

Clean Energy Access: Gender Disparity, Health, and Labor Supply

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Abstract

Women are known to bear the largest share of health and time burden associated with a lack of modern energy. In this paper, we study the impact of clean energy access on adult health and labor supply outcomes by exploiting a nationwide rollout of clean cooking fuel program in Indonesia. This program led to a large-scale switching between fuels - from kerosene, a dirty fuel to liquid petroleum gas, a significantly cleaner and efficient cooking fuel. Using rich longitudinal survey data from the Indonesia Family Life Survey and the staggered structure of the program roll-out, we find that access to clean cooking led to a significant improvement in women's health, particularly among those who spend most of their time indoors doing housework. We also find an increase in the labor supplied by these women on both intensive and extensive margins, suggesting that having clean and efficient cooking fuel may not only improved women's health but also improve their productivity, subsequently allowing them to supply more market labor. For men, we find an increase in the labor supplied only along the intensive margin, with a higher increase among men in households where women accrued the largest health and labor benefits from the program. These results highlight the role of clean energy in reducing gender-disparity in health and labor participation and point to the existence of positive externality from improved health and productivity of women on other members of the household.

JEL classification: H51, I15, I18, J22, O13, Q48, Q53

Keywords: gender inequality, energy access, health, labor supply, Indonesia

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I. Introduction

One of the key sources of inequality between men and women stems from the traditional gender norms in the type of work assigned to each gender. Women spend a considerably higher amount of time on housework than men (Duflo, 2012). Technological advances and efficient time-saving modern energy can fill some of this gap by freeing up women’s time away from housework. For example, diffusion of time-saving appliances in the United States over the last century (Greenwood, Seshadri and Yorukoglu, 2005) or electrification in South Africa (Dinkelman, 2011), led to an increase in women’s labor supply by releasing productive time away from housework that can be used towards market work.

Even though the relationship between access to modern energy and better economic outcomes for women has been widely discussed, its causal relationship is not straightforward.¹ Disentangling the impacts of other development on one’s economic well-being is challenging, especially when the transition to modern energy is slow and mostly voluntary. Households also endogenously sort into places with better infrastructure and thereby better access to affordable energy. A few studies have focused on the impact of electrification (Dinkelman, 2011; Lee, Miguel and Wolfram, 2016), but the question of the impact of clean cooking, an intervention that almost exclusively affects women, remains unclear.²

In this paper, we focus on a critical, yet less understood contributor of gender-disparity in labor supply, the health burden associated with unclean cooking fuel. Cooking is often exclusively categorized as a women’s responsibility, yet, in most of the developing countries, women lack the authority to make fuel choices (Miller and Mobarak, 2013). With unclean cooking fuel emitting a large amount of harmful pollutants, biased gender roles and low bargaining power of women impose a disproportionately higher health and productivity cost on women than men. These costs can be enormous, given that approximately 40 percent of the global population still rely on unclean cooking fuel for their daily requirement. Beyond the adverse health impacts of unclean cooking fuel, which few would deny, this paper aims to quantify how large is the gender-disparity in health-burden that arise due to energy poverty, and its implications on the labor supply outcomes of women as well as men.

We exploit the staggered nature of a nationwide clean cooking intervention in Indonesia, one of a few successful energy transition programs in developing countries, to estimate the impact of clean energy access on health and labor supply outcomes. The program, with the primary aim of reducing the high cost in subsidizing kerosene, replaced the subsidy of kerosene with the subsidy of liquid petroleum gas (LPG). Over a span of five years, this program reached more than 70 percent of the total population, leading to more

¹ For a review, see Köhlin et al. (2011); Rewald (2017).

² Indeed, compared to men, women spend at least four to ten times higher amount of time on housework such as cooking (World Bank 2014; ADB 2016)

than a 90 percent reduction in the use of subsidized kerosene. LPG is a cleaner and more efficient cooking fuel compared to kerosene, hence the program can directly reduce the level of indoor air pollution (IAP) concentration and reduce the time required for food preparation. As women spend significantly more time doing household chores and thereby are likely to be the most affected by a clean cooking intervention, this paper documents the extent to which the program shrinks some of the gender disparities that exist due to lack of access to clean energy.

We use administrative data on the program roll-out and three waves of the longitudinal Indonesian Family Life Survey (IFLS) for 2000, 2007, and 2014, which allow us to track individuals up to fourteen years, nine years before the intervention and up to five years after the intervention.

Our key empirical strategy is to exploit the exogenous variation in the timing of the program to estimate a causal relationship between clean energy access, health, and labor supply. Using a difference-in-differences design, we compare health and labor supply outcomes of individuals living in districts with longer exposure duration (treated in the earlier phases) to the program with health and labor supply outcomes of individuals living in districts with a shorter exposure duration (treated in the later phases) to the program. To address the concern that the program timing may be correlated with other factors that can also influence the outcomes, we show similarity in the pre-trends for outcome variables as well as other demographic and health characteristics.

We find that the program led to an 11 liters/minute (about four percent) increase in the lung capacity of women who were exposed to the program earlier than those exposed to the program later. The size of the magnitude is comparable to lung capacity changes ten years after the exposure to wild forest fire in Indonesia (Rosales-Rueda and Triyana, 2018), or to an increase in the lung capacity of a regular smoker if he quits smoking for approximately 10 pack-years.³ Among men, we find small and statistically insignificant changes in their lung capacity from the program. These results are consistent with our hypothesis that women are the direct user of the cooking fuel and hence, should be impacted the most by the program. Importantly, we find that lung capacity improvements in women are mainly concentrated among those who are more likely to stay indoors and be involved with cooking activities or other housework. As a placebo check, we also do not find any significant improvements in lung capacity among women in the treatment-ineligible households - those who live in the same district but were not eligible for the program - providing strength to our results being driven by the program.

Next, we look into the mechanisms behind our results on health and find that the reduction in indoor air exposure associated with clean cooking access seems to be the relevant channel. Moreover, other observable factors such as concurrent poverty alleviation programs, changes in the access to health care, and changes

³ One pack-year is equal to a person smoking one pack of cigarettes per day, for a year.

in household expenditure, do not play a significant role in explaining our results. Similarly, we do not find any impact on other health outcomes that are not directly associated with exposure to pollution, such as anemia or diabetes.

Improvement in the health or productivity of one gender can lead to changes in labor supply for both genders because the activities of one may affect the opportunities of the other within a household. We illustrate this relationship through a simple intra-household labor supply framework with productivity differences and exogenous change in fuel quality. In maximizing the household's utility, men and women decide how much labor to use either on the farm or at home. We show that an exogenous improvement in the fuel quality that is assumed to improve the health and productivity of women can alter both genders' optimum labor supply on the farm.

Consistent with our hypothesis, we find the program led to changes in labor supply for both genders. On the intensive margin of labor supply, we find an overall increase in the hours of labor supplied by women who primarily did housework in the baseline. We also find an increase in the labor supplied by men along the intensive margin, particularly among men in households where women primarily do housework (i.e., households that were impacted the most by the program). The size of the increase is approximately one-half additional hours of work per day (20 percent) for women and about one additional hour of work per day (9 percent) for men. On the extensive margin, we find a 15 percentage point increase in labor participation in agriculture among women who were primarily doing housework in the baseline. Through improvements in health and less time spent in cooking⁴, the program may open up women's opportunities to increase their participation in agriculture, thus narrowing some of the gender gaps in labor supply. We do not find an increase in the participation rate of in other formal sectors, which seems reasonable as women who do housework may face high barriers to entry in most other formal sectors due to their limited skills.⁵

Our findings on the labor supply are linked with our findings on health. Clean cooking can influence one's labor supply through two main channels: health and time saved. First, our earlier findings in health support the health channel. Health improvements among women can directly reduce the amount of time spent in sickness as well as increase their overall productivity. Second, the less time spent on food preparation and other household chores (e.g., cleaning the kitchen or taking care of sick children) means more time available to do other things, opening one's opportunity to participate in the labor market. Moreover, due

⁴ Cooking with LPG requires less time compared to kerosene, which may explain the time saved due to the fuel-switching induced by the program. For instance, boiling one liter of water using LPG-stoves takes half of the time needed to boil one liter of water using kerosene-stoves (Shrestha, 2001).

⁵ We also, do not find any significant impact on labor supply for men on the extensive margin. One reason could be that most men were already participating in the labor market, thus leaving little margin for improvement along this dimension. It is also plausible that the direct benefits on women were large enough to change their own outcomes at the extensive margin, but, the externality effects on men was not large enough to bring changes on the extensive margin.

to complementarity in the labor inputs and the observed changes in women’s health and productivity, the program can indirectly change men’s labor supply due to time and task re-allocation. Finally, our results are also robust to several specification checks, including matching, different sample selections, and controlling for other poverty alleviation programs.

This paper makes four main contributions to the literature. First, it adds to the literature on the link between indoor air pollution, health, and economic well-being (Duflo, Greenstone and Hanna, 2008). To demonstrate a clear causal link, several studies attempted to address the confounded nature of the adoption using randomized-experiments (Alexander et al., 2018; Hanna, Duflo and Greenstone, 2016; Jack et al., 2015) and using instrumental variable approach (Pitt, Rosenzweig and Hassan, 2006; Silwal and McKay, 2015). However, low take-up rates in modern technology is a common problem, making it harder to estimate the impacts.⁶ We are able to improve on this by using a nationwide clean cooking intervention, with an exceptionally high compliance rate (over 90 percent). This provides an apt quasi-experimental setting to estimate the causal impacts of a transition to clean cooking. Moreover, unlike studies that use a controlled environment to study the impact, using a nationally represented survey allows us to account for household behavioral responses that may exist, an important element to be considered in designing optimum public policy.

Second, our paper contributes to the literature on the intersection of gender, adult health, and clean energy access, where the existing evidence remains scattered and inconclusive (Köhlin et al., 2011).⁷ The majority of the health literature associated with energy poverty focuses on the impact of pollution on infants (Arceo, Hanna and Oliva, 2016; Cesur, Tekin and Ulker, 2016; Imelda, 2019; Rosales-Rueda and Triyana, 2018; Tanaka, 2015) and children (Jayachandran, 2009), but less is known about the impact of energy poverty on adults, especially women. One reason, among others, is that it is more challenging to evaluate and quantify the impact on adults’ health outcomes.⁸ Moreover, many of the health measures used in the literature to study the impact of pollution are self-reported and likely to suffer from measurement and reporting errors. Our paper estimates the effects on adult health outcomes by using lung capacity measures on a longitudinal survey that span over 14 years. More importantly, the lung capacity is a reliable measure of one’s respiratory health that is well-known to be closely linked with exposure to pollution (Gehring et al.,

⁶ This problem has been documented in several studies, for instance, in cooking technology (Bensch, Grimm and Peters, 2015; Hanna, Duflo and Greenstone, 2016; Mobarak et al., 2012), preventive health products (Dupas, 2011), and agricultural technology (Oliva et al., 2019).

⁷ For a summary of current literature on modern energy access, indoor air pollution, health, and labor market outcomes, we refer readers to Köhlin et al., 2011; Pueyo and Maestre, 2019.

⁸ For instance, measuring the impact of clean cooking on adults is difficult because it is likely to be confounded by the accumulated exposures in the past that are unobserved to the researcher. Moreover, unlike infants, where the impact can be measured by their mortality rates, mortality among adults from pollution exposure is not very common and hence, difficult to quantify.

2013; James Gauderman et al., 2000).

Third, we add to the literature on energy poverty, gender roles and its impact on labor supply. While several studies have focused on the disproportionate time-burden associated with energy poverty and its implication on labor supply (Coen-Pirani, León and Lugauer, 2010; de V. Cavalcanti and Tavares, 2008; Dinkelman, 2011; Greenwood, Seshadri and Yorukoglu, 2005), this paper focus on a different channel, the health-burden associated with energy poverty and the gender roles. To the best of our knowledge, we are one of the first few papers to highlight that modern energy access can reduce gender-gaps in labor supply by reducing the health-burden on women. Moreover, our paper shows that if men do not perfectly internalize women’s health costs in making fuel choices, it may lead to large inefficiencies as beyond primarily benefitting women, clean cooking produces positive spillover effects on the labor supply of men within the household as well. This highlights the policy discussion on women’s bargaining power over fuel choice.

Finally, more broadly, this paper contributes to the large literature of “missing women” in developing countries (Anderson and Ray, 2010; Duflo, 2012; Klasen and Wink, 2002). Most of the rigorous evidence on missing women highlights the existence of gender inequality at birth (Abrevaya, 2009). Our paper highlights a different angle. We provide evidence on the link between energy access and the environmental risk arising from the gender norms that disproportionately affect women. Environmental factors associated with energy poverty can indeed contribute to adverse health risks among women. Moreover, heart disease accounts for a large fraction of excess female mortality due to heart disease (Anderson and Ray, 2010). As heart diseases are often associated with impaired lung functions due to the interdependence of cardiac and respiratory failure (Han et al., 2007), our findings provide a first step in understanding the link between missing women and energy poverty in developing countries.

Developing countries will play a major role in driving growth in energy consumption in the next several decades (Wolfram, Shelef and Gertler, 2012). Policy-wise, our results provide important insights for energy transition policies in these countries.⁹ Given the inextricable link between clean energy access and gender equality, this paper suggests that a clean cooking intervention can promote gender equality in health as well as labor supply, a substantial benefit that is often not properly quantified in the energy-related policy discussions.

The rest of the paper is organized as follows: Section II provides some background about the program; Section III describes the data and descriptive statistics; Section IV discusses the empirical strategy; Section V shows the main results and the potential mechanism and; Section VI discusses the robustness checks, and section VII concludes.

⁹ Worldwide, about 1.2 billion people may lack access to electricity, but there are about 2.8 billion people globally who do not have access to modern cooking technology. This number is more than double the number of people who lack access to electricity (Outlook, 2017).

II. LPG Conversion Program in Indonesia

Indonesia, the world’s fourth-most-populous country, has been subsidizing the retail price of kerosene since 1967 (Dillon, Laan and Dillon, 2008). In the 1980s, Indonesia’s oil production was high; hence subsidizing kerosene was affordable. When the global oil prices started rising after 2005 and the consumption of oil increased as the economy expanded, it became onerous to keep subsidizing kerosene (Budya and Arofat, 2011).¹⁰ Hence, in 2007, The Government of Indonesia launched the Kerosene to LPG Conversion Program with the primary aim to reduce the rising state expenditure in subsidized kerosene. The vice president of Indonesia appointed the Ministry of Energy and Mineral Resources as the program coordinator, with the aim to convert more than 70% of the households into LPG using households by the next five years.

The program timing is the key variation used in this paper. The program was implemented with a top-down approach, where the Ministry of Energy and Mineral Resources produced a list of districts in a given fiscal year to be targeted in the following year based on each district’s level of kerosene usage, LPG infrastructure readiness, location and size of the area. Then, Pertamina, the national oil company, implemented the program based on the given order.

