THREE ESSAYS ON LABOR AND DEVELOPMENT ECONOMICS

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Abstract:

My dissertation comprises three chapters. The first chapter analyzes whether the use of Liquefied Petroleum Gas (LPG) as cooking fuel affects the time spent in cooking and employment activities for Indian rural women. The second chapter explores whether use of cleaner energy source for cooking leads to increased female work participation. The third chapter investigates trends in the allocation of time within India between 1999 and 2019.

The first chapter studies whether the use of Liquefied Petroleum Gas (LPG) as cooking fuel affects the time spent in cooking and employment activities for Indian rural women, using the nationally representative Indian Time Use Survey. I instrument use of LPG by a leave-one-out spatial instrument constructed by taking the average level of LPG use in the village where the average is calculated leaving the concerned household. I find no impact of LPG on the probability of women participating in cooking activities. However, use of LPG reduces (increases) time spent in cooking (employment) activities. I also find evidence of rebound effect where use of LPG leads to marginally more cooking events in a day. I find that LPG impact on time spent in cooking and employment is mostly driven by married women.

The second chapter investigates whether use of cleaner energy source for cooking leads to increased female work participation, using the nationally representative Indian Human Development Survey. The methodology used in this paper is difference-in-differences with multivalued treatment. I 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, I do not find any average treatment effect on the female work participation for households who maintain the status quo.

The third chapter analyzes the time allocation trends and inequality of time use in the past 20 years using India's time-use surveys for 1999 and 2019. I observe a sharp rise in leisure time and the concurrent decline in time spent on employment-related activities for both men and women in the six states. Furthermore, the gender gap is widening in employment activities, especially for women in rural India, who lose an average of five hours per week of employment activities. This study concludes that people devote a generally consistent amount of time to childcare, with a declining gender disparity in the amount of time spent providing domestic service due to women's weekly time reductions of between four and seven hours.

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CHAPTER I

DOES ACCESS TO LIQUEFIED PETROLEUM GAS (LPG) REDUCE WOMEN HOUSEHOLD BURDEN? EVIDENCE FROM INDIA

1. Introduction

In this paper, we examine whether the use of Liquefied Petroleum Gas (LPG) reduces the domestic cooking burden for women in rural India. This is an important question in general as nearly 2.6 billion people worldwide do not have access to clean cooking fuel in 2019 as opposed to 3 billion in 2010 (IEA et al., 2021). However, its importance is attenuated in the Indian context where the female labor force participation rate (FLFPR) remains very low compared to other countries and has witnessed a considerable decline over time. The FLFPR in India among 15+ age group declined from 31 percent in 2001 to 19 percent in 2021. In contrast, China's and world's FLFPR stands at 61 percent and 46 percent, respectively in 2021 (World Development Indicators). Given that rural women in age group 18-60 spend about 23.6 percent of their non-sleeping time on food preparation and management in contrast to only 0.6 percent of non-sleeping time for rural men, access to efficient time-saving modern energy can potentially free up women's time away from cooking activities and increase the potential time available for employment activities. For example, 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. Similar to this, in South Africa, electrification of rural households allowed for significant, improvements in home production technology, boosted female employment, and plausibly stimulated an increase in the net labor supply (Dinkelman, 2011).

Ex-ante, it is not clear that access to LPG will lead to a decrease in time devoted to cooking activities. Since LPG is more efficient in cooking compared to biomass, use of LPG should decrease time spent on cooking assuming that the amount of cooking women does remains the same. At the same time, since women are becoming efficient in cooking, they may increase the amount of cooking commonly known in literature as “rebound effect”.[1]. For example, they may increase the variety of foods cooked or increase the frequency of tea/snacks preparation. In addition, since cooking with LPG is less demanding than cooking with biomass, the household may rely less on hired help. Both may lead to an increase in time spent on cooking activities by women considering women do almost all cooking in Indian rural households. Hence, conceptually, the impact of LPG on total time devoted to cooking remains ambiguous and is an empirical question.

Even in 2019, more than 50 percent of rural Indian households reported biomass as their main source of cooking in spite of considerable attempt by the Government of India to increase the use of LPG.[2] The health and environmental benefits of using LPG over biomass is well-documented (Agarwal, 1986; Bruce et al., 2000; Pillarisetti et al., 2019).[3] However, there are only few studies in developing countries context that look into time-saving aspect of access to modern cooking energy such as LPG.[4] Moreover,

[1]Rebound effect is the phenomenon where improving energy efficiency may save less energy than expected due to a rebound of energy use

[2]The Indian Federal Government started a scheme known as Pradhan Mantri Ujjwala Yojna (PMUY) in 2016 with the aim of providing 50 million LPG connections to below poverty line (BPL) families with a support of Indian Rs.1600 per connection in the next three years. By December 2018, 58 million new LPG connections were distributed (source: Sharma, Anshu, ”Government expands eligibility criteria to meet Pradhan Mantri Ujjwala Yojana target”, CNBC TV18, 19 December 2018).

