.0248***	-0.0236***	-0.0178***	-0.0248***	-0.0236***
	(0.0029)	(0.0034)	(0.0024)	(0.0025)	(0.0020)	(0.0020)	(0.0026)	(0.0020)	(0.0020)	(0.0026)
highschool	0.1057***	0.1109***	0.0938***	0.1094***	0.0997***	0.1086***	0.1094***	0.0996***	0.1086***	0.1094***
	(0.0032)	(0.0035)	(0.0026)	(0.0027)	(0.0026)	(0.0027)	(0.0035)	(0.0026)	(0.0027)	(0.0035)
smoke	-0.0088**	-0.0087***	-0.0073***	-0.0070***	-0.0069***	-0.0069***	-0.0089***	-0.0068***	-0.0069***	-0.0088***
	(0.0028)	(0.0026)	(0.0016)	(0.0015)	(0.0016)	(0.0015)	(0.0026)	(0.0016)	(0.0015)	(0.0026)
child is twin	-0.1103***	-0.1217***	-0.1274***	-0.1251***	-0.1270***	-0.1255***	-0.1224***	-0.1268***	-0.1254***	-0.1225***
	(0.0075)	(0.0051)	(0.0038)	(0.0039)	(0.0038)	(0.0039)	(0.0050)	(0.0038)	(0.0039)	(0.0050)
child lives with	0.0223***	0.0252***	0.0177***	0.0179***	0.0183***	0.0177***	0.0248***	0.0183***	0.0178***	0.0249***
	(0.0042)	(0.0049)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0048)	(0.0036)	(0.0036)	(0.0048)
antenatal		0.0071***	0.0085***	0.0061***	0.0076***	0.0061***	0.0071***	0.0076***	0.0061***	0.0071***
		(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0006)
Region Fixed Effects		Y		Y		Y	Y		Y	Y
Cohort Fixed Effects		Y		Y		Y	Y		Y	Y
N	32295	26728	40910	40910	40910	40910	26728	40910	40910	26728
Adj R-squared	0.0625	0.0893	0.0668	0.0876	0.0709	0.0859	0.0872	0.071	0.0859	0.0872

Standard errors in parentheses, clustered by household.

p<0.05 ** p<0.01 *** p<0.001”

Table 3 reports a comparison of different linear models for low weight and stillbirth (other covariates are not shown). The models seems to be consistently predict negative relationship with the probability of low weight birth while no effect on stillbirth. The program is associated with a decrease in 1.3% of the probability being born below average weight.

Table 3: Regression results with low weight and stillbirth as outcome

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low weight birth	Exclude 2012		Full sample		DID 1		Placebo	DID 2		Placebo
lpg/natural gas	-0.0114	-0.0155	-0.0162**	-0.0185**						
	(0.0097)	(0.0100)	(0.0061)	(0.0063)						
kerosene	-0.0112	-0.0107	-0.0107*	-0.0085						
	(0.0062)	(0.0064)	(0.0049)	(0.0051)						
Program					-0.0107	-0.0129*				
					(0.0057)	(0.0057)				
ProgramPlacebo							0.0110			
							(0.0072)			
ProgramDuration								-0.0004	-0.0005*	
								(0.0002)	(0.0002)	
ProgDurPlacebo										-0.0003
N	32,295	32,295	48,954	48,954	48,954	48,954	32,295	48,954	48,954	32,295
Adj R-squared	0.0044	0.0184	0.0057	0.0154	0.0056	0.0154	0.0184	0.0056	0.0154	0.0184
Stillbirth										
lpg/natural gas	-0.0090	0.0110	-0.0241	-0.0203						
	(0.0426)	(0.0442)	(0.0271)	(0.0283)						
kerosene	0.0209	0.0316	0.0196	0.0222						
	(0.0257)	(0.0267)	(0.0216)	(0.0226)						
Program					0.0255	0.0152				
					(0.0274)	(0.0275)				
ProgramPlacebo							-0.0458			
							(0.0345)			
ProgramDuration								0.0018	0.0015	
								(0.0011)	(0.0011)	
ProgDurPlacebo										0.0003
										(0.0010)
Region FE		Y		Y		Y	Y		Y	Y
Cohort FE		Y		Y		Y	Y		Y	Y
N	12,357	12,357	18,815	18,815	18,815	18,815	12,357	18,815	18,815	12,357
Adj R-squared	0.0032	0.0074	0.0042	0.0059	0.0040	0.0058	0.0075	0.0042	0.0059	0.0073

