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

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First Draft: January 2, 2020
This Draft: April 30, 2021

Abstract

Women bear a disproportionate share of the health and time burden associated with lack of access to modern energy. In this paper, we study the impact of clean energy access on adult health and labour supply outcomes by exploiting a nationwide rollout of a clean cooking fuel program in Indonesia. We find that access to clean cooking fuel led to an improvement in women's health and an increase in their work hours. We also find an increase in men's work hours and in their propensity to have an additional job, primarily in those households where women accrued the largest program benefits.

JEL classification: H51, I15, I18, J22, O13, Q48, Q53
Keywords: gender inequality, energy access, health, labour supply, Indonesia

We thank the editor and the two anonymous referees. We are grateful to Tom Vogl, Stephen J. Trejo, Richard Murphy, Mike Geruso, and Sandra E. Black their valuable advice and support throughout the research, and to Nishith Prakash, Marika Cabral, Dean Spears, Frank Schilbach, Tarun Jain, Abhijit Banerjee, Arya Gaduh, Peter Nilsson, Farzana Afridi, John Loeser for their helpful suggestions and feedback. We also thank Kevin Kuruc, Deepak Saraswat, Vinayak Iyer, participants at NEUDC conference, ACEGD conference, SEA conference, EAERE-FEEM Summer School, University of Luxembourg, Paris School of Economics, Paris Dauphine University, NCID, World Bank, IHEID, Loyola University Chicago, UT Austin and UC3M for the comments. Imelda gratefully acknowledges support from European Union's Horizon 2020 research and innovation program (772331). All errors remain our own responsibility.

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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 greater amount of time on housework than men (Duflo, 2012). Existing studies suggest that efficient time-saving technological advances can bridge some of this gap by freeing up women's time away from housework, providing evidence on the 'time-burden' channel. [1]

In this paper, we focus on a critical, yet less understood contributor of gender disparity in the labour supply: the 'health-burden' associated with unclean cooking fuels. Cooking is often exclusively categorized as a woman's responsibility. With unclean cooking fuel emitting a large amount of harmful pollutants, it imposes a disproportionate health and productivity cost on women. These costs can be enormous, given that approximately 40% of the global population still relies on unclean cooking fuel for its daily requirements (WHO, 2020). Beyond the undeniably adverse health impacts of unclean cooking fuel, this paper aims to quantify the magnitude of gender disparity in the health burden that arises due to lack of access to clean fuel and its implications for the labour supply outcomes of women as well as men.

While the relationship between access to modern energy and better economic outcomes for women has been widely discussed (Köhlin *et al.*, 2011; Rewald, 2017), their causal relationship is not straightforward. Disentangling the impacts of other development programs on one's economic well-being is challenging, especially when the transition to modern energy is slow and mostly voluntary. Households endogenously sort into places with better infrastructure and thereby have improved access to affordable energy. Hence, one may confuse the causal effect of modern energy with the effects of other associated economic development.

We exploit the staggered nature of a nationwide clean cooking intervention in Indonesia, one of the few successful energy transition programs in developing countries, to estimate the impact of clean energy access on health and labour supply outcomes. The program, with the primary aim of reducing the high cost of subsidizing kerosene, replaced the subsidy on

[1] For instance, the diffusion of time-saving appliances in the United States during the last century (Greenwood *et al.*, 2005) and electrification in South Africa (Dinkelman, 2011), led to an increase in women's labour supply by freeing up productive time from housework that could be used towards market work.

kerosene with a subsidy on liquid petroleum gas (LPG). Over a five-year period, this program reached more than 70% of the national population, leading to more than a 90% reduction in the use of subsidized kerosene. LPG is a substantially cleaner and more efficient burning fuel than kerosene. Hence, by transition from kerosene to LPG, the program is likely to reduce the level of indoor air pollution (IAP) concentration associated with unclean cooking fuels. As women spend significant time doing household chores and are thereby more likely to be affected by a clean cooking intervention, this paper documents the extent to which the program reduces some of the gender disparities in the health and labour supply that exist due to lack of access to clean energy.

Our 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 labour supply. We use administrative data on the program rollout and three waves of the longitudinal Indonesian Family Life Survey (IFLS) for 2000, 2007, and 2014, which allow us to track individuals nine years before the intervention and up to five years after the intervention. Using a difference-in-differences design, we compare the health and labour supply outcomes of individuals in districts with longer exposure duration to the program (treated in the earlier phases) with outcomes of individuals in districts with shorter exposure duration to the program (treated in the later phases). To address some concerns 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. Further, to ensure the robustness of our results, we also incorporate several specification checks (including matching), use different sample selections, and account for concurrent policy changes.

We find that the program led to an 11 litres per minute (4%) increase in the lung capacity of women exposed to the program earlier than those exposed to the program later. For men, we find a very small and statistically insignificant change in the lung capacity resulting from the program. These results are consistent with our hypothesis that women are the direct users of cooking fuel and hence, should benefit the most by the program. In fact, the average effects on lung capacity of women are driven substantially by the subsample of women who were primarily housekeepers—those who mainly do household chores in their own homes and therefore, are more likely to stay indoors and be involved with cooking alongside other household activities.[2] We explore several plausible channels behind our health findings, such as reduced pollution, change in expenditure, change in income, and change in local economy. Based on the evidence, we argue that the 'reduced pollution' channel is the dominant reason explaining the improvements in lung capacity of women.

One's stock of health is an important determinant for the total amount of time one can spend on work (Grossman, 1972). We find this program led to an increase in the work hours of women, primarily among those who enjoyed the most health benefits from the program. This seems plausible as improvement in health among women can improve their labour productivity and reduce their time spent in sickness, thus allowing them to provide more market work.

Improvement in the health of one member (women) within a household can lead to changes in labour supply for other members (men) depending on the elasticity of substitution between each member's labour supply. We find an increase in the work hours of men, particularly among those living in the households where at least one woman did housework as their primary activity at the baseline. The size of the increase is approximately 1 additional hour of work per day (20%) for women and about 0.9 hours of work per day (13%) for men. We explore several plausible channels, such as health improvements, time saved, and local labour supply that may explain the increase in work hours, and conclude that improvement in women's health is the relevant channel explaining the labour supply increases.

Given that men do not experience any detectable health benefits, the increase in their labour supply points to the existence of potential spillover effect within the household. As women's health improves and they have more time available to do work, the program can indirectly increase men's productivity through shifts in the intra-household division of labour. We provide evidence on two potential channels: the substitution effects and the complementarity effects. First, by improving women's health, the program reduces the need for men to help with unpaid work at home, suggesting that women can substitute some of men's 'housekeeping' efforts. As men become less obliged to help in unpaid housework, they can divert

[2] We will interchangeably refer to women as 'housekeepers' if their primary activity is to take care of their own households. This includes the daily household chores of cleaning, cooking, fetching water, among others.

this time into other paid productive work. In line with this, we find a 13-percentage point increase in the likelihood of men having a second job. Second, we find that men's labour supply increased when both genders were in the sector where complementarity was more likely to happen. In other words, when both genders were in the same sector to begin with, it is arguably easier for women to pick up the slack and complement men's labour supply, as they were likely to have similar skills. We find an increase in the area of cultivation and the crop varieties planted when both men and women in the household were in the agricultural sector (the dominant sector) to begin with. This is to be expected as both men and women increase their work hours.

This paper makes four main contributions to the literature. First, to our knowledge, we are the first to highlight that modern energy access can improve labour supply outcomes of both genders by reducing the 'health-burden' on women. While several studies have focused on the disproportionate time-burden associated with energy poverty and its implication on labour supply (Coen-Pirani *et al.*, 2010; de V. Cavalcanti and Tavares, 2008; Dinkelman, 2011; Greenwood *et al.*, 2005), this paper focuses on a different channel, the health-burden associated with energy poverty and gender roles. Moreover, our findings on men's labour outcome improvements open up the discussion on the potential positive spillover effects of clean energy access, typically difficult to document and therefore often left unaccounted for. Ignoring these spillover effects leads to underestimating the benefits of clean energy access.

Second, our work adds to the literature on the link between indoor air pollution, health, and economic well-being (Duflo *et al.*, 2008). To demonstrate the causal link, several studies attempted to address the confounded nature of the adoption using randomized-experiments (Alexander *et al.*, 2018; Hanna *et al.*, 2016; Jack *et al.*, 2015) and using an instrumental variable approach (Pitt *et al.*, 2006; Silwal and McKay, 2015). [3] However, low take-up rates in modern technology is a common problem, making it harder to estimate the impacts.[4] We are able to

[3] A working paper which is contemporaneous with ours, Bharati *et al.* (2019) studies the same program but with a different identification strategy. The authors show that the program is associated with a large increase in labour supply along the extensive margins. Unlike them, we use the administrative data on the program rollout and document an increase only along the intensive margins of labour supply. Our unique contribution is that of highlighting the role of health in explaining the labour supply increases.

[4] This problem has been documented in several studies, for instance, in cooking technology (Bensch *et al.*, 2015; Hanna *et al.*, 2016; Mobarak *et al.*, 2012), preventive health products (Dupas, 2011), and agricultural technology (Oliva *et al.*, 2019).

improve on this by using a nationwide clean cooking intervention, with an exceptionally high adoption rate. This intervention 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 behavioural responses that may exist, an important element to be considered in designing optimum public policy.

Third, our paper contributes to the literature on the nexus of adult health and clean energy access wherein the existing evidence remains scattered and inconclusive (Köhlin *et al.*, 2011; Pueyo and Maestre, 2019). The majority of the health literature associated with energy poverty focuses on the impact of pollution on infants (Arceo *et al.*, 2016; Cesur *et al.*, 2016; Imelda, 2020; Rosales-Rueda and Triyana, 2019; 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 adults' health is likely to be confounded by accumulated exposures in the past. Moreover, many of the health measures used in the literature to study the impact of pollution are self-reported and may suffer from measurement or reporting errors. We use a longitudinal survey spanning over 14 years that allows us to control for individual unobserved factors and use lung capacity[5] as our main proxy for health.

Finally, this paper contributes broadly to the literature on "missing women" in developing countries (Abrevaya, 2009; Anderson and Ray, 2010; Klasen and Wink, 2002; Sen, 1990). The existence of gender inequality at birth, unequal access to healthcare, and maternal mortality are some of the potential channels. Our paper highlights a new angle. We provide evidence on the link between energy poverty and the environmental risk arising from the gender norms that disproportionately affects 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 (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.

[5] It is well known that lung capacity is closely linked with one's exposure to pollution (Gehring *et al.*, 2013; James Gauderman *et al.*, 2000) and a reliable indicator of respiratory health that is measured using a device.

Developing countries will play a major role in driving growth in energy consumption in the next several decades (Wolfram *et al.*, 2012). Our results provide important insights for energy transition policies in these countries.[6] 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, a substantial benefit that is often not properly quantified in 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 preliminary evidence; Section IV discusses the empirical strategy; Section V shows the main results on health; Section VI presents the labour supply results; Section VII discusses the robustness checks and Section VIII concludes.

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 *et al.*, 2008). In the 1980s, Indonesia's oil production was high; thus subsidizing kerosene was affordable. When 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).[7] Hence, in 2007, the Indonesia government launched the Kerosene to LPG Conversion Program with the primary aim to cut expenditure in subsidized kerosene based on their calculation that subsidizing LPG was cheaper. The vice president of Indonesia appointed the Ministry of Energy and Mineral Resources to coordinate the program and intended to convert more than 70% of the non-LPG using households into LPG-using households within 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

6 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—more than double the number of people who lack access to electricity (IEA, 2017).

7 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).

each district's level of kerosene usage, LPG infrastructure readiness, location and size of the area. Then, Pertamina, a state-own major oil company, implemented the program based on the given order.

Household Eligibility and Adoption.— The eligibility for the program was mainly 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, a hose, 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 cylinders, distributed previously before the program, were not eligible for the subsidy.[8]

The policy rollout was gradual and carried out in multiple phases. When a district received all the allocated LPG, the subsidized kerosene was withdrawn gradually, leaving only unsubsidized kerosene available in that district. The combination of the subsidy on LPG refill price and the withdrawal of subsidized kerosene led to a high adoption rate for LPG after the rollout (Imelda, 2020). This was due to the following: (1) the subsidized price of LPG refill was comparable to the price of kerosene per an equivalent measure (Andadari *et al.*, 2014); (2) the price of unsubsidized kerosene was significantly higher than LPG, while the subsidized kerosene was no longer available. Figure 1 shows the high LPG take-up rates and a sharp drop in kerosene use after the program. We also see that household's propensity to use LPG increases dramatically based on the duration of program exposure (see Figure A.1 in the Appendix).