[3]Imelda and Verma (2019) use the fuel-switching program from kerosene to LPG in Indonesia to study the impact of LPG. They 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.

[4]Several studies have examined the possibility that using cleaner stoves would cut down on the time required for

the existing studies are mostly based on small samples or experiments carried out in specific context on limited number of households. For example, Williams et al. (2020) use data from randomized trial on 180 adults, non-pregnant women between the ages of 25–64 residing in the high-altitude region of Puno, Peru. 90 women, or half of the sample, received the intervention (treatment), which included a three-burner locally produced LPG stove, free continuous LPG refills delivered right to their homes for a year, as well as behavioral training and reinforcement for LPG use. Control participants kept using their usual methods of cooking. They discover that using LPG exclusively results in between 3.2 and 3.9 fewer hours spent cooking and 1.9 fewer hours spent gathering biomass fuel each week, for a potential weekly savings of up to 5.8 hours (Williams et al., 2020). In a close context to ours, Afridi, Debnath and Dinkelman (2020) conduct an experiment in one district in Central India where they divide randomly selected villages from the district into three groups. They provide information on health benefits of LPG in one group of villages, while providing information on both health benefits of LPG and government subsidy for LPG to the second group of villages. For the third group of villages no information was provided. Thus their treatment status is based on the information campaign to improve LPG uptake of households, and they look at the impact of the information campaign on time spent in household chores.

In this paper, we use nationally representative Indian Time Use Survey 2019 (TUS-2019) to address whether the use of LPG leads to a reduction in time spent on cooking activities by adult women residing in rural India. First, we use the OLS to estimate the impact of LPG on the time spent for food management and preparation, and employment activities controlling for a large set of individual's, household's, and village observable characteristics including district fixed effects. Recognizing that the

cooking and fuel collection. However, the majority of them have concentrated on enhanced biomass stoves that aim to decrease the consumption of biomass fuel through enhanced heat transfer efficiency (Rehfuess et al., 2014).

estimate for LPG may suffer from the omitted variable bias, we instrument household-level LPG using the fraction of households in the village that reported LPG as main source of cooking where the concerned household is excluded in calculating the average. We control for village level characteristics in addition to the districts fixed effects to ensure that out instrument is conditionally uncorrelated with village level geographical differences that may affect individual women time use outcome independently. We also use unconditional quantile regression to capture the heterogeneous impact of LPG based on the total time spent in food management and preparation activities.

Our paper contributes to literature in the following ways. First, to our best knowledge, ours is the first paper that looks at the impact of LPG on time spent on cooking activities using a nationally representative household survey data. In addition, we also look at the time spent on total employment activities. As previously stated, the existing studies that looked at the time spent in cooking activities are mostly based on small surveys or some experiments with the limited number of households. A few studies that look at the impact of LPG are based on small surveys from selected sites, and focus mainly on the time saving due to decreased time burden of collecting biomass. The cooking time channel remains relatively unexplored, especially using a nationally representative data. Since cooking activities are repetitive and involve almost universal participation from women irrespective of economic status, time saved in cooking activities will have a much larger impact for the economy. For example, about 90 percent of women in rural India not only reported involvement in cooking activities, but also spent considerable time in cooking activities. Hence, the cooking activities channel is much more important.[5]

[5] In comparison, firewood may be collected by women once every 3-7 days, and may involve children or adult males also. In our data which captures the activities for one day, only 5 percent of the women in 18-60 age group in rural India reported collecting firewood. It is possible that the 5 percent is under counting the women participation in fuel collection because of infrequent nature of the activity. However, given the nature of nationally representative data, one could infer that at any random day only 5 percent of the women in age group 18-60 were involved in fuel collection compared to 90 percent women being involved in cooking activities in rural India.

The following are the paper's primary findings. We find that the instrument variable (IV) estimates have generally the same sign as OLS estimates, but IV estimates are mostly larger in magnitude. We find that having LPG as the main cooking fuel has no impact on the extensive margin as far as cooking activity is concerned, i.e., women's involvement in cooking activities does not depend on LPG use. This is not surprising given very high participation in cooking activities by adult women in rural India. We find that having LPG as the main cooking fuel reduces the total time spent by women in food management and preparation by 5.6 minutes per day. This decline is about 2.6 percent of the average time of 212 minutes spent in food management and preparation by women per day. Looking at the different activities of food preparation and management, we find use of LPG reduces actual cooking time by 2.3 minute which is 1.6 percent of the average time of 136.5 minutes spent on actual cooking per day. We find some evidence of rebound effect mitigating the impact of LPG on actual cooking time. The women who use LPG are more likely to cook meal/snacks more than 3 times a day, while the average time spent per cooking activity is lower with LPG use. We also find LPG use reduces time spent on cleaning, storing, and other food related activities, but increases time spent for serving meals/snacks. Importantly, we find that women residing in household that use LPG as the main cooking fuel are likely to work 8.0 minutes more compared to women who reside in household that do not report LPG as main cooking fuel. Although in terms of minutes, this is not a large gain. However, given that on average, rural Indian women spend around 84.6 minutes on employment activities, this is about 9.5 percent increase in time spent in employment activities. Our unconditional quantile regression estimates suggest that the impact of LPG is only marginally larger at higher quantiles.