Standard errors in parentheses, clustered by household.

p<0.05 ** p<0.01 *** p<0.001”

Table 4 is the result from the third specification which measures the treatment effects from treated household (known as the compliers). The program associated with an increase in child survival rate 6.7%, a reduce in probability of stillbirth 7%, a reduce in probability of acute respiratory infection (ARI) 2%. After the program, households were associated with higher frequency in watching TV and higher probability of working.

Table 4: DID combined with matching specification

	(1)	(2)	(3)	(4)	(5)	(6)
	survrate	stillbirth	lowweight	ARI	watchtv	working
ATET						
Program	0.0672***	-0.0704***	0.0012	-0.0199***	0.0952***	0.0332***
	(0.0048)	(0.0161)	(0.0063)	(0.0054)	(0.0067)	(0.0065)
N	40,455	47,152	35,686	47,244	50,616	48,918

Robust standard errors in parentheses

* p<0.05 ** p<0.01 *** p<0.001

5.4 Heterogeneous Effect on subgroups

The health impact from the program may differ by wealth index. Table 5 shows the estimation results from five wealth index (poorest to richest) separately. The program associated with an increase in the survival rate for poor households ranging from 2.5% to 7.6%. In contrast, the program seems to hurt middle-to-high income households. Since the conversion mostly happen in household with middle-to-high income household (Figure 5), a possible explanation to this is a change in distribution of wealth with lower income household with lower health baseline moving up and classified as middle-to-high income household and thus distort the mean of the health outcomes.

Table 5: DID combined with matching specification within wealth index subgroup

	(1)	(2)	(3)	(4)	(5)	(6)
ATET	survrate	stillbirth	lowweight	ARI	watchtv	working
Poorest						
Program	0.0763***	-0.1948***	-0.0587***	-0.0581***	0.2497***	-0.0431**
	(0.0113)	(0.0355)	(0.0151)	(0.0121)	(0.0226)	(0.0137)
N	12313	15105	10329	15134	15983	15107
Poorer						
Program	0.0254*	-0.1603***	-0.0563***	-0.0562***	0.0945***	0.0484**
	(0.0119)	(0.0362)	(0.0145)	(0.0130)	(0.0162)	(0.0150)
N	8395	9654	7320	9679	10029	9657
Middle						
Program	-0.0531***	-0.0238	0.0543***	0.0785***	0.0398**	0.0387*
	(0.0138)	(0.0372)	(0.0136)	(0.0109)	(0.0138)	(0.0154)
N	7395	8453	6642	8467	8734	8454
Richer						
Program	-0.0304*	-0.1626***	0.0067	0.0294*	0.0115	0.0843***
	(0.0119)	(0.0378)	(0.0138)	(0.0117)	(0.0100)	(0.0150)
N	7053	7982	6436	7989	8211	7985
Richest						
Program	-0.0393***	-0.0115	0.0185	0.0132	-0.0098	0.0576***
	(0.0116)	(0.0308)	(0.0111)	(0.0099)	(0.0079)	(0.0147)
N	6740	7713	6182	7730	7873	7715

Robust standard errors in parentheses
* p<0.05 ** p<0.01 *** p<0.001

5.5 Robustness and validity

Other simultaneous national reforms.— There was global financial crisis happened on 2007-2008 which is about the same time as the program started its stage 1 distribution. The crisis causing the fuel price peak which is the main reason why GOI implement this program. In the government side there was not any interuption on the program continuity. The only concern is if the crisis influence household's health which could was away or exacerbate the effect of the program. My argument is that since the crisis tend to hit a country on national level, both treated and untreated would be exposed, while the level of exposure might be different. As long as the level exposure is differ only on regional level, this should be counted in the region fixed effects.