Kerosene Versus LPG.— LPG was chosen to replace kerosene because it is more efficient and more economical compared to kerosene.[9] 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 because its combustion process is more efficient. Fine particulates from burning LPG are about 46–76% lower than particulates from burning

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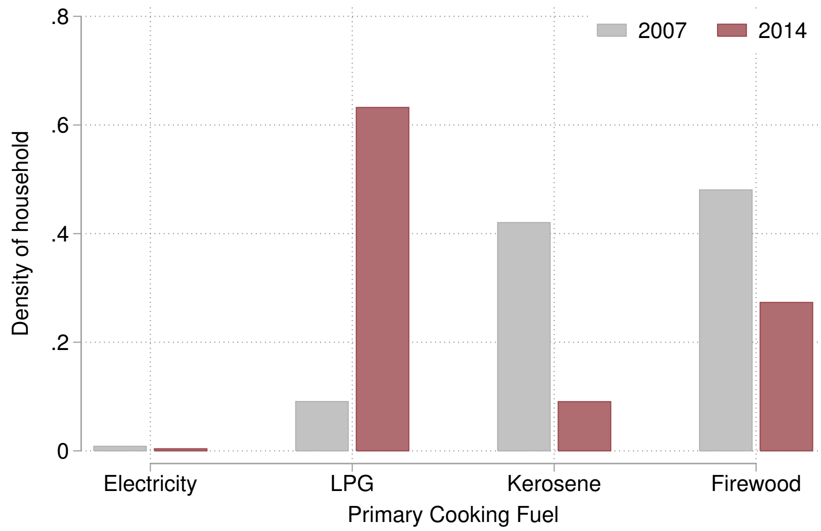
8 The program details are discussed in Budya and Arofat (2011) and Thoday *et al.* (2018).

9 Precisely, LPG's production cost was lower than that of kerosene, about 25% (0.17 USD/litre) less than subsidizing kerosene (Andadari *et al.*, 2014). Moreover, LPG also had an edge over the other alternatives as its existing infrastructures and supply chains were relatively in place compared to the other fuels. While the price per unit for LPG is slightly higher than kerosene, it is still cheaper to subsidize LPG because one litre of kerosene can be replaced by 0.4 kilograms of LPG (Budya and Arofat, 2011). In equivalent measures, the higher calorific value makes LPG more economical to subsidize compared to kerosene.

Figure 1: PRIMARY COOKING FUEL



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

kerosene (Imelda, 2020). Moreover, kerosene emits a significantly lower amount of visible smoke compared to other dirty fuels (e.g., firewood or charcoal).[10] Because of this, one may be misled into thinking that kerosene is not very polluting and therefore less dangerous for health. However, as adverse health risk highly depends on the exposure level, kerosene can be as harmful as firewood. The smoke from burning kerosene is less visible than firewood. As a result, when household members cook with firewood, they tend to cook outside. In contrast, when household members cook with kerosene, they tend to cook inside and much closer to the stove (Saksena *et al.*, 2003). This is consistent with the growing body of evidence about the dangers of kerosene cooking (see Lam *et al.*, 2012 for a review on health risk from kerosene). Imelda (2020) suggests that 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 infants within the households due to reduced pollution exposure.

[10] The 24-hour average human exposure to PM 2.5 from kerosene is at 123 $\mu g/m^3$ while that for LPG is at 56 $\mu g/m^3$ Andresen *et al.* (2005). The pollution exposure is even worse for dirtier fuels with the mean PM 2.5 exposures for wood at 160 $\mu g/m^3$ and from cow-dung at 560 $\mu g/m^3$ (Dees *et al.*, 2018)

III. Data & Summary Statistics

We employ two main datasets. First, we use three waves of the Indonesian Family Life Survey (IFLS) for the years 2000, 2007, and 2014.[11] IFLS is a rich longitudinal survey, containing detailed information at individual, household and community levels on a large array of economic, health, social and labour supply characteristics.[12] Second, we rely on the restricted administrative data on the program rollout to determine variations in the duration of program exposure. The data is obtained from the government-appointed program coordinator, Pertamina, the state-owned energy company.[13] 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.[14] The three rounds of IFLS used in this paper allow us to track individuals nine years before the program and up to five years after the program. In particular, we observe two waves of IFLS before the LPG program that are useful for us to discern any trends in the individual's characteristics and one wave post-program that allows us to capture the program impact (see Figure A.2 in the Appendix that shows the timeline of the program along with the IFLS survey years).

Outcome Variables.—There are two primary outcomes of interest in this study. First, we use lung capacity as a proxy for health. Importantly, fine particulates from burning kerosene can have a direct impact on lungs as the particulates can move deep into the alveoli of the lungs, irritating the walls , and obstructing the normal functioning of the lungs. There are also notable benefits of using lung capacity as our main health outcome: (1) It is an important indicator of health and longevity. For instance, it is an important predictor of morbidity and mortality in elderly people (Ostrowski and Barud, 2006). Reduced lung capacity also interferes with the normal functioning of the lungs; it can affect health, and hence can af-

11 IFLS-1993 is excluded because it does not record some of our variables of interest.

12 This is 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 (Thomas *et al.*, 2012). It covers 13 provinces out of the 26 provinces in Indonesia and represents 83% of the Indonesian population.

13 The Ministry of Energy and Mineral Resources was appointed as the government's authorized representative to coordinate the program, while Pertamina was the program executor and followed instructions from the ministry.

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

fect labour supply indirectly by causing shortness of breath, decreased stamina, reduced endurance, and frequent respiratory infections. (2) It is a reliable, objective, and quantifiable measure of respiratory health among adults (Paulin and Hansel, 2016). (3) Lung capacity is not easily influenced by nutrition or other factors (Ostrowski and Barud, 2006), and thereby minimizes the possibility of capturing a spurious relationship between lung capacity and some concurrent external factors. Lung capacity is measured as Peak Expiratory Flow (PEF) in the survey using a device called Personal Best Peak Flow Meter. This indicates the person's maximum speed of expiration/exhalation in litres per minute (L/min). In our analysis, we use the highest PEF among the three recorded measurements, following Rosales-Rueda and Triyana (2019).[15] In addition, we also use other health outcomes as our alternative measures of health such as cough in the last two weeks prior to the survey, stroke, diabetes, and self-reported health status.

Second, to investigate the program's impact on labour supply, we construct monthly work hours based on three 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? (3) Approximately, what is the total number of weeks you work per year? We add up the weekly work hours for primary and secondary jobs, multiply that by the number of weeks of working per year, and divide it by 12 to get monthly work hours that account for seasonality. Note that this work hours variable reflects hours that are spent on income-generating work, and not on unpaid housework. To capture individual's work participation rate, we construct two dummy variables based on whether individuals were wage earners (as government or private worker) and whether individuals worked in agriculture.[16]

Control Variables.—For the control variables, we use individual's characteristics such as age and height as they are among the key biological factors affecting different ranges of lung capacity among individuals. We also include regional characteristics at the time of the survey and rural-urban status of the region. Our preferred specification uses individual age, height, and district fixed effects, which allow us to control for biological factors that determine indi-

[15] IFLS survey guidelines also recommend using the best of three measurements to capture the individual's lung capacity.

[16] We did not use productivity measures such as agriculture output per area planted due to many missing values.

vidual's lung capacity and time-invariant district characteristics. We include individual fixed effects in our 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 two considerations: (1) we focus on the program during the expansion period by excluding households living in districts that received LPG in 2007–2008, following Imelda (2020)[17]; (2) we restrict our sample to the eligible households—those who did 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.[18] We use the 2007 survey data as the baseline year because it is closer to the date of the intervention, hence providing a cleaner identification.

Table 1 shows the individual and household characteristics at the baseline for the early exposed group and the later exposed group. Table 1 columns 1 and 3 report the mean, while columns 2 and 4 report the standard deviation corresponding to the means. The percentage of households that are not using LPG (the eligible households) is around 90%, and it is similar on average across two groups, as are the demographic, education level and asset ownership in the households. For the health variables, individuals that received LPG early did not seem to be healthier than those who received it later. For the labour outcome variables, individuals' work participation also looks similar across the two groups on average.

IV. Empirical Strategy and Preliminary Evidence

IV.A Identification

The timing of the program and the location where an individual lives jointly determine the duration of an individual's exposure to the program. By 2014, the program reached out to most regions we observed in IFLS 2014. Therefore, we rely on individual's exposure to the program for our identification. We compare eligible individuals in districts that received LPG in 2009-2010 (henceforth called the *early exposed group*), to eligible individuals in districts that

[17] Focusing on the program after 2008 (the expansion period) limits district selection into the program (Imelda, 2020).

[18] Generally, individuals over 16 are no longer of school age and are allowed to be legally married according to Indonesia's 1974 Marriage Law. 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 attention to the relevant sample of women for this analysis. However, the results are robust regardless of this restriction (see Section VII.).

Table 1: SUMMARY STATISTICS OF BASELINE CHARACTERISTICS

	Early Exposed		Later Exposed	
	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)
Demographic				
Age (years)	43.03	15.20	41.64	15.40
Ever Married (0/1)	0.83	0.38	0.79	0.41
Health and Labor Outcomes				
Lung capacity (Litres/Minute)	329.20	113.00	337.78	107.65
Employed (0/1)	0.77	0.42	0.73	0.45
Working hours per month (hours)	189.66	101.39	198.15	102.03
Participation in Agriculture (0/1)	0.35	0.48	0.33	0.47
Housework is Women's Primary Activity (0/1)	0.37	0.48	0.37	0.48
Housework is Men's Primary Activity (0/1)	0.01	0.10	0.01	0.06
Men Help in Household Work (0/1)	0.59	0.49	0.58	0.49
Education				
No school (0/1)	0.13	0.34	0.10	0.30
Primary/Middle School (0/1)	0.47	0.50	0.41	0.49
High School (0/1)	0.34	0.47	0.40	0.49
College and above (0/1)	0.06	0.24	0.09	0.29
Cooking Fuel Used				
Electricity (0/1)	0.01	0.10	0.01	0.10
Gas (0/1)	0.10	0.30	0.09	0.29
Kerosene (0/1)	0.34	0.47	0.45	0.50
Firewood (0/1)	0.54	0.50	0.45	0.50
Charcoal (0/1)	0.01	0.09	0.00	0.04
Income and Assets				
Percapita Income (USD)	141.47	221.07	165.66	216.31
Electricity (0/1)	0.95	0.21	0.94	0.23
Refrigerator (0/1)	0.62	0.85	0.69	0.91
Television (0/1)	0.77	0.42	0.72	0.45
N	3816		2255	

Notes: This table reports the average individual and household characteristics at baseline (2007). The columns show the mean and standard deviation of individuals living in the early exposed districts (received the program in 2009–2010) and in the later exposed districts (received the program after 2010). 1 USD = 13,755 IDR. *Source*: IFLS 2007. *Sample*: All households at the baseline year.

received LPG after 2010 (henceforth called the *later exposed group*).[19] The individuals in the early exposed group were exposed to the program 3 years longer relative to the later exposed control group on average. Those who were exposed early are likely to experience longer duration of reduced pollution exposure from switching to a cleaner fuel. At the same time, they are also more likely to have adjusted their behaviour with the cleaner cooking fuel and are likely to have formed some habit of using it. This is important because any changes in health and labour outcomes are likely not immediate and require sustained use of the clean fuel.[20] While interpreting the results, keep in mind that individuals in the control group were exposed to the program for 1.5 years, on average, by 2014. Hence, our estimates may serve as the lower bound of the full treatment effects if the treatment effects are assumed to be monotonic.

