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IZA DP No. 15852

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ABSTRACT

Health Effects of Fuel Transitions in India: Evidence from Panel Data

We use a nationally representative panel data and combine difference-in-differences methodology with multivalued treatments to look at the impact of cooking fuel switch towards LPG on the probability of short-term adverse respiratory health outcomes such as cough and cough with breathing issues. We find that a switch by households from polluting fuels to LPG reduces the probability of any household member reporting adverse short-term respiratory issues. However, a switch from polluting fuels to a fuel stacking strategy has no impact on the adverse respiratory health issues. A reverse switch by households from LPG to polluting fuels increases the probability of household members reporting adverse health outcomes. Importantly, the clean switch to LPG has a much larger impact for women in reducing the incidence of short-term adverse respiratory outcomes.

JEL Classification: I1, O12

Keywords: fuel switching, difference-in-differences, multivalued treatments

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1 Introduction

Around 2.4 billion people cook using polluting open fires or simple stoves fueled by kerosene, biomass (wood, animal dung and crop waste) and coal. A number of premature deaths resulting from pneumonia, stroke, ischaemic heart disease, chronic obstructive pulmonary disease, and lung cancer, are attributable to household air pollution (HAP), mostly from cooking smoke. There is also evidence of links between HAP and tuberculosis, and cataract.[1]

Hence a switch from polluting cooking fuels to cleaner cooking fuels should theoretically reduce HAP leading to a reduction in incidence of diseases associated with HAP. However, evidence regarding the causal impact of HAP on health is inconclusive, mainly due to data and methodological challenges (Duflo et al., 2008). Imelda (2020) states that studies on cook-stove intervention using randomized controlled trials have made a substantial contribution to this topic, however, she argues that a highly controlled environment may not capture some important behavioral aspects and, hence, lack external validity. A number of papers using observational data has looked at the relationship between fuel choice and different health outcomes (e.g., Liu et al., 2020; Stabridis and van Gameren, 2018; Silwal and Mackay, 2015).[2] While most of this literature has relied on cross-section data (e.g., Liu et al., 2020), few have used panel data to account for unobserved heterogeneity (e.g., Silwal and Mckay, 2015). Liu et al. (2020) use a cross-section data and propensity score matching to study effect of using non-solid cooking fuels on an individual's ability to cope with daily activities among age 45 and above in China. Silwal and Mckay (2015) use a panel data from Indonesia to compare change in respiratory health of individuals that live in households that switched from biomass to clean fuel to households that continued using biomass.

Another set of studies uses policy changes to establish causal impact of fuel transition on health (e.g., Imelda, 2020; Imelda and Verma, 2022). For example, Imelda (2020) focuses on fuel choice and uses the Indonesian government LPG expansion program to compare changes

[1]https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health.

[2]Liu et al. (2020) provides a table summarizing the main results and methodologies of a list of papers that have addressed fuel choice and health (see Table A1 of Liu et al., 2020, p7-8).

in infant mortality in the "treated" districts to changes in infant mortality in the "planned-but-untreated" districts. Imelda and Verma (2022) use the same Indonesian government LPG expansion program and find that access to LPG leads to a significant improvement in women's health, particularly among those who spend most of their time indoors doing housework. In essence, both Imelda (2020) and Imelda and Verma (2019) estimates capture "intent-to-treat" and do not provide effect on the households who actually switched the fuel choice known as "average treatment effect on treated (ATET)" in the program evaluation literature.

For the Indian context, although there exists a large literature that looks at the determinants of clean fuel adoption (few examples are Farsi et al., 2007; Gould and Urpelainen, 2018; Choudhuri and Desai, 2020; Pelz et al, 2021; and Vyas et al., 2021), the question of health impacts of fuel transition has received surprisingly limited attention. Maji et al. (2021) use the India Human Development Survey, and interact the fuel use (solid fuels vs LPG) and cookstove (improved cookstove with chimney vs traditional cookstove without chimney) to categorize households in multiple categories, and use a mixed effect logit model that allows for household and state random effects to account for non-independence of individuals within a household, and households within states, respectively (p3, Maji et al., 2021). Using estimated parameters from their model, they predict mean probability of cough in adult men and women for different categories of households. They report that predicted probabilities of cough in women are 30–60% higher than men in solid-fuel using households. Since, their mixed effect logit model exploit cross-section variation where selection in different categories are non-random, their estimates do not capture the causal impact of fuel switch, and the predicted probabilities should closely mimic the sample averages across different household categories.[3] Basu et al. (2020) use three rounds of National Family Health Surveys (cross-

[3] It is not clear how Maji et al. (2021) use the panel structure of IHDS data. The main text or Web appendix do not report the empirical results or sample sizes. In Figure 1, authors show fuel transition categories between 2004-05 and 2011-12, however, in their model and results they use categories generated from interactions of fuel type and cooking stove type using a single cross-section (probably) from 2012. Their main interest variable, "Cooking" is defined by interacting fuel type (solid fuels, stack solid fuels with LPG, or LPG), and stove type (improved with a chimney, or traditional biomass cookstove without chimney)

section) data collected in 1992-93, 1998-99, and 2015-16 to study the impact of biomass fuel on infant mortality rate. They instrument for cooking fuel choice using a speed of change in forest cover and ownership status of agricultural land.[4]

A common theme across the literature on the health impacts of cooking fuel transition is the assumption of complete transition from biomass to clean cooking fuel, i.e., binary fuel choice. However, the experience in developing countries suggests that fuel stacking remains a reality.[5] For example, in the case of India, Cheng and Urpelainen (2014) use two rounds of NSS data collected in 1987-88 and 2009-10, and find that stacking of LPG and traditional biomass has grown rapidly in India over 1987 and 2010. In a separate study covering six Indian states, Jain et al. (2018) document that an increase in LPG ownership between 2015 and 2018 was accompanied by an increase in fuel stacking. Fuel stacking behavior from the households could potentially attenuate the impact of fuel transition on health outcomes. Moreover, it is important to know that whether a shift (switch) from polluting fuels to clean fuels have any impact on health outcomes for the same household. Looking at the health outcomes of the same household could mitigate the effects of many confounders most importantly, practices and genetics which are not captured in observational data. Does the impact differ if the shift from biomass remains incomplete? In addition, given the high incidence of fuel stacking, what kind of health benefits are expected to the households using mixed fuels if they shift completely to clean fuels. In addition, it will be useful for public awareness and policy to know the relative magnitude of the impact on health outcomes of a clean switch from polluting cooking fuels to clean fuels vs. a switch to fuel stacking strategy.

(p5, Maji et al., 2021). Moreover, the empirical model presented on page 5 does not have a time. In Web appendix, Table A3, they report comparing predicted and observed occurrence of cough in non-smoking adult household members with a sample size of 83,952 adult individuals which suggest that their analysis is based on a single cross section data as their outcome variable is cough_30days (0=no cough reported within the previous month, 1=cough reported).

