Fuel Switching and Labor Supply of Rural Women in India

Qinghe Su[1]

Texas State University

Abstract

Using the nationally representative Indian Human Development Survey, we study whether use of cleaner energy source for cooking leads to increased female work participation. We categorize women household into three groups by the cooking fuel they use: biomass, mixed fuel, and modern fuel. The methodology used in this paper is difference-in-differences with multivalued treatment. We find that switching from solid to mixed fuel negatively affects women's work participation. This study also confirms that switching from mixed to modern fuel will increase the probability of female work participation in rural India significantly. Moreover, we do not find any average treatment effect on the female work participation for households who maintain the status quo.

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Key Words: fuel switching, work participation, difference-in-differences, multivalued treatments, energy, gender, India

[1] qwv10@txstate.edu

1. Introduction

In this paper, we address the question of whether switch from traditional to modern cooking fuels lead to increased female work participation. Although benefits of modern/cleaner cooking energy sources in the context of reducing indoor air pollution (IAP) is well documented (Agarwal, 1986; Bruce et al., 2000; Pillarisetti et al., 2019), the potential secondary time-saving benefits are relatively less explored. A switch from traditional biomass to a modern cooking energy source also come with the ease of use and timesaving in starting a fire and cooking time (Grogan & Sadanand 2013; Williams et al., 2020; Afridi et al.,2020). A few studies that have looked at time saving issue mainly focused on whether switching to cleaner stoves can reduce time spent on cooking and collecting fuel. Their focus has been on improved biomass stoves that intend to reduce biomass fuel consumption through improved heat transfer efficiency (Rehfuess et al., 2014). Greenwood, Seshadri, and Yorukoglu (2005) find that technological changes in home production, e.g., washing machines, refrigeration, saved time spent on domestic chores, and increased women's labor supply in developed countries. Similarly, electrification of rural households in South Africa enabled large, immediate shifts in home production technology, increased female employment and plausibly stimulated net labor supply increase (Dinkelman, 2011).

The case of female labor force participation in India has been quite an aberration from what is witnessed in developed countries and other south Asian countries. For example, Drèze and Sen (2013) discuss the large differences in female labor force participation between countries in South Asia, and report that the female labor force participation rate in India was only 30% in 2012, compared to 60% in Bangladesh. Moreover, work participation of women is inversely associated with their education or socio-economic status of family (Klasen and Pieters, 2015). There are many other cofounders (such as culture or family traditions) which remain unobserved to the researchers making the identification of impact of modern energy on female work participation challenging. Hence, it is important that we observe the same women at different points of time with different source of cooking fuels. Looking at the same women could mitigate the effects of cofounders most importantly traditions or culture. In addition, in developing country context majority of households do not switch from traditional to modern fuels directly but adapt a fuel stacking strategy where they continue to use traditional fuels with the modern fuels. In this context, it is also important from policy perspective to know the relative magnitude of the impact on female labor supply as households fuel stacking behavior may potentially reduce the effectiveness of government policies of promoting modern fuels.

In this paper, we address the issue of causal impact of switching of cooking fuels on female work participation. 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. Use of panel data allows us to adopt econometric strategies that eliminate the time-invariant household/individual characteristics to arrive at estimates that can be inferred as causal effect. More specifically, we categorize households in three groups based on their cooking fuel use 1) traditional fuels 2) mixed fuels or fuel stacking, and 3) modern fuels, and identify households who switched cooking fuels between 2005 and 2012, and who maintain status quo. Our main interest lies in estimating the change in female work participation based on fuel switch, i.e., we compare change in work participation outcome of individual women in households that switch the cooking fuels to the households that did not switch cooking fuels. To address the selection issues in the switch, we use adopt a difference-in-differences with multivalued treatment strategy.

This paper contributes to the literature in the following way. First, to my best knowledge, this is the first paper to investigate the causal impact fuel switching on the labor supply in India for the households that actually switched fuels. This paper adopts the diff-in-diff strategy with the multivalued treatment effects, which eliminates the role of time-invariant unobserved factors. The empirical strategy allows to estimate the impact of the switch from traditional biomass to modern energy or from modern energy to traditional biomass.