Household Eligibility and Adoption.– The eligibility for the program was based on the households not having used LPG in the past. The eligible households would receive a free starter kit that included one LPG stove and one 3-kilogram LPG cylinder. Later, those who owned this specific cylinder were eligible to refill it at the subsidized price, while the other types of LPG cylinder, distributed previously before the program, were not eligible for the subsidy.¹¹

The policy roll-out was gradual and through multiple phases. When a district received all the allocated LPG, the subsidized kerosene would be withdrawn gradually, leaving only unsubsidized kerosene available in that district. As a result, households were incentivized to adopt and start using LPG. Since the LPG refill was subsidized under this program, its price was similar to the price of kerosene (per an equivalent measure). Hence, if households were rational, they would have preferred using LPG than using kerosene, as the unsubsidized kerosene was significantly more expensive than LPG. Figure 1 shows the high LPG take-up rates and a sharp drop in the kerosene use.

Kerosene Versus LPG.– LPG was chosen to replace kerosene because it is more efficient and more economical compared to kerosene. Foremost, LPG’s production cost was lower than that of kerosene.¹² LPG also had an edge over the other alternatives as it’s existing infrastructures and supply chain was relatively

¹⁰ The amount of subsidy the government was providing for household kerosene climbed from USD \$1.96 billion in 2005 to USD \$5.24 billion in 2008 (Budya and Arofat, 2011).

¹¹ The program details are discussed in Budya and Arofat (2011); Thoday (2018).

¹² The cost is about 25% (0.17 USD/liter) less than subsidizing kerosene (Andadari, Mulder and Rietveld, 2014).

in place compared to the other fuels.¹³ Although LPG was primarily chosen for cost-saving purposes, there was also an obvious environmental benefit in switching to LPG. LPG is significantly less polluting than kerosene due to its high-efficiency combustion process. Figure 2 illustrates the emission level (proxied by $PM_{2.5}$ concentration level) from LPG and kerosene stoves. It shows that the mean as well the maximum amount of $PM_{2.5}$ emitted by kerosene-stove is significantly more compared to LPG-stove, and way above the WHO recommended-level of safe $PM_{2.5}$ exposure.¹⁴ Thus, even though the program was not designed for health benefits, a transition from kerosene to LPG induced by the program can lead to significant health gains among the households due to reduced pollution exposure.

III. Data

We employ three waves of the Indonesian Family Life Survey (IFLS)¹⁵ for the years 2000, 2007, and 2014.¹⁶ IFLS is a rich longitudinal survey, containing a diverse amount of information at individual, household and community levels on a large array of economic, health, social and labor supply characteristics.

We rely on the restricted administrative data on the program roll-out to determine variations in the duration of program exposure. The data is obtained from Pertamina, the appointed program coordinator. It consists of a year-wise list of districts that received the program in that year, allowing us to group the districts by the year of their program implementation, and thus, by the duration of their exposure to the program. We merge the district code from the administrative program data with the district code from the survey data.¹⁷ Figure B in the Appendix shows the timeline of the program along with the IFLS survey years. Note that, the three rounds of IFLS used in this paper allows us to track individuals nine years before

¹³ The price per unit for LPG is slightly higher than kerosene, but it is still cheaper to subsidize LPG. One liter of kerosene can replace by 0.4 kilograms of LPG (Budya and Arofat, 2011). Hence, in equivalent measures, the higher calorific value makes LPG more economical to subsidize compared to kerosene.

¹⁴ Kerosene emits significantly less amount of visible smoke compared to other dirty fuels (e.g., firewood or charcoal). Because of this, one may be misled into thinking that kerosene is not a 'dirty' fuel and hence, less dangerous for health. However, as the adverse health risk highly depends on the exposure level, kerosene can be as harmful as firewood. Incomplete combustion from kerosene is less visible than firewood. As a result, when household members cook with firewood, they are more likely to cook outside. In contrast, when household members cook with kerosene, they are more likely to cook inside and much closer to the stove (Saksena et al., 2003). Indeed, in the controlled tests of good quality kerosene stoves show low emissions, but field data suggests that many kerosene stoves are actually highly polluting (Energy, 2014). This is consistent with the growing body of evidence about the dangers of kerosene cooking (see Lam et al. (2012) for a review).

¹⁵ A longitudinal survey carried out by the RAND Corporation, known as one of the best individual-level longitudinal data with a very low level of attrition due to its successful follow-up rates despite the mobility of the respondents. It covers 13 provinces out of the 26 provinces in Indonesia and represents 83% of the Indonesian population.

¹⁶ IFLS-1993 is excluded since it does not have data on lung capacity – our primary respiratory health measure.

¹⁷ The district codes from the survey data indicate a household's location on the year of the survey.

the program and up to five years post the program.

Key Variables.— There are two primary outcomes of interest in this study. First, we use lung capacity as a proxy for health.¹⁸ Lung capacity is measured as Peak Expiratory Flow (PEF) in the survey using a Personal Best Peak Flow Meter in the survey. It indicates the person’s maximum speed of expiration/exhalation in liters per minute (L/min). In our analysis, we use the highest PEF among the three recorded measurements, following (Rosales-Rueda and Triyana, 2018).¹⁹ In addition, we also use various health outcomes including weight, current illness at the time of survey (i.e., cough and headache in the last two weeks prior to the survey), chronic and acute illnesses (i.e., hypertension, anemia, diabetes), and self-reported health status.²⁰ These variables are used as alternative measures of health.

Second, to investigate the program’s impact on labor supply, we use two variables. First, we use a dummy variable indicating the sector of an individual’s primary job, a job that consumes most of individual’s time.²¹ For convenience in the analysis, we reclassify the sectors into four broad categories: agriculture, social sector, retail, and self-employed.²² The participation rate by sectors captures the extensive margins of labor supply. Second, we use aggregated total work hours of an individual’s primary and secondary jobs (measured in work hours in a month) to measure the intensive margins of labor supply. For this, we rely on two survey questions: (1) what was the total number of hours you worked during the past week (on your job)? and (2) normally, what is the approximate total number of hours you work per week?

For the control variables, we use the information on socio-economic and regional characteristics at the time of the survey, such as age, height, education, asset ownership and rural versus the urban status of the region. Our preferred specification uses individual level controls - age, height, and rural-urban control to control for two main factors: (1) physical build of the individual which determines the natural lung capacity;

¹⁸ There are at least three benefits of using lung capacity as our main health outcome. First, it is an important predictor of morbidity and mortality in elderly people (Ostrowski and Barud, 2006). Second, it is a reliable, objective, and quantifiable measure of one’s respiratory health for adults (Paulin and Hansel, 2016). In particular, fine particles, from the incomplete combustion from kerosene, are known to have direct impacts on lungs as it can move deep into the alveoli of the lungs, irritating and swallowing up the walls, obstructing the normal functioning of the lungs. Third, the changes in lung capacity are usually age-dependent and not easily influenced by many other factors (Ostrowski and Barud, 2006), thus minimizing the omitted variable bias.

¹⁹ IFLS survey guidelines also recommend using the best of three measurements to capture the lung capacity of an individual.

²⁰ We reclassify the self-reported health status into a dummy, 1 indicating the good health (with the original scale of 1-4) and 0 indicates the bad health status (with the original scale of 1).

²¹ There can be some overlap between the sectors if an individual reports two or more sectors to be their primary participating sector.

²² Agriculture sector includes agriculture, forestry, fishing, hunting, mining; retail sector includes electricity, gas, water, constructions, wholesale, retail, restaurants, hotels, transportation, storage, and communications. The social service sector includes social service, finance, insurance, real estate, and business services. Note that we do not include the manufacturing sector as the sample is very small.

and (2) exposure to the pollution, which varies between the rural and urban regions. We include other control variables, such as dummy for education and asset ownership, in the most comprehensive specification to ensure the robustness of the results.

Sample.— The unit of observation is an individual. In our main analysis, we restrict the sample based on three considerations. Foremost, we exclude households living in districts that received LPG in 2007-2008. We use the 2007 survey data as the baseline year, and these households had already received the program.²³ Furthermore, we restrict our sample to the treatment eligible households - those who do not report LPG as their primary fuel in the pre-periods, and to individuals older than 16 years old at the time of the baseline survey.²⁴ Lastly, we exclude the sample of inter-district migrants to eliminate possible bias due to selection driven by individuals who moved in or out of the treatment districts after the program.²⁵

IV. Empirical Strategy and Descriptive Statistics

IV.A Identification

One of the empirical challenges in earlier studies has been that cooking fuel choice is correlated with other factors that also influence health and labor supply outcomes. To alleviate this issue, we use the timing of the program as a plausibly exogenous determinant of cooking fuel choice that is uncorrelated with health or labor supply outcomes.²⁶

The timing of the program and the location where an individual lives, jointly determine the duration of an individual’s exposure to the program. Since the program was rolled out in most parts of the nation by the time we observe them in IFLS 2014, we do not have a good pure control group. Hence, we use variation in the differential treatment duration by comparing eligible individuals living in districts that received LPG in the early phase i.e. between 2009-2010 (henceforth, called the *Early Treated Group*), to eligible individuals living

²³ We do have 2000 survey data. Nonetheless, we chose 2007 for the baseline year as it has at least two advantages. First, it is closer to the date of the intervention, providing a cleaner identification. Second, it allows us to have two periods of the survey for testing the pre-trend assumption. This is useful for ensuring the validity of our empirical strategy (in Section IV.A). In addition, focusing on households that received the program during the expansion years (after 2009) also limits the possibility of selection bias due to district selection. (Imelda, 2019) argues that program targeting during these expansion years was arguably weaker given the implementation constraint and an ambitious target to be achieved the goal of the program with only a few years.

²⁴ Generally, individuals above 16 are out of the schooling age and allowed to be legally married according to the Indonesian Marriage Law 1974. This limits possible omitted variable bias due to schooling choices. As they are more likely to be married after this age and be involved with housework, it draws focus on the relevant sample of women for this analysis.

²⁵ Note that the sample for inter-district migrants is very small. Our robustness checks also confirm that including the inter-district migrants do not change our results.

²⁶ As discussed earlier, the program is not targeted based on individuals’ health characteristics.

in districts that received LPG in the later phase i.e. between 2010-14 (henceforth, called the *Later Treated group*).²⁷ Therefore, it is important to keep in mind when interpreting the results that the two groups i.e., the Early Treated group and the Later Treated group, are both treated, and differs in the average duration of treatment exposure by three years.²⁸ If the treatment effects are assumed to be monotonic, our estimates can serve as the lower bound of the full treatment effects.

As our empirical strategy, we use the following event study style of difference-in-difference (DID) equation. It is similar to a standard difference in difference, however instead of having one Post treatment dummy, we include both post-treatment and pre-treatment time dummies to capture the pre-trends in the same equation. Estimating equation is given by:

$$Y_{idt} = \sum_{\substack{t \neq 2007 \\ k = 1 \text{ if } 2014 \\ k = -1 \text{ if } 2000}} \beta_t \times \text{EarlyTreat}_d \times \mathbb{1}(t = k) + \gamma \text{EarlyTreat}_d + \delta_t + X_{idt}\theta + \epsilon_{idt} \quad (1)$$

Y_{idt} represents the outcome variables for individual i , in district d , at time t . EarlyTreat_d is the early treatment dummy, which takes a value of 1 if the district received LPG in the early-treated phase (2009-2010) and 0 if the district received LPG in the later-treated phase (after 2010).

We normalize β_{2007} to zero, so all coefficients can be interpreted as changes relative to the levels in the year 2007 i.e. the year just before the treatment began. $t=1$ if the year of observation is 2014 i.e. the *Post* treatment year and $t=-1$ if the year of observation is 2000 i.e. the *Pre* treatment year. Thus, β_1 gives the Early Treatment Effect, and $\beta_{-1} = 0$ tests the parallel pre-trend relative to our baseline year, 2007. Thus, β_1 (or β_{-1}) gives the intent-to-treat effects and can be interpreted as the change in outcomes in early treated regions compared to later treated regions, in 2014 (or 2000) i.e., in the *Post* (or *Pre*) treatment year, relative to their values in the baseline i.e., 2007. β_t estimates causal effect under the assumption that in the absence of the program, outcome variables would exhibit similar trends over time between the early-treated and the later-treated regions.

Identifying Assumptions.— Causal identification in the DID design relies on the common-trends assumption, where the treatment group would have moved similarly as the control group in the absence of the program. $\beta_{-1} = 0$ in Equation 1 tests the parallel pre-trend between the early-treated and the later-treated regions. In Table 1, we show the pre-trends in each outcome variable in the corresponding column header

²⁷ Figure 10 in the Appendix shows three histograms for each year of survey (2000, 2007, and 2014) and the years of the program roll-out on the x-axis. Most of the households switched to LPG, except those who received the program after 2014.

²⁸ Early treated group is treated for 4.5 yrs on an average, whereas the Later Treated group is treated for 1.5 years on an average, resulting in 3 years of difference in the average treatment duration

by reporting the coefficient from $EarlyTreat \times Pre$.²⁹ Given the parallel trends in health (in Table 1 and Table I in the Appendix) and labor supply outcomes (in Table 3) between these two groups, it is reasonable to assume that those who received the LPG earlier would behave in a similar way to those who received the LPG later, in the absence of the program. As an additional validity check for similarity in the trends between the two regions before the treatment began, we also test for parallel pre-trends in several socioeconomic and demographic variables (Table 2).

Sample Characteristics.— Table 4 shows the individual and household characteristics at the baseline for the early treated group and the later treated group. Table 4 columns (1) and (3) report the mean, while columns (2) and (4) report the standard deviation corresponding to the means. Overall, from the health variables, individuals that received LPG early do not look healthier than those who received it later. The primary cooking fuels in 2007 also looked similar between the groups, as do the education level and asset ownership in the households.

IV.B Descriptive Statistics

In this section, we provide several descriptive evidence showing the interlinkages between fuel choice, gender-disparity in health, and labor supply.

Energy and Health.— Figure 3 presents the associative relationship between fuel quality and lung capacity for individuals in our sample. We group the individuals in our sample into three different categories based on their set of fuel choices in 2000, 2007 and 2014 survey rounds - first, those who used kerosene in all the three rounds; second, those who used kerosene in 2000 and 2007 but changed to LPG in 2014, and third, those who used firewood in 2000, kerosene in 2007, and LPG in 2014. This gives us three mutually exclusive samples. We then plot the average lung capacity for these groups over the three survey years. The figure shows that on average, switching to a better fuel is associated with better lung capacity, whereas continuous usage of dirty fuel is associated with declining lung capacity. This presents a preliminary piece of evidence for the existence of potentially causal impact of fuel quality on health outcomes.

Gender-Disparity in Health and the Type of work.— Due to traditional gender roles, women’s time spent on food preparation is generally more than double the men’s. Figure C in the Appendix illustrates that among both men and women who do not work full-time, women spent, on average, two hours per day, double the time spent by men.³⁰ Given the evidence on positive relationship between fuel quality and lung capacity, biased gender roles within housework can lead to a disproportionate health burden on women compared to

²⁹ Table I and Table 3 show the pre-trends in the lung capacity and work hours respectively, by gender.

³⁰ This plot uses Spain data, as data on time use in developing countries is often unavailable and noisier due to measurement error.

men.

Figure 4 presents descriptive evidence for the existence of gender-disparity in lung capacity distribution for men and women in our baseline sample. While some of these differences may be attributed to natural factors such as the larger build of men’s bodies and higher physical activity by men, our goal, however, is to understand the extent to which these differences can be explained by the disproportionate gender burden imposed by energy poverty. If after the implementation of the program, households shifted to using LPG (assuming higher efficiency in the combustion process of LPG leading to lower exposure of indoor air pollution) and spent less time on food preparation, it can be expected that women will have higher health benefits due to lower exposure to indoor pollutants.