[4] Hanna et al. (2016) conduct a RCT with a 4-year of follow-up in the Indian state of Odisha, to address the long-term impacts of improved cookstoves. They find that improved cookstoves did not reduce smoke exposure following the second year of installation or improve health of recipients at all because they were not used regularly, and recipients did not maintain them properly.

[5] Fuel stacking is the strategy where households continue to use polluting fuels even if they adopt/use cleaner fuels.

In this paper, we address the issue of causal impact of household switch of cooking fuels to different alternatives on short-term adverse respiratory health outcomes in India captured by cough or cough with breathing issues. For this, we use two waves of nationally representative Indian Human Development Survey collected in 2004-05 and 2011-12 (2005 and 2012, henceforth). This data is quite suitable to address the above questions because besides being a panel, the survey contains a rich set of information. The survey also contains individual health modules that inquire about short-term morbidity faced by household members during the last 30 days.[6] Use of panel data allows us to adopt econometric strategies that eliminate time-invariant household/individual characteristics to arrive at estimates that can be inferred as causal effect.

Specifically, we categorize households in three groups based on their cooking fuel use 1) polluting fuels 2) mixed fuels or fuel stacking and 3) LPG, and identify households who switched cooking fuels between 2005 and 2012, and who maintain the status quo. Our main interest lies in estimating the change in incidence of specific health issues based on the fuel switch, i.e., we compare the change in incidence of health problems of household members for households that switch cooking fuels to households that did not switch cooking fuels. To address the selection issues in the switch, we use two strategies: 1) individual/household fixed effects strategy and 2) difference-in-differences with multivalued treatment.

Thus, we estimate the causal impact of fuel switching on the incidence of short-term respiratory adverse health outcomes for the households that actually switched fuels (ATET). For this, we combine the multivalued treatment effects strategy with difference-in-difference strategy to estimate the causal effect of each type of fuel switch. Our empirical setup (difference-in-differences) eliminates the role of time-invariant unobserved factors, and allows us (multivalued treatment) to compare a switch to fuel stacking vs. clean fuels from polluting

[6]IHDS also inquires about diagnosis of major morbidity such as incidence of cataract, asthma, or tuberculosis that are generally associated with HAP, however, we do not consider them because of the following reasons. First, these diseases develop over longer duration, hence it not clear whether a switch to clean fuels will have an impact on already developing, but not diagnosed diseases. Second, our definition of fuel switch is based on the fuel choice information supplied by the households at the time of survey, and we do not know the time horizon of the switch.

fuels. Since, cooking fuel switch can also be towards less-cleaner options, our empirical setup also allows to estimate of the impact of the switch towards less clean fuels which can serve as a placebo as we expect the effects should be of opposite signs for a switch towards cleaner vs less-clean fuel option. We also look at the heterogeneous effects of the fuel switch across genders and children.

Our paper contributes to the existing literature in following ways. Unlike, the existing literature that focuses on binary fuel choice while estimating the impact of fuel switch, we allow for fuel stacking, and not only estimate the causal impact on health of fuel switch from biomass to clean fuels but also from biomass to mixed fuels. We also provide estimate for the impact of a switch from mixed fuels to clean fuels for households that do engage in fuel stacking behavior. In addition, we also contribute to the scarce empirical literature on the causal relationships between fuel choice and health for India using a nationally representative panel data.

The findings of the paper are following. The households that switched from either polluting fuels or mixed fuels to LPG experienced a considerable decline in the probability of any household member reporting cough or cough with breathing issues compared to the households who continued using polluting or mixed fuels. Importantly, the households that switched from polluting fuels to fuel stacking/mixed fuels do not see any impact on the probability of any household member reporting cough or cough with breathing issues compared to the households that continued using polluting fuels. Moreover, a reverse switch from LPG to either mixed fuels or polluting fuels by a household increases the probability of adverse health outcomes reported by any member compared to a household that continued using LPG. Our individual level analysis suggests that the beneficial effect (in terms of reducing the incidence of cough or cough with breathing issues) of a switch from polluting or mixed fuels to LPG is larger for adult women compared to adult men which conform with the idea that women spend more time in the kitchen area.

Our findings have important policy implications. The findings emphasize the health benefits of transition to clean energy like LPG and brings out the importance of Government of India initiative launched in May 2016, known as Pradhan Mantri Ujjwala Yojana (PMUY) in May 2016 that provided cash assistance of 1600 Indian Rupees (INR) for LPG connection to rural and deprived households which were otherwise using traditional cooking fuels. Additionally, all PMUY beneficiaries are provided with first LPG refill and stove free of cost by the Oil Marketing Companies. The free set up and first refill led to substantial take-off of new LPG connections. Government of India claims distributing 90 million LPG connection under this scheme by 1st April 2022. Government of India also claims 305.3 million domestic customers for LPG as of 1st April 2022.[7] These numbers look impressive on face value, however, the principal constraint to widespread use has been the fuel cost and a large fraction of households in rural areas continue with fuel stacking (Gould and Urpelainen, 2018). In a study covering six Indian states, Jain et al. (2018) document that an increase in LPG ownership between 2015 and 2018 was accompanied by an increase in fuel stacking. In this context, our finding that the health benefits are only accrued if households switch towards clean fuels, and a switch towards fuel stacking does not have significant beneficial impact on health has important policy implications. High fuel cost often remains a major challenge for rural households even when LPG is subsidized (Jain et al., 2015; Kumar et al., 2016, Gould and Urpelainen, 2018). However, over time the subsidy provided by the Indian government is reduced considerably and from June 2020 only the subsidy of 200 INR (up to 12 cylinders) is given to PMUY beneficiaries.[8] The cost of non-subsidized 14.2 Kg LPG cylinder increased from about 580 INR in May 2020 to about 1000 INR in May 2022.[9] There are evidence that several PMUY beneficiaries did not use the LPG beyond the initial refill, mostly due to economic reasons. Despite wide coverage, LPG refills ordered by consumers have been constantly declining in recent years. In 2018-19, refills consumed on an average reduced to

[7] https://www.pmuy.gov.in/about.html.

[8] https://www.news18.com/news/business/lpg-subsidy-rule-change-who-are-eligible-how-much-subsidy-you-will-get-other-key-details-5302369.html

[9] https://iocl.com/indane-14Kg-nonsubsid-previous-price.

2.98 instances per year from 3.4 per year in 2017-18.[10] Hence, for full transition to LPG and discouraging fuel stacking behavior, subsidizing the use of LPG fuel for poor rural households more generously may be an important policy measure. Gould and Urpelainen (2018) who use a survey of households use of LPG for various cooking activities, collected from six north Indian states, also suggest subsidizing LPG more generously for poor for sustained use of LPG.