The findings of the paper are as follows. Solid fuel user women are 2.6 percentage points less likely to work if they switch the cooking fuel to mixed. Although we find that switching from solid fuels to modern fuels increase the labor supply for women households by 9.6 percentage point, the impact is not statistically significant. We do not find any significant impact on the female work participation for solid fuel users switching to mixed or vice versa. Moreover, we find statistically significant impacts on women labor supply of mixed fuel users who switch to modern fuels. However, there is no effect on women's work participation for modern fuels users who switch to other fuels.

This paper is organized as follows. Section 2 describes the data set. Section 3 details the empirical strategy, and Section 4 presents the results. 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). The IHDS are multi-topic surveys collected jointly by 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). IHDS-2 (2012) 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. Besides, we only keep women members of households in age group 28-64 based on the age reported in 2012 data. Since we compare outcome of same women, they should be above the age of 21 in 2005 data, and hence in the working age group. Thus, our final data contains a balanced panel of 19,563 rural women.[2]

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. Figure A1 presents the use of different fuels in 2005 and 2012 data. We group firewood, dung, crop residuals, and coal/charcoal together as solid fuel, and LPG and Kerosene as the clean fuel. From 2014, WHO started treating Kerosene as polluting fuel, however, several studies have used Kerosene as clean fuel. Since our main interest is at looking at the work participation through time saving channel, we grouped Kerosene with LPG as modern

[2] Majority of households have only one woman in the sample. Total number of households is 19,586.

fuel. In terms of efforts needed can heat generated, kerosene might not be as good as LPG, but it is much better to biomass fuels.

The appendix reports the descriptive statistics of variables in 2005 that might plausibly be correlated with the fuel switching. The household characteristics can be roughly divided into different categories such as household's head education, household's demographic composition, household's economic indicators, household's health issues and any shocks in 2005, household's participation in different bodies, household social networks, and village characteristics in the case of rural area.

Table 1 presents the cooking fuel switching between 2005 and 2012 in rural India. This table suggests that more than half of the solid fuel users maintain status quo or switch to mixed fuel, only about three percent of the households that used solid fuels in 2005 switch to modern fuels, whereas 37 percent of the households moved to mixed fuels or fuel stacking. Similarly, over 50 percent of mixed fuel users maintain status quo, there is still 36 percent of women households switch to solid fuel. About 10 percent of mix fuel users switch to modern fuel users in 2011-12. It is probably because some households use modern fuel as a backup considering higher cost of modern fuel compared with traditional biomass. Besides, access to modern fuel is also dependent on modern fuels distribution networks across the country. Further, the high upfront cost and subsequent high refill cost often act as deterrents for households to use modern fuels as their primary choice of cooking fuel, particularly among the poorest. Even though Most of modern fuel users remain status quo, 39 percent of modern fuel users became mixed fuel users. It suggests that Households adopt modern fuels but not phase out dependence on biomass energy. Rural households are more likely to go through stages where they shift to mixed fuel and later on to clean fuel (Kuo and Azam, 2018). If households use both modern and traditional fuels together, they are categorized as using mixed fuels. Table 1 presents the transition between 2005 and 2012 in terms of fuel use. 60 percent of households who used solid fuels in 2005 continued to use solid fuels in 2012 also, while 37 percent moved to mixed fuels. The clean transition towards modern fuels from solid fuels is very limited.

Table 2 reports the labor participation rate for women in 2005 and 2012 from balanced panel sample. As evident, labor participation rate saw a decline irrespective of the 2005 cooking fuel. Noteworthy, the labor participation rate of women is much higher among households that use solid or mixed cooking fuels compared to households that rely on modern fuels. The energy ladder hypothesis states that households move toward more expensive and cleaner fuels with increases in income (Muller and Yan, 2018). Households who exclusively rely on solid cooking fuel are not that rich. Women in that household need to work. That is why the labor participation rate is higher. The female labor participation rate for mixed fuel users is lower compared with solid fuel users. However, modern fuel users have the lowest female labor force participation rate compared with other cooking fuel users, considering the modern fuel users are rich people, who can afford the cost for women unemployed. It is consistent with the U-shaped relationship between women's labor force participation rate and economic development (Goldin 1994).