Next, we look into the gender disparity in the type of work performed by men and women at the baseline. There are a few important differences that emerge in our sample - one, in figure 5, we show the density plot of primary work performed by men and by women in our sample. The figure shows that approximately 40 percent of women perform housework as their primary activity compared to less than 2 percent of men, thus establishing the existence of gender-disparity in the housework and indirectly, in the amount of time spent indoors. Second, in figure 6 we plot the age distribution for non-employed women and men.³¹ The figure highlights the fact that approx. 60 percent of non-employed women are in their prime-working age group of 25-55 years, whereas only 10-15 percent of non-employed men are in their prime working age. Thus, the two figures together present evidence on the gender-disparity in the type of work as well as the skewed gender ratio for non-employed adults in their prime working-age groups.

V. Health Outcomes

We first present the impact on lung capacity, our key respiratory health outcome, and then discuss the plausible channel driving those results. In the next section, we will look at the impact on the labor supply outcomes, on the extensive as well as on the intensive margin and discuss the potential channels.

V.A Impact of the Program on Health Outcomes

Table 5 summarizes the impact on lung capacity by gender. Columns (1)-(4) consists of a sample of women and columns (5)-(8) consists of a sample of men. Consistent with the earlier hypothesis, we find that the program led to a higher increase in the lung capacity among women in the early treated households than those in the later treated districts by approximately 4 percent (10.55-11.34 L/min). This magnitude is

³¹ The term ‘non-employed’ is used in the paper to refer to individuals who are not employed in any form of formal labor. This includes individuals who are out-of-labor-force and not actively looking for work (for example - housewives, students) but excludes entrepreneurs or self-employed individuals who run their own businesses.

comparable to the impact of air pollution on lung capacity ten years post the exposure to wild forest fire in Indonesia (Rosales-Rueda and Triyana, 2018). In contrast, for men, there is a very small (1.03-1.94 L/min) and statistically insignificant improvement in their lung capacity due to the program.³²

The results highlight that the health benefits from clean cooking access are mostly accrued by women, who are responsible for most of the household chores and cooking activities. Hence, when these households switch to a cleaner cooking fuel, women are likely to benefit the most from the reduced exposure to indoor air pollution. Unlike women, men have minimal participation in cooking activities and are most likely to spend more time outside (e.g., working in the field and exposed to outdoor air pollution). Therefore, it is not surprising that the health impact among men is very small and statistically insignificant.³³

To put the magnitude of the treatment effects into perspective, we compare our estimates to the impact of smoking on lung capacity. The improvement in lung capacity among women in column (4), an average increase of 11.34 L/min, is comparable to the improvement in lung capacity if a regular smoker quits smoking for approximately 10 pack-years.³⁴ Our results correspond to an average three years difference in the treatment duration between the early-treated and the later-treated groups and indicate that larger duration of access to clean cooking fuel leads to a larger improvement in the lung capacity among women.

Next, we look at other self-reported health outcomes that can be associated with indoor air pollution (IAP) such as hypertension, cough, body weight, headaches, and self-reported health indicators (see Table 6). We find an increase in the body weight, a lower probability of experiencing cough in the last two weeks preceding the survey, and a higher probability of reporting having good health in general. While the coefficients are in the right direction, none of these coefficients are statistically significant. Several common reasons that can explain these are (1) some of these health outcomes are self-reported and subject to measurement error, and (2) these measures are weakly affected by pollution, and unlike the lung capacity, these can be impacted by various other factors as well. Hence, in the existing studies, these outcomes are rarely used as a reliable measure for health outcomes.³⁵

³² The difference in the early treatment effect for women and men are also statistically different from each other.

³³ In our sample, almost all men are employed. Hence, they spent significantly less time in the house than women, and therefore less exposed to indoor air pollution at the baseline.

³⁴ One pack-year of smoking means the person smokes one pack of cigarettes every day, for one year. These calculations are inferred from <http://berkeleyearth.org/air-pollution-and-cigarette-equivalence/>.

³⁵ Smoking habits of an individual may also affect their lung capacity. However, due to missing values on smoking variables, we are not able to control for smoking habits. Nonetheless, if individuals' smoking habits are time-invariant, it will be absorbed by the individual fixed effects. Hence, not controlling for their smoking behavior will not bias our results.

V.A.1 Heterogeneity in the Impact by Time Spent Indoors

In this section, we explore heterogeneity in the Early Treatment effects for women by their propensity to spend time indoors. To test this, we use two proxies for time spent indoors: (1) an indicator if individuals' primary activity is housework, (2) an indicator if individuals are non-employed.³⁶ Note that, these two proxies are individuals' status at baseline year, hence it is uncorrelated with the program.

To look at the heterogeneity in the treatment effect, we use an empirical specification akin to triple difference, where we interact the proxy dummy variables and add those interaction terms in equation 1 to arrive at the following regression equation 2 below -

$$\begin{aligned}
Y_{idt} = & \sum_{\substack{t \neq 2007 \\ k = 1 \text{ if } 2014 \\ k = -1 \text{ if } 2000}} \lambda_t \times \text{EarlyTreat}_d \times \mathbb{1}(t = k) \times \text{Dummy}_i + \sum_{\substack{t \neq 2007 \\ k = 1 \text{ if } 2014 \\ k = -1 \text{ if } 2000}} \beta_t \times \text{EarlyTreat}_d \times \mathbb{1}(t = k) \\
& + \sum_{\substack{t \neq 2007 \\ k = 1 \text{ if } 2014 \\ k = -1 \text{ if } 2000}} \varphi_t \times \mathbb{1}(t = k) \times \text{Dummy}_i + \alpha \times \text{EarlyTreat}_d \times \text{Dummy}_i + \zeta \text{Dummy}_i + \gamma \text{EarlyTreat}_d \\
& + \delta_t + X_{idt}\theta + \epsilon_{idt}
\end{aligned} \tag{2}$$

Our coefficient of interest is the coefficient λ_1 which gives the heterogenous treatment effect in the Post period i.e., $\text{EarlyTreat}_d \times \text{Post}_t(t = 1) \times \text{Dummy}$.

Table 7 summarizes the heterogeneity in the program's impact using this specification. Column (1) shows the early-treatment effect for women who primarily perform housework relative to women with other primary activities, and column (3) for non-employed women relative to employed subsample. For regression in column (1) $\text{Dummy}=1$ if primary activity is housework, else 0, and for column (2), $\text{Dummy}=1$ if non-employed, else 0. Each column corresponds to a separate regression with a different Dummy variable to estimate heterogeneity by activity type and employment status respectively.

Heterogeneity results in Table 7, columns (1) and (2) shows that the increase in lung capacity due to the program is 11.83 L/min larger among those who housework compared to those who do not and 11.91 L/min larger among non-employed women compared to employed women.³⁷ Thus, the results confirm our initial hypothesis that the impact is primarily concentrated among those women who are most likely to benefit

³⁶ As a 24-hour time-use diary is not available in Indonesia during these years, we use these proxies as a simple way to contrast individuals based on their propensity to stay indoors.

³⁷ One caveat is that it is that the unhealthiest member of the household is more likely to do housework. The implications to our estimates will depend on the linearity assumption between treatment and health improvement. It will overestimate the program's impact if the underlying assumption is that the poorer the initial health, the larger is the marginal benefit from clean cooking. However, it will underestimate the program's impact if the assumption is the poorer the initial health, the harder it is to improve in a given timeframe.

from a reduction in indoor pollution exposure.

V.B Plausible Channel: Reduced Indoor Pollution Exposure

In this subsection, we discuss evidence to establish that the plausible channel driving our health impacts is the reduced exposure to indoor air pollution from access to clean fuel, induced by the program.

Impact concentrated among samples with higher exposure to IAP.— Previously in the descriptive evidence section, we showed that approximately 40 percent of women perform housework as their primary activity (see, Figure 5) and approximately 35 percent of women are unemployed. In contrast, less than 2 percent of men perform housework as their primary activity and only 10 percent of men are non-employed, with most of the unemployed men being either sick or in their retirement age. Hence, women on average are more likely to spend time indoors and be involved with cooking than men. Thus, women are also more exposed to indoor air pollution from unclean cooking fuel than men. Hence, if reduced pollution exposure is likely the channel driving our results, we should also see a larger impact among subsamples of women who spend more time indoors (those who do housework), or those who are non-employed.

The main health result in Table 5 and the heterogeneous treatment effect in Table 7 highlights this channel by showing that longer access to clean fuel primarily impacts women and more so, women who are more likely to spend time indoors and be involved with cooking. Hence, it is reasonable to say that the impact of the program is mainly concentrated among samples with higher exposure to indoor air pollution - those likely to benefit the most from access to a cleaner cooking fuel.³⁸

Improved health from the switch to a clean fuel.— An improvement in the lung capacity that is driven by a reduction in the IAP exposure and induced by the program, is likely to occur via fuel-switching.³⁹ To investigate this channel, in Figure 7, we plot the impact on fuel choice and lung capacity by program duration, following Equation 3, by year of exposure. The fuel choice variable consists of three main cooking

³⁸ In Table H of Appendix, we show the early treatment effects separately for the sample of women who do housework, and who are non-employed. Compared to the treatment effect of 11.22 L/min for sample of all women in (column(1)), we find a higher treatment among these two sub-samples i.e., 18.70 L/min for women who do housework (column(2)) and 17.85 L/min among the non-employed women (column(3)).

³⁹ As discussed earlier in Section II., kerosene is much more polluting compared to LPG due to its inefficient combustion process. Fine particulate matters (PM) and carbon monoxide (CO), the main products of incomplete combustion, are among the most hazardous components found in air pollution affecting human health (He et al., 2001; Janssen et al., 2011). Particles of the size larger than 50 microns tend to settle down quickly, however smaller particles, such as PM_{10} (1/6th the diameter of a human hair) and $PM_{2.5}$ (1/20th the diameter of a human hair), behave like molecules and stay high up in the breathable zone. They can easily enter the lungs because of their small size. $PM_{2.5}$, in particular, can move deep into the alveoli of the lungs, where they irritate and swallow up the walls. This obstructs the normal functioning of the lungs, leading to serious health effects such as a decline in the lung capacity, increase in long-term risk of chronic bronchitis, lung cancer, and even death (Brändli, 1996).

fuel: LPG, kerosene, or firewood. Since we observe individuals post the program in 2014, individuals who received LPG in 2013-2014 are considered exposed to the program for 1-2 years, those who received LPG in 2011-2012 are considered exposed for 3-4 years, and those who received LPG in 2009-2010 are considered exposed for 5-6 years. The reference group is individuals living in districts that have not received LPG by 2014.

The longer a district is exposed to the program, the higher is households' propensity to use LPG as their primary cooking fuel (see the first plot in Figure 7). Similarly, the longer a district is exposed to the program, the lower the households' propensity to use kerosene (see the second plot in Figure 7).⁴⁰ The monotonic increase in the propensity to use LPG following the program duration corresponds to the monotonic increase in the lung capacity among women. This result is shown in Figure 8. It indicates that the longer a district is exposed to the program the higher is the improvement in lung capacity among women. We do not find significant improvement in men's lung capacity in any duration of the exposures, consistent with our earlier findings. These two figures show consistent patterns of our earlier estimates, highlighting that fuel switching due to the policy is an important factor in explaining the increase in lung capacity among women.

No health impact on treatment-ineligible households.— If the main channel driving our results is the reduced pollution exposure due to the clean fuel access from the program, we should not see any impact if pollution exposures do not change. Although we cannot directly measure the pollution levels in these households, we conduct a placebo test on the treatment ineligible women (i.e., women living in households who use LPG at baseline years) to test this claim. Since these women were using LPG before the treatment as well, there should not be any change in the pollution exposure in these households after the treatment. Table 8 presents the treatment effect on the lung capacity of women in treatment-ineligible households. Column (1) is the sample of all women, column (2) restricts the sample to women who do housework as their primary activity and column (3) restricts the sample to non-employed women. One may argue that there can be unobservable changes that coincide with the timing of the treatment and drive the results.

For treatment-ineligible households, we do not find any statistically significant treatment effects on the lung capacity of women in all the three samples. One might argue that the sample size for women in this group is relatively small, which can lead to large standard errors and hence insignificant results. However, even the magnitude of the treatment effects for treatment-ineligible women is quite small compared to the magnitudes for treatment-eligible women in these subgroups (refer to Table H in the Appendix), assuring us it is not simply a story of insufficient statistical power.

⁴⁰ There are very small changes in the households' propensity to use firewood due to the program (see the third plot in Figure 7). Because households often stack fuels (Kowsari and Zerriffi, 2011), it is possible that the impact on the propensity to use firewood is non-zero. They may report firewood as their main cooking fuel, but in reality, they may use both firewood and kerosene. Hence, as long as they have not used LPG, they would still be eligible for the program.

No Impact on placebo outcomes, those unrelated to pollution.— As another piece of evidence to establish the channel being reduced pollution exposure, we estimate the treatment effect on three different health outcomes that are unlikely to be related to pollution exposure (i.e., anemia, diabetes and haemoglobin level). These outcomes are not directly impacted by a reduction in pollution exposure and hence we should not find any treatment effect on any of these outcomes. Table J in the Appendix shows that we do not find any impact on these other health outcomes, thus providing strength to the pollution reduction channel.

Other Non-health Outcomes: While IAP exposure can affect health directly, the program may improve health through other indirect channels. To investigate this, we test the correlation between the program dummy and several other non-health outcome variables. Table 9 reports the Early Treatment effect of Equation 1 by changing the outcome variables to those corresponding to the table header. Column (1) shows that there is no change in the propensity to work for both men and women. Similarly, column (2) shows that there isn't a significant change in the probability of having an education higher than the primary due to the program. Column (3) shows that the program does not lead to an increase in household income per capita.⁴¹ Lastly, columns (4)-(8) show that the program does not lead to changes in any household characteristics such as whether the households have access to electricity, or whether they own a refrigerator, a TV, a toilet, or whether they have access to clean water. Overall results from this Table seem to indicate a weak correlation between the program and the other indirect channels. Although it's possible that small improvements may have occurred in some cases through these channels, it is plausible to say that these are not the drivers for the large health improvements.

The last possible channel that we consider is that the program may lead to changes in household expenditure, considering that LPG is more efficient compared to kerosene. However, using the same dataset, [Imelda \(2018\)](#) shows that households who switch from kerosene to LPG only experienced about a 2% reduction in their monthly expenditure or less than 2 USD. Moreover, these extra savings, due to the program, are not only very small, but are also not necessarily spent on health-related investments (e.g., the extra money can be spent on healthy food, but can also be spent on cigarettes). Hence, there is unlikely a clear direct link in which the program could affect an individual's respiratory health through the expenditure channel.

VI. Labor Supply Outcomes

In the previous section, we established the link between clean fuel access and improved health of women. In this section, we will investigate the impact of clean fuel access and the associated health improvements, on

⁴¹ One caveat is that the income from informal and casual work is unlikely to be documented because we only have the wage income from formal employment. However, informal work is usually a low-paid job or even unpaid. We convert the original currency to USD for convenience (conversion rate used: 1 USD = 13755 IDR)

the labor supply changes among agents in the household. We first motivate a simple conceptual framework to understand the potential link between fuel quality and health, with labor the supply of women and men. We do not intend to provide a full rigorous optimization model of household fuel choice and labor supply. Instead, we simply aim to demonstrate how an exogenous shift in cooking fuel (induced by the program) that leads to health improvements of only women - as seen in the health outcome results - can impact the labor supply outcomes for both women and men. Followed by this conceptual framework, we will then present our empirical labor supply results.