The rest of the paper is organized in following ways. The next section details the data, Section 3 presents the empirical framework. Section 4 presents the results, and Section 5 concludes.

2 Data

We use two waves of India Human Development Survey (IHDS) collected in 2011-12 and 2004-05 (henceforth, 2012 and 2005, respectively).[11] The IHDS are multi-topic surveys collected jointly by the University of Maryland and National Council of Applied Economic Research (NCAER) in New Delhi, India (See Desai et al. 2010; Desai and Vanneman, 2015 for details). Both waves are publicly available through the Inter-university Consortium for Political and Social Research (ICPSR). 2012 IHDS surveyed 42,153 households (27,580 rural and 14,573 urban) in 1,503 villages and 971 urban neighborhoods across India. Out of these 42,153 households, 40,018 households were also surveyed in the 2005 IHDS. We use only those households that were surveyed in both rounds. We further drop 653 households who do not report cooking. Thus our final data contains a balanced panel of 39,365 households (26,927 rural and 12,438 urban) and a balanced panel of 148,760 individuals.

[10] https://www.thehindu.com/data/data-how-effective-has-the-pradhan-mantri-ujjwala-yojana-been/article30338388.ece.

[11] Although, the 2012 IHDS data remains the last available nationally representative multi-topic panel data for India at the time of writing (December 2022), it seems outdated given the impressive improvement in the access to LPG in India since 2012 (discussed earlier). However, the nature of estimate provided in the paper is ATET, i.e., impact on the health outcomes of the households which experienced the switch. The validity of the estimate should not be affected by the year of the data if the nature of (pollution generated from) biomass and LPG remains similar.

The IHDS surveys include a health module that inquires about each household member's health through questions about issues related to short-term morbidity, such as coughs, fevers, and diarrhea, and long-term morbidity from chronic diseases ranging from asthma to cancer category.[12] The IHDS data contain several socioeconomic information at the household and individual level. The IHDS also have a detailed energy module where respondents were asked detailed questions about their use of all energy sources. In our data, there are total six fuels used for cooking firewood, dung, crop residuals, coal/charcoal, kerosene, and LPG. IHDS questionnaire lists each fuel type and asks from the respondent whether the household has used the fuel for cooking purposes. The use of electricity as fuel type is not listed, however, according to 2011 Census data, only 0.10 percent of households in India listed electricity as their main cooking fuel. Appendix Figure 1 presents the use of different fuels in 2005 and 2012 data. We group firewood, dung, crop residuals, and coal/charcoal, and kerosene together as polluting fuels, and LPG as a separate clean fuel. The World Health Organization (2014), in its indoor air quality guidelines, defines solid fuels, including coal and biomass (e.g., charcoal, wood, dung and crop residues), and kerosene as "polluting". If households report using polluting fuels with LPG, it is categorized separately as using mixed fuels or adopting fuel stacking strategy.

Table 1 presents the incidence of cooking fuel switching between 2005 and 2012. About three quarters of the households maintained the status quo in terms of cooking fuels (diagonal terms in Table 1). Only 4.5 percent of the households that used solid fuels in 2005 moved to LPG, whereas 17 percent of households moved to mixed fuels or fuel stacking. Similarly 14.4 percent of the households that were using mixed fuels in 2005 moved to solid fuels in 2012. A reverse movement from LPG is also observed for some households that were relying only on LPG in 2005.

Table 2 presents the average incidence of short-term respiratory issues, such as cough

[12] In essence, IHDS surveys inquire whether an individual has been diagnosed for cataract, tuberculosis, high blood pressure, heart disease, leprosy, cancer, asthma, polio, paralysis, epilepsy, STD/AIDS, accident, or other long term disease.

and cough with breathing issues. Panel 1 of Table 2 presents the outcome of interest at the household level that takes a value of one if any member in the household report the issue in last 30 days. As expected, there is a large difference in the incidence rate between households that use sole LPG vs. households that rely on solid fuels or mixed fuels. Many of these differences may be the result of socioeconomic, demographic, educational, or living arrangement differences as LPG user households generally tend to be well-off compared to households who rely solely on solid fuels. What is striking is that there exists only small differences in incidence rates between households that adopt fuel stacking compared to households that rely solely on solid fuels. In Panel 2 of Table 2, we report incidence of cough and cough with breathing issues reported by individuals grouped by households fuel choice and gender. Incidence of both the adverse health issues is higher among females compared to males irrespective of choice of fuels by households. Less incidence is reported among LPG using households compared to households using solid or mixed fuels.

3 Empirical Framework

3.1 Fixed effects

We start with a model that assumes that the adverse health outcome for household i in time period t, y_{it}, depends on household characteristics and household fuel choice in period t.

$$y_{it} = f(x_{it}) + \beta.fuel_{it} + \gamma_i + \varepsilon_{it} \; where \;\; t = 2005, 2012 \tag{1}$$

where γ_i is the household specific time invariant unobservables, and $fuel_{it} \in [-1, 0, 1]$. The solid fuels, mixed fuels, and LPG are coded as $-1, 0$, or 1, respectively. In this set up, a fixed effect estimation will get rid of household specific time-invariant factors (γ_i), and β will capture the impact of fuel transition on the outcome of interest. A negative β will imply that movement up the fuel ladder reduces the probability of adverse health outcome for the households. Although, fixed effects estimate is easily interpretable, it treats movement from solid to mixed and mixed to LPG as same, and may not be useful to policy makers or households who are considering a switch. To allow for differential impacts of different type of fuel transitions based on the baseline fuel choice, we implement a difference-in-differences strategy with multivalued treatments.

3.2 Difference-in-differences with multivalued treatments

At any point of time, households may choose between solid fuels, mixed fuels, or sole LPG. Since, we observe household's choice in 2005 and 2012, we can identify the switch in fuel between 2005 and 2012, conditional on 2005 fuel choice. Our main interest lies in finding out the impact on health outcomes because of the switch in fuel choice. Conditional on the fuel choice in 2005, households have three possible choices for 2012: maintain the status quo and there is no switch of fuel; switch to any of the two other fuel options available. For example, if a household was using solid fuels in 2005, it may keep using solid fuels in 2012 (status quo), or choose either of mixed fuels or sole LPG fuel in 2012. So, basically we compare the change in health outcomes of households which switched fuels to households that maintain the status quo. Household's 2012 choice is not necessarily moving up the fuel ladder but they also may also move down the fuel ladder. A sole LPG using household in 2005 may use a mixed fuels or move completely to solid fuels in 2012. Let switch (τ_i) capture the change in fuel choice between 2005 and 2012 for household i.

$$\tau_i = \begin{cases} 0 & if\ fuel_{2005} = fuel_{2012} \\ 1\ or\ 2 & if\ fuel_{2005} \neq fuel_{2012} \end{cases}$$

where 1 or 2 are other two different fuel options available to households for 2012 conditional on their fuel choice in 2005. Thus in this set up, the fuel transition choice is not binary but has three options. Hence we utilize the multivalued treatment effect (MVTE) model to address the selection into the three choices, where the change in health outcomes is used as outcome variable. Cattaneo (2010), Imbens (2000), and Wooldridge (2010, sec. 21.6.3) discuss aspects of treatment effect estimation with multivalued treatments.