3 Empirical Framework

At any point of time households may choose between solid fuels, mixed fuels, or sole modern fuels. 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 change in work participation rate among women in households that actually switched the fuels between 2005 and 2012. Therefore, our main parameter of interest is average treatment effect on treated (ATET). 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 chose either of mixed or sole modern fuels in 2012. So, basically, we compare the change in work participation of households which switched fuels to households that maintain 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 modern fuel using household in 2005 may use a mixed fuel or move completely to solid fuels in 2012. Let switch or treatment (T) capture the change in fuel choice between 2005 and 2012.

$$T_i = \begin{cases} 0, & \text{if } fuel_{2005} = fuel_{2012}, \\ 1 \text{ or } 2, & \text{if } fuel_{2005} \neq fuel_{2012}. \end{cases}$$

where 1 or 2 are other two different fuel options available to the 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 work participation outcomes is used as outcome. variable. Multivalued treatment effects have been developed by Wooldridge (2010), Cattaneo (2010) and Cattaneo et al. (2013).

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

$$\Delta y_i \left| fuel_{i,2005} = \sum_{t=0}^{2} D_{it}(T_i)\, \Delta y_{it} \right.$$

As 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 modern fuels). The MVTE estimates are valid under the conditional independence (CI) and overlap assumptions. Conditional independence imposes that among households with the same observable characteristics ($X = x$), treatment assignment should be independent of the potential outcome (Cattaneo, 2013). Overlap condition says that for every possible characteristic's combination ($X = x$) in the population, there is a strictly positive probability that someone with that covariates pattern could be assigned to each treatment level. 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 conditional probability of receiving a particular level of the treatment given the pretreatment variables such as:

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

We employ a rich set of observed baselines, 2005, household characteristics and multi logit model to estimate the GPS. Imbens (2000) shows that, as in the binary treatment case, one can identify the unconditional means of the potential outcomes by weighting (inverse probability weighting, IPW): Although, propensity score matching methods have not been fully developed for more than a single value of treatment, one can use the weighting methods similar to binary case.

$$E\left[\frac{\Delta y_i\, D_{it}(T_i)}{r(t, X_i)}\right] = E[\Delta y_{it}]$$

Based on the above hypotheses, the average treatment effect on treated (ATET) of treatment m (switch) relative to treatment l (no switch) is given by:

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

4 Results

Table 3 presents the ATET estimates of fuel switch on women's labor supply in rural India. In rural areas, the women households who switch from solid fuel to mixed are 2.6 percentage points less likely to go to work, and most of this probably is driven by an increase in income, as there is an inverse relation between household income and women labor participation. Moreover, although the impact of the fuel switch from solid to modern fuel increased the women's labor supply by about 9.6 percentage points, it is not statistically significant. There is no impact on the work participation for women households that remain status quo. Results of panel A Table 3 are echoed with the decreasing trend of female labor force participation rate for solid fuel users, shown in Table 2.

In Panel 2 of Table 3, we find that switching from mixed fuels to modern fuels is positively associated with the women's labor supply. Compared with mixed users who remain status quo, the probability of women households being employed is about ten percentage points and is statistically significant. The ease of starting a fire frees women from the cooking burden and increases the probability of getting to work. We find the probability of women who switch from mixed to solid fuel decreases work participation by 1.1 percentage points, but it is not statistically significant. It is noteworthy that it is about 9.5 percent of mixed fuel users switch to modern fuels, but about 36 percent of them become solid fuel users. This is partly explained why the female work participation rate for mixed fuels users decreased by 3.3 percent. While there is about 55 percent of mixed fuel users remain status quo, it has no impact on the women labor supply.

Panel 3 of Table 3 shows the ATET of fuel switches for modern fuel users. Here, we report the ATET for status quo and switching from modern fuel to mixed fuel since less than eight percent of modern fuel users switch back to solid fuel. Panel 3 shows that there is no statistically significant impact of fuel switch on women's labor supply, even though the probability of modern fuel users who remain status quo decreases by 0.8 percentage points. Moreover, switching from modern fuel to mixed fuel increase the probability of employment by 6.5 percentage point. Nevertheless, it is not statistically significant. It is worth noting that over 53 percent of modern fuel users remain status quo and that the decreased female work participation may relate to the social status culture, that women in the rich family prefer not to work.