Consider a household consisting of two agents - men (denoted with a m subscript) and women (denoted with a w subscript). We consider a household as a single economic unit with utility function $u(C, P)$ over household consumption C and housework services P .⁴² Each household consists of men and women. The total combined labor endowment for a household is one. Each member can allocate their labor endowments either for farm work (L_w and L_m) or for household work (H_w and H_m). Household consumes their own farm-produced goods $C = L_w^\alpha L_m^{1-\alpha}$ and housework services $P = H_w^\beta H_m^{1-\beta}$. α and β are the output elasticity parameter for each gender in the farm and housework production function, respectively. Household maximizes $\log(C) + \log(P)$ by choosing their farm labor inputs by men (L_m) and women (L_w), and housework labor by men (H_m) and women (H_w). Household is subjected to a fixed amount of time \bar{z} required for housework given that, in general, there is a lower bound on how much housework is needed. We introduce θ to capture the inverse quality of fuel (the lower the θ , the higher is the quality of fuel). In line with our findings earlier, we assume that lower quality of fuel is linked to only women. Hence, the effective labor of women is decreasing in θ (for more detail about the model, see the Appendix Section A).

The comparative statics from the model in Equations 6 and 7 implies that an improvement in the fuel quality can be lead to changes in the labor supply for both men and women depending on the farm productivity parameter, α . When women have sufficiently high productivity in farm work, we should see an increase in their farm labor inputs. On the other hand, when women are not equipped with the skills needed on the farm, it is intuitive to see that there won't be an increase in the farm labor supplied by women. We also find that farm labor input from men always increases when the fuel quality improves even though fuel quality only influence women's health and productivity. This seems reasonable given that men are influenced indirectly through changes in women's productivity. Keeping this motivating conceptual framework in mind, we continue this section by presenting our empirical results for program's impact on labor supply outcomes.

⁴² This can include activities such as cleaning, washing clothes, taking care of children etc

VI.A Impact of the Program on Labor Supply Outcomes

To estimate the labor supply on the intensive margin, we use the variable ‘hours of work’ supplied by individuals, whereas for labor supply on the extensive margin, we use the ‘participation rates’ of individuals in the labor market. We start by first presenting our results for the overall labor market. We will then take a closer look at the labor supply results in the agriculture sector, one of the highest participating sectors among these agents.

Intensive Margin.— In Table 10, we present the early treatment impact along the intensive margin using the hours of labor supplied by women and men. Columns (1) and (4) show estimates for the sample of all women and men, respectively, whereas columns (2)-(3) and columns (5)-(6) show estimates for the subsamples of women and men, respectively, conditional on their baseline work/activity status of women. For women, we split the sample into women who primarily do housework in column (2) and to women who do not in column (3). Clean cooking program primarily improved the health of women who did housework at the baseline, hence, we expect a higher labor supply impact among these women than among those who did not.⁴³ For men, since we do not see any direct health improvements among them, we believe any impact on the labor supply of men to be related to the health improvements among women. Hence, we divide the sample of men based on the primary activity of women in the household. Columns (5) and (6) consists of sample of men belonging to households in which women primarily did housework and those in which they did not, respectively, in the baseline.⁴⁴

We find an increase in the hours of work among women who did housework in the baseline (Column 2, Table 10). Considering a 5-day work week, the size of the impact corresponds to a 1.5 hours of additional labor per day for women (approx. 20 percent increase). We do not find any significant impact on hours of work for the overall sample of women or for the sample of women who did not do housework as their primary activity. We also find an increase in the hours of work supplied by men. Importantly, we see a higher and significant impact among men in households where women primarily did housework in the baseline compared to small and insignificant impact among men in households where women did not primarily do housework.⁴⁵ The size of the impact among men is approximately 1 to 1.3 hours of additional labor per day (approx. 9 to 11 percent increase).

There are two main explanations for these findings. First, if women have more productive time due to improved health and saved-time, the ‘excess’ time now can be allocated to other activities. Since the health

⁴³ For men, it doesn’t make sense to do a similar categorization given that the sample of men who do housework is very small.

⁴⁴ Note that this sample splitting is also based on their characteristics at the baseline year, hence is also not endogenous to the program.

⁴⁵ We are not able to statistically reject the hypothesis that the difference between these two groups is not zero.

results from clean cooking access were mainly concentrated among women who did housework, it makes sense that the labor supply improvements are also mainly concentrated within this group. Second, improvement in the health and productive time of women can impact the labor supply of men. If women have more productive time due to better health now, it can increase the marginal productivity of men in sectors where labor inputs of men and women are complementary, thus providing incentives for men to increase their labor supply too. Moreover, improved health of women means less time lost in sickness. This also means less time spent by men in taking care of her, visiting the hospital, taking care of children, etc. As a result, men can reallocate this ‘time saved’ due to improved health of women towards their existing job, explaining some of the post-program increase in work hours among men.

Extensive Margin.— In Table K of the Appendix we show the early treatment effects on labor participation rates in four major sectors, by gender.⁴⁶ Although we see increases in women’s participation in these sectors, most of the coefficients are statistically insignificant and small in magnitude. We also do not find any significant changes in the participation rates of men along any of these sectors.

Changes along the extensive margin are more difficult than those along the intensive margin. Labor participation changes are contingent on various sector-specific factors such as sector specific skill requirements, the flexibility of the sector to absorb increases in labor supply and local economic conditions. Even though women who were primarily involved with housework may now enjoy some ‘free’ time due to the program (either through improvements in health or less time spent in cooking), it is likely that this group of women has limited skills or resources to increase their work participation even with the extra time. Hence, in the next subsection, we focus on the labor supply outcomes in a sector which has relatively low-skill requirement and a higher flexibility to absorb additional labor, agriculture.

VI.A.1 Labor Supply in the Agriculture Sector

In this section, we take a closer look at the labor supply changes in the agriculture sector due to three reasons. First, from the density plot in figure 9, we see that agriculture is the top participating sector among women who did housework at the baseline, hence we may have enough statistical power to detect any changes in the labor supply outcomes for these women. Second, the skill sets required to do agriculture is generally lower compared to other formal jobs. As a result, it is possible that women who do housework have the option to increase their participation in agriculture despite their low skill sets. Third, given that the agriculture sector is generally a labor-intensive sector, this sector is more likely to have the ability to absorb the extra supply of labors (if any). We summarize the program’s impact on the labor supply outcomes in the agricultural sector for both extensive and intensive margin in Table 11.

⁴⁶ We limit our analysis to the top four sectors with the highest participation rate in our sample.

Intensive Margin.— For estimating the impact along the intensive margin of labor supply in agriculture, we limit our sample to individuals who participated in agriculture at the baseline (Panel A of Table 11). For women, we find an increase in the hours of work supplied in agriculture among sample who primarily do housework in the baseline, but not among those who do not. The size of the impact is about 1.3 hours additional work per day or 18 percent. This is similar to our earlier findings for the overall sample of woman who do housework in Table 10. However, because of restricting the sample to only those who did housework and participated in agriculture at the baseline, we have a much smaller sample and hence, lack the statistical power. For work hours among men in agriculture, we find an increase in their work hours by 1.3 hours per day or 13 percent. As before, we see a higher and significant impact - 2 hours of additional labor per day or 19 percent increase - among men in households where women primarily did housework in the baseline, as compared to small and insignificant impact among men in households where women did not do housework primarily.

Extensive Margin.— On the extensive margin of labor supply in agriculture (Panel B of Table 11), we find a large increase in the participation rates among women who did housework. Among women in this group, those treated early are 15.8 percentage points more likely to participate in the agriculture sector after the program than those treated later by the program. Moreover, we do not find any sizable or significant impact on the participation rates for women who did not do housework primarily, or for men. Thus, by increasing the participation rates among women who experience the largest health benefits from the program, a clean fuel intervention can narrow some of the gender-gaps in labor supply. The lack of increase in participation rate among men seems reasonable, as figure 9 shows that labor force participation is already saturated for men, with ‘employed’ being their default job status. On contrary, almost 50-55 percent of women who did housework in the baseline are those who never-worked or were involved in unpaid work, providing plenty of scope for improvement in the labor participation among these women.

Thus, the large improvements in the labor supply along both extensive and intensive margins in agriculture sector, point towards the large benefits of access to a clean fuel - a benefit that is often not fully internalized in households’ cost-benefit analysis while choosing a cooking fuel.

VII. Robustness Checks

In this section, we conduct several tests and specification checks to test the robustness of our main findings. We test the correlation between the timing of the program with other ongoing poverty alleviation programs, re-estimate the impact using the coarsened exact matching method, and finally use different ways of sample restrictions. Overall, we find the results are similar to our original findings, reassuring the robustness of our main results.

Poverty Alleviation Programs.— There are several public social safety nets provided by the government in the form of various Poverty Alleviation programs (PAP) such as rice subsidy programs, health insurance subsidies, conditional, and unconditional cash transfers. Since these programs run parallel to the clean cooking program studied here, one may think that our findings include some of the effects of the other programs. However, these other programs can only bias our estimates if they are systematically correlated with the timing and the eligibility of the clean cooking program.

To test this, we first check if there is any significant correlation between the indicator of a household’s eligibility to the Kerosene to LPG program and the indicator if the household received benefits from each of the PAPs. Given that there are a large number of such programs and they all start at different years, we group the PAPs by the year when each program started. For example, PAP_2007 includes all the programs that started in 2007.⁴⁷ Table 12 shows coefficients from the regression of program eligibility on the eight groups of programs. We do not find any statistically significant correlation across any of these groups. Moreover, the size of the correlation is very small, indicating that the other PAPs are unlikely to drive our results. As an additional check, we also include the poverty alleviation programs as a control variable in our main Difference in Difference specification and still find similar results.

Coarsened Exact Matching.— In this exercise, we use the Coarsened Exact Matching (Blackwell et al., 2009). In particular, we match the early treated and the later treated sample based on households’ primary cooking fuel and their location-specific rural-urban classification at the baseline years. Table 13, columns (1) and (2), show the treatment effects on the lung capacity for women and men using the coarsened matched sample. We find statistically significant treatment effects among women, about 11.75 L/min, which is almost identical with the estimates from our main specification (11.34 L/min). We do not find any statistically significant treatment effects among men, similar to our earlier results (2.92 L/min compared to 1.94 L/min in the main specification). We also regress the monthly hours of labor supply on the coarsened matched sample in columns (3) and (4) and find that the estimates are very similar to our earlier findings.

Sample Restrictions.— Here we test if our results are robust to different sample restrictions. We find that the results do not change significantly with the inclusion of inter-district migrants, all age groups, and households who reported using kerosene exclusively at the baseline year.

One may be concerned with some anticipation of the program. For instance, individuals migrated into districts that are designed to receive the benefits earlier. As there is no dissemination of information regarding the timing of the program to households, hence we believe that migration across districts is unlikely due to the program. Nonetheless, we check if our results are sensitive to the inclusion of the group of migrants.

⁴⁷ We only focus on the PAPs that were implemented between 2007 and 2014, the same time frame with the Kerosene to LPG program.

Table 14, columns (1) & (5) show the treatment effect on the lung capacity with a migrant-inclusive sample is 10.89 L/min, which is very similar to 11.34 L/min corresponding to migrant-exclusive sample. In both the samples, we do not find any significant treatment effects on the lung capacity of men. Next, we check if our results are sensitive to the age restriction. Table 14 columns (2) and (6) show the results without age-restrictions, while columns (3) and (7) show the results for only individuals in the prime working-age group of 25-55 yrs. For both cases, we do find similar results as in our main findings. Lastly, we check the sensitivity of the result if we restrict our sample to only households that reported using kerosene as their primary fuel at the baseline. Note that, with this restriction, we have a much smaller sample size compared to the sample in our main analysis. Table 14, columns (4) and (8) show a significant treatment effect among women, but not among men. Again, the size of the treatment effect does not fluctuate much because of this restriction.

VIII. Conclusion

We show that access to modern energy can be a strong determinant of health, productivity, and economic opportunities, particularly among women. We use a nationwide clean cooking intervention in Indonesia, one of the few successful energy transition programs in developing countries, to investigate the impact of clean energy access on gender disparities that arise mainly due to the disproportionate burden of energy poverty on women. In particular, we exploit the exogenous variation in the timing of the program to estimate a causal relationship between clean energy access, health, and labor participation.

We find that the program led to a significant increase in lung capacity for women who were exposed earlier to the program compared to those exposed later to the program, and an increase in their labor supply on the extensive and the intensive margin. The program’s impact is higher among women who spend more time indoors and cook, while among men the impact is very small and statistically insignificant. This suggests that a part of gender disparity in health can be explained by the lack of access to clean energy. Further, we find a significant increase in men’s work hours which is likely due to households re-optimizing their task and time allocation. We investigate several key possible mechanisms, and conclude that the reduction in indoor air pollution exposure due to adoption of clean fuel is likely the leading mechanism that explains the observed health improvements, while the observed health improvements and time saved from less time spent on food preparation are likely the main channels for the impacts on labor supply.

Women, while being the most susceptible to adverse outcomes of unclean energy, may not be fully aware of its consequences and thus lack incentives for a fast transition to clean energy(Mobarak et al., 2012).⁴⁸

⁴⁸ (Mobarak et al., 2012) finds evidence that women in rural Bangladesh do not perceive indoor air pollution as a significant health hazard.

On the other hand, women who may have stronger preferences for healthier fuel, often lack authority in the intra-household bargaining process to make independent use of household resources (Miller and Mobarak, 2013). We show that adverse health impacts from dirty fuel affects other productive outcomes such as labor supply of women too. Thus, if women cannot make independent resource choices in dimensions that disproportionately harms them, well-designed policy interventions to incentivize modern energy adoption can have a positive impact in reducing the gender gap in health and productivity.

The total benefits of clean energy access are likely to exceed those documented in this study.⁴⁹ A calculation for total welfare from clean energy access as well as the long term benefits of clean cooking should be the focus of future research. Nonetheless, using a back-of-the-envelope calculation, we estimate that the estimated improvement in lung capacity is equivalent to a reduction in the probability of dying from lung cancer by 45 percent. Using the lower bound for VSL (Kniesner et al., 2012) at \$4 million, the estimated VSL associated with the observed lung capacity changes is approximately \$1.44 million per person.

The fuel conversion program in Indonesia presents an exemplary model of successful large-scale policy implementation, where a combined utilization of a price subsidy and quantity restriction resulted in high adoption rates within a small period of time. The policy led to a major shift in Indonesia’s position within the developing regions in the world, from being one with the lowest share of the population with clean cooking access to being one with the highest share of the population with clean cooking access, in less than ten years (see Figure D in Appendix). Hence, there are important lessons to be learnt for policymakers in sub-Saharan Africa and developing Asia in their attempts to achieve the Sustainable Development Goals (SDG) goals that aim to achieve universal access to affordable, reliable and modern energy by 2030.

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⁴⁹ For instance, some studies discuss the other benefits from clean energy access such as a reduction in CO emissions (Budya and Arofat, 2011), expenditure savings (Imelda, 2018).