Let $\triangle y_i = y_{i,2012} - y_{i,2005}$ is the observed change in health outcomes for household i. Following the framework of Cattaneo (2010), Linden et al. (2015), Uysal (2015), the change in the outcome can be expressed as a function of fuel switch indicator $D_{it}(T_i)$.

$$\triangle y_i | fuel_{i,2005} = \sum_{t=0}^{2} D_{i\tau}(T_i) \triangle y_{i\tau} \tag{2}$$

where $D_{it}(T_i) = \mathbf{1}(T = \tau)$ for $\tau \in [0, 1, 2]$, and $\mathbf{1}()$ is an indicator function. Since, the switch values capture different types of fuel transitions based on initial fuel use, we condition the change in outcomes on 2005 fuel choice. Empirically, it will be equivalent to carrying out similar analysis on three sub samples of data divided on the basis of 2005 fuel choice (solid, mixed, or LPG).[13] In multiple treatment settings, Lechner (2001) presents several pairwise comparison of effect of treatments m and l. We are interested in the effect on the household who actually switched fuels in 2012 conditional on fuel choice in 2005 (i.e., $m(\tau = 1$ or $2)$ and $l(\tau = 0)$).

$$\gamma_{m|l} = E[\triangle y_{im} - \triangle y_{il} | T_i = m] \tag{3}$$

The notation $E(.|m = 1)$ denotes the mean in the population of all households who implemented switch m. Since $\triangle y_{il}$ (change under the status quo) is not observed for households who switched the fuels, the average treatment effects on treated (ATET) defined above cannot be identified from the observed data without further assumptions. The MVTE model provide us estimates for ATET, and the estimates are valid under the two assumptions: For all $\tau = 0, 1$,or 2, a) selection on observables $(\Delta y_i(\tau) \perp D_{i\tau}(T_i) \;|x)$; b) Non-empty-cells: $0 < p_{min} < P(T = \tau|X)$ (Cattaneo, 2013). Assumption (1) implies that the distribution of each potential outcome $\mathit{\Delta} y(\tau)$ is independent of the random treatment $D_{it}(T)$, conditional

[13] We omit the conditional on 2005 fuel choice term from the rest of the equations.

on the covariates x. Assumption (2) says that for every possible x in the population, there is a strictly positive probability that someone with that covariate pattern could be assigned to each treatment level.[14] Under this assumption, Cattaneo (2010) derives the large-sample properties of inverse-probability weighted (IPW) estimators and efficient-influence-function (EIF) estimators for the means, quantiles, and other features of the potential-outcome distributions when the treatment variable can have multiple distinct values.

Imbens (2000) introduced generalized propensity score (GPS) as a practical alternative to conditioning directly on X_i in case of multivalued treatments (Linden et al., 2016). The GPS is the conditional probability of receiving a particular level of the treatment given the pretreatment variables such as:

$$r(\tau, x) = P[T_i = \tau | X_i = x]$$

The GPS is estimated using a multinomial logistic model as the response variable has three categories. We employ a rich set of observed baseline 2005 characteristics that include demographic, education, economic, household members health conditions, and social network information and multinomial logistic model to estimate the GPS. The multinomial logistic model also includes indicators for any kind of shock experienced by household between 2005 and 2012, indicators for month of survey in both 2005 and 2012, and state of residence. The variables used in multinomial logistics model are pre fuel switch, and are not affected by the fuel switch by the households (Jalan and Ravallion, 2003). The full set of variables used to estimate GPS is reported in appendix Table A1. Using the GPS, Imbens (2000) shows that, as in the binary treatment case, one can identify the unconditional means of the potential

[14] One can estimate the ATET under less restrictive versions of the conditional independence assumption and the sufficient overlap assumption than those required for the average treatment effect (ATE). While ATE estimation requires that the potential outcomes for both the treated and the not treated be conditionally independent of treatment assignment, ATET estimation requires that only the not treated potential outcome be conditionally independent of treatment assignment (StataCorp, 2021, p134).

outcomes by weighting, and we use inverse probability weighting, IPW:[15]

$$E\left[\frac{\triangle y_i D_{i\tau}(T_i)}{r(\tau, X_i)}\right] = E[\triangle y_i(\tau)] \tag{4}$$

Based on the above hypotheses, the average treatment effect on treated (ATET) for treatment m (switch) relative to treatment l (the status quo) is given by (Uysal, 2015):

$$\gamma_{m|l}^{IPW} = \frac{1}{N_m}\sum_{i=1}^{N} \Delta y_i D_{im}(T_i) - \frac{1}{N_l}\sum_{i=1}^{N} \Delta y_i D_{il}(T_i)\frac{\hat{r}(m, X_i)}{\hat{r}(l, X_i)}$$

where $\hat{r}(m, X_i)$ and $\hat{r}(l, X_i)$ are estimated GPS for switch m and l (the status quo), and the superscript 'IPW' denotes inverse probability weighting. Busso, DiNardo, and McCrary (2014) demonstrate that reweighting exhibits the best finite sample performance of any of the estimators they considered.

4 Results

4.1 Fixed Effects

In Panel 1 of Table 3, we present the results from household fixed effects. All the specifications control for month of survey, and a large set of variables reported in Web Appendix Table W1. The dependent variable is the probability that any of the household members reported adverse health outcome. The coefficient on the fuel term is negative and statistically significant for both the adverse health outcomes, suggesting negative effect of fuel switch towards a cleaner option on the probability of households reporting adverse health outcomes. Households using LPG are 6 percentage points less likely to report cough compared to households that use polluting fuels ($\Delta fuel = 2$). This is about 17.6 percent reduction in incidence of cough resulting from a clean switch from polluting fuels to LPG. Similarly, a fuel switch

[15] Although, propensity score matching methods have not been fully developed for more than a single value of treatment, one can use weighting methods similar to the binary case.

from polluting fuels to LPG reduces the probability of households reporting cough with breathing issues by 3.8 percentage point which translates into 22 percent reduction based on 2005 average incidence level.