We use the following event study style of difference-in-differences (DiD)—we include both post-treatment and pre-treatment time dummies to capture the pre-trends in the same equation.[21] Estimating equation is given by:

$$Y_{idt} = c_i + \beta_1 \text{EarlyExposure}_d \times \text{Post}_t + \beta_2 \text{EarlyExposure}_d \times \text{Pre}_t + \gamma_t + \delta_d + \theta X_{idt} + \epsilon_{idt} \quad (1)$$

Y_{idt} represents the outcome variables for individual i, in district d, at year t. EarlyExposure is the treatment dummy, which takes a value of 1 if the district received LPG in 2009-2010 and 0 if the district received LPG after 2010. Post (Pre) is the dummy variable which takes a value of 1 if the year is 2014 (2000), else 0. Baseline year (2007) is the omitted reference year. γ_t and δ_d are the year of survey and district fixed effects. X_{idt} is the set of individual controls in the year 2007. In our most comprehensive specification, we include individual fixed effects (α_i) into Equation 1. Our coefficient of interest is β_1, the intent-to-treat effect. Hence, β_1 captures the difference in the outcome variables of those in the early vs. later exposed groups in 2014 relative to 2007.

19 Originally, the program was set to be finished by 2012, therefore we use 2010 cut-off as the middle year. After 2012, the Government decided to extend the program further.

20 Figure A.6 in the Appendix shows that the last month purchased of kerosene for those exposed later has not yet changed that much as there could be some operational lag (i.e., removal of the kerosene was gradual and took time).

21 This approach has been used in some studies, for instance Equation 4 in Bertrand *et al.* 2019.

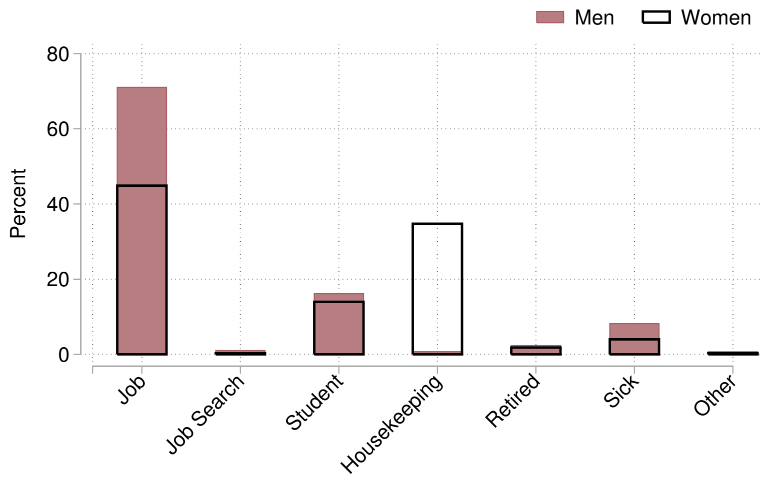
Identifying Assumptions.– Causal identification in the DiD design relies on the common-trends assumption, where the treatment group would have behaved similarly to the control group in the absence of the program. This assumption is satisfied when the β_2 is not statistically different from 0. In Table B.2 in the Appendix, we show the pre-trends in each outcome variable in the corresponding column header by reporting the β_2. Given the parallel trends in all of the outcome variables between these two groups, it is reasonable to assume that, in the absence of the program, those who received the LPG earlier would behave in a way similar to those who received the LPG later. We add two additional validity checks for similarity in the trends between the two regions before the treatment began: (1) the kernel density for the average of household kerosene purchased is very similar between the two regions before the program (Figure A.6 in the Appendix); (2) we also see parallel pre-trends in other alternative health measures (Table B.3 in the Appendix) and in several socioeconomic and demographic variables (Table B.4 in the Appendix). Based on these results, we argue that β_1 captures the causal effect of early access to the program on the outcome variables.

IV.B Preliminary Evidence

Gender Disparity in Housework.—Due to traditional gender roles, women spend significantly more time in unpaid household activities compared to men. This is shown in Table 1 and Figure 2. In particular, 37% of women in our sample perform housework as their '*primary activity*' compared to 1% of men. Therefore, women spend a considerably higher amount of time indoors doing household chores relative to men. Table 1 also shows that 59% of men did provide some help in the household work. However, a large share of the work is likely done by women. For instance, Hermawati and Saari (2011) show that, in Indonesia, housework is shared between men and women but a large portion was done by women (Table B.1 in the Appendix) and Ferrant *et al.* (2014) show that women spend on average 3–6 hours on unpaid domestic work, while men spend 0.5–2 hours. This evidence establishes the existence of gender disparity in housework as well as in the amount of time spent indoors. As a result, women are more likely to be exposed to IAP from polluting cooking fuel than men.

Gender Disparity in Health.—There is a difference in the lung capacity distribution for men and women in our baseline sample (solid lines, Figure A.3 in the Appendix). The gap between

Figure 2: PRIMARY ACTIVITY BY GENDER



Notes: This figure shows the primary activity of men and women in the baseline year (2007). Almost 37% of women in our sample perform housework as their '*primary activity*' compared to less than 1% of men. This highlights the large gender disparity in household work. Note that this figure depicts only the *primary* activities of individuals. While a negligible proportion of men perform housework as their primary activity, they can still provide some help with the housework on top of their primary activity. *Sample:* Eligible households. *Source:* IFLS 2007.

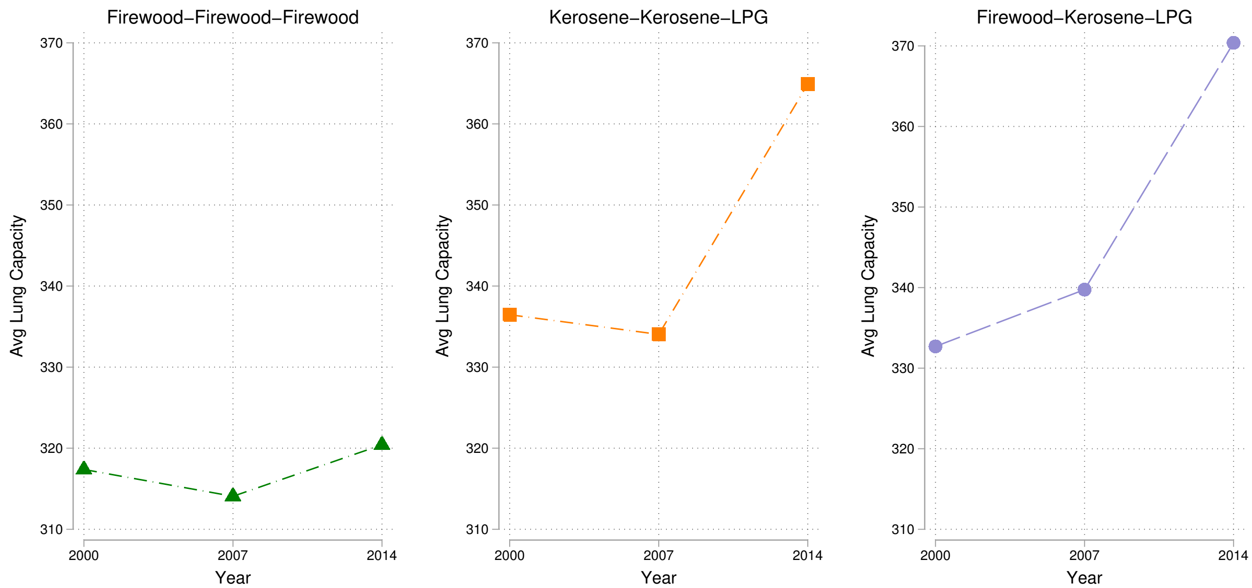
men and women's lung capacity is similar (or wider if any) relative to the gaps documented in the existing studies.[22] Some of the gap can be attributed to biological factors (e.g., men's larger build and higher level of physical activity). However, even after accounting for individual's age and height, which absorbs some of the differences in lung capacity between individuals, the gap persists (dashed lines, Figure A.3 in the Appendix). Ultimately, the goal of this paper is to document the extent to which some of these differences can be explained by the disproportionate gender burden imposed on women by a lack of access to clean cooking.

Fuel Choice and Health.—Lastly, we show an associative relationship between fuel quality and lung capacity for individuals in our sample. In Figure 3, we compare three different groups of individuals and their average lung capacity: (1) individuals who used firewood in all the three rounds; (2) who used kerosene in 2000 and 2007 but changed to LPG in 2014; and (3) who used firewood in 2000, kerosene in 2007, and LPG in 2014. The figure suggests that switching to cleaner fuel is associated with an increase in lung capacity, whereas continuous usage of dirty fuel is not. This presents a preliminary piece of evidence for the existence of

[22] Figure A.4 in the Appendix shows the comparison of the observed lung capacity distribution in our sample with those of Singaporean adults (Da Costa and Goh, 1973).

a potential causal impact of fuel quality on health outcomes. Linking this with the gender roles, use of dirty fuel can lead to a disproportionate health burden on women. If after the implementation of the program, households shifted to using LPG, we can expect that women will experience greater improvements in health than men will.

Figure 3: AVERAGE LUNG CAPACITY BY FUEL CHOICES OVER TIME



Notes: This figure plots the average lung capacity in 2000, 2007, and 2014, for individuals in three separate group of households (1) "Firewood-Firewood-Firewood" shows average lung capacity over time for individuals in households who keep using firewood as their main cooking fuel from 2000-2014 (this figure looks very similar to those in "Kerosene-Kerosene-Kerosene" households); (2) "Kerosene-Kerosene-LPG" are those who used kerosene as their main cooking fuel in 2000 and 2007 but switched to LPG in 2014; (3) "Firewood-Kerosene-LPG" are those who use firewood as their primary fuel in 2000, kerosene in 2007 and LPG in 2014. *Source*: IFLS 2000, 2007 and 2014.

V. Main Result I: Program Impact on Health

Table 2 summarizes the main health result. The table shows the impact of the program on lung capacity for the women subsample (columns 1–4) and the men subsample (columns 5–8). The results suggest that three years of early access to the program led to an increase in the lung capacity among women by about 4% (or 11.22 L/min with a 95% confidence level). In contrast, among men, we find a very small and statistically insignificant change in their lung capacity due to the program (2.02 L/min on average). This difference in the impact on lung capacity between men and women is statistically different with a p-value of 0.046 (not shown). The coefficients are very stable across different regression specifications implying that the treatment variable explains most of the variations in the lung capacity, while the control variables do not.

Table 2: MAIN RESULT I: PROGRAM IMPACT ON LUNG CAPACITY

Sample:	Women				Men			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EarlyExposure × Post	11.22**	11.22**	11.22**	11.22**	2.022	2.022	2.022	2.022
	(5.506)	(5.506)	(5.547)	(5.505)	(6.054)	(6.055)	(6.112)	(6.053)
Mean Dep. Var	283	283	283	283	411	411	411	411
Observations	7788	7788	7788	7788	6057	6057	6057	6057
Rural-Urban FE	✓	✓			✓	✓		
Individual Controls		✓	✓			✓	✓	
District FE			✓				✓	
Individual FE				✓				✓

Notes: Table 2 shows the program impact (β_1 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) use only rural dummy, columns (2) and (6) add the individual level controls (age and height) at the baseline, columns (3) and (7) add district fixed effects, and columns (4) and (8) show results with individual fixed effects. Standard errors (in parenthesis) are clustered at the district level. The mean of the dependent variable for the later exposed group is also reported. *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01. *Source*: IFLS 2000, 2007, 2014. *Sample*: Individuals living in eligible households.

The results highlight that health benefits from clean cooking access are mostly accrued by women—those who are responsible for most of the household chores and cooking activities. It is perhaps not surprising that the health impact among men is almost zero because, unlike women, men have minimal participation in cooking activities and are more likely to spend most of their time outdoors (e.g., working in the field and possibly exposed to outdoor air pollution). Indeed, the majority of the men are employed (see Figure 2). Hence, they are likely to spend significantly less time in the house than women and therefore, experience a minimal health burden associated with the use of unclean fuel.

To put the magnitude of the treatment effects into perspective, we compare our estimates to the impact of smoking on lung capacity. The average increase of 11.22 L/min in lung capacity is comparable to the improvement in lung capacity if a regular smoker quits smoking for approximately 5 pack-years.[23] This magnitude is also comparable to the impact of air pollution on lung capacity ten years post-exposure to a forest wildfire in Indonesia (Rosales-

[23] One pack-year of smoking means the person smokes one pack of cigarettes every day for one year. These calculations are inferred from (Muller and Muller, 2015)

Rueda and Triyana, 2019).