Overall, switching to modern fuels seems to have increased the labor supply of women households in rural India. However, the impact of cleaner cooking fuel on labor supply is limited. These findings are in line with the existing evidence regarding clean fuel and female work participation in other countries. Stabridis and Van Gameren(2018) use the Mexican Family Life Survey, with a utility-maximization framework that integrates the household choice of fuels for cooking and heating with the presence of health problems and find firewood usage keeps women at home while the respiratory problems caused by firewood reduce work participation. Using up to 175 countries during 1990-2010, Burke and Dundas (2015) examine drivers of household biomass energy and find that female labor force involvement is associated with less household biomass energy use.

Figure1 - Figure3 present the conditional density for the fuel switching. The purpose of the plot is to look for potential problematic cases (Busso et al., 2013). Figure 1 depicts the conditional density for switching solid to Mixed and modern fuels. There is considerable overlap of the propensity scores across treatment (women households who switched the fuel) and control group (women households who remain status quo) in figure 1A. The density distributions of the estimated probability show little mass around zero or one, supporting the overlap assumption. For Figure 1B, the density for the control group (households who remain status quo) is skewed to the left. However, given the large sample size of the comparison group compared to the treatment group (about 21:1), there are plenty of households with larger probabilities of being treated but who are not actually switching their cooking fuel. Figure 2 is for switch mixed to solid and modern fuels. Graph 2A and 2B presents no evidence that there is any mass of observations with predicted probabilities close to either 0 or 1. Figure 3 shows the conditional density for switching modern fuels to mixed. There is little mass around o and 1, supporting the overlap assumption.

Even though there are many methods used to match control observations to treated observations, there is no consensus about the matching method. Following Azam (2018), we use kernel matching in our paper. Kernel matching defines a neighborhood for each treated observation. It constructs the counterfactual using all control observations within the neighborhood, weighing each observation based on the distance between the treated and the control being matched, where the weighting function decreases in the distance (Azam 2018). Blundell and Dais (2009) argue that kernel weights reduce the variability of the estimator when compared with nearest neighbor weights and produce less bias than the nearest neighbor with many matches per treated if we use more observations per treated.

5. Conclusion

In this paper, we address the question of whether switching from traditional to modern cooking fuels leads to increased female labor supply in rural India, using the nationally representative Indian Human Development Survey (2004-05 and 2011-12). We exclude women households younger than 28 and older than 64 to minimize the role of employment decisions with a strong intertemporal component, such as education and retirement. We categorize women households into three groups by the cooking fuel they use: biomass, mixed fuel, and modern fuel. To address the ATET of fuel switching on the probability of work participation, we adopt two methods that are individual/household fix effects strategy and difference-in-differences with multivalued treatment. This study also confirms that switching from mixed to modern fuel will increase the probability of female work participation in rural India significantly. Moreover, we do not find any average treatment effect for women who maintain the status quo.

Labor supply increased due to switching traditional biomass fuel to cleaner cooking energy is one dimension of the potential benefits of the fuel switch. Other benefits, such as environmental and health benefits of switching from dirty to modern fuels, are well documented. Our paper mainly focuses on the ATET of fuel switching on women work participation. Our paper provides the evidence that the government policy that targeting to promote modern fuels may not that effective because of fuel stacking behavior among households.

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Tables and Figures

Table 1. Number of women based on household's fuel switches, Rural India

		Fuel Choice 2011-12			
		Solid Fuel	Mixed Fuel	Modern fuel	Total
Fuel choice 2004-05	Solid Fuels	6,016	3,779	287	10,082
		59.67	37.48	2.85	100
	Mixed Fuels	3,035	4,627	809	8,471
		35.83	54.62	9.55	100
	Modern Fuels	82	398	553	1,033
		7.94	38.53	53.53	100
	Total	9,133	8,804	1,649	19,586

Note: This table presents the number of women based on households' fuel switches in rural India in 2011-12. The second number in each cell represents the percentage.

Table 2. Female Labor Force Participation (aged 28-64) in 2011

Fuel Stacking in 2004	2004-05	2011-12
Solid Fuels	0.776	0.742
Mixed Fuels	0.705	0.672
Modern fuel	0.464	0.448

Note: Table 2 presents the female labor force participation rate for women household in rural India aged 28-64 in 2011.