Panel 2 of Table 3 presents the results from individual fixed effects specifications. All specifications control for age, education, whether the person smoke, month of survey and other variables reported in Web appendix Table W2. Overall, the individual level fixed effects model provides similar results as discussed for household level fixed effect. An individual is 2.12 percentage points less likely to report cough if the household has shifted from polluting fuels to LPG. This is about 24 percent reduction in cough incidence based on 2005 average incidence. Similarly, a complete shift towards LPG from solid fuels reduces the probability of an individual reporting cough with breathing issue by about 1 percentage points, which translates into about 24 percent reduction in incidence based on 2005 average incidence. Panel 2a and Panel 2b of Table 3 present estimates for males and females, respectively. Since women spend more time in the kitchen, one would expect a switch from polluting fuels to LPG should have larger effect on females. In terms of percentage points, we see a marginally larger reduction in incidence of short-term respiratory issues for females. However, given that the incidence of short-term respiratory issues was larger among women in 2005, the percent decline over 2005 is marginally higher among men for cough with breathing issues. Though, the fixed effect models suggest that a switch towards cleaner fuels reduces probability of short-term adverse respiratory outcomes reported by household, they treat movement towards mixed fuels or LPG same. Next we move to results from multivalued treatment effect models that distinguish different moves.

4.2 Multivalued treatment effects

Table 4 presents estimates for the impact of fuel switch conditional on baseline fuel choice. In Panel 1 of Table 4, the population of interest is the households who were using polluting or solid fuels in 2005. If all those households continued to use solid fuels, the incidence of cough reported by those households should have shown an increase of 4.8 percentage points (potential outcome mean). For households who shifted from the solid fuels to LPG between 2005 and 2012, the probability of any household member reporting cough decreased by 12 percentage points compared to households who continued to use solid fuels in 2012 (ATET). Similarly, the households that shifted to LPG from solid fuels reported 7.3 percentage points less incidence of cough with breathing issues. Hence, a switch from solid fuels to LPG reduces the incidence of short-term respiratory issues in households that switched by about one-third given the 2005 reported levels. While the impact of fuel switch from solid fuels to LPG is clear for short-term respiratory health outcomes, there is no evidence that an incomplete shift towards mixed fuels has any effect in reducing the probability of any household member reporting adverse health outcomes. In column (3) and (4), we consider the share of household members who reported cough or cough with breathing issues as outcome variable to rule out that probability of a household reporting short-term respiratory issues is driven by relatively different changes in number of members in household across the three categories over time. The findings for the share of members reporting cough or cough with breathing issues outcomes are similar to the findings with the probability of households reporting outcomes.

In Panel 2 of the Table 4, we report the estimates for the households who were using mixed fuels in 2005. If the households who were using mixed fuels continued to use mixed fuels, they may not have seen any changes in the probability of any household member reporting cough or cough with breathing issues. For mixed fuels using households in 2005 who shifted to LPG in 2012, the estimates suggest a decline in incidences of cough and cough with breathing issues compared to the case where they continued the status quo. Although the estimates are negative and large based on 2005 incidence levels, they are not statistically significant at conventional level. Noteworthy, a downward shift from mixed to solid fuels has no impact on the probability of any household member reporting cough or cough with breathing issues. The results are qualitatively similar for the share of household members reporting outcomes. The point estimates are negative for a switch from mixed fuels to LPG, whereas positive for a switch from mixed fuels to solid fuels.

Panel 3 of Table 4 presents estimates for the households that were using LPG in 2005. The ATET estimates are large and positive for the LPG using households that moved to either solid or mixed fuels suggesting that those households experienced an increase in incidence of cough or cough with breathing issues compared to households that continued to use LPG. We get similar results for the share of household member reporting short-term respiratory issues. Although the ATET estimates are not statistically significant at conventional level (partly because of limited number of households involved in this type of switch), the positive signs on the ATET estimates reinforces the idea that the negative impact on the probability of adverse health outcomes resulting from a shift towards LPG from either solid fuels or mixed fuels are picking up the causal effect. In the next subsection, we explore the impact using individual level data.

4.2.1 Multivalued treatment effects: Individual level analysis

In Table 5, we report the estimates based on individual level data for adult male, adult female, and children, separately. Anyone age 21 and above in 2012 data are classified as adult, while below 21 years of age in 2012 data are classified as children. Note that the adults would have been 14 years or above age in 2005 data, while children should be less than 14 years of age in 2005 data. Since women do most of the cooking in Indian context (GOI, 2020), they may be more vulnerable to diseases caused by indoor air pollution from polluting biomass fuels (Gordon et al., 2014). However, other members of the household also get exposed to HAP, particularly children. For example, in a study conducted in rural India, Balakrishnan et al. (2002) find that 24- hour average exposure concentrations for respirable particulate matter in wood-using households was about at 226 $\mu g/m^3$ for cooks, while for non-cooks it was 172 $\mu g/m^3$. At the same time, mean daily exposure concentrations were similar for cooks and non-cooks at 76–79 $\mu g/m^3$ for LPG using households.

In Panel 1 of Table 5, the relevant population group is the households who were using solid fuels in 2005. Adult individuals who belong to the households who switched to LPG from solid fuels saw a decline in the incidence of cough or cough with breathing issues compared to the case where they continued using solid fuels. Importantly, the negative impact on adult females is considerably larger compared to the impact on adult males. Surprisingly, we do not see any impact on children in households who switched from solid fuels to LPG compared with the households who continued using solid fuels. Noteworthy, the households who continued using biomass saw a decline in the probability of a child reporting either cough or cough with breathing issues. This is dramatically different than the impact on adult men and women. It is worth pointing out that children were classified as individuals aged 14 and below in 2005 data, these individuals will be around 7-21 years of age in 2012 data. Since children under the age of five spend most of their time with their mothers in developing countries, young children tend to be more exposed to HAP along with women (Edwards and Langpap, 2012). Give that children in 2005 have grown up during the panel time period, and probably spend more time outside kitchen area, potentially explain why households who continued to use solid fuels saw a decline in incidence of cough and cough with breathing issues for children defined as someone who was age 14 or below in 2005 IHDS data. Consistent with the household level analysis, there is no effect of a switch from solid fuels to mixed fuels on individuals' health outcomes.

In Panel 2 of Table 5, we look at the individual level health outcomes for households that were using mixed fuels in 2005. Consistent with the earlier results, we find a larger negative impact on the probability of adverse health outcomes for adult women compared to adult men in the households that shifted to LPG from mixed fuels. We also find that incidence of adverse outcomes decreases among children in households that moved to LPG from mixed fuels compared to the case where they continued using mixed fuels. Surprisingly, a downward movement towards solid fuels from mixed fuels reduces the incidence of adverse health outcomes in adult women, however, no impact among adult men and children. Although it is not clear why a downward shift to solid fuels from mixed fuels reduces incidence of adverse health outcomes among adult females, one can only speculate that having access to clean fuels while practicing fuel stacking can give rise to false sense of safety leading to some lax cooking practices that may be driving the results.