Next, we look at other self-reported health outcomes that can be associated with IAP such as cough, stroke, diabetes, and self-reported health indicators (see Table B.5 in the Appendix). We find lower probability of experiencing cough (in the last two weeks preceding the survey), stroke, diabetes, and a higher probability of reporting having good health. While the coefficients suggest some improvements in these alternative health measures, most of these coefficients are statistically insignificant. These could be because: (1) some of these health outcomes are self-reported and hence, subject to measurement error, and (2) these measures are more likely to be affected by contemporaneous factors such as weather, and unlike lung capacity, which is relatively more stable over time.

V.A Plausible Channels Explaining Health Improvements

Pollution channel.—One of the most likely channels for the observed improvement in lung capacity is the potential reduction in pollution exposure due to households switching from kerosene to LPG after the program. First, we hypothesize that women who spend more time indoors should experience greater improvement in their lung capacity than those who spend less. Second, the longer individuals are exposed to the program, the greater their lung capacity improvements should be because the health impact from exposure to pollution can accumulate over time. To test the first hypothesis, we explore heterogeneity in the program impact by adding a dummy variable if individuals' *primary* activity is housekeeping. These individuals tend to be responsible for cooking in their own house and not be involved in formal work.[24] As the survey lacks a time-use diary, we use this proxy variable as a simple way to contrast individuals based on their propensity to stay indoors and be exposed to indoor air pollution.[25] We include the interaction of the individual's housekeeper status dummy, the program dummy, and the time dummy to equation 1 along with all the double interactions to estimate these results. The coefficient of the program effect on lung capacity between women who were more likely to spend the majority of time indoors vs. the rest of the women.

[24] In our sample, there are very few individuals that work with agencies that provide opportunities to work as a housemaid who does housekeeping for other households.

[25] Note that this dummy is based on individual's status at baseline year, hence it is uncorrelated with the program.

We show evidence in support of the hypothesis that health effects are concentrated among those who spent more of their time indoors in Table 3. Results suggest that lung capacity improvements are driven by women who were primarily responsible for housekeeping at their homes in the baseline. This is as expected because they are most likely to benefit from any reduction in indoor pollution exposure due to the program.

Table 3: HETEROGENEITY RESULTS: PROGRAM IMPACT BY TIME SPENT INDOORS

Sample:	Women			
	(1)	(2)	(3)	(4)
EarlyExposure × Post × Housekeeper	11.91**	11.91**	11.91**	11.91**
	(5.67)	(5.67)	(5.71)	(5.67)
EarlyExposure × Post	6.79	6.79	6.79	6.79
	(5.43)	(5.43)	(5.47)	(5.43)
Mean Dep. Var	283	283	283	283
Observations	7788	7788	7788	7788
Rural-Urban FE	✓	✓		
Individual Controls		✓	✓	
District FE			✓	
Individual FE				✓

Notes: This presents heterogeneity in the program impact based on women's baseline housekeeping status (housekeeper dummy is equal to 1 if in 2007, women's primary activity is housekeeping. We add the interaction of women's housekeeper status dummy, the program dummy, and the time dummy to equation 1 along with all the double interactions to estimate these results. *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01. *Source*: IFLS 2000, 2007, 2014. *Sample*: Women in eligible households.

Second, Figure A.7 in the Appendix shows the coefficient of the treatment effect for individuals exposed to the program for 3–4 years and 5–6 years, relative to those who were exposed for 0–2 years. Indeed, we see that the increase in lung capacity is driven by those who were exposed longer (5–6 years). In other words, there is an increasing effect in lung capacity as the exposure-duration increases. Hence, it seems plausible that the pollution channel is likely the leading channel explaining the health impact of the program.

Expenditure Channel.—Another possible channel is that the program may lead to changes in household expenditure, considering that LPG is more efficient compared to kerosene. However, in an unreported result, we find that the program reduced monthly fuel expenditure by about 0.4–2.0 USD (p-value of 0.003). The magnitude is very similar to Imelda (2020) who finds that households who switch from kerosene to LPG experienced about a 2 USD reduction in their monthly expenditure. These savings are not only very small but also not necessarily spent on health-related investments for women. Therefore, it is unlikely that the expenditure channel is the main driver of the significant increase in women's lung capacity.

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 B.6 (Panel A) in the Appendix reports the program impact using Equation 1 on different outcome variables indicated in the table header. Column (1) shows that there isn't a significant change in the probability of having an education higher than primary due to the program. Columns (2)–(6) 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 indicate a weak correlation between the program and the other possible indirect outcomes. Therefore, it is plausible to say that these are not the drivers for the large health improvements.

Income Channel.—This channel relates to our next results on labour supply. We may see some changes in household income as a result of labour supply changes due to the program. One can argue that the increase in income can lead to a healthier lifestyle, which in turn might have led to improvements in the lung capacity. However, a healthier lifestyle should be linked to the health improvement of both women and men within the household, not only women as we showed. Columns 1–2 in Table B.7 in the Appendix show that the program is associated with an increase in self-reported annual earnings particularly among the housekeeper households, although not statistically significant. We also do not find an increase in wages (results are available upon request). This result can be due to measurement errors in the income data (e.g., income from informal and seasonal jobs are difficult to quantify). Nonetheless, improvements in women's health can possibly increase their time available, and allow both women and men who want to work additional hours to do so simply because they now can. We explore the program impact on productive work hours in Section VI.

Local Economic Changes.— One may expect that the program timing is associated with local economic conditions, and therefore associated with improvement in local health facilities. However, we rule out this channel mainly due to three reasons. First, we explore the correlation of the program timing with other social protection programs which can be correlated to local economic conditions (see the robustness checks in Section VII.) and conclude that the timing of the LPG program is not correlated with the timing of other programs. Second, improvements in infrastructure and health services in developing countries tend to be a slow process and may take decades. At the same time, more developed regions are also likely to have a higher level of outdoor air pollution that works against finding any health improvements . Third, even if the healthcare facilities are improved, individuals' decisions to take advantage of them depend on many other things such as their income, bargaining power over access to healthcare , among others. Nonetheless, if there are local economic changes that explain health outcomes in the early exposed regions, we should see some positive changes in lung capacity among those living in the same regions but that were ineligible for the LPG program. Our placebo tests (in Table B.6 Panel B, columns 1–2, in the Appendix) on the women living in ineligible households—women living in households who use LPG at baseline year—suggest no health impact among them and its magnitude is also very small compared to our earlier estimates on the eligible women. This provides some reassurance that the health we observed earlier is not due to local economic changes, but driven by households' eligibility for the program.

VI. Main Result II: Program Impact on Labour Supply

One's stock of health determines how much time one can spend on work. On one hand, when women are healthier, they are likely to increase their work hours and to participate in market work (Cai, 2010; Stabridis and van Gameren, 2018). On the other hand, there are many reasons why clean energy access may not increase labour supply (e.g., the health impact from clean energy access is not large enough to influence labour supply, individual preference on leisure, limited opportunities to participate in the market work, among others).

Here we document the impact of clean energy access on labour supply empirically and discuss the possible channels. Given our earlier findings on health among women, we hypothesize that clean energy access can influence labour supply through improvements in women's lung capacity. Changes in lung capacity can impact the labour supply and productivity of individuals by affecting the normal functioning of the body. When lung capacity is low, it limits the lungs' ability to breathe in and hold air, which in turn reduces oxygen flow to cells. This can force the heart to work harder to pump oxygen throughout the body. As a result, reduced lung capacity can lead to shortness of breath, decreased stamina and reduced endurance.[26] For example, Hanna and Oliva 2015 shows the existence of a positive relationship between reduction in pollution exposure and an increase in labour supply. As discussed earlier, labour inputs within households are shared, hence improvement in women's health can induce changes in labour supply for both women and men depending on the elasticity of substitution between men's and women's labour inputs.

To better reconcile the link between labour supply and health, we use two additional dummy variables based on: (1) Whether women did housekeeping as their primary activity at baseline (used in Table 3) for the women subsample as our proxy for women's likelihood of experiencing positive health shock. (2) Whether there was at least one woman in the household primarily doing housekeeping at the baseline for the men subsample.[27] Then, we split the sample of men and women into subsamples and conduct the same regressions as in Equation 1 on each of the subsamples. If the health channel is relevant, we expect that the program impact on labour supply should be concentrated among the subsamples who are more likely to enjoy the health benefits of the program.

In Table 4, we present the program impact on women's and men's monthly hours of work. Panel A consists of women subsamples who are likely to experience health benefits after the program (columns 1–4) and subsamples of men living in households that are likely to enjoy the health benefits of the program (columns 5–8), while panel B consists of the remaining subsamples—men and women who are less likely to enjoy the health benefits. We find that the increase in work hours due to the clean cooking program is mainly concentrated in panel A. It indicates that individuals and households that are most likely to enjoy health improvements due to the program experienced higher labour supply impact. In contrast, we do not see any significant changes in the work hours in panel B. The difference in the coefficients

[26] Harms *et al.* (1997) suggest that lower lung capacity can limit the respiratory muscles' blood flow, and thereby limit their maximum physical exercise.

[27] Since only a handful of men do housework as their primary activity and there is insignificant health impact on men, we use women's housekeeping status to identify men who belong to households with positive health shocks. This is our proxy for the individual's belonging to households with a high likelihood to enjoy positive health shock. Note that these dummy variables are based on baseline value and hence they are not endogenous to the program.

between panel A and B are statistically significant at a 95% confidence level.

Table 4: MAIN RESULT II: PROGRAM IMPACTS ON HOURS OF WORK (INTENSIVE MARGIN)

Sample:	Women				Men			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PANEL A : Housekeeper/Belong to Housekeeper Household							
EarlyExposure × Post	32.77*	32.11*	32.36*	28.36	28.19***	28.29***	28.41**	29.28***
	(17.49)	(17.42)	(18.49)	(18.24)	(10.62)	(10.63)	(10.89)	(10.73)
Mean Dep. Var	153	153	153	153	211	211	211	211
Observations	880	880	880	880	1718	1718	1718	1718
	PANEL B : Non-housekeeper/ Does not belong to Housekeeper Household							
EarlyExposure × Post	-3.322	-3.409	-3.044	-6.307	11.92	11.84	11.34	8.005
	(8.149)	(8.157)	(8.238)	(8.310)	(10.23)	(10.22)	(10.40)	(10.28)
Mean Dep. Var	181	181	181	181	211	211	211	211
Observations	3478	3478	3478	3478	3232	3232	3231	3232
Rural-Urban FE	✓	✓			✓	✓		
Individual Controls		✓	✓			✓	✓	
District FE			✓				✓	
Individual FE				✓				✓

Notes: This reports the program impact (β_1 in Equation 1) on monthly hours dedicated to market work. Panel A includes 'housekeeper women' sample (columns 1–4) and 'men in households with at least one housekeeper women' sample (columns 5–8). Panel B includes 'non-housekeeper women' sample (columns 1–4) and 'men in households with no housekeeper women' sample (columns 5–8). Each column corresponds to a different specification similar to Table 2. The 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*: Individuals living in eligible households who had worked in 2007.

We find an increase in the work hours among women who did housework and had worked in the baseline (intensive margin impact). The size of the impact is around 1 hour (20%) of additional market labour per day for women (column 3 in Table 4, Panel A). We do not find any significant impact on hours of work for the sample of women who did not do housework as their primary activity (Table 4, Panel B). We also find an increase in the hours of work supplied by men who reside in households where women are likely to enjoy the health benefits. Table 4, Panel A shows the impact on the men subsamples. We find that the program led to approximately 0.9 hours of additional market labour per day (13% increase) among men in households with housekeeper women. In contrast, the program impact is small and insignificant among men in households without housekeeper women. We are not able to reject the hypothesis that the difference in the coefficients between panel A and B is zero.