The remainder of the paper is organized as follows. Section 2 discusses the empirical methodology. Section 3 describes the data. Section 4 presents the results. Section

5 concludes.

2. Empirical Methodology

Our objective is to estimate the causal effect of use of LPG on the time spent in cooking activities by women, hence, we estimate the following equation:

$$Y_{ihvd} = \alpha + \delta LPG_{hvd} + \beta X_{ihvd} + \varsigma X_{vd} + \eta_d + d_\tau + \varepsilon_{ihvd} \tag{1}$$

where Y_{ihvd} denotes the time spent in cooking activities by women i, residing in household h, in village v of district d. X_{ihvd} is a matrix of both women's and household's observed characteristics, while X_{vd} contains village characteristics. η_d are districts fixed effects, d_τ represents fixed effects for the day of the week when household time use information was collected, and ε_{ihvd} is the randomly distributed error. LPG_{hvd} is the binary indicator that captures whether household's main source of cooking is LPG, and δ is our main interest parameter that captures the impact of LPG on the outcome variable. We first estimate the Equation (1) using the Ordinary Least Squares (OLS).

One potential issue with the use of OLS is that the outcome variable is zero for a significant proportion of women, especially when we consider some sub-categories of cooking activities. In the case of censoring, alternative remains a Tobit model. Frazis and Stewart (2012) argue that OLS models are favoured in the analysis of time allocation decisions because one cannot estimate means of long-run time consumption from a sample of daily data using estimating techniques for constrained dependent variables that assume a nonlinear functional structure, such as the Tobit model. Stewart (2013) finds that zero time usage is not caused by censorship, but by a discrepancy between the data reference period (diary days) and the period of interest (usually much longer than a day), and the Tobit model estimation will be inconsistent, but OLS estimates are unbiased. Gershuny (2012) asserts that there is a problem with too many zeros originating from single-day diaries, but traditional diary studies can accurately estimate the mean times in activities for samples and subsamples. Moreover, Foster and Kalenkoski (2013) find that the qualitative conclusions are similar for Tobit and OLS methods when analyzing the time allocated to childcare activities. Hence, we chose OLS over Tobit model for simplicity and ease of interpretation.

2.1. Instrument Variable Framework

The OLS estimate provides an unbiased estimate of the impact of LPG use on time spent on cooking activities if the choice of LPG is not correlated with the error term after controlling for other observables. Although we control for a large set of characteristics including household demographics and income (proxy by per capita consumption expenditure), village characteristics, and district fixed effects, it is difficult to rule out some unobserved factors that may be correlated with both the outcome and LPG use. Hence, the endogeneity of LPG cannot be ruled out.

To address the issue of the potential endogeneity of the LPG variable, we adopt an instrument variable (IV) strategy. We use the fraction of households in the village that reported LPG as main source of cooking where the concerned household is excluded in calculating average.[6] There are many studies that have used similar leave-one-out or spatial instrument, i.e. they instrument person i's endogeneous variable with the average of endogenous variable among person i's peers, excluding i himself or herself in this average (For example, Fruehwirth et al., 2019; Khandker et al. 2014; Persson and Tabellini, 2009). Using village level average LPG use as an instrument,

[6] We also use average use of LPG where average is based on all households as an instrument, and results are similar.

we estimate the following two-stage least square model:

$$LPG_{ihvd} = \gamma_0 + \gamma_1.meanLPG_{-(ih),vd} + \gamma_2 X_{ihvd} + \gamma_3 X_{vd} + \eta_d + d_\tau + \vartheta_{ihvd} \quad (2)$$

$$Y_{ihvd} = \pi_0 + \pi_1 \widehat{LPG_{ihvd}} + \pi_2 X_{ihvd} + \pi_3 X_{vd} + \eta_d + d_\tau + \sigma_{ihvd} \quad (3)$$

where $meanLPG_{-(ih),vd}$ is the fraction of households in the village v that reported LPG as their main source of cooking, where the concerned household is excluded in calculating average for the village. There are two identifying assumptions here. First, average LPG use in a village must be correlated with the household use of LPG, i.e. $\gamma_1 \neq 0$ in Equation (2). The second condition, known as the exclusion restriction, implies that $meanLPG$ affects the outcome Y_{ihvd} only through LPG use by the household.

The fraction of households in village that reported use of LPG as main source of cooking is expected to serve as an instrument because peer pressure or demonstration effect is likely to affect a household's decision to use LPG as households tend to follow their neighbors or other associates in the village. If neighbors obtain LPG, then a household without LPG can signal lower socioeconomic standing, which households would be expected to avoid if they can afford it. There is a large body of literature on peer effects. For example, Arcidiacono and Nicholson (2005) and Jackson and Bruegmann (2009) analyze the peer effect in the context of students' academic achievement. Krauth (2003) incorporates both peer effects and selection effects to investigate the youth's decision to smoke. Cornelissen et al. (2017) focus on estimating the effect of the long-term or predetermined quality of a worker's current peers on the current wage. According to Nicoletti et al. (2018), there is empirical proof that the influence of family peers amplifies the increase in mothers' working hours. Therefore, we hypothesize that the likelihood that a household will switch to LPG in a village increases with the proportion of families utilizing LPG.