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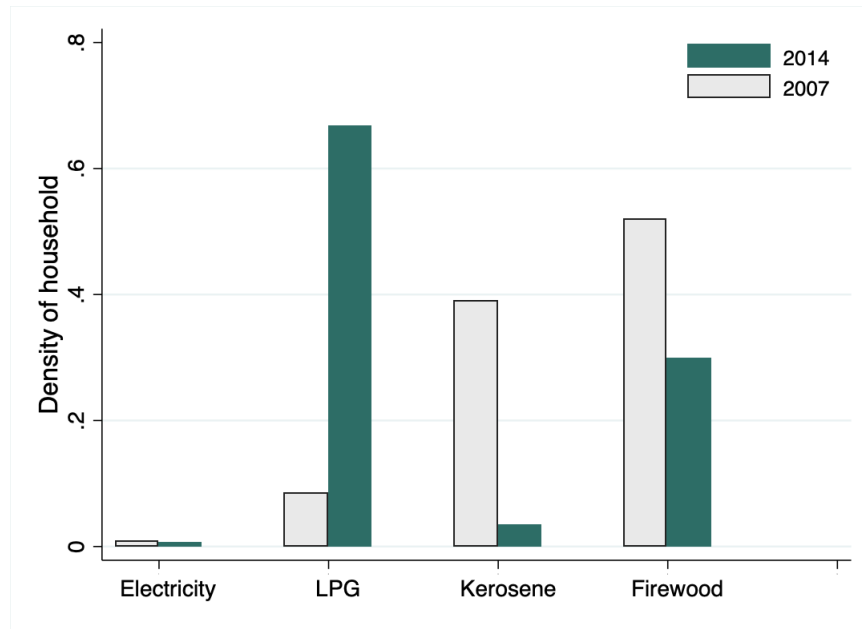
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Figures and Tables

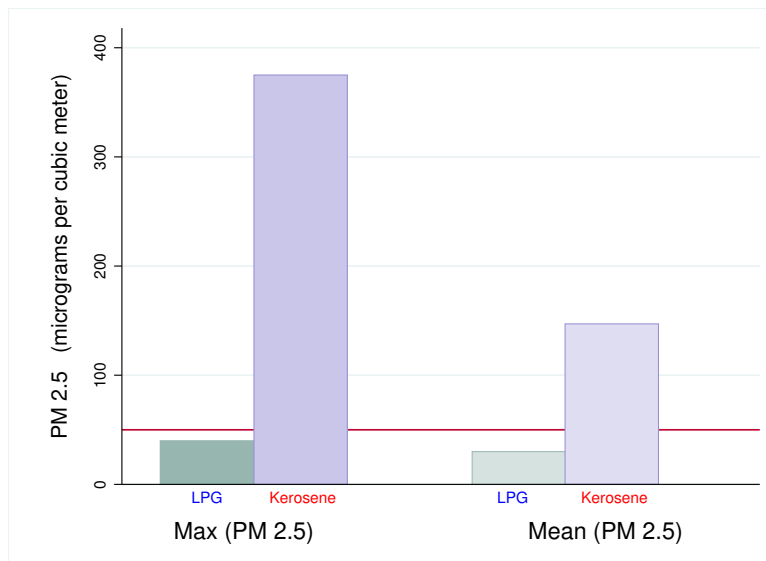
Figure 1: PRIMARY COOKING FUEL



Notes: Figure 1 plots the density of households by their cooking fuel choice, before the program began in (2007) and after the program (2014).

Source: Author's calculation using IFLS 2007 and 2014.

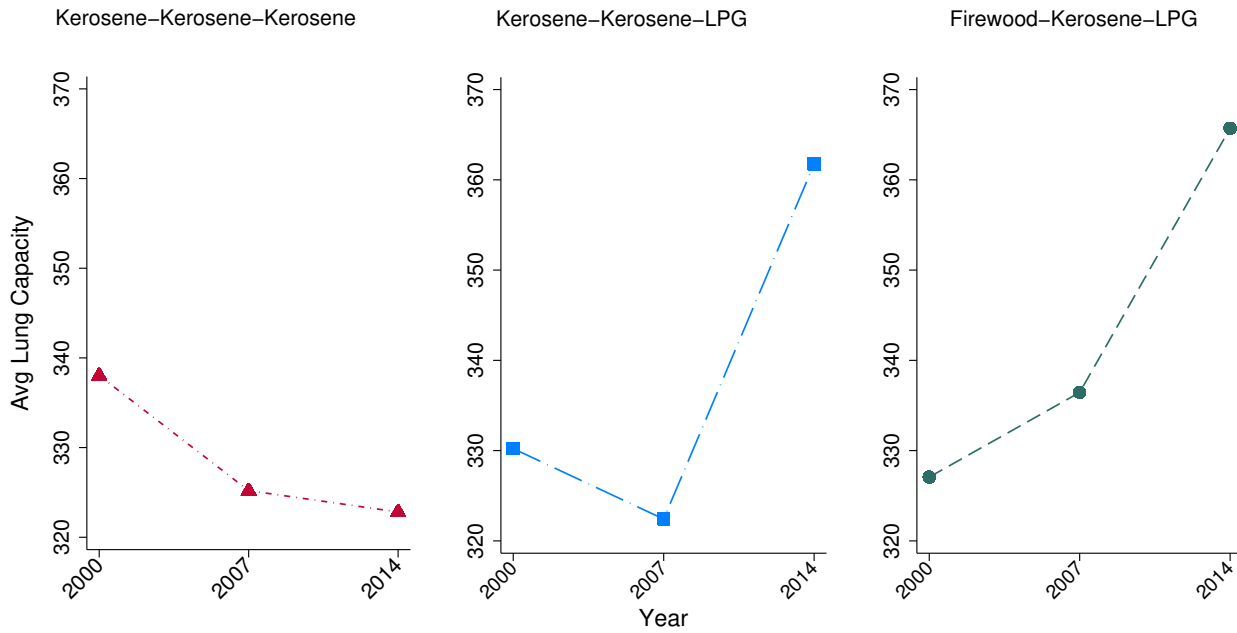
Figure 2: $PM_{2.5}$ CONCENTRATION LEVELS FROM LPG AND KEROSENE



Notes: Figure 2 depicts the mean and the maximum level of $PM_{2.5}$ found in LPG and kerosene stoves. The red horizontal line shows the World Health Organization's recommended guideline for the upper bound on safeguard limit of $PM_{2.5}$ level, annual mean concentration of $50\mu g/m^3$.

Source: Authors' compilation using data from www.ncbi.nlm.nih.gov.

Figure 3: AVERAGE LUNG CAPACITY OVER TIME



Notes: Figures plots the average lung capacity (on the y-axis) of groups of individuals over the three survey years i.e., 2000, 2007, and 2014 (on the x-axis). Kerosene-Kerosene-Kerosene depicts the average lung capacity for those who stay using kerosene as their main cooking fuel from 2000 - 2014. Kerosene-Kerosene-LPG depicts the average lung capacity for those who used kerosene as their main cooking fuel 2000 and 2007 but switched to LPG in 2014. Lastly, Firewood-Kerosene-LPG depicts the average lung capacity for those who use firewood as their primary fuel in 2000, kerosene in 2007 and LPG in 2014.

Source: Author's calculation using IFLS 2000, 2007 and 2014.

Figure 4: GENDER DISPARITY IN LUNG CAPACITY

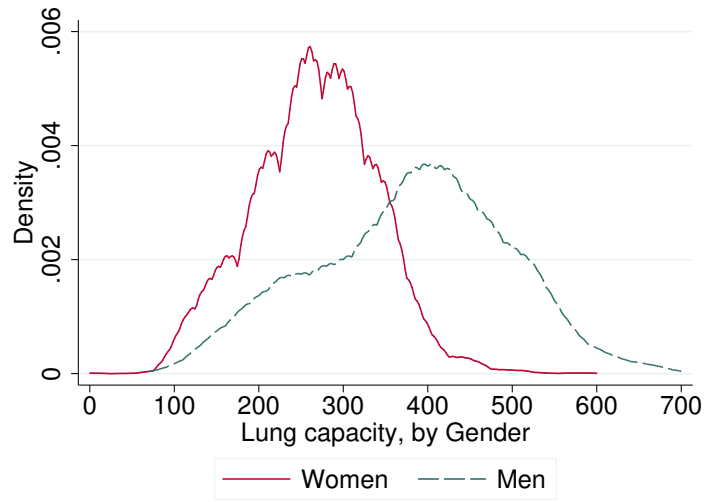
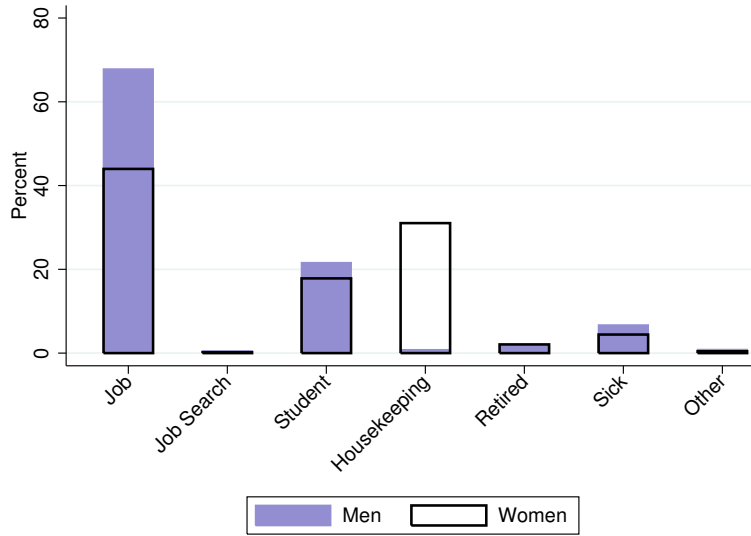


Figure 4 plots the lung capacity distribution among men and women. While the lung capacity distribution is more dispersed among the men, it also stochastically dominates the lung capacity distribution among the women. The unit of measurement for lung capacity is liters/minute.

Source: Author's calculation using IFLS 2007. *Sample:* Men and women in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

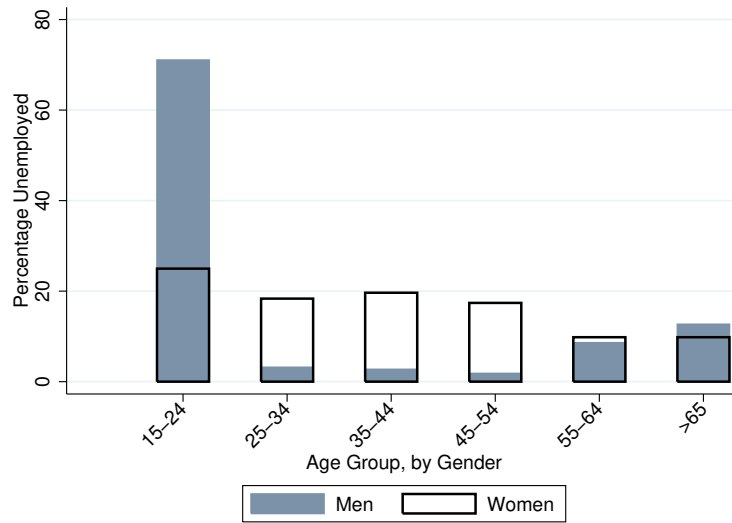
Figure 5: GENDER DISPARITY IN HOUSEHOLD ACTIVITY



Notes: Figure 5 plots the histogram of the type of primary activity reported by the individuals, by gender. The figure highlights the huge gender disparity in the percentage of men and women who did housework primarily. While approx. 33 percent of women primarily do housework in the sample, the percentage of men who do housework is close to 2 percent.

Source: Author's calculation using IFLS 2007. Sample: All men and women in the baseline year (2007).

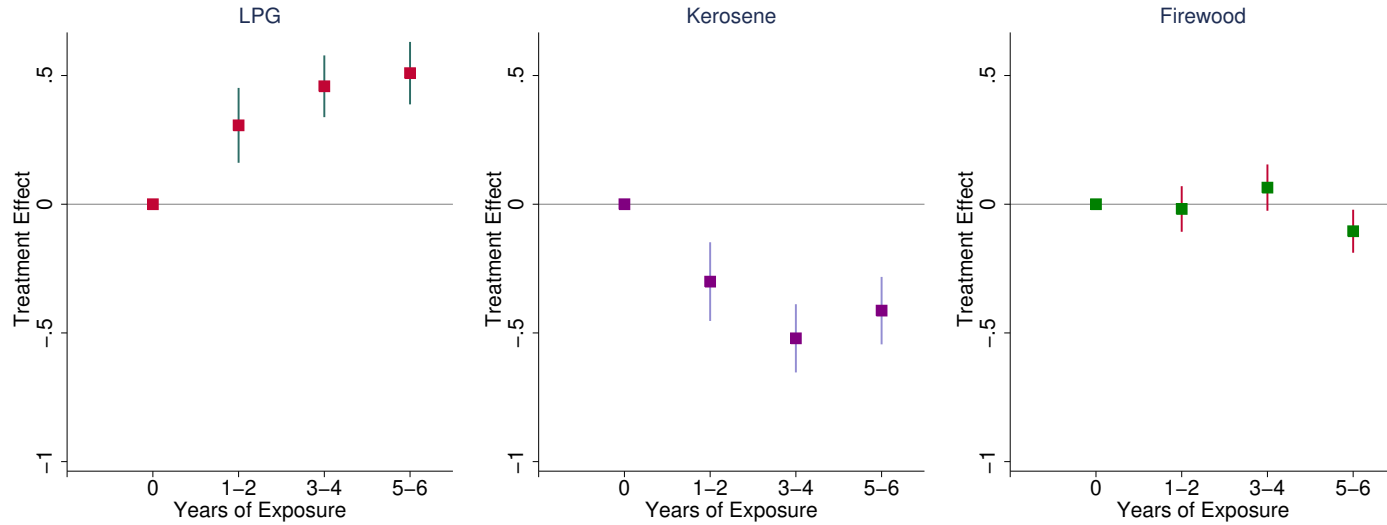
Figure 6: GENDER DISPARITY WITHIN NON-EMPLOYED POPULATION, BY AGE



Notes: The figure 6 shows the age distribution for non-employed individuals, by gender. The figure shows that a majority of unemployed women are in their prime working age group of 25-55 years age, however very few unemployed men are in their primary working age.

Source: Author's calculation using IFLS 2007. Sample: All men and women in the baseline year (2007).