The increase in monthly work hours for both men and women is concentrated among those who were in the agriculture sector at baseline (Table B.9 in the Appendix). This is perhaps not surprising as 35% of the individuals were in the agriculture sector in 2007 (see Table 1), making agriculture the dominant sector in our sample. The increase in work hours in the agriculture sector is also plausible given that it is a labour-intensive sector, and therefore the individual has more flexibility to increase their labour supply in this sector. Moreover, labour supply in agriculture is less likely to be constrained by the labour demand or by the lack of necessary skills relative to other sectors.[28]

There are no changes in the work participation rate for either men or women due to the early exposure to the program (Table B.8 the Appendix). There could be several possibilities. First, most of the men in the eligible household sample were already working (86%), hence the labour force participation may already be saturated for men. Second, among women, lack of opportunity to participate in the labour force may be due to a lack of necessary skills. Around 55% of women who did housework in the baseline are those who have never worked or were only involved in unpaid and informal work. Hence, even when they can provide some extra labour and want to participate in market work, it may not be enough to increase their participation rate. Lastly, it could be that there is no sizeable increase in the demand for new workers and therefore, we did not see changes in the participation rate.

VI.A Plausible Channels Explaining Labour Supply Impact

Health Channel.— Our four pieces of evidence seem to suggest that the health channel is likely the primary channel. First, as discussed earlier (in Table 4), the increase in work hours is driven by those who are likely to enjoy the health benefits. Second, the increase in work hours is driven by individuals that were exposed to the program the longest, which is also the group who experienced the most health benefits from the program (Figure A.1 in the Appendix which shows a similar pattern of increase in lung capacity and work hours as the exposure-duration increases). Third, we find that the labour effects are concentrated among households that have more children (Table B.10 in the Appendix). Women with children are likely to spend more time cooking than those in households with no children. Hence,

[28] The other sectors are retail, social service, and manufacturing. We do not find any significant increase within these sectors (see Table B.9 in the appendix).

we can expect these women to experience larger health benefits after clean fuel adoption. In addition, the presence of children in the household is also a crucial determinant of the couples' labour supply response (Halla *et al.*, 2020). If improvement in indoor air quality leads to children getting sick less often, it may free up some of women's time in taking care of their sick children.[29] Fourth, the increase in the labour supply of both men and women is concentrated in households where there were actual positive changes in the lung capacity of the household members (Table B.12 in the Appendix, columns 1 and 2).[30] Overall, the labour benefits appear to be enjoyed by those who are more likely to have enjoyed the health benefits regardless of how we split the sample.

Time Channel.— The time impact is another potential channel because cooking with LPG is faster than cooking with kerosene due to differences in the combustion efficiency.[31] Subsequently, this time impact directly links to more time available to do other things, opening up one's opportunity to participate in the labour market (see Rewald (2017) for a review on this channel). Note that, however, the time impact can also be mixed with the health impact because health improvements can lead to reduced days in sickness, less time taking care of sick children or elders, or shorter duration of exposure to IAP as cooking duration is shorter.[32]

We do not find strong evidence in support of the time saved due to technological improvement being the primary channel explaining the increase in work hours.[33] Primarily, based on the results in Table 4 panel B, there is no significant program impact on work hours for either men or women who are less likely to enjoy the health benefits of the program. Individuals in this group are similarly affected by the program. If there is a substantial time savings that drive the labour supply, we should see the program impact within this group too. Similarly,

[29] While we could not test the program impact on children's health using our data because children's health was not recorded in the survey, Imelda (2020) shows that this program has a positive effect on infant health.

[30] We define a household level dummy variable that is equal to one if the average of the actual changes in the lung capacity of household members between 2007 and 2014 is positive, and zero if it is non-positive. We are aware of possible selection, hence these coefficients need to be interpreted carefully. Nevertheless, if the health channel is relevant, we should see that the increase in work hours is driven by households with positive changes in their lung capacity.

[31] LPG-stoves have 53% efficiency rates (ratio between output and input energy), while kerosene-stoves have only 37% (Shrestha, 2001).

[32] As data on the time use on cooking is not available, we are not able to disentangle the health and time impact and our estimates reflect the net effect of the program on labour supply.

[33] On average, households consume about 3–5 cylinders per month (based on monthly fuel consumption observed in IFLS 2014 and the retail price of the subsidized LPG cylinder). Based on anecdotal evidence, there are many appointed retailers that allow households to easily refill their LPG cylinder in a similar way to when they were still using kerosene. Therefore, we do not think that there are significant differences in the time spent between purchasing kerosene and LPG.

Table B.12 column 2 in the Appendix also suggests that there is no significant program impact on work hours for either men or women who were living in households without actual positive changes in their lung capacity.

There are two possibilities for why the time channel is likely not the primary driver of the increase in work hours. First, leisure preference is unlikely to be negligible. The closest comparison to ours, Afridi *et al.* (2020) conducts a time-use survey and documents that a shift from traditional solid stoves to LPG in India led to at most 30 minutes of time savings, which were mostly directed towards leisure.[34] Second, people can spend more time cooking when the cooking process is more convenient. Existing literature points towards the existence of rebound effects—individuals increase usage of an appliance after replacing it with a better and more energy-efficient one. For instance, when a cooking appliance improves, from the woodstove to kerosene stove, Saksena *et al.* (2003) find that individuals cook more and for longer duration as the cooking process is more convenient. Note that we do not claim that the time savings did not occur. Instead, we argue that the time channel itself is not likely to be the leading channel that explains the increase in work hours that we see.

Local Economic Condition.— One may think that program placement is correlated with some other economic changes affecting women's and men's labour supply choices such as changes in the local labour market condition. It might then lead to changes in the labour demand that may not have anything to do with the program. However, we do not find any significant changes in labour supply on ineligible households residing in the same districts (Table B.12 column 3 in the Appendix), suggesting that the effects are driven by household's eligibility for the program and not by region-specific factors. We also see no changes in work hours among non-housekeeper households (see Table 4 Panel B), despite them living in the same district and facing similar local labour market conditions. Hence, it appears that direct local labour market effects are not driving our results.

[34] Also, a piece of qualitative evidence from a focus group discussion in Nigeria suggests that most women stated that if they switch to preferred cooking fuel and are able to spend less time on cooking, they would use the time to do more cooking or spend more time with their family (IISD, 2020).

VI.B Plausible Channels for Spillover Effects on Men

Since men are not the primary beneficiary of the cleaner fuel, it is intuitive that they experience only small (and statistically insignificant) health benefits from the program. Hence, the increase in the labour supply by men may be driven by the potential positive spillover effects of clean energy access within the households. In particular, if labour inputs for unpaid housework are shared by both gender (as shown in Table B.1 in the Appendix), the health shock on women due to access to clean energy can indirectly influence men's labour supply depending on the elasticity of substitution between men's and women's labour inputs. Below we show the relevance of the substitution and complementarity effects within a household in explaining the spillover effects on the labour supply of men.

First, when unpaid housework is shared by both genders, women with improved health and productivity can substitute some of men's unpaid housework. To test these substitution effects, we use a dummy variable indicating whether men have helped with any housekeeping activities during the past week as the outcome variable.[35] Table 5 columns 1–3 indicate that the program reduces the men's propensity to help with unpaid work at home, with effects concentrated on households with at least one woman who did housekeeping at baseline. This suggests that women might act as a substitute for men's housekeeping efforts and therefore reduce the need for men's help. This might have released extra time for men that could be utilized for paid work. Coherent with this, in Table 5 columns 4–6, we show that the program increased men's propensity to have a second job in these households as they are likely to have some extra time from reduced unpaid housework. Specifically, men who were helping in household chores at baseline are the ones who increased their propensity to have a second job (not shown).

[35] Note that this indicator does not reflect individual's primary activity, unlike the previously used housekeeping indicator for women.

Table 5: SUBSTITUTION OF HOUSEHOLD LABOUR

Outcome Variable:	Help in Housework			Secondary Job		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	All men	Men in Housekpr HH	Men in Non-Housekpr HH	All men	Men in Housekpr HH	Men in Non-Housekpr HH
EarlyExposure × Post	-0.09*	-0.16***	-0.06	0.08*	0.13**	0.05
	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)
Mean Dep. Var	0.245	0.227	0.255	0.351	0.325	0.365
Observations	4222	1485	2737	5344	1830	3514

Notes: This shows the program impact (β_1 in Equation 1) on the indicator whether men help in doing housekeeping (columns 1–3) and on the indicator of having a second job (columns 4–6). For the sample used, columns 1 and 4 include all men; columns 2 and 5 include men in households where at least one women did housekeeping (housekeeper households); columns 3 and 6 include men in households where no women did housekeeping at baseline (non-housekeeper households). All regressions include individual level controls at the baseline and district fixed effects. The standard errors (in parenthesis) are clustered at the district level. *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01. *Source*: IFLS 2007, 2014. IFLS 2000 did not record the two outcome variables. *Sample*: Men living in eligible households.

Second, we hypothesize that when men and women have similar skills, it is likely easier for women to pick up the slack (as a substitute) or act as a complement for men at work. To do this, we define a dummy variable that indicates whether men and women were employed in the same sector at baseline year. The logic behind it is that when men and women are both in the same sector, they are more likely to have similar skills; hence, any substitution or complementarity effects should be more pronounced in this 'same sector' subsample.[36] As discussed earlier, the increase in work hours is driven by individuals in the agriculture sector. Therefore, we expect that program effects should be concentrated among households where men and women were both in agriculture to begin with. Table 6 columns 2 and 5 show that the program led to an increase in the area of cultivation and the varieties of crops planted in households where both men and women are in the same agriculture sector. In contrast, in households where men and women were not in the same sector, the point estimates are very small and insignificant. These results show the relevance of both the subsitution and complementarity effects.[37]

[36] Examples for both cases + back up complementarity by citation by Imelda + even citation by referee shows complementarity can hold if separability fails)

[37] Adhvaryu and Nyshadham (2017) suggest that labor complementarities exist in at least one sector of household production. Particularly, sick individuals shift labor away from the farm and into enterprise, and other household members do the same, suggesting that complementarities exist in some sector of household production.

Table 6: IMPACT WHEN HOUSEHOLD MEMBERS ARE IN THE SAME SECTOR

Outcome Variable:	Agriculture Area Cultivated			Number of Different Crops (Variety)		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	All HH	Both in Agriculture	At least one not in Agriculture	All HH	Both in Agriculture	At least one not in Agriculture
EarlyExposure × Post	0.25**	0.61*	0.10	0.37*	0.63	0.23
	(0.12)	(0.31)	(0.15)	(0.21)	(0.38)	(0.21)
Mean Dep. Var	0.588	0.717	0.539	1.485	1.629	1.430
Observations	1871	532	1332	1868	531	1330

Notes: This shows the program impact (β_1 in Equation 1) on the farm land cultivated in the last 12 months in hectare (columns 1–3) and on the number of crops (columns 4–6). The data is at the household level. For the sample, columns 1 and 4 include all households (HH); columns 2 and 5 include only households that were in the same agricultural sector at baseline; columns 3 and 6 include households that were not in the same agricultural sector at baseline. All regressions include individual level controls at the baseline and district fixed effects. The standard errors (in parenthesis) are clustered at the district level. *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01. *Source*: IFLS 2007, 2014. These outcome variables are not recorded in IFLS 2000. *Sample*: Eligible households.

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, validating 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 (PAPs) such as rice subsidy programs, health insurance subsidies, conditional, and unconditional cash transfers.[38] 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

[38] The PAPs that are included are Jamkesda, Jamkesmas, Jampersal, Raskin, Rice Market operation, PKPS, BBM-SLT (UCT), Keluarga Harapan (CCT), PNPM Mandiri, BLSM 2013, BSM (Cash transfer for poor students), 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).

household's eligibility for 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 Poverty Alleviation Programs that started in 2007.[39] Table B.13 in the Appendix 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 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 exposed and the later exposed sample based on households' primary cooking fuel and their location-specific rural-urban classification at the baseline years. Table B.14 in the Appendix, columns (1) and (2), show the treatment effects on lung capacity for women and men using the coarsened matched sample. We find statistically significant treatment effects among women, which is very similar in magnitude to the estimate from our main specification. We do not find any statistically significant treatment effects among men, similar to our main results. We also regress the monthly hours of labour 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.—One may be concerned with some individuals anticipating the program. For instance, individuals migrated into districts that were designed to receive the benefits earlier. As there is no dissemination of information regarding the timing of the program to households, we hence 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. Table B.15 in the Appendix, columns (1) & (5) show the treatment effect on lung capacity with a migrant-inclusive sample is 10.89 L/min, which is very similar to our main results (migrant-exclusive sample). In both the samples, we do not find any significant treat-

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

ment effects on the lung capacity of men. Next, we check if our results are sensitive to the age restriction. Table B.15 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 years. For both cases, the results are similar to our main findings. Lastly, we check the sensitivity of the results 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 B.15, 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. Hence, despite various sample restrictions, our results remain largely robust.