Outdoor air pollution.— One possible link that might cause such thing is that outdoor pollution might drive the individual's health thus overrule the benefit of fuel-switching. External event such as forest fires or other natural disaster like flood or earth quake thus could exacerbate the health outcomes. The outdoor pollution might also be trigger by the rising economic activities after the financial crisis. Resosudarmo and Napitupulu (2004) show that health costs are associated with a higher air pollution in the biggest city in Indonesia, Jakarta. As long as the external event is differ only on regional and time level, this should be counted in the region and cohort fixed effects.

Income effect.—There could be other channel which the program could improve or worsen individual's health which is the income effect. This which could lead to bias estimation of the true effect of the program. Both LPG and kerosene are offered to household in subsidized price (LPG USD$ 0.45/kg, kerosene USD$0.28/lt). By a rough calculation using efficiency ratio assumption (1 litre kerosene $\approx$ 0.4 kg LPG) then household could save approximately $0.1 every kg of LPG consumed. Budya and Arofat (2011) report the subsidized LPG surveys with sample size of 288 respondents, that the average monthly savings in switching to LPG from kerosene is $1.64. It accounts for 30% reduction in household's total energy expenditure, which equal to 6% of total household's non-food expenditure. At this point, it is plausible to assume that the income effect might be small and negligible.

6 Conclusion

Many of existing literatures show that the pollution exposure at early ages can have not only short and direct but also long lasting influences on health outcomes and productivity. In fact, the evidence on the relationship between IAP and health is far from conclusive. Most of the evidence is based on associations rather than causal. Moreover most of studies relied upon the estimates that is observational, i.e. they examined the health conditions of populations with existing differences in exposure patterns. Such studies are always subject to potential bias due to confounders (i.e. low education level, malnutrition, and other factors associated with poverty). Even the studies have accounted for some related household's characteristics, it is hard to guarantee that all potential confounders has been taking into account to eliminate the bias. Major studies are focused more on solid fuel such as wood, while very limited studies conducted on comparing kerosene and LPG.

This paper examines the effect of cooking-fuel on early-life health and measures the impact of a LPG subsidy policy in Indonesia. In 2007 the government of Indonesia introduced a massive energy program to encourage kerosene users to switch to LPG. By offering subsidized gas cylinders and stoves, the government effectively increased the supply of LPG to rural areas. The fuel-switching did happen and it was reflected by a significant rise of LPG users to almost five fold within three years.

This paper contributes to the literature in two ways. First, it added to the thin literature on cleaner cooking fuel impact on health by addressing endogeneity problem in fuel-switching through plausibly exogenous shifter, the LPG conversion program. Second, as far to my knowledge, this paper is the first that investigates health outcomes associated with this policy. This paper applies difference-in-difference with matching method. I compare three specifications: DID with binary treatment, DID with continuous treatment and DID with matching. I show an OLS model that regress fuel-choice on health outcomes could result in a bias estimates. A positive effect from the program is consistently showed in both DID specification which is lower than the OLS model. This could indicate that OLS model maybe over estimated the true impact of the fuel-switching on health. I find that switching to a cleaner cooking-fuel leads to an increase in survival rate of child, lower probability of low birth weight and pneumonia symptom.

More research needed to be done to quantify the impact of the policy on adults health, pregnancy problems and gender related health outcomes. The results of this paper, however, suggest an important implication of clean energy subsidy program that have a significant short term effect on children's health. The results also add more evidence that providing energy subsidy that promotes a lower level of emission could be beneficial for children's health in the short term and possibly in the long term.

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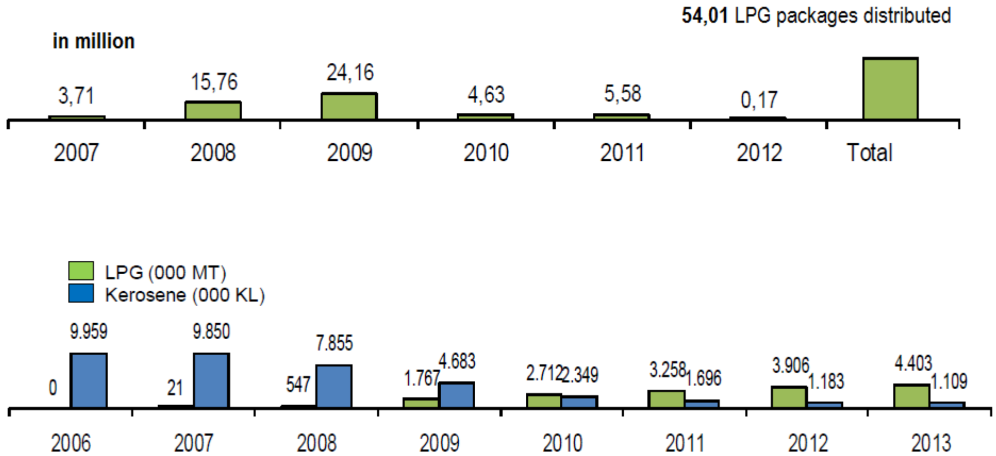
Tables and Figures