Figure 7: FUEL-SWITCHING BY PROGRAM DURATION



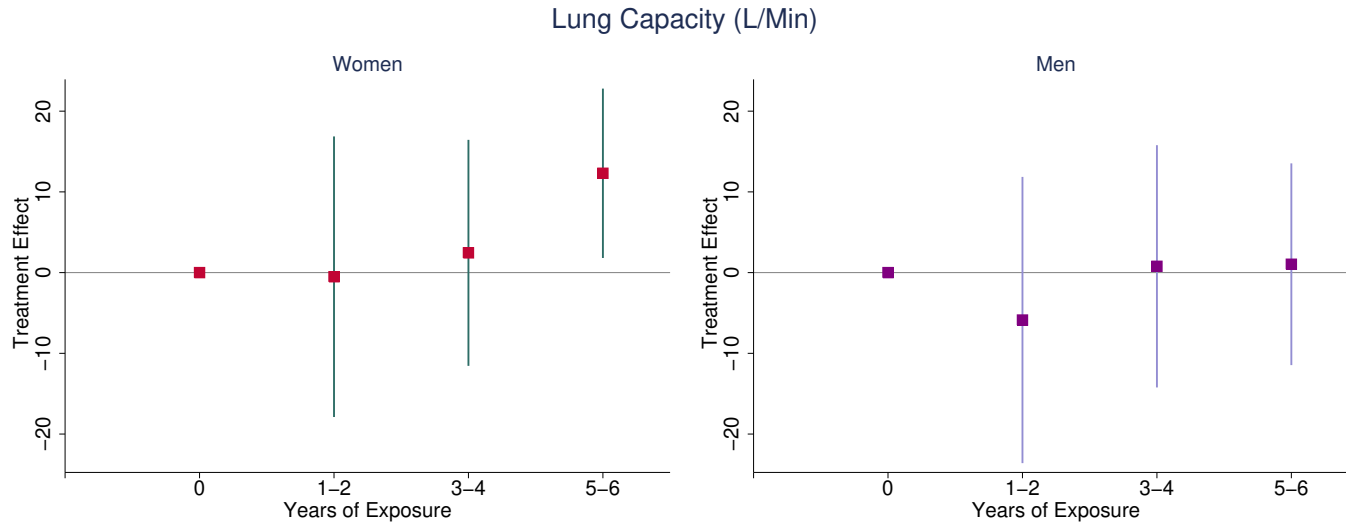
Notes: This figure plots the interaction coefficient $\beta_{d,1}$ in equation 3 by years of exposure. $\beta_{0,2007}$ is normalized to zero and thus each coefficient can be interpreted relative to their values in 2007. Each $\beta_{d,1}$ gives the treatment effect for districts with successively increasing length of treatment duration compared to untreated districts, in post treatment period (2014) relative to their baseline values (2007).^a The outcome variables is if household's primary cooking fuel is LPG, kerosene, or firewood. Individuals were exposed to the program for 1-2 years if they received LPG in 2013-2014, for 3-4 years if they received LPG in 2011-2012, and for 5-6 years if they received LPG in 2009-2010. The reference group is individual living in district that receive LPG beyond 2014.

Source: Author's calculation using IFLS 2000, 2007, 2014.

^a Regression equation corresponding to the plot is as below, where d varies from 0 to 3 depending on the years of exposure. d=0 is regions with no exposure by 2014, d=1 are districts with 1-2 yrs of exposure, d=2 are districts with 3-4 yrs of exposure and d=3 for 5-6 yrs of exposure.

$$Y_{idt} = \sum_{\substack{d=1 \\ d \neq 0}}^3 \sum_{\substack{t \neq 2007 \\ k=1 \text{ if } 2014 \\ k=-1 \text{ if } 2000}} \beta_{d,t} \times \text{EarlyTreat}_d \times \mathbb{1}(t=k) + \sum_{\substack{d=1 \\ d \neq 0}}^3 \gamma_d \times \text{EarlyTreat}_d + \delta_k + X_{idt}\theta + \epsilon_{idt} \quad (3)$$

Figure 8: PROGRAM IMPACT ON LUNG CAPACITY BY PROGRAM DURATION

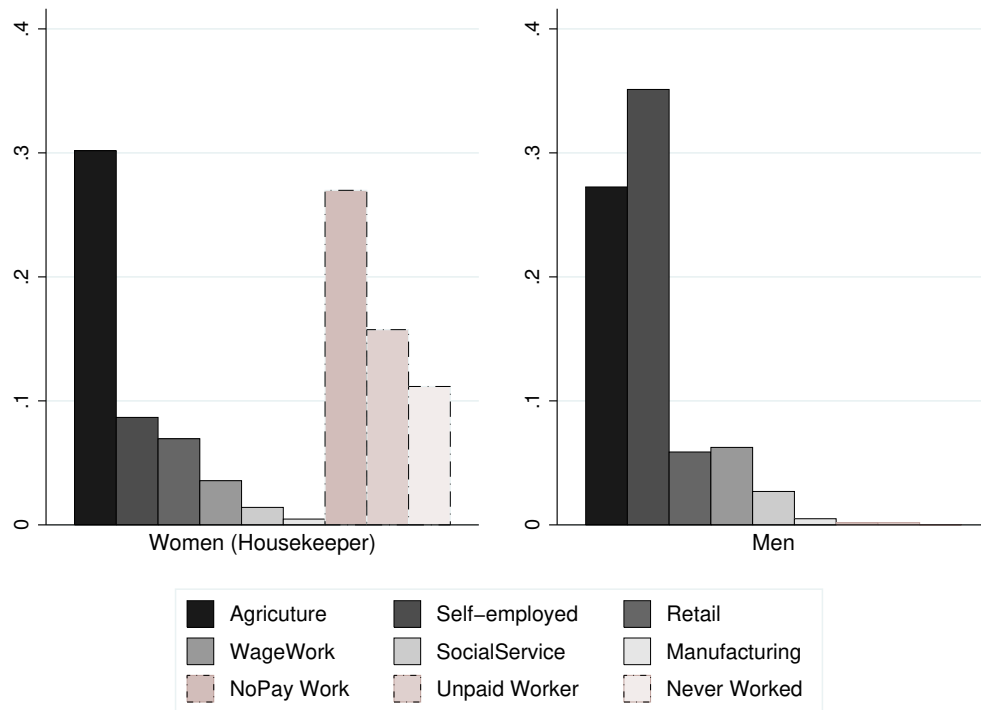


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Notes: This figure plots the shows the program impact (coefficient $\beta_{d,1}$ in equation 3) on the lung capacity of women and men, by the years of exposure of the region to treatment in 2014. The excluded category are the untreated regions and the baseline year, 2007. Hence, $\beta_{d,t}$ shows effect relative to this group. Individuals were exposed to the program for 1-2 years if they received LPG in 2013-2014, for 3-4 years if they received LPG in 2011-2012, and for 5-6 years if they received LPG in 2009-2010. The reference group is individual living in a district that receives LPG beyond 2014.

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to women above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Figure 9: PARTICIPATION RATES IN DIFFERENT SECTORS IN 2007
(BY GENDER)



Notes: The figure 9 shows the participation rates of individuals in our sample. For women as well as men in this sample, agriculture has one of the highest participation rates. The figure shows that a large of women who did housework are either not paid for the work or do not work, whereas a large proportion of men are self-employed.

Source: Author's calculation using IFLS 2007. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e., above the high-school age and legal marriage age in Indonesia)

Table 1: PRE-TREND IN HEALTH VARIABLES

	Lung Capacity (L/min)	Hypertension (1/0)	Anemia (1/0)	Diabetes (1/0)	Self Health (1/0)	Weight (Kg)	Cough (1/0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EarlyTreat \times Pre	6.050 (7.298)	0.005 (0.007)	0.006 (0.005)	-0.002 (0.002)	0.047 (0.031)	0.502 (0.347)	0.000 (0.031)
Control Mean	341.860	0.016	0.014	0.006	0.745	52.755	0.361
Observations	14567	14567	14567	14567	14567	14552	13854

Notes: Table 1 presents the pre-trend in several health variables. Each column shows the $EarlyTreat \times Pre$ coefficient (i.e., β_{-1} in Equation 1) corresponding to separate regressions with different outcome variables. The outcome variable corresponding to each regression is displayed in the column header (Unit of the variables are displayed in the bracket, where (1/0) represents dummy variables). All regressions include controls for baseline value of age and height of the individuals and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Table 2: PRE-TREND IN SEVERAL DEMOGRAPHIC VARIABLES

	Work (1/0)	Education (1/0)	Income (Log pci)	Electricity (1/0)	Refrigerator (1/0)	TV (1/0)	Toilet (1/0)	Water (1/0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EarlyTreat \times Pre	0.002 (0.009)	0.001 (0.008)	0.029 (0.075)	-0.008 (0.035)	0.035 (0.065)	-0.022 (0.035)	0.030 (0.037)	0.063 (0.046)
Control Mean	0.493	0.922	4.665	0.961	0.757	0.800	0.749	0.497
Observations	14567	14567	13279	14567	14567	14567	14567	14567

Notes: Table 2 presents the pre-trend in several demographic variables. Each column shows the $EarlyTreat \times Pre$ coefficient (i.e., β_{-1} in Equation 1) corresponding to separate regressions with different outcome variables. The outcome variable corresponding to each regression is displayed in the column header (Unit of the variables are displayed in the bracket, where (1/0) represents dummy variables). All regressions include controls for baseline value of age and height of the individuals and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Table 3: PRE-TREND IN PARTICIPATION RATES AND HOURS OF WORK, BY GENDER

Labor supply in :	Women					Men				
	Social Sector	Agriculture	Self Employed	Retail	Hours of Work	Social Sector	Agriculture	Self Employed	Retail	Hours of Work
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EarlyTreat \times Pre	0.001 (0.019)	0.017 (0.032)	0.052 (0.033)	0.014 (0.027)	12.439 (8.217)	-0.005 (0.018)	0.019 (0.030)	0.004 (0.029)	0.012 (0.028)	10.612 (8.645)
Observations	3945	3945	4253	3945	3965	3514	3514	3609	3514	3521

Notes: Each column is a separate Difference-in-Difference regression on different outcomes representing labor provided in various sectors as well as the hours of work provided, labeled on the column header. The coefficient values EarlyTreat \times Pre corresponds to the treatment effect in the pre-period (2000) with the baseline period (2007) as the reference point. Columns (1)-(5) presents coefficients for women, whereas columns (6)-(10) for men. The table shows that there was not any evidence of pre-trend in the past period corresponding to each of the sectors as well as in the hours of work provided. All columns include the district fixed effects and the rural-urban fixed effect. The standard errors (in parentheses) are clustered by district. *p < 0.10, **p < 0.05, ***p < 0.01

Source: IFLS 2000, 2007.

Table 4: SUMMARY STATISTICS OF BASELINE CHARACTERISTICS

	Early Treated		Later Treated	
	Mean (1)	SD (2)	Mean (3)	SD (4)
Age	34.42	17.76	32.88	17.38
Ever Married (1/0)	.672	.469	.636	.481
Employed (1/0)	.623	.484	.586	.492
Large Household, N>=5 (1/0)	.730	.443	.751	.432
Per-capita Income (USD)	175.6	337.9	190.4	260.2
Weight (kg)	48.81	14.63	47.95	15.40
Lung capacity (litres/min)	313.6	113.7	322.1	106.9
Handgrip (kg)	27.28	12.05	28.17	10.21
Self reported health (1/0)	.487	.499	.454	.497
<i>Do you take medicine for</i>				
Hypertension (1/0)	.007	.084	.013	.115
Anemia (1/0)	.006	.082	.007	.085
Diabetes (1/0)	.001	.036	.001	.031
<i>Primary Cooking Fuel</i>				
Electricity (1/0)	.009	.095	.008	.093
Gas (1/0)	.104	.305	.080	.271
Kerosene (1/0)	.377	.484	.476	.499
Firewood (1/0)	.493	.499	.428	.494
Charcoal (1/0)	.009	.096	.001	.034
<i>Highest Level of Education</i>				
No school (1/0)	.092	.289	.061	.240
Primary/Middle School (1/0)	.484	.499	.457	.498
High School (1/0)	.369	.482	.408	.491
<i>Participation rate</i>				
Agriculture (1/0)	.186	.192	.185	.192
Retail (1/0)	.088	.140	.089	.141
Social Service (1/0)	.031	.071	.037	.077
Manufacturing (1/0)	.007	.027	.004	.021
Self-employed (1/0)	.225	.223	.218	.223
<i>Ownership of Asset</i>				
Electricity (1/0)	.945	.226	.939	.238
Refrigerator(1/0)	.622	.856	.659	.886
Television (1/0)	.753	.431	.709	.454
Observations	6944		4308	

Notes: This table reports the average individual and households characteristics at baseline. The rows are grouped by health, education and household characteristics; and the columns show averages in the early treated districts (2009-2010), the later treated districts (after 2010). *Source:* Author's calculation using IFLS 2007. *Sample:* All individuals

Table 5: PROGRAM IMPACT ON LUNG CAPACITY

	Women				Men			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EarlyTreat × Post	10.55*	10.55*	11.22**	11.34**	1.039	1.039	2.041	1.940
	(5.484)	(5.524)	(5.547)	(5.500)	(6.062)	(6.118)	(6.109)	(6.042)
Post	9.012**	9.012**	8.174**	8.058*	23.89***	23.89***	22.47***	22.47***
	(4.139)	(4.170)	(4.170)	(4.132)	(4.183)	(4.222)	(4.246)	(4.206)
EarlyTreat	-17.01**	-95.34***	-99.87***		-10.16	-8.724**	-188.1***	
	(7.065)	(3.810)	(3.835)		(8.026)	(4.050)	(9.267)	
Clustering	✓	✓	✓	✓	✓	✓	✓	✓
District FE		✓	✓	✓		✓	✓	✓
Rural-Urban FE			✓	✓			✓	✓
Individual FE & Controls				✓				✓
Control Mean	282	282	282	282	409	409	409	409
Observations	7954	7954	7788	7782	6215	6215	6054	6049

Notes: Table 5 shows the program impact (coefficient β_1 corresponding to $\text{EarlyTreat} \times \text{Post}$ in equation 1) on the lung capacity (in L/min), by gender. Columns (1)-(4) show the impact on women, whereas columns (5)-(8) show the impact on men. Columns (1) and (5) show the treatment effect corresponding to the basic difference in difference analysis with no additional control variables, columns (2) and (6) include the individual level controls such as age and height at the baseline, columns (3) and (7) include the rural-urban dummy, and columns (4) and (8) include the district and the individual fixed effects. Standard errors (in parenthesis) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: IFLS 2000, 2007, 2014. Sample: Treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Table 6: PROGRAM IMPACT ON SECONDARY HEALTH OUTCOMES

	Cough (1/0)	Self Health (1/0)	Weight (kg)	Hypertension (1/0)
	(1)	(2)	(3)	(4)
EarlyTreat \times Post	-0.027 (0.041)	0.017 (0.024)	0.359 (0.280)	0.011 (0.008)
Control Mean	0.361	0.745	52.755	0.016
Observations	13854	14567	14552	14567

Notes: Table 6 presents the program impact in secondary health variables that may be related to pollution exposure. Each column shows the EarlyTreat \times Post coefficient (i.e., β_1 in Equation 1) corresponding to separate regressions with different outcome variables. The outcome variable corresponding to each regression is displayed in the column header (Unit of the variables are displayed in the bracket, where (1/0) represents dummy variables). All regressions include controls for baseline value of age and height of the individuals and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Table 7: HETEROGENEITY RESULTS: PROGRAM IMPACT BY TIME SPENT INDOORS

Dimension of Heterogeneity	Primary Activity	Employment Status
	(1)	(2)
EarlyTreat \times Post \times Housekeeper	11.91** (5.672)	
EarlyTreat \times Post \times Non-employed		11.83* (7.071)
EarlyTreat \times Post	6.785 (5.429)	9.110 (5.617)
Control Mean	337	337
Observations	7788	7103