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 a 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 labour supply.

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 work hours. The program's impact is higher among women who are responsible for housework at their home, while among men the impact is very small and statistically insignificant. This suggests that part of the 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, suggesting the positive spillover effects of the policy. We investigate several key mechanisms and conclude that the reduction in indoor air pollution exposure due to the adoption of clean fuel is likely the leading mechanism that explains the observed health improvements. We also argue that health improvements due to the program are likely the leading channels for the impacts on labour supply.

This study provides a lesson on how a clean energy intervention can lead to a massive and fast transition and subsequently lead to improved health and labour outcomes for both genders. However, the total benefits of clean energy access are likely to exceed those documented in this study.[40] 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 19.5%.[41] Using the lower bound for the Value of Statistical Life (VSL) (Kniesner *et al.*, 2012) at $4 million, the estimated VSL associated with the observed lung capacity changes is approximately $0.8 million per person.

It is often challenging to study the impact of technology adoption when the take-up rate is low and the adoption is not sustained. 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 relatively short 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 (WHO, 2020). This study serves as a lesson for policymakers in sub-Saharan Africa and developing Asia in their attempts to achieve the Sustainable Development Goals (SDG) goals that aim to attain universal access to affordable, reliable and modern energy by 2030.

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[40] For instance, some studies discuss the other benefits of clean energy access such as a reduction in CO emissions (Budya and Arofat, 2011; Permadi *et al.*, 2017), expenditure savings (Imelda, 2018).

[41] See Table B.16 in the Appendix.

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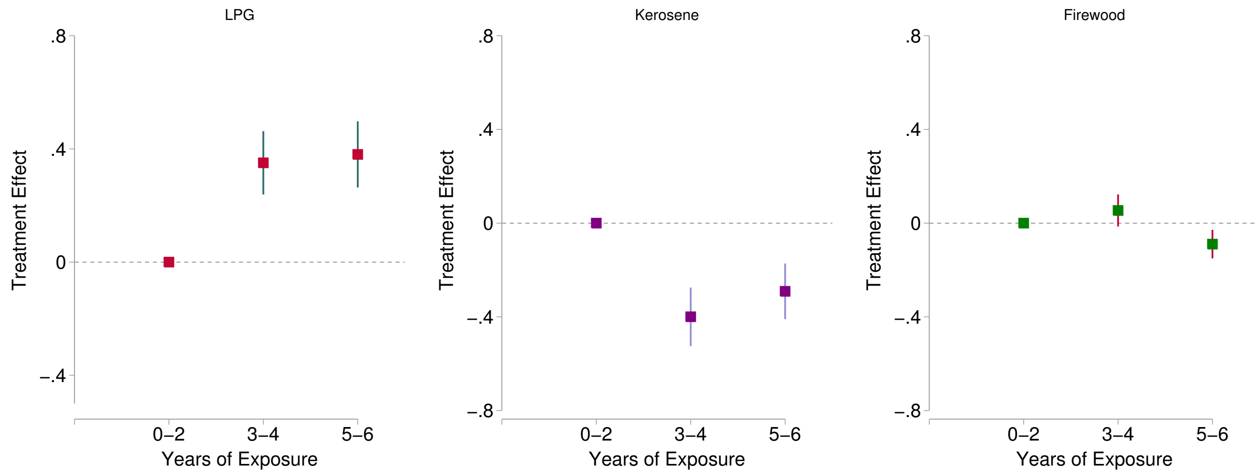
Online Appendix

"Clean Energy Access: Gender Disparity, Health, and Labour Supply"

Anjali P. Verma Imelda

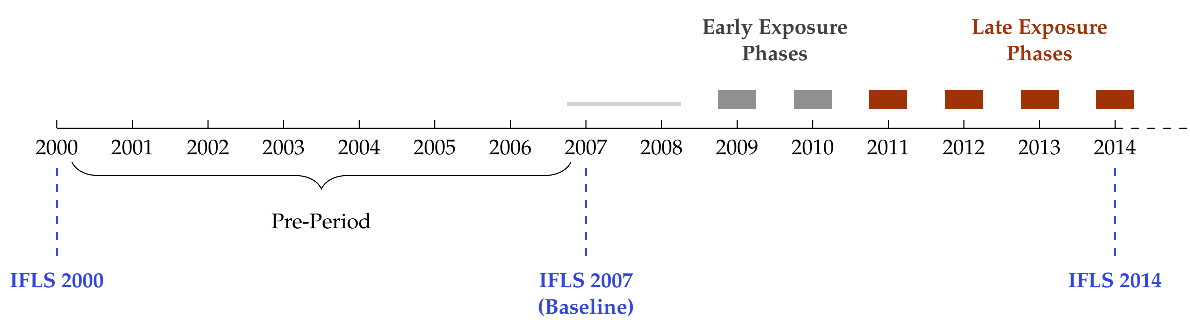
A Figures

Figure A.1: FUEL-SWITCHING BY PROGRAM DURATION



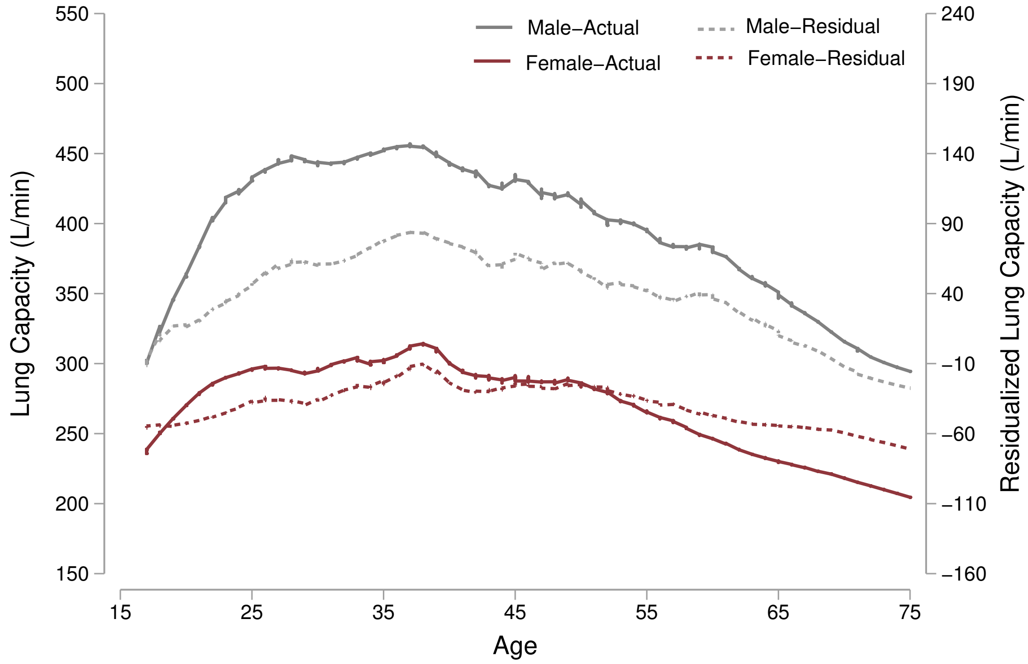
Notes: This figure plots the interaction coefficient β_1 in equation 1 by years of exposure. The outcome variables is dummy variables indicating household's primary cooking fuel: LPG, kerosene, or firewood. Individuals were exposed to the program for 0-2 years if they received LPG after 2012 (the reference group), for 3-4 years if they received LPG in 2011-2012, and for 5-6 years if they received LPG in 2009-2010.
Source: IFLS 2000, 2007, 2014.

Figure A.2: PROGRAM IMPLEMENTATION AND THE YEAR OF SURVEY



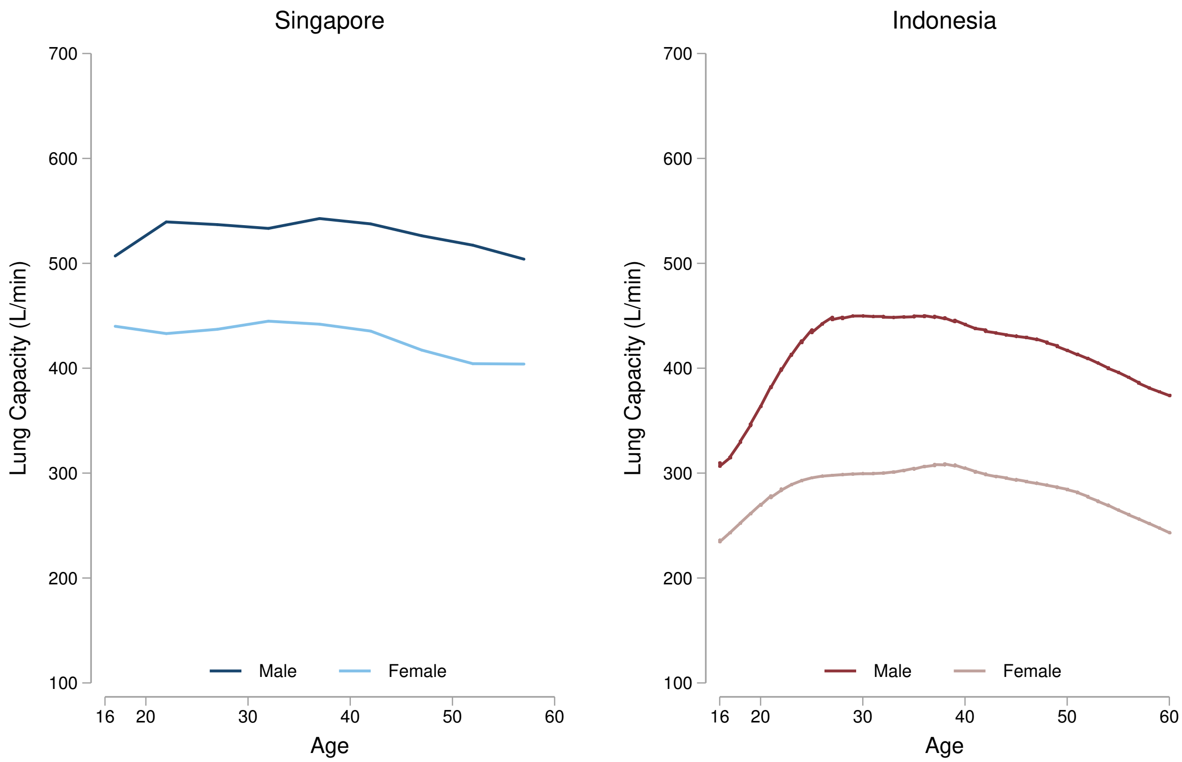
Notes: This figure shows the phases of program roll out and the timing of the survey used for the study. IFLS 2000 and 2007 provide the pre-policy estimates, while IFLS 2014 is used to study the post-policy estimates.

Figure A.3: GENDER DISPARITY IN LUNG CAPACITY



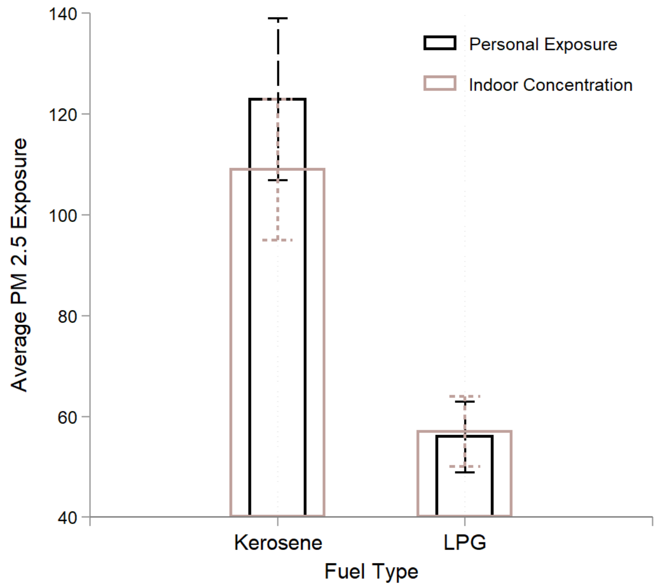
Notes: This figure plots the observed lung capacity for men and women (solid lines), as well as the lung capacity residualized for age and height (dashed lines). It shows that even after controlling for some of the biological factors that create differences in lung capacity, there still exists a large gap between the lung capacity of women and men. Age and height differences between men and women may not fully explain the relatively worse lung capacity of women. The left-vertical axis shows the labels for actual lung capacity measures (in L/min), while the right-vertical axis shows labels for residualized lung capacity (in L/min). *Source*: IFLS 2000 and 2007.