Table 3. ATET of fuel switch on women labor supply

	Switch	Work (1/0)
Panel 1: 2004-05 fuels: Solid		
11.switch	NO	0.015
		(0.010)
r12vs11.switch	Mixed	-0.026**
		(0.013)
r13vs11.switch	Modern fuel	0.096
		(0.082)
Panel 2: 2004-05 fuels: Mixed		
22.switch	NO	-0.011
		(0.016)
r21vs22.switch	Solid	0.011
		(0.019)
r23vs22.switch	Modern fuel	0.095**
		(0.039)
Panel 3: 2004-05 fuel: Modern fuel		
33.switch	NO	-0.008
		(0.031)
r32vs33.switch	Mixed	0.065
		(0.042)

Note: Table 3 represents the average treatment effect on the treated of fuel switch. The work is a dummy variable, 1represents from unemployed to employed; 0 represents the employment status does not change from 2004 to 2012. The result omits the Modern fuel switch to solid because only 82 out of 1033 household switch from Modern fuel to solid in our sample. P values are in the parenthesis. ***p<0.001, **p<0.05, *p<0.1.

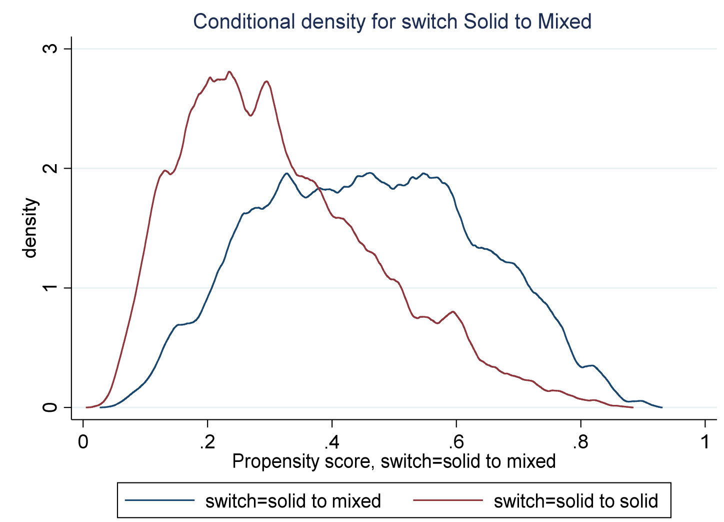


Figure 1A

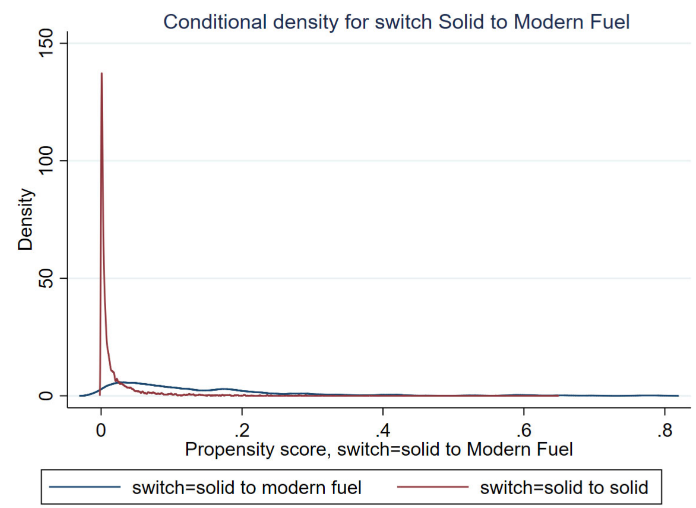
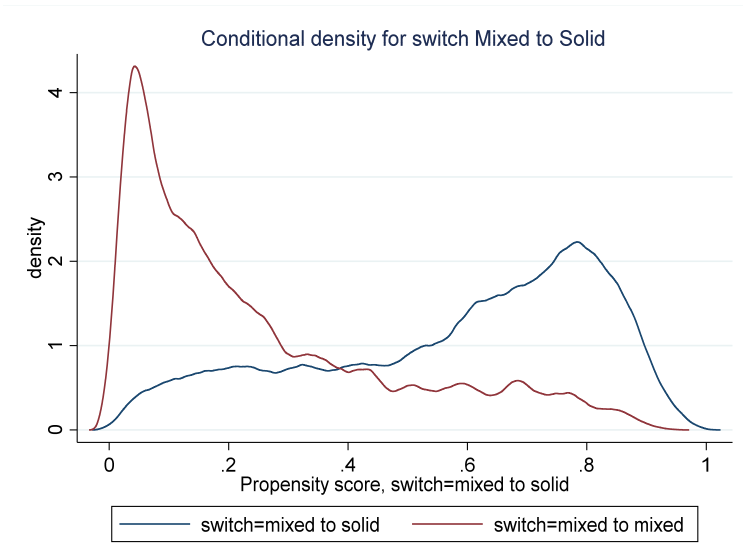