The second condition is also expected to hold as the incidence of LPG use at the village level should not directly impact the time devoted by women to cooking activities that are primarily based on individual household needs. While the first identifying assumption can be validated in the data, the exclusion restriction is debatable. One potential issue with our IV is that it may be correlated with other omitted village level geographical characteristics, and the impact on cooking time is through the correlation with omitted village level variables. To mitigate the concerns, we not only control for district fixed effects but also a set of village level characteristics. We believe that conditional on all the explanatory variables included in the estimation, only route through which village average LPG use affects individual women's time spent in cooking activities is through the influence on the household use of LPG.

3. Data

We use the Time Use Survey (TUS) 2019 collected by the Indian National Sample Survey Organization (NSSO). The survey is nationally representative and covers 1,38,799 households in both rural (82,897 households) and urban (55,902 households) India. The survey provides detailed information on time use collected over 24 hours starting from 4:00 A.M. on the day before the date of interview to 4:00 A.M. on the day of the interview. Thus, the diary time frame is 24 consecutive hours and is divided into 30-minute intervals. If multiple activities are performed during the 30-minute slot, time used in each activity is documented. The Indian TUS uses the International Classification of Activities for Time Use Statistics 2016 (ICATUS 2016) to record 3-digit codes for different activities carried out by an individual in 30-minute slots over 24 hours. Overall, the TUS has detailed time use information of 4,47,250 persons of age six years and above (rural: 2,73,195 and urban:1,74,055).

Appendix Table A1 presents the distribution of households based on the main cooking fuel used. About 86.2 percent of urban households reported LPG as main source of cooking compared to only 51.5 percent of rural households. Since our main objective is to look at the impact of LPG use on cooking time, we restrict our sample to rural India as most of the households in urban India report use of LPG as main cooking fuel source. A household is classified as using LPG if the main cooking fuel is LPG or other natural gas. Non-LPG fuel include firewood and chips, dung cake, coke or coal, and charcoal.[7]

Given that the main burden of cooking falls on women, we restrict our sample to rural women in age 18-60 and exclude students. So, our final sample consists of 86,970 non-student women in age group 18-60 residing in rural India.[8] Table 1 shows the summary statistics of the time spent in the activities of interest for this study. On average, women (18-60 age group) in rural India spend about 3 hour and 33 minutes on food management and preparation activities that constitute about 14.8 percent of the total time available in 24 hours. However, once we exclude the sleeping time, this constitutes a staggering 23.6 percent of non-sleeping time. In contrast, the average time spent on employment activities is only 1 hour and 25 minutes which is about one third of time spent on cooking activities. Women in rural India on average cook 2.7 times in a day, and each cooking event takes about an hour.

Table 2 provides summary statistics for the control variables used in the regression analysis. The control variables include individual characteristics such as education, age, marital status, and employment types; household level characteristics such as monthly per capita expenditure, religion, caste, household demographic composition, house type, household head's education, gender, and employment types. The

[7]About 0.68 percent of the households in rural India reported using electricity, gobar gas, other bio gas, or other fuels as theirs main fuel source. We exclude those households from our sample. In addition, we also exclude 0.46 percent of the households from our sample who do not report cooking.

[8]The survey day are coded "normal day" and " the other day". The normal days are the days on which a household member mainly pursues their routine activities, whereas the day on which the regular activities of a household member are altered for any reason is treated as "other day". We only use the data if individual reported the survey day as typical normal day.

explanatory variables also include village characteristics such as mean consumption expenditure, employment rate, percentage of population with higher secondary or above education, percentage of upper castes in the population, percentage of households which contain a regular salaried member, and percentage of households living in mud house.

4. Results

Panel A of Table 3 presents OLS estimates for the impact of LPG use estimated using Equation (1). The first column of the Table 3 looks at the probability of a woman involved in cooking. As argued earlier, the ease of use for LPG compared to biomass may provide an incentive for some to get involved in cooking, i.e. the cooking increases at extensive margin. In rural India, women involvement in cooking activities is very high as 90 percent of the women in our sample report spending some time in a day in cooking activities defined as preparation of meals/snacks. The OLS estimate from column (1) suggests no impact of LPG use by household on the probability of women's involvement in the cooking activities implying that LPG has no impact on the extensive margin. This is not surprising as access to more efficient cooking methods is more likely to affect cooking time on intensive margin in a society where cooking is primarily considered as women's responsibility and a large share of women already report being involved in cooking activities. In contrast, only 3.8 percent of rural men in age group 18-60 reported spending any time in cooking activities. Hence, the probability of intra-household substitution of cooking activities across genders remains extremely low. Therefore, we do not consider men sample in our analysis.