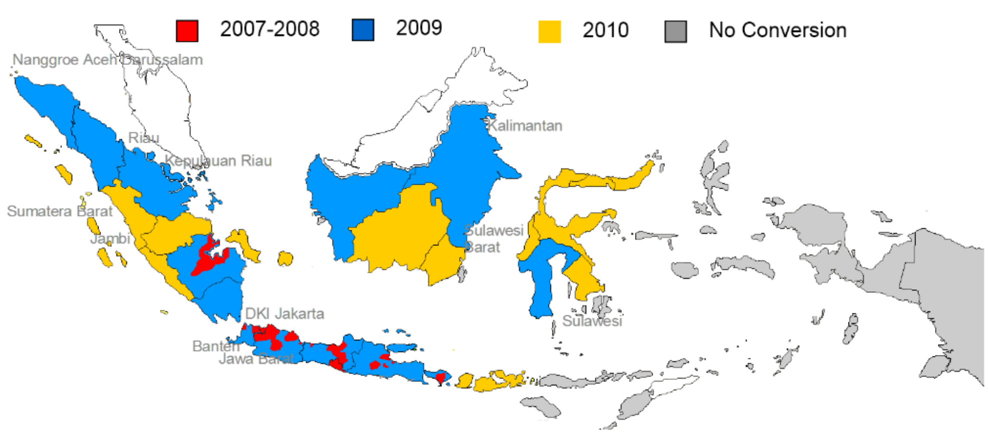
Figure 2: Total LPG Distributed and Total Kerosene Demand



Source: Pertamina, 2014

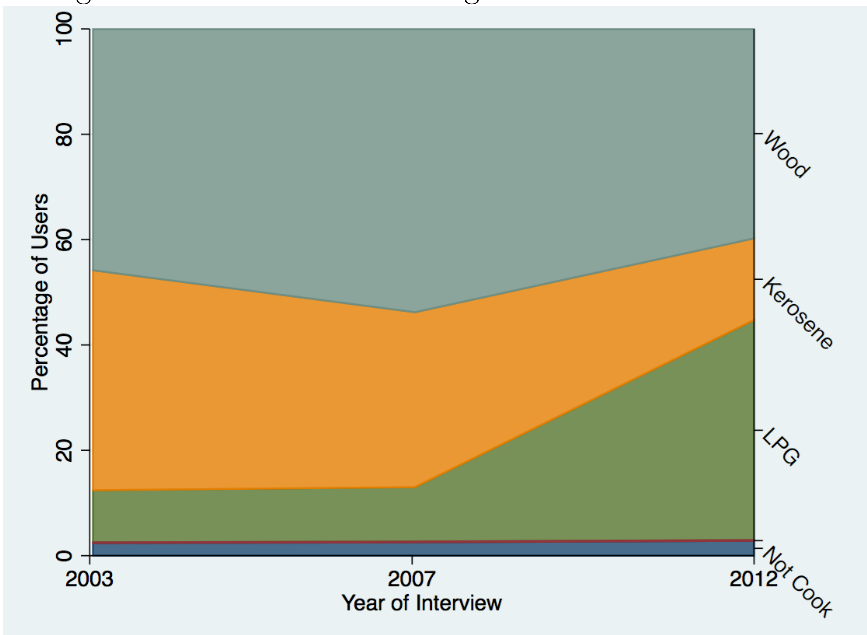
Notes: The first part shows total of LPG packages (sylnder gas and stoves) distributed up to 2012, with the total of 54 million packages. The second part shows the demand of LPG (in million ton) and kerosene (in litre).