Figure 1B

Figure 1. Conditional Density for Switch Solid to Mixed/Modern fuel



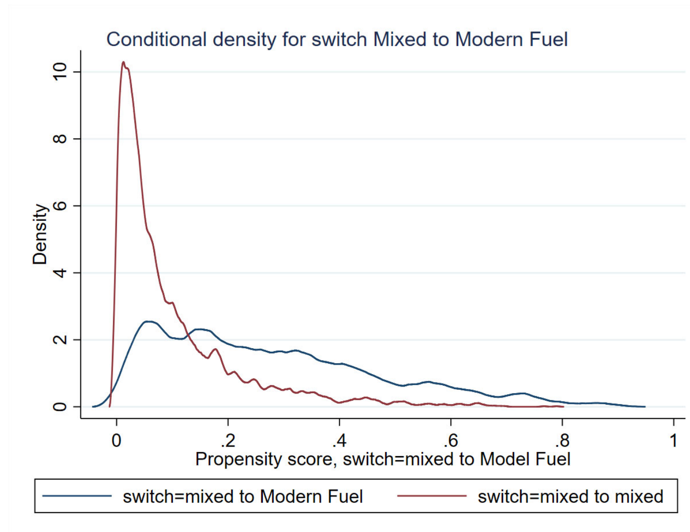


Figure 2A

Figure 2B

Figure 2. Conditional Density for Switch Mixed to Solid/Modern fuel

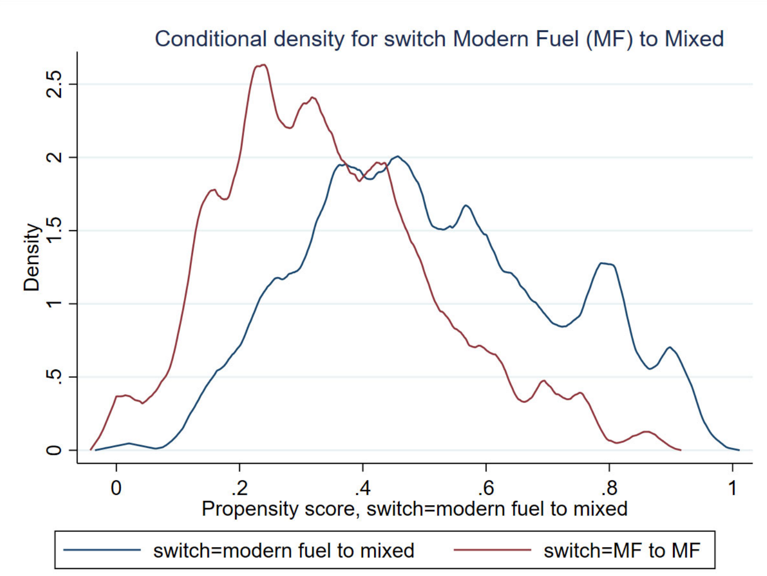


Figure 3. Conditional Density for Switch Modern Fuel to Mixed

Appendix

Table A1. Baseline, 2004 households' characteristics

	Solid	Mixed	Mean	All
Other Backward Castes+	0.370	0.370	0.350	0.370
Scheduled Castes+	0.250	0.180	0.120	0.210
Scheduled Tribes+	0.120	0.090	0.040	0.100
Muslim+	0.100	0.080	0.070	0.090
Household Size	6.240	6.300	5.480	6.220
Household Size Square	48.600	50.260	37.950	48.760
% of age 0-14 in HH	0.330	0.290	0.240	0.310
% of age 61 and above in HH	0.050	0.060	0.060	0.050
% of age 15-49 female in HH	0.260	0.270	0.290	0.270
log per capita consumption	6.890	7.140	7.660	7.040
log of per capita income+B16	8.790	9.210	9.860	9.030
No ration card+	0.120	0.110	0.100	0.110
BPL card+	0.420	0.340	0.190	0.370
Poor+	0.250	0.190	0.020	0.210
Head age	47.650	49.240	49.630	48.440
Head is female+	0.090	0.090	0.070	0.090
Head's education	3.480	4.980	8.250	4.380
Head's work type-casual+	0.520	0.400	0.200	0.450
Head Salaried job+	0.040	0.090	0.230	0.080
Head's work-type-government+	0.040	0.080	0.170	0.060
% of members reported- cough	0.090	0.080	0.060	0.090
% of members reported- cough with breathing issue	0.040	0.030	0.020	0.040
% of members reported- cataract	0.010	0.000	0.000	0.010