Table 7 presents heterogeneity in the program impact (coefficient of EarlyTreat_r \times Post_t \times Dummy i.e λ_1 in equation 2, where Dummy for column(1) is gender, in column (2) is an indicator for doing housework primarily and in column(3) is employment status. Each dummy variables (Dummy) provides proxy for the relative propensity of the sub-group in the sample to stay indoors and be involved with cooking activities. Column (1) shows the heterogeneity in the program impact for women relative to men, column (2) shows the heterogeneity for women who do housework relative to those who do not, and column (3) shows the heterogeneity in the impact for non-employed women relative to employed women. Column (1) consists of men as well as women, whereas columns (2) and (3) consists of only women sample. All columns includes the rural-urban fixed effect and individual fixed effects. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to women above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Table 8: PROGRAM IMPACT ON LUNG CAPACITY FOR PLACEBO GROUP
(TREATMENT INELIGIBLE SAMPLE)

Sample of women	All	Housekeeper	Non-employed
	(1)	(2)	(3)
EarlyTreat \times Post	-0.632 (7.528)	2.926 (14.05)	6.726 (11.29)
Control Mean	299	298	293
Observations	851	282	323

Notes: Table 8 shows the program impact (coefficient of EarlyTreat \times Post i.e., β_1 in Equation 1) on the lung capacity of women for the placebo treatment group i.e., women belonging to treatment-ineligible group or households that have used LPG before the program. Each column corresponds to a different sample of women. Column (1) is the sample of all women, column (2) restricts the sample to women who do housework primarily and column (3) restricts the sample to non-employed women. Regression corresponding to all three samples include individual level controls at the baseline and rural-urban fixed effects. Standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Women in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to women above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Table 9: PROGRAM IMPACT ON OTHER OUTCOMES

	Work (1/0)	Education (1/0)	Income (Log pci)	Electricity (1/0)	Refrigerator (1/0)	TV (1/0)	Toilet (1/0)	Water (1/0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EarlyTreat \times Post	-0.011 (0.011)	0.009* (0.006)	-0.070 (0.082)	-0.001 (0.017)	-0.008 (0.051)	-0.014 (0.026)	-0.000 (0.026)	0.002 (0.055)
Control Mean	0.493	0.922	4.665	0.961	0.757	0.800	0.749	0.497
Observations	14567	14567	13279	14567	14567	14567	14567	14567

Notes: Table 9 presents the program impact in several demographic variables. Each column shows the EarlyTreat \times Post coefficient (i.e., β_1 in Equation 1) corresponding to separate regressions with different outcome variables. The outcome variable corresponding to each regression is displayed in the column header (Unit of the variables are displayed in the bracket, where (1/0) represents dummy variables). All regressions include controls for baseline value of age and height of the individuals and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Table 10: PROGRAM IMPACTS ON HOURS OF WORK

	Women			Men		
	All	Houskeeper	Non-housekeeper	All	If women is housekeeper	If women is NOT housekeeper
	(1)	(2)	(3)	(4)	(5)	(6)
EarlyTreat \times Post	2.624 (8.143)	31.69* (17.20)	-6.972 (9.320)	19.06** (7.705)	25.82* (13.61)	15.06 (11.17)
Control Mean	176	154	184	210	212	209
Observations	3962	1043	2919	3521	1283	2238

Notes: Table 10 shows the program impact (coefficient of $\text{EarlyTreat} \times \text{Post}$ i.e., β_1 in Equation 1) on the number of hours of monthly labor supplied, by gender and work type status. Each column corresponds to a different sample. Column (1) shows the results for all women. In the next 2 columns, we show results for the two complementary sub-samples of women who do housework primarily. Column (2) shows results for women who primarily did not do housework whereas column (3) shows results for women who did housework primarily and hence, likely to spend most of their time indoors. Similarly, column (4) shows estimates for all men, while columns (5) and (6) show results corresponding to men in those households where women did housework, and did not, respectively. All regressions include individual level controls at the baseline and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Author's calculation using IFLS 2000, 2007, 2014. *Sample:* Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Table 11: PROGRAM IMPACT ON LABOR SUPPLY IN AGRICULTURE

	Women			Men		
	All (1)	Houskeeper (2)	Non-housekeeper (3)	All (4)	If women is housekeeper (5)	If women is NOT housekeeper (6)
A. Intensive Margin: Hours of Labor supplied in Agriculture						
EarlyTreat \times Post	5.775 (10.99)	26.456 (17.67)	-3.536 (13.51)	27.69** (11.42)	40.39** (19.34)	20.958 (15.09)
Control Mean	154	142	160	203	206	202
Observations	1715	493	1222	1818	622	1196
B. Extensive margin : Participation Rate in Agriculture						
EarlyTreat \times Post	0.048 (0.070)	0.158** (0.078)	0.019 (0.073)	-0.036 (0.072)	0.010 (0.081)	-0.060 (0.081)
Control Mean	0.408	0.449	0.392	0.488	0.469	0.500
Observations	3942	1033	2909	3514	1281	2233

Notes: Table 11 shows program impacts (coefficient of $\text{EarlyTreat} \times \text{Post}$ i.e., β_1 in Equation 1) on the labor supplied in agricultural sector, by gender and sub-samples. Panel A. displays results for impact on the participation rates of the agents (i.e., extensive margin) in the agricultural sector, whereas Panel B. shows the impact on the number of hours of labor supplied (i.e., intensive margin) by participants in the agricultural sector. For both the panels, Columns (1) consists of a sample of all women, column (2) consists of sub-sample of women who did not do housework primarily, column and (3) consists of women who did housework primarily. For men, column (4) consists of a sample of all men, whereas columns (5) and (6) show results corresponding to men in those households where women does housework, and does not, respectively. All regressions include individual level controls at the baseline and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

Table 12: CORRELATION BETWEEN PROGRAM ELIGIBILITY AND POVERTY ALLEVIATION PROGRAMS

PAP_Year in which program started							
PAP_2007	PAP_2008	PAP_2009	PAP_2010	PAP_2011	PAP_2012	PAP_2013	PAP_2014
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0.040	-0.018	0.010	0.039	0.001	0.022	0.031	-0.013
(0.031)	(0.030)	(0.030)	(0.032)	(0.026)	(0.033)	(0.024)	(0.034)
Control Mean	0.855	Observations		11251			

Notes: Table 12 shows the correlation between the eligibility for the Kerosene to LPG program and the various poverty alleviation programs. Each column shows the coefficients derived by regression of program eligibility on the eight groups of poverty alleviation programs. Each column consists of the set of poverty alleviation programs (PAP) that started in the year mentioned in the header (e.g., PAP_2007 includes all the programs that started in 2007). Starting years are restricted between 2007 and 2014 to include any influences of these program between the baseline (2007) and the final year of observation post the program (2014) *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014.

Table 13: PROGRAM EFFECT ON COARSENEDED EXACT MATCHED SAMPLE

Outcome:	Lung Capacity		Monthly Hours of Work	
	(1)	(2)	(3)	(4)
Sample:	Women	Men	Women (Housekeeper)	Men
EarlyTreat × Post	11.75**	2.927	33.90*	22.22***
	(5.599)	(6.208)	(17.83)	(7.665)
Control Mean	282	409	154	210
Observations	7782	6043	1043	3521

Notes: Table 13 shows the program effects (coefficient of EarlyTreat × Post i.e., β_1 in Equation 1) on two types of outcome variables - lung capacity (columns (1)-(2)) and monthly hours of work (columns (3)-(4)), corresponding to the sample matched using *coarsened exact matching (CEM) technique* and using the CEM weights. For lung capacity outcomes, Columns (1) presents estimates for the sample of all women and columns (2) for the sample of all men. For monthly hours of work, Columns (3) presents estimates for the sample of women who do housework, while columns (4) for the sample of all men. All regressions include individual level controls at the baseline and rural-urban fixed effects. Standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households and is restricted to individuals above 16 yrs of age.

Table 14: PROGRAM IMPACT ON LUNG CAPACITY BY SAMPLE RESTRICTIONS

	Women				Men			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EarlyTreat \times Post	10.89** (5.249)	10.50* (5.556)	14.37** (6.501)	11.38* (6.701)	3.304 (5.765)	-3.665 (6.451)	9.634 (7.033)	6.322 (7.871)
Control Mean	282	279	296	289	409	400	432	426
Observations	7782	8963	5119	3508	6043	7151	4792	2625

Notes: Table 14 shows the program impact (coefficient of $\text{EarlyTreat} \times \text{Post}$ i.e., β_1 in Equation 1) on the lung capacity, by gender. Columns(1)-(4) shows the impact on women, whereas columns (5)-(8) shows the impact on men. For both genders, each column corresponds a different kind of sample restriction. Column (1) & (5) shows program impact on sample inclusive of inter-district migrants. Columns (2) & (6) shows impact for the age-unrestricted sample. Columns(3) & (7) restricts the sample to prime working age group of 25-55 and, columns (4) & (8) restricts the sample to households using kerosene as their primary fuel in the baseline. All regressions include individual level controls at the baseline and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Author's calculation using IFLS 2000, 2007, 2014.

Appendix

A Conceptual Framework: Household Labor Supply

Consider a household as a single economic unit that consists of men (denoted with a m subscript) and women (denoted with a w subscript), and gains utility from consumption goods (C) and household services (P). Consumption goods are produced in the farm that takes farm labor by men (L_m) and women (L_w) as the input, whereas, household services are produced at home that takes household labor by men (H_m) and women (H_w) as the input.⁵⁰ The total amount of combined available labor time is normalized to 1. Household services demand a fixed amount of time \bar{z} for conducting the daily necessary household chores. The combined remaining amount of time can be utilized for providing farm labor, with a caveat that the time lost in sickness reduced the amount of time available for farm work. We also assume that the total combined labor input in farm work or housework is less than the individual endowments of labor. The production function for both consumption goods as well as household services, takes a Cobb Douglas functional form and thus, assumes complementarity in the labor supplied by men and women for each good.

θ captures the inverse quality of fuel (lower the $\theta \rightarrow$ better the quality of fuel) and is exogenously given.⁵¹ Using a dirty quality of fuel can make agents sick and enters the labor supply time constraint through $s(\theta)$. Thus, worse the quality of fuel, higher is the time lost in sickness, and lower is the time available for farm work. In line with the empirical evidence presented above, we assume that only women are involved in cooking, and hence, only they experience the adverse productivity impact from unclean fuel that reduces their effective labor in farm work. \hat{L}_w , the effective labor of women in farm work, decreases in θ .⁵² Unclean fuel does not directly affect the productivity or effective per unit labor of men, however, they may lose productive time from sickness of women in taking care of her or taking her to hospital etc.

Thus, each household solves the following optimization problem given the production functions of consumption and household services, the time constraint in each sector and the exogenous quality of fuel, θ :

$$\begin{aligned} \text{Max}_{L_w, L_m, H_w, H_m} \quad & \log(C) + \log(P) \\ \text{s.t.} \quad & \end{aligned}$$

⁵⁰ Household services consist of cooking and non-cooking labor inputs. Women perform cooking activities, whereas men perform non-cooking activities.

⁵¹ Sickness is a function of the inverse quality of fuel, denoted by θ . We assume θ to be exogenous to reflect the policy changes in the empirical section. $S = s(\theta)$ for women

⁵² The effective labor of women is such that lower the inverse quality of fuel θ i.e better the quality of fuel, higher the effective labor of women. Effective labor of women corresponding to labor supply of (L_w) in presence of inverse fuel quality θ , is given by ($L_w - \theta$)

$$\begin{aligned}
C &= \hat{L}_w^\alpha L_m^{1-\alpha} \\
P &= H_w^\beta H_m^{1-\beta} \\
H_w + H_m &= \bar{z} \\
L_w + L_m &= 1 - \bar{z} - s(\theta)
\end{aligned}$$

For simplicity, we make two further assumptions :

1. $\hat{L}_w = L_w - \theta$
2. $s(\theta) = \theta$

The Langrangian for the above optimization problem is thus given by :

$$\mathcal{L} = \log[(L_w - \theta)^\alpha L_m^{1-\alpha}] + \log[H_w^\beta H_m^{1-\beta}] + \lambda[1 - \theta - \bar{z} - L_w - L_m] + \mu[\bar{z} - H_w - H_m]$$

Equilibrium labor supply by women and men in farm work and household work is given by -

$$L_w^* = (1 - \bar{z})\alpha - (2\alpha - 1)\theta \quad (4)$$

$$L_m^* = (1 - \bar{z})(1 - \alpha) - 2(1 - \alpha)\theta \quad (5)$$

Change in equilibrium labor supply w.r.t an exogenous change in θ , is given by

$$\frac{\partial L_w^*}{\partial \theta} = -(2\alpha - 1) < 0 \quad \text{for } \alpha > 0.5 \quad (6)$$

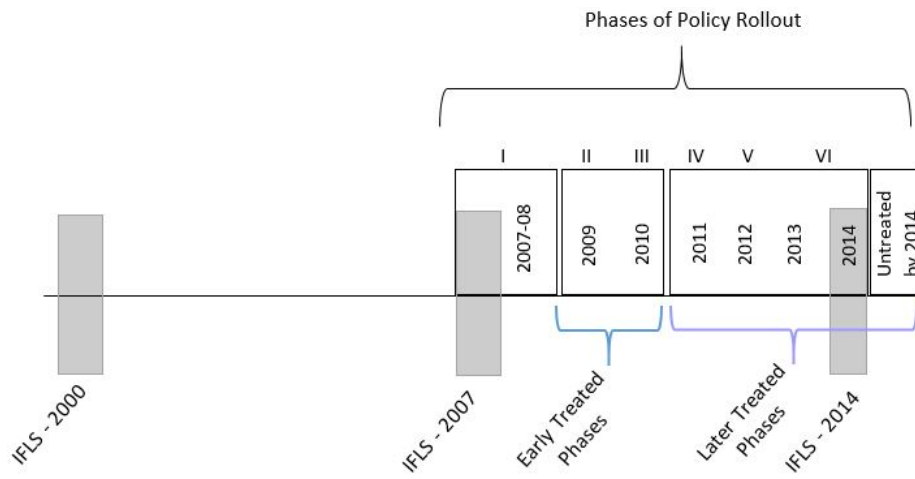
$$\frac{\partial L_m^*}{\partial \theta} = -2(1 - \alpha) < 0 \quad \text{for all } \alpha \quad (7)$$

Thus, corresponding to an exogenous decrease in θ post the intervention, the model shows that an \uparrow in fuel quality (\downarrow in θ) \implies \uparrow in farm labor of both men and women, if women have sufficiently high output elasticity of farm labor, α .⁵³ The predictions of the model makes sense - an increase in the quality of fuel, through overall time-saved and improved productivity of women, increases the amount of productive time and marginal productivity of agents, thus leading to an increase in the labor supplied by both women and men.

⁵³ (Udry, 1996) shows that shifting labor and fertilizer from men's plots to women's plots within the same household would substantially increase total household output.