Column (2) of Table 3 provides estimates for the impact of LPG use on total time spent on food preparation and management activities. Although the OLS estimate suggests a negative impact of LPG on total time spent, the magnitude of the impact remains very small, i.e. 1.8 minutes decline on an average of 212.5 minutes spent in a day in food preparation and management activities that translates into only 0.8 percent decline in time spent on food preparation activities. Hence based on OLS estimate, one could argue that the impact on LPG on freeing up time from the kitchen activities is limited.[9] In column (3) of Table 3, we consider different activities under food preparation and management. Column (3A) looks at the actual time spent in cooking. Given the superiority of LPG in providing heat, one would expect a reduced time in actual cooking assuming that the amount of food cooked is not affected by LPG use. We find no impact on total time spent in cooking activities. Since LPG provides quick cooking start and heating compared to traditional biomass in addition to the higher thermal heat, it is surprising that there is no impact of LPG on time spent in actual cooking.[10] Perhaps, women with LPG increased the frequency of cooking, or cook more items because of ease to start heat. Since, the time and efforts required to start biomass heat are substantial, it is plausible that women club the entire day of cooking together when using biomass providing some economies of scale. We find a statistically significant negative impact on time spent on cleaning up, storing food, and other food related activities. However, minutes saved in those activities remain small to have any considerable impact on total time spent on food management and preparation. In column (4), we look at the impact of LPG on time

[9]In literature, one of the potential channels for time saving discussed is through reduced burden of collection of firewood and dungs. This is captured in our data by ICATUS code 241: Gathering firewood and other natural products used as fuel for own final use. We do not consider the time spent on collecting firewood as separate outcomes, as only 5 percent of women (and 1.2 percent of men) in age group 18-60 in rural India reported spending time in collection of firewood. As stated earlier, it is possible that the 5 percent of women participation in firewood collection may be understating the true participation because of 24 hour recall period for the survey and infrequent nature of firewood collection activity. However, the survey is representative of the population activity on a given day, so on any given day only 5 percent of women participate in firewood collection. Another source of discrepancy may be because of the target population of small surveys, mostly poor residing around forest areas. The firewood collection participation is higher in poor and population residing closer to forest areas.

[10]Bruce et al. (2017) find that the reported thermal combustion efficiency of LPG is in the range of 45-60 percent depending on the stove used. They also find that, when tested in the laboratory, although some fan-assisted advanced biomass cookstoves can reach efficiency of 30-55 percent but their efficiency is quite low in everyday use. Muralidharan et al. (2015) found that the in-home efficiency of two types of advanced biomass fan stove is between 17 to 25 percent. WLPGA (2018) models the potential for mitigating greenhouse gas emissions and finds that annual per capita cooking requires 43 kg LPG instead of 400 kg of wood.

spent in employment activities, and find a positive impact of 2 minutes. Since average time spent by women on employment activities is 84.5 minutes, this translates into an impact of about 2.5 percent increase in time in employment activities. Interestingly, the time reduction in food management and preparation (about 1.8 minutes) and time increased in employment activities are comparable in magnitude.

4.1. Instrument Variable Estimatesitle

As discussed in the empirical strategy section, OLS estimates may be biased because of omitted variables. To address the endogeneity concerns, we implement the instrumental variable strategy. Appendix Table A2 presents estimates for the first stage regression, where we regress the indicator variable LPG on the meanLPG and other variables discussed earlier. The first stage results confirm a strong relationship between LPG use by the household and average of LPG use by other households in the village. The point estimate suggests that a ten-percentage point increase in the fraction of LPG usage in the village is associated with a 8.4 percentage point increase in the probability of LPG use by the household.

In Table 4, we report the results of the Durbin and Wu-Hausman tests that examine whether LPG variable can be treated as an exogenous variable in the outcome equation. For all the time outcomes except time spent in cleaning or storing, we reject the null of exogeneity of LPG variable at 5% significance level. For time spent in cleaning also, the exogeneity of LPG can be rejected at 10% significance level. For binary variable involvement in cooking activities and time spent in storing food, exogeneity of LPG cannot be rejected. Given that exogeneity of LPG is rejected for majority of our outcomes, we proceed with IV estimation and report IV estimates for all outcomes. However, recall that OLS estimates will be efficient in the case LPG variable is exogenous.

Panel B of Table 3 reports the IV estimates for all outcomes. IV estimate also suggests that having LPG as the main cooking source will not affect the probability of a woman involved in cooking, and IV estimate is similar in magnitude to OLS estimate. Hence, one can conclude that having LPG as main cooking fuel does not affect cooking activities on extensive margin. Column (2) in panel B, Table 3 indicates that the total time spent on food management and preparation is reduced because of use of LPG as main cooking fuel source. Recall that, we reject the null of exogeneity of LPG variable in the case of aggregated time spent in food management and preparation, hence, the IV estimate is preferable. Although, the signs of both OLS and IV estimates are negative suggesting a reduction in time spent, the magnitude of the IV estimate is more than three times of the OLS estimate. This suggests positive omitted variable bias in the OLS estimate reducing the negative impact of LPG. The IV estimate suggests that use of LPG reduces time spent on food management by 5.7 minute per day that translates into 2.7 percent reduction in time spent on food management activities per day. In terms of practical impact, this suggests reduction of 40 minutes in a week, which may not seem a large impact for an individual but given 93 percent participation of rural women in food preparation and management activities, it will translate into a large number of absolute hours saved for the entire economy which could be used alternatively.