Figure 3: Variation in the LPG Distribution Based on Time and Region



Source: Pertamina, 2014

Figure 4: Share of each cooking fuel choice based on time



Source: Author's calculation from DHS 2002-2012

Figure 5: Predicted probability of each cooking fuel choice based on wealth index

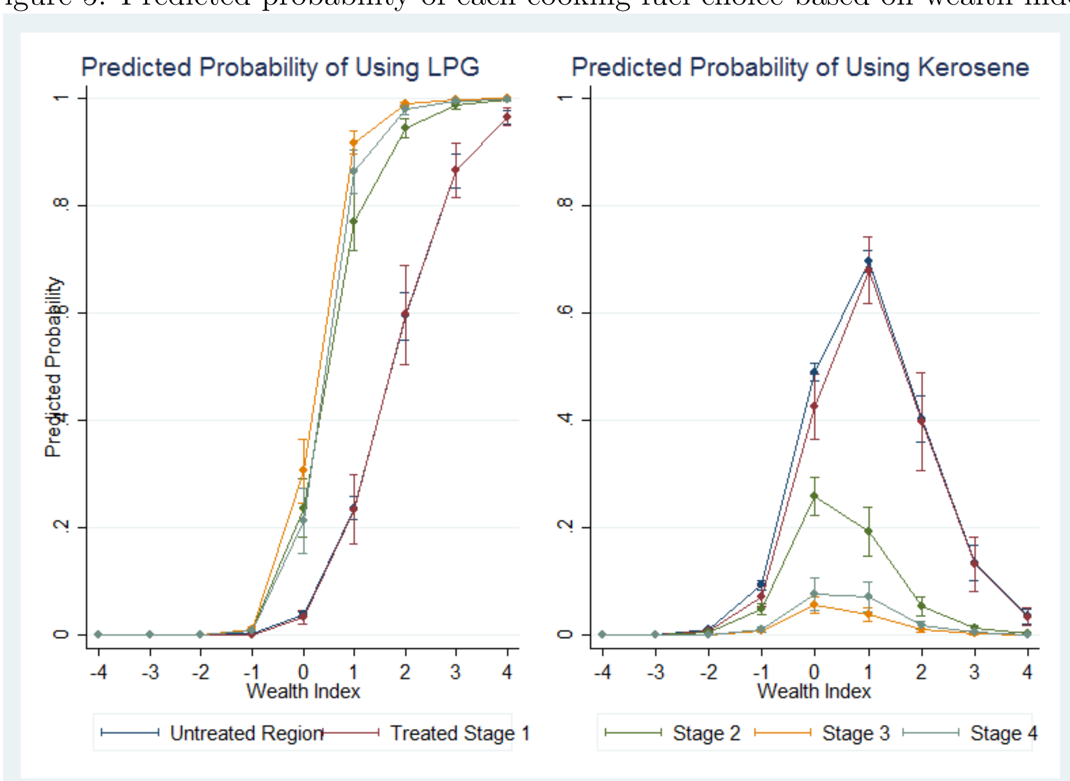


Figure 6: Predicted probability of each cooking fuel choice based on location

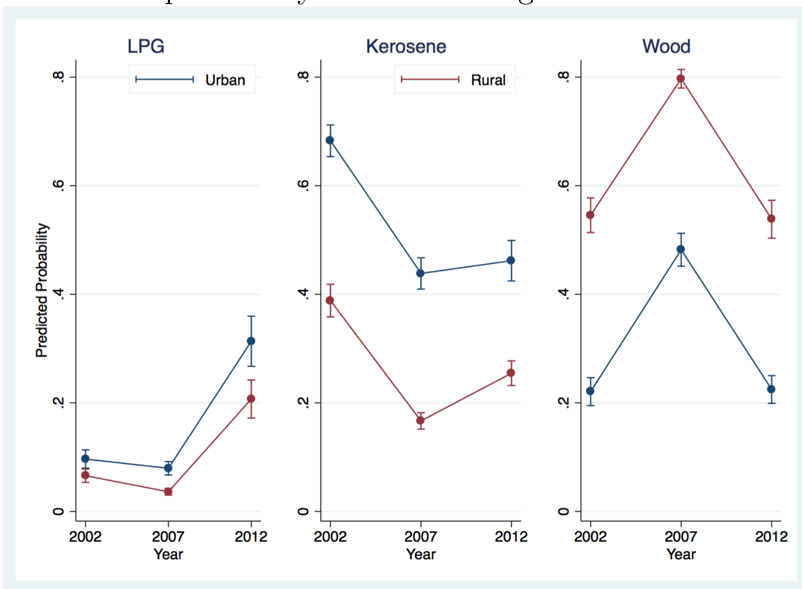
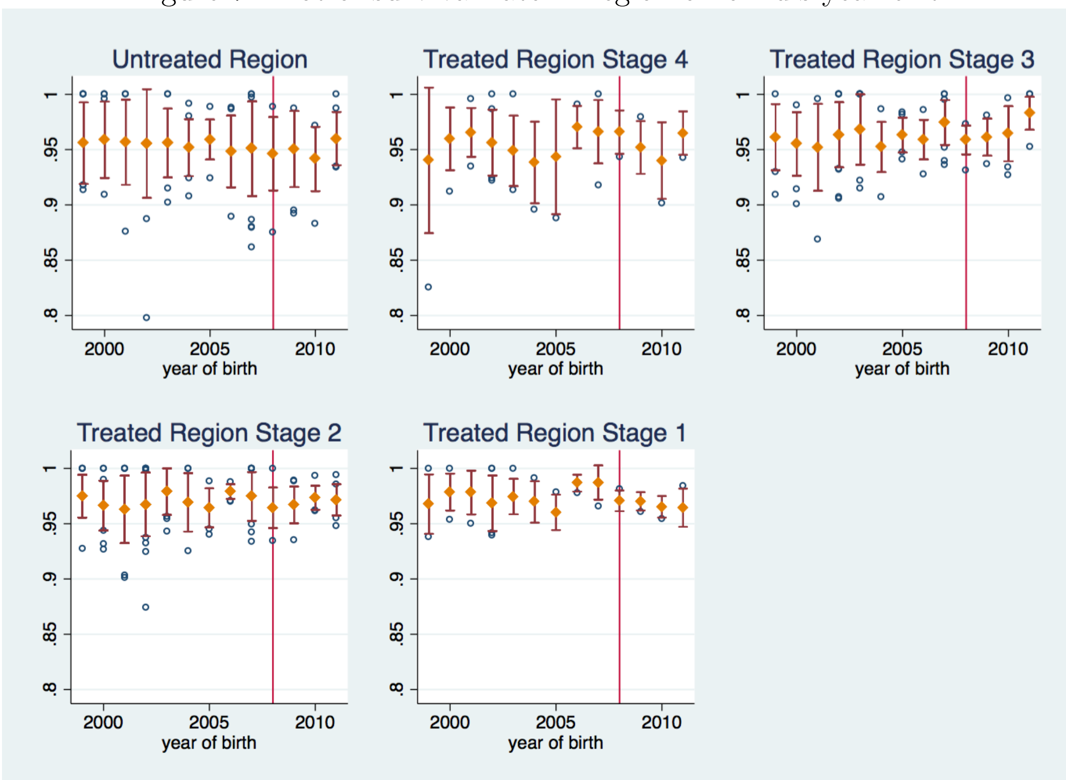