Figure A.4: Lung Capacity Distribution by Gender and Country



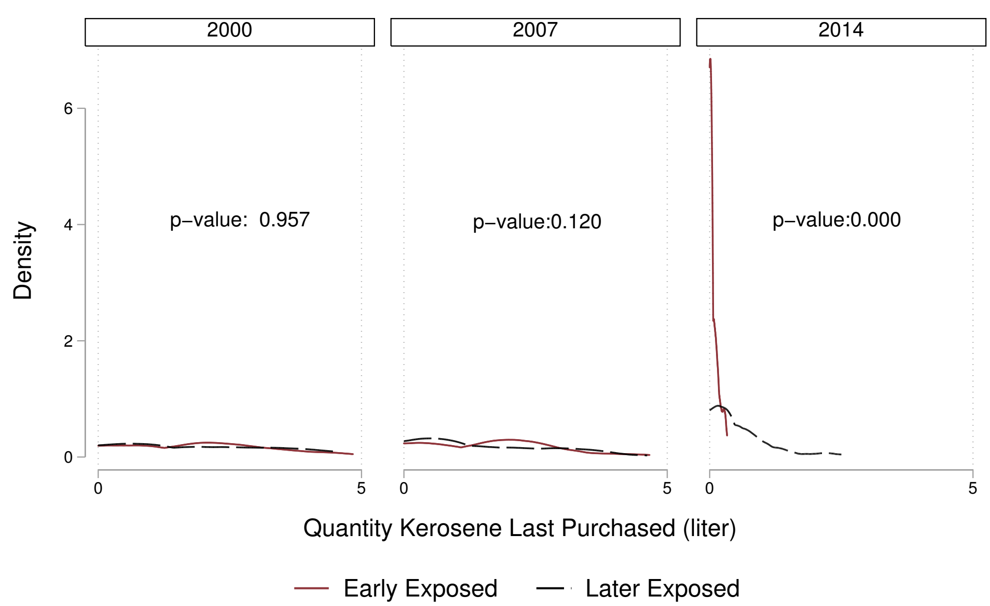
Notes: This figure plots the lung capacity for men and women by age in Singapore (left) and in Indonesia (right). Overall, it shows that while lung capacity for men and women in Indonesia is lower than the respective samples in Singapore, the gender differences in lung capacity is somewhat similar (or wider if any) compared to that of Singaporeans. *Sample*: Da Costa and Goh (1973) for Singapore and IFLS 2000 and 2007 for Indonesia.

Figure A.5: PM 2.5 Exposure among Kerosene and LPG users



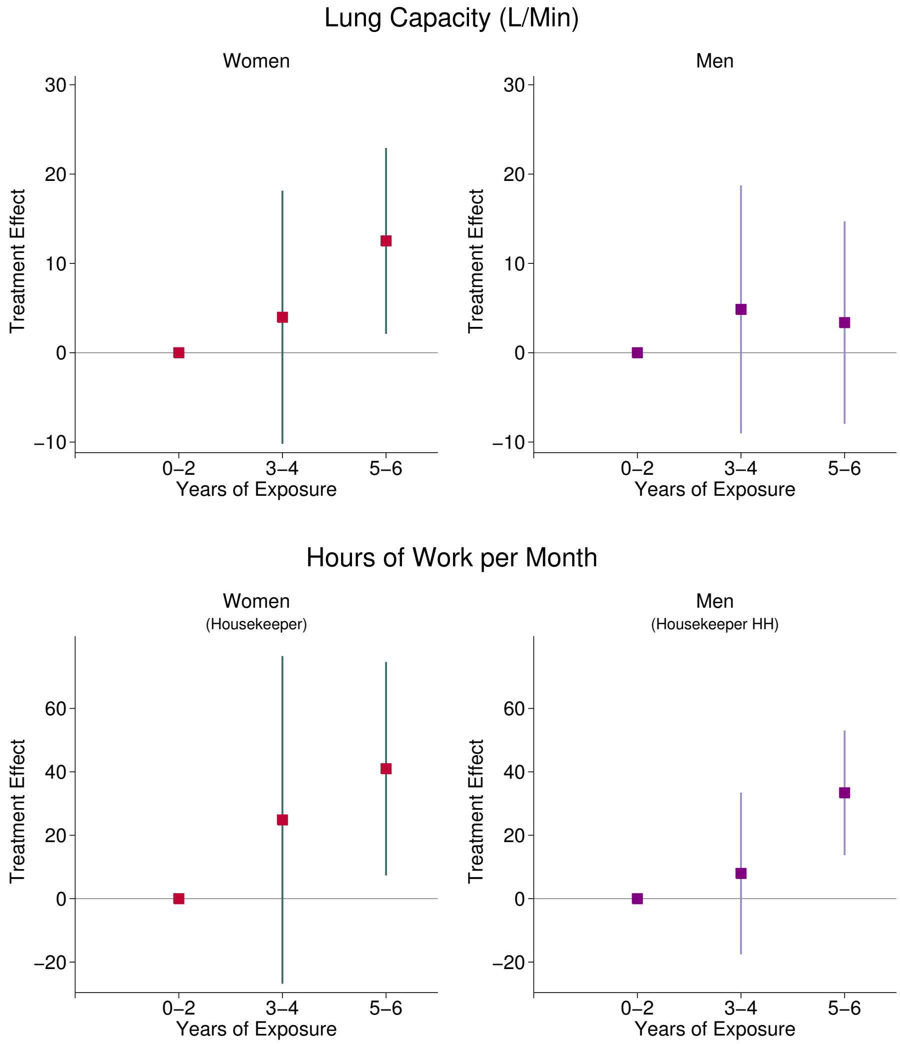
Notes: This figure shows the 24 hour average personal and indoor concentration of PM 2.5 exposure levels for women using kerosene and LPG for cooking. Personal PM 2.5 exposures averaged 123 (SD=16) $\mu g\ m^{-3}$ for kerosene users and 56 (SD=7) $\mu g\ m^{-3}$ for LPG users. The PM2.5 indoor concentrations averaged 109 (SD=14) $\mu g\ m^{-3}$ for kerosene users and 57(SD=7) $\mu g\ m^{-3}$ for LPG users. Source: Andresen *et al.* (2005) .

Figure A.6: Kerosene Purchased of Early vs. Later Exposed Households



Notes: This plots household's last purchase of kerosene in litre. In 2014, the average of kerosene purchased by households in the later-exposed group has not yet changed that much as there could be some operational lag because the removal of the kerosene was gradual and took time. The p-values from Kolmogorov-Smirnov test are reported in the figure, indicating that the distribution of kerosene purchased between early and later exposed households are not different in 2000 and 2007, but it is different in 2014. *Sample*: IFLS 2000, 2007 and 2014.

Figure A.7: IMPACT OF THE PROGRAM BY EXPOSURE-DURATION



Notes: This figure plots the shows the program impact (β_1 in equation 1) on the lung capacity (the top row) and hours of work for women and men (the bottom row) by the years of exposure, similar to Figure A.1. We split the years of exposure into three groups based on the duration of program exposure, indicated in the x-axis: 0-2 years if households received LPG after 2012 (the reference group), 3-4 years if they received LPG in 2011-2012, and 5-6 years if they received LPG in 2009-2010. *Source*: IFLS 2000, 2007, 2014. *Sample*: Individuals living in the eligible households. For lung capacity (the top row), sample consists of all eligible individuals, whereas for hours of work (the bottom row), sample consists of all eligible individuals in the housekeeper households.

B Tables

Table B.1: GENDER DIVISION OF LABOUR IN HOUSEWORK

Activities	Women (in hours per day)	Men & Women (in hours per day)	Women (in %)	Men & Women (in %)
Cooking	2.76	0.24	92%	8%
Fetching water	0.37	0.63	37%	63%
Cleaning	2.64	0.36	88%	12%
Shop for necessities	1.34	0.66	67%	33%

Source: Authors' calculation from a survey among 24 households in Indonesia in 2004 (Hermawati and Saari, 2011).

Table B.2: PRE-TREND IN THE MAIN VARIABLES

Outcome Variable:	Lung Capacity		Hours Worked per Month	
	(1)	(2)	(3)	(4)
Sample:	Women	Men	Women (Housekeeper)	Men (Housekeeper HH)
EarlyExposure × Pre	9.98	0.59	18.17	11.76
	(7.30)	(9.08)	(19.14)	(14.42)
Mean Dep. Var	283.3	410.8	152.6	211.1
Observations	7788	6054	874	1718

Notes: This presents the pre-trend in the main variables. Each column shows the β_2 coefficient in Equation 1 corresponding to separate regressions on outcome variable corresponding to the column header. Column 1 (2) uses all women (men) sample; column 3 (4) uses women who did housekeeping at baseline (men living in households with at least one woman did housekeeping at baseline) sample. All regressions include age and height at the baseline and district fixed effects. The 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*: Individuals living in eligible households.

Table B.3: PRE-TREND IN THE ALTERNATIVE HEALTH OUTCOMES

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Variable:	Cough	Diabetes	Self report Health	Cough	Diabetes	Self report Health
EarlyExposure × Pre	-0.03	0.00	0.04	-0.04	-0.00	-0.01
	(0.04)	(0.00)	(0.04)	(0.06)	(0.00)	(0.04)
Mean Dep. Var	0.335	2.984	0.803	0.393	2.988	0.834
Observations	3551	3551	3551	2064	2064	2064

Notes: Table B.3 presents the pre-trend in several self-reported health variables. Each column shows the β_2 coefficient in Equation 1 corresponding to separate regressions with different outcome variables shown in the column header. All of the variables are dummy variables, except columns 3 and 4, which are in 4 values from -2 (very bad) to 2 (very good health) and in kilograms, respectively. All regressions include controls for baseline value of age and height of the individuals and district fixed effects. The 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*: Individuals living in eligible households where at least one women did housekeeping at baseline.

Table B.4: PRE-TREND IN SEVERAL DEMOGRAPHIC VARIABLES

Outcome Variable:	Education	Log Income	Electricity	Refrigerator	TV	Toilet	Water in/out
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EarlyExposure × Pre	0.00	0.08	-0.01	0.04	-0.02	0.03	0.06
	(0.01)	(0.07)	(0.04)	(0.07)	(0.03)	(0.04)	(0.04)
Mean Dep. Var	0.887	4.191	0.948	0.557	0.744	0.700	0.460
Observations	14172	12200	14172	14172	14172	14172	14172

Notes: Table B.4 presents the pre-trend in several demographic variables. Each column shows the β_2 coefficient in Equation 1 corresponding to separate regressions with different outcome variables shown in the column header. Column 2 uses percapita income, which is the total household's last year income (self-reported) divided by the number of household members. Most of the variables are dummy variables, except column 2, which is in log percapita income. All regressions include controls for baseline value of age and height of the individuals and district fixed effects. The 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*: Individuals living in eligible households both women and men.

Table B.5: IMPACT ON SECONDARY HEALTH OUTCOMES

Outcome Variable:	Cough	Stroke	Diabetes	Self-reported Health
	(1)	(2)	(3)	(4)
EarlyExposure × Post	-0.060	-0.004	-0.021	0.023
	(0.05)	(0.01)	(0.01)	(0.10)
Mean Dep. Var	0.353	0.008	0.031	0.595
Observations	1848	1848	1848	1848

Notes: This shows the program impact (β_1 in Equation 1) on self-reported secondary health outcomes indicated on the corresponding column header. All the outcome are dummy variable, except column 5 which consists of 4 values: from -2 (very bad health) to 2 (very good health). The parallel trend test for these outcomes are shown in Table B.3 (stroke is not recorded in IFLS 2000, therefore we do not have the parallel trend test for this). All regressions include individual level controls at the baseline and district fixed effects. The 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*: Women living in eligible households where at least one women did housekeeping at baseline.