Column (3A) of Table 3 presents IV estimate for the time spent in preparing meal/snacks. Compared to OLS estimate, the magnitude of the IV estimate is considerably larger, and the IV estimate is statistically significant. The IV estimate suggests saving of 2.4 minutes on the mean 136.5 minutes which translates into 1.8 percent reduction in time spent on actual cooking activities. As stated earlier, the limited impact on actual cooking time is a little bit puzzling given the superiority of LPG on biomass in generating heat. It is entirely plausible that the women who use LPG cook more items that is not captured in data. In appendix Table A3, we check for the rebound effect. We find that women with LPG access are 1.9 percentage points more likely to cook more than three times in a day. The women with LPG access on average cook 0.06 times more in a day where the average number of cooking events are 2.73. While on average per cooking activity takes about 57.6 minutes, having access to LPG reduces average time by 3.0 minutes per cooking activity. This is about 5 percent reduction in time per cooking activity. It is important to point out that the amount of cooked food is not captured in the data. Nonetheless, there is some evidence of rebound effect where women with LPG access cook marginally more times although spend less time per cooking activity. This potentially leads to smaller effect on total time spent in cooking activities in a day.

The time spent in serving meals/snacks increased by about 2.7 minutes (column 3B, panel B of Table 3). The ease to start fire to prepare meals also implies LPG users may have tea/coffee or other snacks more easily than traditional biomass users probably driving the positive impact. IV result for cleaning up outcome suggests that women who use LPG spend less time in cleaning up perhaps because the pots and pans are no longer covered in soot from cooking over a wood fire (Clancy et al., 2012). Similarly, LPG users spend less time in storing and other food management activities. Importantly, while both IV and OLS estimate for time spent in employment activity suggest positive impact of LPG, the IV estimate is about four times stronger than the OLS estimate (panel B, column (4) of Table 3). Women who use LPG are likely to spend 8.1 minutes more in employment activities per day compared to women who use biomass. Although in terms of minutes spent in employment activities, 8.1 minutes per day do not seem large, but given a very low employment rate in women, this translates into a 9.5 percent increase in time devoted to employment activities on an average time of 84.5 minutes.

4.2. Heterogeneity in LPG impact

The discussion so far looks at the impact of LPG on average time spent without distinguishing among LPG users. However, we do not expect that every LPG user will benefit similarly, irrespective of their cooking needs. To capture the heterogeneity in the impact of LPG, we use unconditional quantile regression (Firpo, Fortin, and Lemieux, 2009) and focus on total time spent in food management and preparation, since quantiles for other outcomes are not well defined in the presence of a large fraction of the outcome being zero. For the total time spent on food management and preparation activities, zero values only account for about 7 percent of rural women. For unconditional quantile regression, we do not instrument LPG use because of computational issues. Frolich and Melly (2013) propose a IV implementation of the quantile regression, and a STATA routine 'ivqte' is available to implement their strategy. However, the Frolich and Melly (2013) approach requires use of indicator variable as an instrument, and our instrument is a continuous variable. Khandker et al. (2014) converts their IV which is continuous average village level electrification to binary IV by using a 50 percent electrification rate as cut off. Importantly, incorporation of survey weights in the IV implementation of the quantiles is not discussed in Frolich and Melly (2013), and not incorporated in 'ivqte'. Given that the time use survey we use in our paper is a stratified sample, an unweighted IV implementation of quantiles will not provide the right answer.

In Table 5 we present the results of the unconditional quantile regressions for total time spent on food management and preparation. We considered all observations in column (1). In column (2), we dropped the observation where the reported total time spent in food management and preparation is zero. We find that the time reductions in total time spent on food management because of LPG use are larger at higher quantiles. While LPG user women spend 15.5 minutes less than non-user women at the 90th percentile of time spent, the LPG user women spend 11.5 minutes less compared to non-user at the 25th percentile of time spent.

Another source of heterogeneity in Indian context is caste, where individuals acquire their caste by virtue of birth. Historically in pre-independence era, certain groups were delegated to do menial works or were geographically isolated. At the time of independence, the Constitution of India recognized the injustice suffered by those groups and lists them under Article 341 and 342 as Scheduled Castes and Scheduled Tribes (SCs/STs). The Constitution also provided affirmative action protection for the SCs/STs in the form of reserved seats in higher educational institutions, in public sector jobs, in state legislatures and the Indian parliament. In addition to the SCs/STs, the government of India also groups a number of castes who do not belong to the SCs/STs but on economic/educational parameters they are not doing well as Other Backward Castes (OBCs), and has reserved a fraction of seats in higher education and public sector jobs for OBCs since 1993. The groups who do not belong to the SCs, STs, or OBCs form higher castes and do not get any affirmative benefits from the government. Normally in economic and social hierarchy, higher (upper) castes stand at the top, followed by the OBCs and SCs/STs. A large body of literature exist that documents the gaps among these castes on various economic outcomes (e.g., Kijima, 2006; and Hnatkovska, Lahiri, and Paul, 2012).