Panel 3 of Table 5 presents estimates for individuals whose households were using LPG in 2005. ATET estimates for the downward shift from LPG to solid or mixed fuels are positive for all three groups with the exception for adult females for the outcome cough with breathing issues, where point estimate is close to zero though negative. A shift to mixed fuels from LPG increases the incidence of cough in adult females and children (statistically significant). Positive coefficients for downward shift from LPG support the causal interpretation of earlier results.

5 Conclusion

In this paper, we combine multivalued treatment set up with difference-in-differences methodology to evaluate the impact of cooking fuel switch by households on the incidence of short-term respiratory issues such as cough and cough with breathing issues. Unlike the literature that treats fuel choice as binary outcome, i.e., biomass or clean fuel, we allow fuel stacking or mixed fuels as a third choice. We compare the change in the probability of adverse health outcomes for households that switched fuels to households that maintain the status quo. Our estimates capture the causal effect of switch on the households who implemented that switch, known as average treatment effect on treated (ATET) in the program evaluation literature.

We find that a switch from solid fuels or mixed fuels to LPG reduces the probability of any member in the household reporting short-term respiratory issues. However, a shift from solid fuels to mixed fuels (commonly known as fuel stacking) does not affect health outcomes. We also find that a reverse shift from LPG to either solid fuels or fuel stacking increases the probability of any household member reporting short-term respiratory issues. We find qualitatively similar results using individual level data. We also find that a switch to LPG lead to a larger reduction in terms percentage points for adult women compared to adult men.

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Table-1: Fuel Switches between 2004-05 and 2011-12

		Fuel Choice 2011-12			
		Solid	**Mixed**	**LPG**	**N**
Fuel choice in 2004-05	**Solid**	**20,543**	4,389	1,186	26,118
		(78.65)	(16.8)	(4.54)	(100)
	Mixed	1,034	**4,402**	1,751	7,187
		(14.39)	(61.25)	(24.36)	(100)
	LPG	287	1,533	**4,226**	6,046
		(4.75)	(25.36)	(69.9)	(100)
	N (households)	21,864	10,324	7,163	39,351

Note: Percentages are reported in parenthesis.

Table 2: Incidence of adverse health outcomes

Panel 1: Household-level outcome, Probability of any household member reporting (1/0)				
	2004-05		2011-12	
Household Fuel Choice	**Cough**	**Cough with breathing issue**	**Cough**	**Cough with breathing issue**
Solid Fuels	0.359	0.189	0.432	0.201
Mixed Fuels	0.342	0.162	0.381	0.160
LPG	0.254	0.104	0.287	0.108
Panel 2: Individual-level outcome, Probability of an individual reporting (1/0)				
2a: Male				
Solid	0.092	0.046	0.129	0.056
Mixed	0.074	0.030	0.104	0.044
LPG	0.057	0.024	0.082	0.028
2b: Female				
Solid	0.107	0.053	0.149	0.059
Mixed	0.090	0.036	0.125	0.052
LPG	0.076	0.029	0.099	0.034

Table 3: Impact of fuel switches on adverse health outcomes, fixed effects model

	Cough	Cough with breathing issue
Panel 1: Household Fixed Effects, Probability (Any household member reporting)		
Fuel	-0.030***	-0.019***
	(0.005)	(0.004)
Mean in 2004/05	*0.340*	*0.171*
Observations	78,347	78,347
R-squared	0.569	0.544
Panel 2: Individual Fixed Effects, Probability (individual member reporting)		
Fuel	-0.0106***	-0.0046***
	(0.002)	(0.001)
Mean in 2004/05	*0.087*	*0.039*
Observations	295,564	295,564
R-squared	0.542	0.521
Panel 2a: Individual Fixed Effects, Female, Probability (female member reporting)		
Fuel	-0.0122***	-0.0047***
	(0.002)	(0.002)
Mean in 2004/05, female	0.0949	0.0423
Panel 2b: Individual Fixed Effects, male, Probability (male member reporting)		
Fuel	-0.0091***	-0.0045***
	(0.002)	(0.001)
Mean in 2004/05, male	0.0790	0.0365

Note: A negative coefficient implies that a fuel switch in cleaner direction reduces the probability of adverse outcome. Standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The models control for indicators for year 2011 and month of survey in addition to a set of characteristics. Full model is reported in Web appendix Table A1.

Table 4: Impact of fuel switches on incidence of adverse health outcomes (household level)

		Probability of any member reporting		Share of households' members reported	
	Switch in 2011-12	**Cough**	**Cough with breathing issue**	**Cough**	**Cough with breathing issue**
		(1)	(2)	(3)	(4)
Panel 1: 2004-05 fuels: Solid (N=25848)					
2012: Solid vs. 2005: Solid	*Status Quo*	0.048***	0.016*	0.045***	0.020***
		(0.012)	(0.010)	(0.005)	(0.003)
2012: Mixed vs. 2005: Solid	*Mixed*	0.012	-0.004	-0.010*	-0.009***
		(0.014)	(0.011)	(0.005)	(0.003)
2012: LPG vs. 2005: Solid	*LPG*	-0.122***	-0.073***	-0.056***	-0.027***
		(0.030)	(0.021)	(0.017)	(0.007)
Mean in 2004/05, Solid fuel users		*0.359*	*0.189*	0.093	0.044
Panel 2: 2004-05 fuels: Mixed (N=7134)					
2012: mixed vs. 2005: mixed	*Status Quo*	0.010	-0.016	0.023***	0.009**
		(0.019)	(0.015)	(0.007)	(0.004)
2012: Solid vs. 2005: mixed	*Solid*	0.016	-0.002	0.019**	0.009
		(0.023)	(0.017)	(0.008)	(0.006)
2012: LPG vs. 2005: mixed	*LPG*	-0.045	-0.054*	-0.017	-0.021***
		(0.041)	(0.030)	(0.013)	(0.008)
Mean in 2004/05, Mixed fuel users		*0.342*	*0.162*	0.087	0.036
Panel 3: 2004-05 fuels: LPG (N=5998)					
2012: LPG vs. 2005: LPG	*Status Quo*	-0.044	-0.070	0.004	-0.015
		(0.069)	(0.063)	(0.019)	(0.017)
2012: Solid vs. 2005: LPG	*Solid*	0.086	0.052	0.022	0.015
		(0.073)	(0.064)	(0.021)	(0.016)
2012: Mixed vs. 2005: LPG	*Mixed*	0.131*	0.090	0.031	0.023
		(0.072)	(0.063)	(0.020)	(0.017)
Mean in 2004/05, LPG users		*0.254*	*0.104*	0.067	0.026