% of members reported- tuberculosis	0.000	0.000	0.000	0.000
% of members reported- cancer	0.000	0.000	0.000	0.000
% of members reported- asthma	0.010	0.010	0.010	0.010
HH has piped water access+	0.270	0.350	0.550	0.320
HH has hand pump water access+	0.390	0.320	0.190	0.350
HH has no access to toilet+	0.810	0.600	0.260	0.690
HH has no electricity+	0.400	0.170	0.030	0.280
House building in poor conditions+	0.210	0.150	0.100	0.180
HH use radio+	0.130	0.140	0.220	0.140
HH use paper+	0.070	0.200	0.420	0.140
HH use Television+	0.190	0.360	0.630	0.290
HH know some doctor+	0.270	0.340	0.480	0.310
HH know some teacher+	0.370	0.450	0.600	0.420

HH know some government servant+	0.250	0.360	0.560	0.310
Anyone in HH member of self-help group+	0.120	0.130	0.110	0.120
Anyone in HH member of Development of NGO+	0.010	0.020	0.050	0.020
Attended local body meeting+	0.370	0.370	0.360	0.370
Great deal of confidence in state govt+	0.280	0.260	0.250	0.270
Cooking in living area	0.230	0.150	0.120	0.190
Use improved stove for solid	0.020	0.070	0.000	0.040
Shock between 2005 and 2001: Major illness/Accidents	0.280	0.280	0.290	0.280
Shock between 2005 and 2001: Drought, Flood, Fire	0.130	0.090	0.060	0.110
Shock between 2005 and 2001: Crop Failure	0.270	0.240	0.130	0.250
Indicators: survey month 2004	NA	NA	NA	NA
Indicators: survey month 2011	NA	NA	NA	NA
Indicators for states	NA	NA	NA	NA
Observations	10075	8459	1029	19563

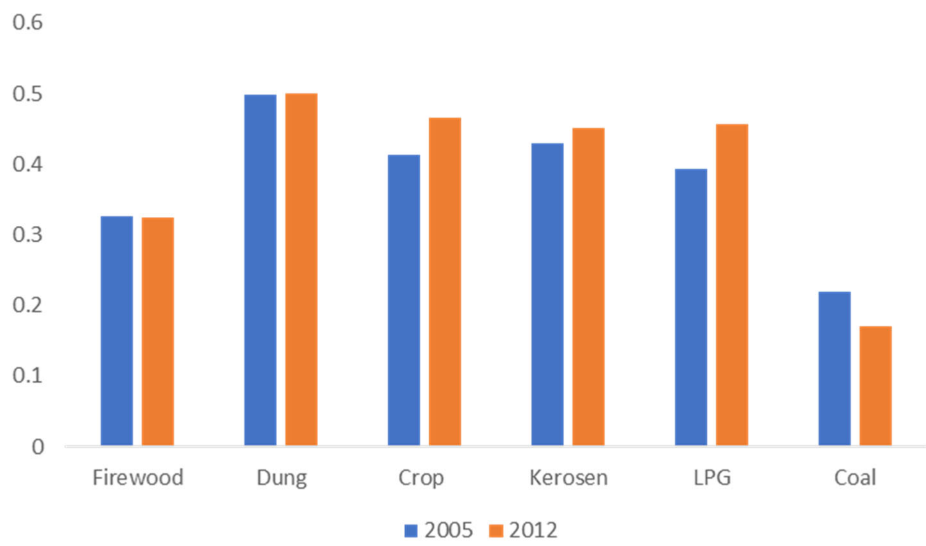


Figure A1. Fuel Use Index in 2005 and 2012