Table 6: Treated and Untreated Region List

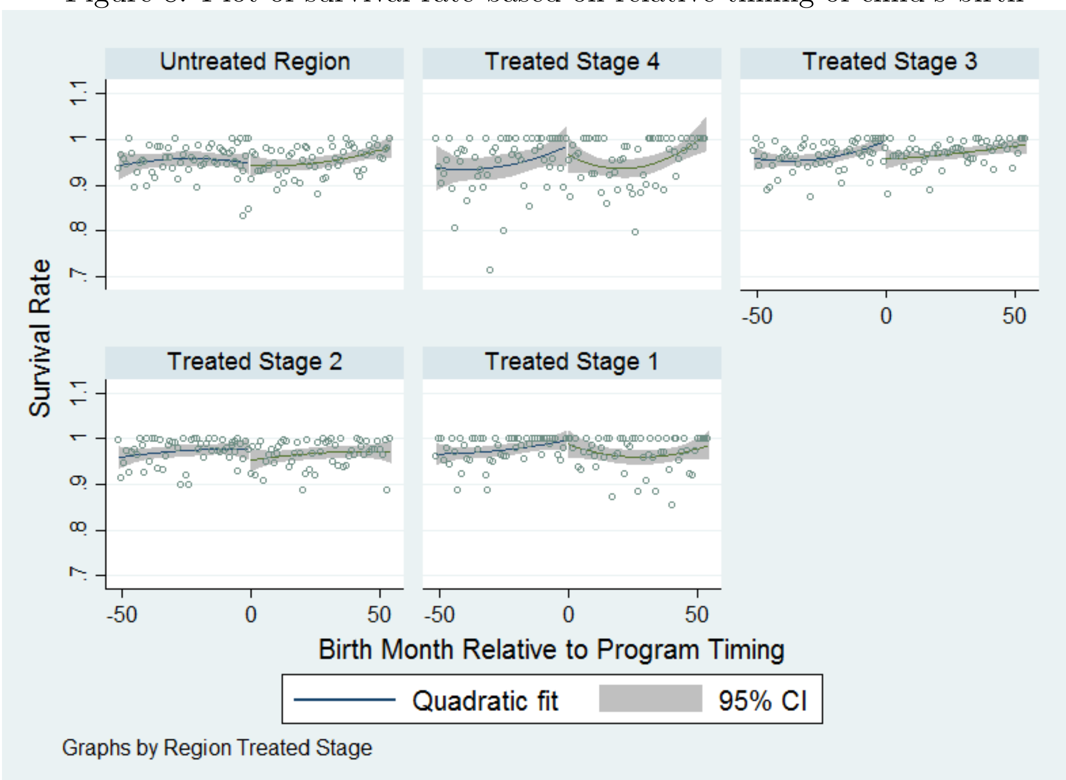
No	Year Region	0 Untreated	2011 Treated Stage 4	2010 Treated Stage 3	2009 Treated Stage 2	2007-2008 Treated Stage 1	Total
1	Aceh	0	0	1,150	0	0	
2	North Sumatera	0	0	2,531	0	0	
3	West Sumatera	0	1,805	0	0	0	
4	Riau	0	0	1,868	0	0	
5	Jambi	0	0	1,301	0	0	
6	South Sumatera	0	0	0	1,648	0	
7	Bengkulu	0	0	1,195	0	0	
8	Lampung	0	0	0	1,452	0	
9	Bangka Belitung	0	1,182	0	0	0	
10	Riau Islands	0	0	905	0	0	
11	Jakarta	0	0	0	0	2,498	
12	West Java	0	0	0	2,413	0	
13	Central Java	0	0	0	1,864	0	
14	Yogyakarta	0	0	0	0	1,213	
15	East Java	0	0	0	1,751	0	
16	Banten	0	0	0	0	2,209	
17	Bali	0	0	0	1,579	0	
18	West Nusa Tenggara	0	1,623	0	0	0	
19	East Nusa Tenggara	1,871	0	0	0	0	
20	West Kalimantan	0	0	0	1,660	0	
21	Central Kalimantan	1,359	0	0	0	0	
22	South Kalimantan	0	0	1,446	0	0	
23	East Kalimantan	0	0	0	1,348	0	
24	North Sulawesi	1,391	0	0	0	0	
25	Central Sulawesi	1,590	0	0	0	0	
26	South Sulawesi	0	0	0	1,921	0	
27	Southeast Sulawesi	1,730	0	0	0	0	
28	Gorontalo	1,399	0	0	0	0	
29	West Sulawesi	0	0	1,048	0	0	
30	Maluku	1,203	0	0	0	0	
31	North Maluku	1,004	0	0	0	0	
32	West Papua	1,000	0	0	0	0	
33	Papua	891	0	0	0	0	
	N	13,438	4,610	11,444	15,636	5,920	51,048

Figure 7: Plot of survival rate in region on child's year birth



Notes: This is a plot for mean and standard error of child's cohort (year) in every region based on the time of intervention.

Figure 8: Plot of survival rate based on relative timing of child's birth



Notes: x-axis shows the months of child's cohort relative to the time of program intervention. y-axis shows the correspondence mean survival rate of the cohort.