According to Eswaran, Ramaswami, and Wadhwa's (2013) hypotheses, as one rises in the caste system, women's labor market work should decrease in comparison to that of their husbands implying higher participation in SCs, STs, and OBCs compared to higher castes. To allow for LPG impact to vary across castes, we introduce interactions of LPG use with indicators for SCs, STs, and OBCs in Equation (1) whereas higher casters serve as the omitted group. We also instrument LPG and caste interactions with 'our leave-one-out instrument' discussed earlier and interactions of it with caste indicators. The Durbin and Wu-Hausman tests that examine whether the interaction of LPG with castes can be treated as exogenous variables show that, for all the time spent outcomes, the exogeneity of LPG variable can be rejected at the conventional 5% significance level (reported in appendix Table A4). Hence, we focus on the IV results in Table 6.[11]

Column (1) of Table 6 presents the results for the probability of involvement in cooking. Compared to higher castes, the use of LPG decreases the probability of participation in cooking for the SC and ST women but no differential impact for the OBC women. The labor force participation among the SC/ST women is much higher compared to the higher caste women. The female labor force participation in India shows an inverse relation with household income/wealth/status. Probably access to easy cooking may free up additional women from the SC/ST household from cooking requirement. With regards to the time spent on food management and preparation, there exists no statistically significant difference in the impact of LPG between higher castes and SC/ST households. Both higher caste and SC/ST households spend less time on food management and preparation with LPG than without LPG being the main source of cooking. Interestingly, the LPG users from the OBCs spend more time than non-users in food management and preparation. We do not find statistically significant differentials across castes for the impact of LPG on time spent in employment activities. Overall, the heterogeneity across castes in terms of impact of LPG on the time spent in food preparation and management activities do not seem strong.

Besides the caste, the marriage status may also affect the time spent in food preparation. Pepin, Sayer, and Casper (2018) find that marital status differentiated housework and the number of employment hours. To capture the impact of LPG based on marital status, we carried out our analysis separately for married women and single

[11] OLS results are reported in Appendix Table A5.

women. It is noteworthy that the custom of patrilocal marriage shifts a woman from her natal family to being part of her husband's household, hence a single woman is more likely to be daughters of the households while married women are daughters-in-law of the households. Panel A and Panel B of Table 7 report the IV results for married women and single women, respectively. It is interesting that while LPG access has no impact on the involvement in cooking for married women, it increases the probability of involvement in cooking for single women by 4.5 percentage points. It is important to point out that while 93 percent of married women reported participation in cooking compared to only 71 percent of single women. While the participation of single women or daughters is higher with LPG use, there is no impact of LPG on time spent in food management activities or employment activities for single women. In contrast, we see 7 minutes decrease in time spent on food management for married women. Similarly, for married women time spent in employment activities increased by 10 minutes which 13.5 percent increase in total time spent in employment activities.

5. Conclusion

We address the question of whether use of LPG reduces the time burden of cooking for rural Indian women and free up time for employment activities using the nationally representative Time Use Survey collected in 2019 by the Indian National Sample Survey Organization. To address the endogeneity of LPG, we use a leave-one-out spatial instrument constructed through taking mean level of LPG use in the village where the mean is calculated excluding the concerned household. The OLS and IV estimates are similar in sign, however, the magnitude of IV estimates turn out much larger than the OLS estimates. We find that the LPG does not influence the probability of women's involvement in cooking activities. However, the use of LPG reduces the time spent in food management and preparation activities. Nevertheless, the magnitude of the reduction in time spent in cooking activities remains low. We find evidence of rebound effect where women with LPG access cook marginally more times potentially mitigating some of the time reducing effect of LPG on total time spent in cooking. Moreover, we find use of LPG increases time spent in employment activities by married women by 10 minutes per day. Although in terms of minutes, the time saved does not seems large, given the low amount of time spent in employment activities by married women, this translates into 13.5 percent increase in time spent in employment activities. Moreover, given that 93 percent of married women in rural India are involved in cooking with about half of them with no access to LPG, a 70 minute gain per week as a result of LPG in employment activities suggests a potential for huge amount of additional employment hours for the economy.

Time saved (or increased) in cooking (employment) activities is one dimension of potential benefits of LPG use. There are other benefits, such as environmental and health benefits, of LPG use which are well documented. The benefits of increased employment time and reduced burden (although limited) of cooking activities add to the potential benefits of LPG for the society, and reinforce the urgency shown by Indian policymakers in ensuring LPG access to majority of Indian population. There are a few caveats with our studies. Our LPG use is based on the question about the main source of household cooking fuel. LPG being main source of cooking fuel does not guarantee exclusive use of LPG. It is possible and probably expected that rural households engage in fuel stacking behavior potentially reducing the impact. For example, Using two rounds of NSS data gathered in 1987-88 and 2009-10, Cheng and Urpelainen (2014) discover that LPG and traditional biomass stacking has increased significantly in India between 1987 and 2010. In the absence of exclusive use of LPG, the impact of LPG on time saved will be an underestimation.