B Timeline for the study: Program Implementation and Year of Survey

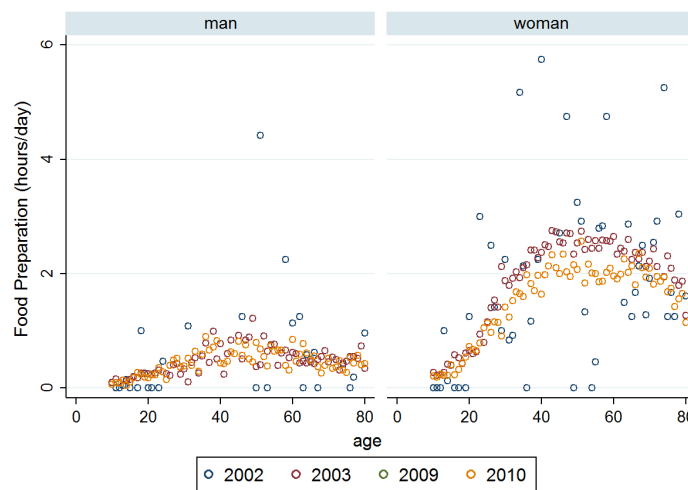
Figure 10: PROGRAM IMPLEMENTATION AND THE YEAR OF SURVEY



Notes: Figure shows the phases of program roll out and the timing of the survey used for the study. IFLS 2000 and 2007 provide the pre-policy estimates, while IFLS 2014 is used to study the post-policy estimates.

C Gender Disparity in Time Spent for Food Preparation

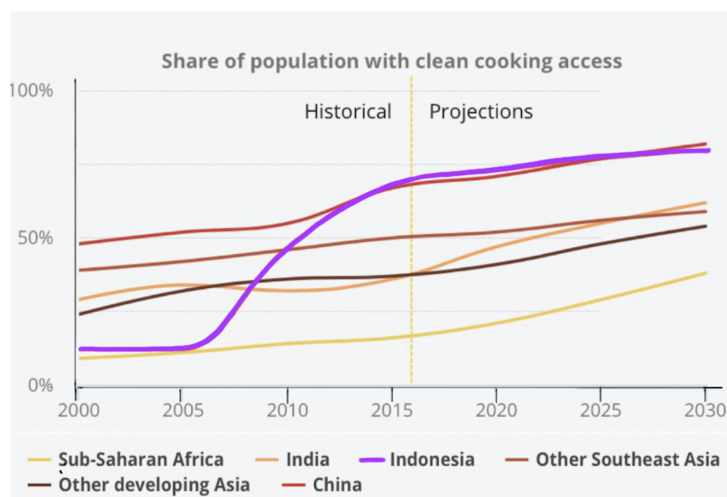
(Time Spent for Food Preparation by Gender)



Notes: This figure shows the time spent in food preparation by gender among individuals who are not in paid work in Spain. Women spent about two hours per day on food preparation and it varies based on age. Contrasting 2002 and 2010, women's time spent on food preparation has gone down (this may be due to technological progress in food preparation), but not much. Among men, the time spent on food preparation has been constantly low, less than one hour per day on average.

Source: Fisher and Gershuny (2013)

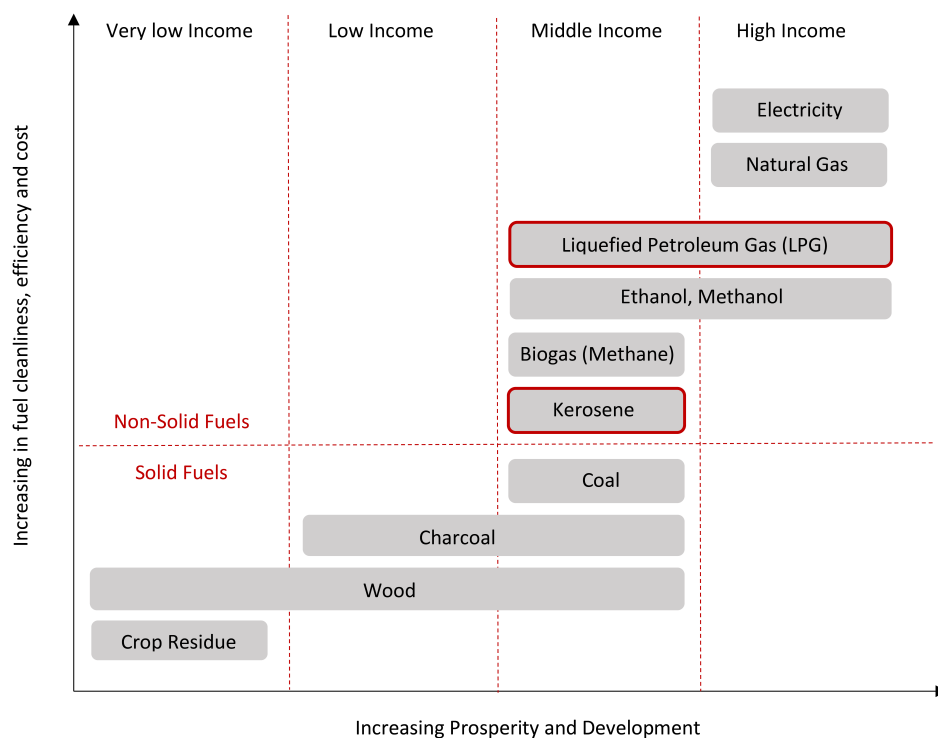
D Trajectories in Clean Cooking Access: Share of population with clean cooking access (2000-2030)



Notes: Figure shows the historical and the projected trajectory of the share of the population with clean cooking access by dividing the developing regions into six major parts - Sub-Saharan Africa, India, Indonesia, China, Other-Southeast Asia, and other developing areas. During the early 2000s, the share of clean cooking access was below 50% for most of the regions, with China at the top and Sub-Saharan Africa and Indonesia at the bottom of the ranking. While most of the other regions display a slow growth in energy access, figure highlights the strikingly steep and positive gradient for Indonesia after 2007, the starting year of clean cooking program in Indonesia. In just eight years of time-span between 2007 to 2015, Indonesia went from having the lowest share of clean energy access (close to 12%) to the highest share of clean cooking access (close to 70%), surpassing even China's share.

Source: Energy Access Outlook, 2017, IEA

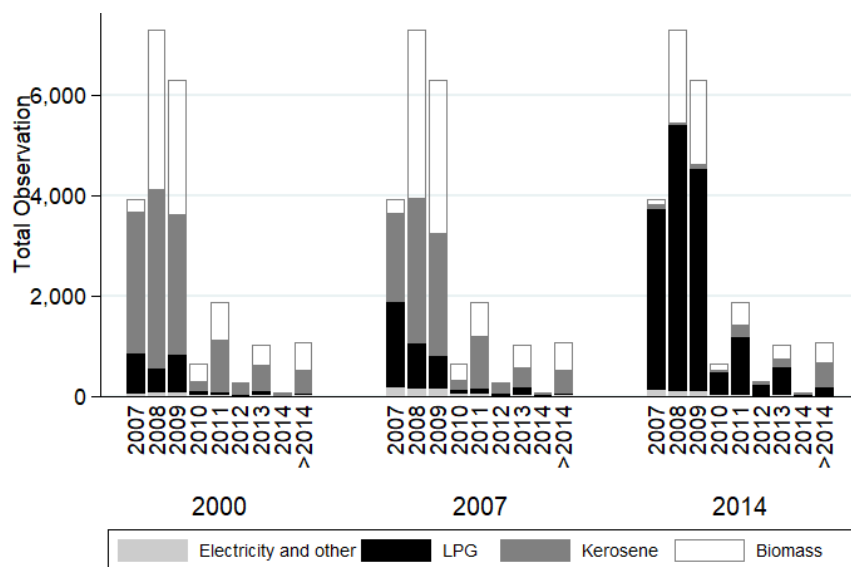
E Energy Ladder



Notes: Figure shows the energy ladder diagram describing the commonly used cooking fuels in terms of efficiency, cleanliness, convenience, and income. Higher income (increasing x axis) is associated with cleaner, efficient and convenient modes of cooking (increasing Y axis). The strong positive correlation between income and the adoption of better fuels is mostly driven by the fact that cleaner fuels are also the more expensive ones, and require better-developed infrastructure for their continuous supply.^a

^a Urban areas are more likely to have developed infrastructure, which is also the higher-income regions, resulting in a positive association between income and clean fuel adoption

F Total Observation in Each Survey Year by Year of Implementation

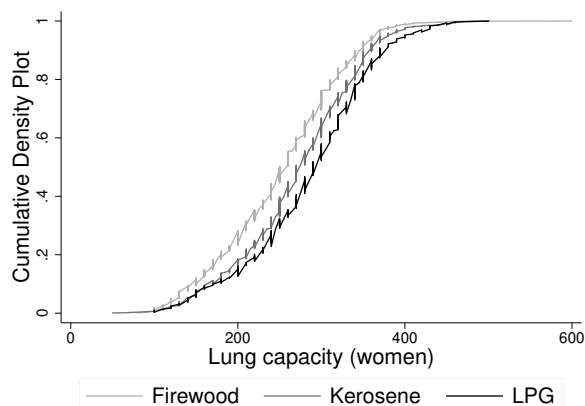


Notes: Figure shows the number of observation in each survey year by program year. The bar color indicates the fuel types in each survey year. Note that in the 2014 survey, there is a sharp increase in the number of individuals who use LPG.

Source: Author's calculation using IFLS 2000, 2007, 2014.

G Lung capacity, by Fuel Type

Figure 11: CUMULATIVE DENSITY PLOT OF LUNG CAPACITY FOR WOMEN IN 2007



Notes: The figure shows a non-parametric cumulative density plot for lung capacity of women belonging to different households. Firewood, kerosene, and LPG (left to right in order) denotes the sample of women using firewood, kerosene, and LPG respectively as their primary cooking fuel. It presents a cross-sectional evidence on the relationship between fuel type and lung capacity. The distribution of lung capacity among women using LPG for cooking strictly dominates that for women using kerosene for cooking, which in turn dominates for women using firewood for cooking.

Source: Author's calculation using IFLS 2007

H Impact on Lung Capacity of Women, by Sub-samples

Sample of women	All Women (1)	Housekeeper (2)	Nonemployed (3)
EarlyTreat \times Post	11.22** (5.505)	18.70** (7.161)	17.85** (7.565)
Observations	7788	2934	2597
Control Mean	282	286	279

Notes: Table shows the program impact (coefficient β_1 corresponding to EarlyTreat \times Post in equation 1) on the lung capacity (in L/min), for three different samples of women. Columns (1) shows impact on the sample of all women, column (2) for the sample of women who did housework at the baseline, and column (3) for the sample of women who were unemployed at the baseline. All regressions include controls for baseline value of age and height of the individuals and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

I Pre-Trend in Lung Capacity, by Gender

	Women (1)	Men (2)
EarlyTreat \times Pre	10.29 (7.198)	1.229 (9.109)
Control Mean	282	409
Observations	7782	6049

Notes: Table I shows the pre-trend on the lung capacity (in Litres/minute), by gender. Columns(1) shows the impact on women, whereas columns(2) shows the impact on men. Both the columns include controls for individual characteristics such as age and height at the baseline and rural-urban fixed effects. Standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia)

J Treatment effect on Health Outcomes Unrelated to Pollution

	Anemia (1/0) (1)	Diabetes (1/0) (2)	Hb Level (level) (3)
EarlyTreat \times Post	-0.0001 (0.006)	-0.0004 (0.003)	0.037 (0.110)
Control Mean	0.014	0.006	13.24
Observations	14567	14567	14456

Notes: Table shows the program impact (coefficient of EarlyTreat \times Post i.e., β_1 in Equation 1) on three different health variables that are unrelated to pollution changes. Each column corresponds to a different regression equation. Column (1) shows the results for Anemia, column (2) for Diabetes and column (3) for Haemoglobin levels. All regressions include individual level controls at the baseline and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

K Program Impact on Participation Rate in Various Sectors

Type of Sector	Women				Men			
	Social Sector (1)	Agri-culture (2)	Self Employed (3)	Retail (4)	Social Sector (5)	Agri-culture (6)	Self Employed (7)	Retail (8)
EarlyTreat \times Post	0.072** (0.036)	0.048 (0.070)	0.025 (0.034)	0.011 (0.032)	0.058 (0.040)	-0.036 (0.072)	-0.032 (0.036)	0.021 (0.032)
Control Mean	0.150	0.407	0.428	0.291	0.186	0.488	0.574	0.206
Observations	3945	3942	4250	3942	3514	3514	3609	3514

Notes: Table K shows the program impact on the participation rate in the four highest density sectors, by gender. Each column shows the EarlyTreat \times Post coefficient (i.e., β_1 in Equation 1) corresponding to separate regressions with outcome variables being the participation rates in different sectors. The sectors corresponding to each regression is displayed in the column header. All regressions include controls for baseline value of individual level controls and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. *p < 0.10, **p < 0.05, ***p < 0.01

Source: Author's calculation using IFLS 2000, 2007, 2014. Sample: Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

L Placebo Test for Hours of Work

(Placebo Group: Treatment Ineligible Sample)

	Women			Men	
	(1)	(2)	(3)	(4)	(5)
	All	Non-houskeeper	Housekeeper	All	Employed
EarlyTreat \times Post	-48.044 (31.555)	-51.253 (32.997)	-32.460 (73.161)	-17.741 (17.752)	-22.499 (17.925)
Control Mean	188	196	164	210	210
Observations	583	444	139	547	526

Notes: Table shows the program impact (coefficient of $\text{EarlyTreat} \times \text{Post}$ i.e., β_1 in Equation 1 on the number of hours of monthly labor supplied, by gender and work type status for the placebo treatment group i.e., households that have used LPG before the program. Each column corresponds to a different sample. Column (1) shows the results for all women. In the next 2 columns, we show results for the two complementary sub-samples of women based on whether they did housework at baseline. Column (2) shows results for women who did not do housework whereas column (3) shows results for women who did housework. Similarly, column (4) shows estimates for all men, while columns (6) shows results corresponding to only employed sub-sample of men. All regressions include individual level controls at the baseline and rural-urban fixed effect. The standard errors (in parenthesis) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Author's calculation using IFLS 2000, 2007, 2014. *Sample:* Individuals in the treatment-eligible households (i.e., households that have never used LPG in the pre-periods) and is restricted to individuals above 16 yrs of age (i.e above the high-school age and legal marriage age in Indonesia).

M List of Poverty Alleviation Programs

Jamkesda, Jamkesmas, Jampersal, Raskin, Rice Market operation, PKPS, BBM – SLT (UCT), Keluarga Harapan (CCT), PNPM Mandiri, BLSM 2013, BSM (Cash transfer for poor student), JSPACA/JSODK (Disabled Social Insurance), JSLU/ASLUT (Elderly Social Insurance), KUBE/UEP (Joint Enterprise Group), RTLH (Renovation program for home), PKSA (Children social welfare program), KPS (Social Security Card), JKN (National Health Insurance)

N Value of Statistical Life

Given the risk of lung cancer from IAP have become increasingly comparable to the risks associated with smoking cigarettes (Behera and Balamugesh, 2005; Cohen and Pope 3rd, 1995), we use the available data on the risk of lung cancer from cigarette smoking and equate it to understand the level of risks IAP.⁵⁴

Avg yearly decline in lung capacity for each extra pack yr of smoking	1.2 L/min
Pack years of reduced smoking for 11.34 L/min treatment effect	9.5
Reduced risk of developing lung cancer by quitting smoking for 9.5 pack yrs	40 %
Average rate of non-survival for women with lung cancer (using 5 yr survival rate)	90%
Estimated per person reduced rate of dying from lung cancer	36%
Lower bound value of statistical life (Kniesner et al. (2012))	\$4 million
Value of Statistical Life for 1 person at given risk	\$1.44 million
Total estimated Value of Statistical Life for 50 million people with no access to clean fuel	\$72 million

⁵⁴ (Lan et al., 2002) shows a long-term reduction in lung cancer incidence after stove improvement