Table B.6: IMPACT ON NON-HEALTH OUTCOMES IN ELIGIBLE SAMPLE AND HEALTH OUTCOME IN INELIGIBLE SAMPLE

PANEL A: Treatment Eligible Sample

Outcome Variable:	(1) Education	(2) Electricity	(3) Refrigerator	(4) TV	(5) Toilet	(6) Water
	0.01	-0.00	-0.03	0.01	0.01	0.02
	(0.01)	(0.02)	(0.06)	(0.03)	(0.03)	(0.06)
Mean Dep. Var	0.92	0.96	0.72	0.79	0.74	0.49
Observations	7954	7954	7954	7954	7954	7954

PANEL B: Treatment Ineligible Sample

Outcome Variable:	Lung Capacity	
	(1)	(2)
Sample:	All Women	Housekeeper Women
EarlyExposure × Post	-1.69	3.39
	(7.39)	(13.61)
Mean Dep. Var	300.42	297.91
Observations	872	294

Notes: This shows the program impact (β_1 in Equation 1) on the education and household characteristics for both men and women (Panel A—main sample) and on women's lung capacity living in ineligible households who used LPG before the program (Panel B—placebo sample). In panel B, column 1 uses all ineligible women sample, while column 2 uses only housekeeper women living in ineligible households. All of the variables in Panel A are dummy variables , while the variables in Panel B are in L/min. All regressions include individual level controls at the baseline and district fixed effects. The 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*: Individuals living in eligible households (Panel A) and individuals living in ineligible households (Panel B).

Table B.7: IMPACT ON ANNUAL SELF-REPORTED EARNINGS

Sample:	Housekeeper Households		Non-housekeeper Households	
	(1)	(2)	(3)	(4)
Outcome Variable:	Per Capita Household Earning	Log Per Capita Household Earning	Per Capita Household Earning	Log Per Capita Household Earning
EarlyExposure × Post	40.977	0.233	6.597	-0.069
	(31.03)	(0.19)	(33.10)	(0.13)
Mean Dep. Var	312.66	4.85	461.34	5.11
Observations	1054	1054	1839	1839

Notes: This shows the program impact (β_1 in Equation 1) on reported earnings of individuals that are aggregated to household level. The eligible sample is divided by whether there was any housekeeper at baseline (columns 1-2) or not (columns 3-4). The outcome variable is the sum of self-reported earnings from both primary and additional job, based on survey question: "approximately what was your salary/wage during the last year (including the value of all benefits)?". Particularly, columns 1 and 3 use total household earnings converted from the original currency (IDR) to USD (1 USD = 13,755 IDR), while columns 2 and 4 are in log. All regressions include district fixed effects. The 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*: Eligible households.

Table B.8: Impact on Participation in Paid Work and Agriculture

Sample:	Women		Men	
	(1)	(2)	(3)	(4)
subsample:	Housekeeper	Non-housekeeper	Housekeeper HH	Non-housekeeper HH
	Panel A: Impact on Participation in Paid Work			
EarlyExposure × Post	0.01	-0.03	0.03	0.02
	(0.04)	(0.03)	(0.04)	(0.04)
Mean Dep. Var	0.201	0.234	0.343	0.289
Observations	1645	3895	1901	3553
	Panel B: Agricultural Participation			
EarlyExposure × Post	0.01	-0.01	0.01	-0.08
	(0.04)	(0.06)	(0.05)	(0.06)
Mean Dep. Var	0.229	0.339	0.424	0.485
Observations	2979	4973	2191	4026

Notes: This shows the program impact (β_1 in Equation 1) on reported the participation in paid work (Panel A) and agriculture (Panel B). The eligible sample is divided by whether women were housekeeper at baseline (column 1), non-housekeeper women (column 2), men in households with any housekeeper at baseline (column 3), and men in households without housekeeper (column 4). All regressions include district fixed effects. The 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*: Individuals living in eligible households.

Table B.9: Impact on Monthly Hours of Work by Baseline Sector

Sample:	Women (Housekeper)			
	(1)	(2)	(3)	(4)
Baseline Sector:	Agriculture	Manufacturing	Social Service	Retail
EarlyExposure × Post	30.15*	21.95	-17.09	40.68
	(16.50)	(29.27)	(59.11)	(42.96)
Mean Dep. Var	148.428	144.767	147.587	168.717
Observations	493	85	91	196

Notes: This shows the program impact (β_1 in Equation 1) on women's work hours on different baseline sector: agriculture (column 1), manufacturing (column 2), social service (column 3), and retail (column 4). The sample includes only women who did housekeeping primarily at baseline. All regressions include individual level controls at the baseline and district fixed effects. The 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*: Individuals living in eligible households.

Table B.10: IMPACT ON MONTHLY HOURS OF WORK BY NUMBER OF CHILDREN

Sample:	Number of Children in the Household		
	0	1	>1
	(1)	(2)	(3)
EarlyExposure × Post	15.99	24.33	34.64**
	(17.68)	(15.22)	(13.19)
Mean Dep. Var	183.45	198.53	195.84
Observations	747	1054	1236

Notes: This shows the program impact (β_1 in Equation 1) on monthly work hours of both men and women. Each column represents a different subsample depending on the number of children at baseline: 0, 1, and more than one children, respectively. All regressions include individual level controls at the baseline and district fixed effects. The 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*: Households with at least one woman who did housekeeping primarily at baseline.

Table B.11: IMPACT ON MONTHLY HOURS OF WORK BY HOUSEHOLD'S BASELINE SECTOR (AGRICULTURE VS. NON-AGRICULTURE SECTOR)

Sample:	Women (Housekeeper)		Men	
	(1)	(2)	(3)	(4)
HH's Baseline sector is Agriculture	Yes	No	Yes	No
EarlyExposure × Post	45.59*	27.41	30.81*	2.35
	(23.85)	(25.93)	(17.57)	(15.13)
Mean Dep. Var	157.71	154.20	203.85	213.33
Observations	267	626	655	1223

Notes: This shows the program impact (β_1 in Equation 1) on the monthly work hours. Columns 1 and 3 (2 and 4) are households where women or men were (not) working in agriculture at baseline. All regressions include individual level controls at the baseline and district fixed effects. The 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*: Individuals living in eligible households who worked in agriculture in 2007.

Table B.12: EVIDENCE ON HEALTH CHANNEL FOR LABOR SUPPLY IMPACT (OUTCOME: MONTHLY HOURS OF WORKS)

	PANEL A : WOMEN (Housekeeper)		
Caterogy:	Mean Change in HH's Lung Capacity		Ineligible HHs
	(1)	(2)	(3)
Sample:	Mean$\triangle > 0$	Mean$\triangle \leq 0$	All
EarlyExposure $\times$ Post	48.42**	18.68	22.41
	(20.88)	(28.53)	(67.62)
Mean Dep. Var	153	154	158
Observations	964	415	93
	PANEL B : MEN		
Category:	Mean Change in HH Lung Capacity		Ineligible HHs
	(1)	(2)	(3)
Sample:	Mean$\triangle > 0$	Mean$\triangle \leq 0$	All
EarlyExposure $\times$ Post	22.58**	-1.41	-6.73
	(9.04)	(11.91)	(17.16)
Mean Dep. Var	212	204	201
Observations	3666	1541	515
Sample	Eligible	Eligible	Ineligible

Notes: This shows the program impact (β_1 in Equation 1) on work hours using a different sample. We compute the changes in lung capacity between 2007 and 2014 for each member of the household and take the average at the household level. Column 1 (2) includes individuals living in households (HHs) with positive (non-positive) changes in lung capacity between 2007 and 2014, column 3 includes all individuals living in ineligible households. Panel A includes women sample that did housework primarily at baseline; Panel B consists of only men. All regressions include individual level controls at the baseline and district fixed effects. The 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*: Individuals living in eligible households (columns 1-2) and in ineligible households (column 3).

Table B.13: 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)
Mean Dep. Var	0.855		Observations	11255			

Notes: Table B.13 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: IFLS 2000, 2007, 2014.

Table B.14: PROGRAM EFFECT ON COARSENED EXACT MATCHED SAMPLE

Outcome:	Lung Capacity		Monthly Hours of Work (Housekeeper HH)	
	(1)	(2)	(3)	(4)
Sample:	Women	Men	Women	Men
EarlyTreat × Post	10.97**	1.561	37.21***	29.85***
	(5.499)	(6.317)	(12.58)	(10.69)
Mean Dep. Var	283	411	159	209
Observations	7954	6218	1871	1853

Notes: Table B.14 shows the program effects (β_1 in Equation 1) on two types of outcome variables: lung capacity (columns 1-2) and monthly work hours (columns 3-4), corresponding to the sample matched using Coarsened Exact Matching (CEM) technique weighted with the CEM weights (Blackwell *et al.*, 2009). For lung capacity outcomes, column (1) uses all women and column (2) uses all men. For monthly work hours (columns 3 and 4), the sample consists of individuals in households (HH) where at least one women did housekeeping at the baseline. All regressions include individual level controls at the baseline and district 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*: Individuals living in the eligible households.

Table B.15: PROGRAM IMPACT ON LUNG CAPACITY BY SAMPLE RESTRICTIONS

Sample:	Women				Men			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Early Exposure × Post	10.89**	10.08*	13.03**	13.67*	3.304	-4.91	7.79	10.12
	(5.249)	(5.58)	(6.55)	(7.54)	(5.765)	(6.34)	(7.25)	(10.18)
Mean Dep. Var	282	279	296	289	409	401	433	428
Observations	7782	9180	5253	2683	6043	7361	3585	1937

Notes: Table B.15 shows the program impact (β_1 in Equation 1) on the lung capacity by gender. Columns (1)-(4) show the impact on women, whereas columns (5)-(8) show the impact on men. For both genders, each column corresponds a different kind of sample restriction. Columns (1) & (5) show program impact on sample inclusive of inter-district migrants. Columns (2) & (6) show impact for the age-unrestricted sample. Columns (3) & (7) restrict the sample to prime working age group of 25-55 and, columns (4) & (8) restrict the sample to households using kerosene as their primary fuel in the baseline. All regressions include individual level controls at the baseline and district fixed effects. The standard errors (in parenthesis) are clustered at the district level. *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01
Source: IFLS 2000, 2007, 2014.

Table B.16: VALUE OF STATISTICAL LIFE

Average yearly decline in lung capacity for each extra pack year of smoking (Tambi Medabala *et al.*, 2013)	2 L/min
Pack years of reduced smoking required for treatment effect of 11.22 L/min increase in lung capacity	5.61 pack years
Reduced risk of developing lung cancer from quitting smoking for 5 or above pack years (Tindle *et al.*, 2018)	39 %
Average rate of non-survival for individuals with lung cancer, using 10 year survival rate (CancerStat, 2018)	50 %
Therefore, estimated per person reduced rate of dying from lung cancer	19.5 %
Lower bound value of statistical life (Kniesner *et al.*, 2012)	$4 million
Value of Statistical Life for 1 person at given risk	$0.78 million
Total estimated Value of Statistical Life for 50 million people with no access to clean fuel in Indonesia	$39 million

Notes: This table documents our back-of-the-envelope calculation on the Value of Statistical Life associated with the program impact on lung capacity. Improvement in the stove can be associated with a long-term reduction in lung cancer incidence (Lan *et al.*, 2002). Given the risk of lung cancer from IAP has become increasingly comparable to the risks associated with smoking cigarettes (Behera and Balamugesh, 2005; Cohen and Pope 3rd, 1995), we use the risk of lung cancer from cigarette smoking and equate it to understand the level of risks from IAP.
Sources used for the calculation: CancerStat (2018); Kniesner *et al.* (2012); Muller and Muller (2015); SEER (2016); Tambi Medabala *et al.* (2013); Tindle *et al.* (2018); Woloshin *et al.* (2008)