Note: Potential outcome is reported in first row of each panel, rows 3 and 5 of each panel report average treatment effect on treated (ATET). Standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Impact of fuel switches on incidence of adverse health outcomes (individual level)

		Male Adult		Female Adult		Child	
	Switch	Cough	Cough with breathing issue	Cough	Cough with breathing issue	Cough	Cough with breathing issue
		(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: 2004-05 fuels: Solid							
2012: Solid vs. 2005: Solid	*Status Quo*	0.034***	0.015***	0.055***	0.021***	-0.036***	-0.037***
		(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.004)
2012: Mixed vs. 2005: Solid	*Mixed*	-0.006	-0.001	-0.004	-0.003	-0.008	0.002
		(0.005)	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)
2012: LPG vs. 2005: Solid	*LPG*	-0.021	-0.025***	-0.091***	-0.041***	-0.028	0.001
		(0.014)	(0.010)	(0.021)	(0.014)	(0.026)	(0.017)
Mean in 2004/05, Solid fuel users		0.054	0.024	0.089	0.041	0.154	0.083
N		22394		20888		22369	
Panel 2: 2004-05 fuels: Mixed							
2012: mixed vs. 2005: mixed	*Status Quo*	0.048***	0.031***	0.079***	0.045***	-0.004	0.000
		(0.006)	(0.005)	(0.008)	(0.007)	(0.009)	(0.006)
2012: Solid vs. 2005: mixed	*Solid*	0.000	-0.009	-0.025**	-0.025***	0.012	-0.012*
		(0.007)	(0.006)	(0.010)	(0.007)	(0.011)	(0.006)
2012: LPG vs. 2005: mixed	*LPG*	-0.040***	-0.031***	-0.063**	-0.038	-0.123***	-0.101***
		(0.013)	(0.007)	(0.029)	(0.030)	(0.036)	(0.032)
Mean in 2004/05, Mixed fuel users		0.045	0.017	0.072	0.028	0.138	0.058
N		19317		18002		16388	
Panel 3: 2004-05 fuels: LPG							
2012: LPG vs. 2005: LPG	*Status Quo*	-0.006	-0.024	0.014	0.003	-0.092***	-0.063***
		(0.033)	(0.027)	(0.019)	(0.009)	(0.031)	(0.021)
2012: Solid vs. 2005: LPG	*Solid*	0.056	0.054*	0.018	-0.008	0.067	0.038
		(0.038)	(0.032)	(0.036)	(0.022)	(0.041)	(0.027)
2012: Mixed vs. 2005: LPG	*Mixed*	0.028	0.038	0.058**	0.026	0.088**	0.051*
		(0.037)	(0.030)	(0.028)	(0.020)	(0.039)	(0.027)
Mean in 2004/05, LPG users		0.029	0.012	0.055	0.02	0.139	0.057
N		10520		9601		6938	

Note: Potential outcome is reported in first row of each panel, rows 3 and 5 of each panel report average treatment effect on treated (ATET). Standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Figure-A1: Proportion of households using different sources of fuel for cooking

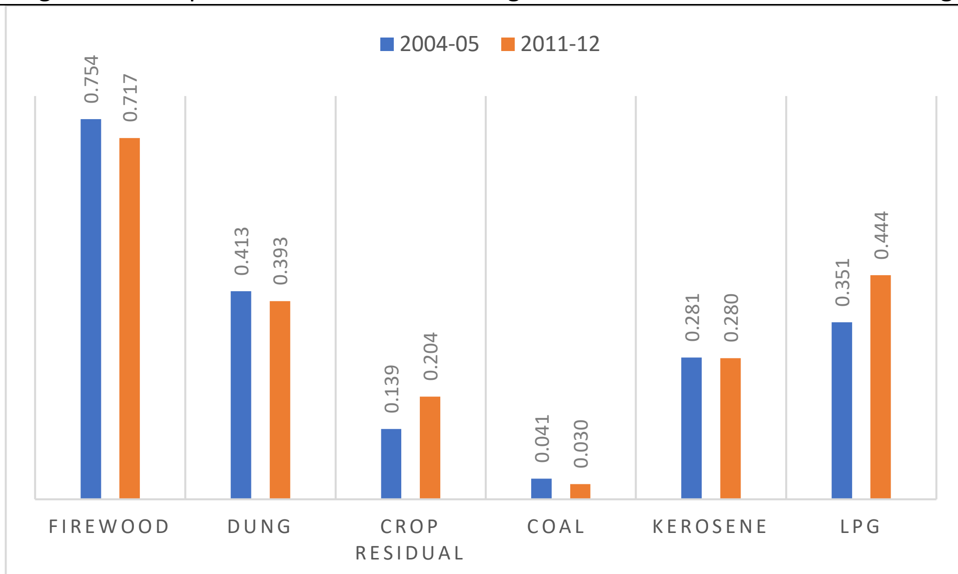

Table1 A1: Baseline (2004/05) characteristics used in multinomial model of households' fuel switch

	Solid fuels	Mixed fuels	Solid fuels
Other Backward Castes+	0.37	0.30	0.30
Scheduled Castes+	0.25	0.15	0.12
Scheduled Tribes+	0.11	0.03	0.03
Muslim+	0.12	0.12	0.09
Household Size	5.95	6.17	5.09
Household Size Square	44.95	48.10	31.53
% of age 0-14 in HH	0.31	0.25	0.23
% of age 61 and above in HH	0.07	0.08	0.08
% of age 15-49 female in HH	0.25	0.27	0.29
log per capita consumption	6.88	7.49	7.69
log of per capita income	8.89	9.67	10.11
No ration card+	0.15	0.09	0.16
BPL card+	0.41	0.20	0.14
Poor+	0.30	0.08	0.06
Head age	47.32	50.58	48.58
Head is female+	0.09	0.10	0.09
Head's education	3.49	6.90	9.33
Head's work type-casual+	0.53	0.26	0.21
Head's work type-salaried+	0.05	0.17	0.29
Head's work-type-government+	0.04	0.14	0.23
% of members who smoke	0.09	0.06	0.04
% of members reported- cough	0.09	0.09	0.07
% of members reported- cough with breathing issues	0.04	0.04	0.03
% of members reported- cataract	0.01	0.01	0.00
% of members reported- tuberculosis	0.00	0.00	0.00
% of members reported- cancer	0.00	0.00	0.00
% of members reported- asthma	0.01	0.01	0.00
HH has piped water access+	0.32	0.52	0.74
HH has hand pump water access+	0.36	0.24	0.13
HH has no access to toilet+	0.78	0.28	0.13
HH has no electricity+	0.35	0.02	0.01
House building in poor conditions+	0.22	0.09	0.10
HH use radio+	0.11	0.17	0.16
HH use paper+	0.07	0.37	0.54
HH use Television+	0.21	0.58	0.69
HH know some doctor+	0.25	0.42	0.46
HH know some teacher+	0.33	0.52	0.53
HH know some government servant+	0.23	0.51	0.54
Anyone in HH member of self-help group+	0.11	0.11	0.05
Anyone in HH member of Development of NGO+	0.01	0.03	0.03
Attended local body meeting+	0.32	0.32	0.18

Great deal of confidence in state govt+	0.27	0.24	0.25
Cooking in living area	0.24	0.11	0.12
Used improved stove	0.03	0.08	NA
Shocks between 2005 and 2012			
Major illness/Accidents - large amount of expenditure/loss	0.27	0.26	0.25
Drought, Flood, Fire - large amount of expenditure/loss	0.10	0.05	0.03
Crop Failure - large amount of expenditure/loss	0.21	0.11	0.03
Urban	0.15	0.35	0.83
N	**26118**	**7187**	**6046**

Note: Indicators for month of survey in 2004/05 and 20011/12, and state of residence are also controlled for but not reported.

Table W1: Impact of fuel switches on adverse health outcomes, household fixed effects model

	(1)	(2)
	Probability of a household member reporting	
	Cough	Cough with breathing issue
Fuel	-0.030***	-0.019***
	(0.005)	(0.004)
Household Size	0.030***	0.018***
	(0.003)	(0.002)
Household Size Square	-0.000***	-0.000
	(0.000)	(0.000)
% of age 0-14 in HH	0.193***	0.083***
	(0.016)	(0.013)
% of age 61 and above in HH	0.053***	0.063***
	(0.018)	(0.015)
% of age 15-49 female in HH	0.033*	0.002
	(0.019)	(0.016)
log per capita consumption	0.050***	0.036***
	(0.006)	(0.005)
log of per capita income	-0.005***	-0.004***
	(0.002)	(0.001)
No ration card+	0.006	0.011*
	(0.008)	(0.006)
BPL card+	0.005	-0.002
	(0.006)	(0.005)
Poor+	-0.038***	-0.033***
	(0.008)	(0.006)
Head age	-0.000	-0.000
	(0.000)	(0.000)
Head is female+	-0.003	0.008
	(0.011)	(0.009)
Head's education	-0.000	0.002***
	(0.001)	(0.001)
Head's work type-casual+	0.022***	0.016***
	(0.006)	(0.005)
Head's work-type-government+	-0.003	-0.008
	(0.012)	(0.010)
% of members reported- smoking daily	0.147***	0.041**
	(0.022)	(0.018)
HH has piped water access+	-0.011	-0.004
	(0.008)	(0.006)
HH has hand pump water access+	-0.008	-0.013*

	(0.008)	(0.007)
HH has no access to toilet+	-0.004	-0.003
	(0.007)	(0.005)
HH has no electricity+	-0.005	0.001
	(0.008)	(0.007)
House building in poor conditions+	-0.009	-0.012*
	(0.008)	(0.006)
HH use radio+	0.015*	0.011
	(0.009)	(0.007)
HH use paper+	-0.001	-0.007
	(0.008)	(0.006)
HH use Television+	-0.016***	-0.013***
	(0.006)	(0.005)
HH know some doctor+	0.032***	0.007
	(0.006)	(0.005)
HH know some teacher+	0.012**	-0.006
	(0.006)	(0.005)
HH know some government servant+	-0.002	-0.003
	(0.006)	(0.005)
Anyone in HH member of self-help group+	0.016**	0.004
	(0.008)	(0.006)
Anyone in HH member of Development of NGO+	0.009	-0.030*
	(0.020)	(0.016)
Attended local body meeting+	0.014**	0.016***
	(0.006)	(0.004)
Confident in medical facility	0.009	-0.014***
	(0.006)	(0.004)
Confidence in state	-0.001	-0.005
	(0.005)	(0.004)
Cook in living area	-0.003	-0.001
	(0.006)	(0.005)
Used improved Chula for biomass	-0.007	-0.005
	(0.011)	(0.009)
Constant	-0.147***	-0.142***
	(0.053)	(0.042)
Observations	78,347	78,347
R-squared	0.569	0.544

Note: The model includes household fixed effects, fixed effects for month of survey and year. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table W2: **Impact of fuel switches on adverse health outcomes, individual fixed effects model**

VARIABLES	(1) Cough	(2) Cough with breathing issue
Fuel	-0.0107***	-0.0047***
	(0.002)	(0.001)
age	0.0009***	0.0008***
	(0.000)	(0.000)
Years of schooling	-0.0071***	-0.0038***
	(0.000)	(0.000)
female	-0.0031	-0.0024
	(0.013)	(0.009)
casual worker	0.0011	0.0001
	(0.002)	(0.002)
Smoke daily	0.0142***	0.0012
	(0.004)	(0.003)
Head's education	0.0001	0.0004**
	(0.000)	(0.000)
Poor+	-0.0109***	-0.0073***
	(0.002)	(0.002)
House building in poor conditions+	0.0028	-0.0011
	(0.003)	(0.002)
Household Size	-0.0046***	-0.0016***
	(0.000)	(0.000)
log per capita consumption	0.0269***	0.0138***
	(0.002)	(0.001)
HH use radio+	0.0058**	0.0026
	(0.003)	(0.002)
HH use paper+	-0.0015	-0.0029*
	(0.002)	(0.002)
HH use Television+	-0.0029	-0.0020
	(0.002)	(0.001)
HH know some doctor+	0.0123***	0.0040***
	(0.002)	(0.001)
HH know some teacher+	0.0047***	-0.0004
	(0.002)	(0.001)
HH know some government servant+	-0.0054***	-0.0040***
	(0.002)	(0.001)
Cook in living area	0.0060***	-0.0002
	(0.002)	(0.001)
used improved Chula for biomass	-0.0034	0.0004
	(0.003)	(0.002)
HH has piped water access+	-0.0079***	-0.0015
	(0.003)	(0.002)
HH has hand pump water access+	-0.0121***	-0.0053***
	(0.003)	(0.002)
HH has no access to toilet+	-0.0041*	0.0000
	(0.002)	(0.001)

HH has no electricity+	0.0075***	0.0065***
	(0.003)	(0.002)
Anyone in HH member of self-help group+	0.0024	-0.0004
	(0.002)	(0.002)
Anyone in HH member of Development of NGO+	0.0052	-0.0036
	(0.006)	(0.004)
Attended local body meeting+	0.0053***	0.0043***
	(0.002)	(0.001)
Constant	-0.0565***	-0.0497***
	(0.019)	(0.013)
Observations	295,564	295,564
R-squared	0.542	0.521

Note: The model includes individual fixed effects, fixed effects for month of survey and year. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1