CHAPTER II

FUEL SWITCHING AND LABOR SUPPLY OF RURAL WOMEN IN INDIA

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 and Sadanand 2013; Williams et al., 2020; Afridi et al., 2020). A few studies that examined the problem of time savings mostly examined if using cleaner stoves may cut down on the amount of time needed for cooking and fuel collection. Their attention has been on enhanced biomass stoves that aim to cut down on the usage of biomass fuel by increasing 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. Similar to this, in South Africa, electrification of rural families allowed for significant, immediate changes in home production technology, boosted female employment, and maybe sparked an increase in the net labor supply. (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.

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 employ the 2004-05 (henceforth, 2005) and 2011-12 (henceforth 2012) waves of the India Human Development Survey (IHDS) . The National Council of Applied Economic Research (NCAER) in New Delhi, India and the University of Maryland collaborate to gather the IHDS, which are multi-topic surveys (Desai et al. 2010; Desai and Vanneman, 2015). Through the Inter-university Consortium for Political and Social Research (ICPSR), both waves are accessible to the general public. 42,153 households (27,580 rural and 14,573 urban) were surveyed as part of IHDS-2 (2012) in 971 urban neighborhoods and 1,503 villages throughout India. 40,018 of these 42,153 homes participated in the 2005 IHDS survey. Only households that were surveyed in both rounds are used. 653 households that don't report cooking are further removed. 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.

Several socioeconomic details about households and individuals are included in the IHDS data. The IHDS also included a comprehensive energy module that included in-depth questions about respondents' use of all energy sources. According to our data, a total of six cooking fuels are used: kerosene, LPG, coal, charcoal, dung, and crop residues. Each fuel type is listed in the IHDS questionnaire, and respondents are asked whether their household has ever used that particular fuel for cooking. Although the use of electricity as a fuel type is not specified, just 0.10 percent of Indian households reported using electricity as their primary source of fuel for cooking in the 2011 Census. Figure 11 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 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.

Table A8 reports the descriptive statistics of variables in 2005 that might plausibly be correlated with the fuel switching. The characteristics of the household can be broadly categorized into a number of groups, including the level of education of the household head, the demographic composition of the household, the economic indicators of the household, the health issues and shocks that the household experienced in 2005, the participation of the household in different bodies, the social networks of the household, and the village characteristics in the case of a rural area.

Table 8 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. Additionally, distribution networks for modern fuels across the nation are necessary for access to modern fuel. Furthermore, households are frequently discouraged from using modern fuels as their primary choice of cooking fuel, especially the poorest households, due to the high initial cost and subsequent high refill cost. 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 shows that there is about 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 9 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. According to the energy ladder concept, as income rises, households switch to more expensive, cleaner fuels (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 association between the rate of women entering the work force and economic growth (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.

$$T_i = \begin{cases} 0, & \text{if } fuel_{2005} = fuel_{2012}, \\ 1 \text{ or } 2, & \text{if } fuel_{2005} \neq fuel_{2012}. \end{cases} \tag{4}$$

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. Cattaneo et al. (2013), Wooldridge (2010), and Cattaneo (2010) have developed multivalued treatment effects.

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$D_{it}(T_i)$.

$$\Delta y_i \Big| fuel_{i,2005} = \sum_{t=0}^{2} D_{it}\left(T_i\right) \Delta y_{it} \tag{5}$$

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 conditional independence (CI) and overlap assumptions support the validity of the MVTE estimates. 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. In the case of multivalued treatments, Imbens (2000) presented the generalized propensity score (GPS) as a useful substitute for conditioning directly on Xi. (Linden et al., 2016). The GPS is the conditional likelihood of receiving a specific degree of therapy in light of the pretreatment factors like:

$$r(t, x) = P[T_i = t|X_i = x] \tag{6}$$

In order to estimate the GPS, we use a comprehensive set of observed baselines from 2005, household characteristics, and a multi logit model. Imbens (2000) demonstrates how weighing (inverse probability weighting, IPW) can be used to determine the unconditional means of conceivable outcomes, much as in the case of binary treatment: Although propensity score matching methods for more than one value of treatment have not yet been fully developed, one can utilize weighting techniques similar to binary case (Smale et al., 2018).

$$E\left[\frac{\Delta y_i D_{it}(T_i)}{r(t, X_i)}\right] = E\left[\Delta y_{it}\right] \tag{7}$$

According to the aforementioned hypotheses, treatment m (switch) has a greater average treatment impact on treated (ATET) than treatment l (no switch), as shown by:

$$ATET^{IPW}_{ml|m} = \frac{1}{N_m}\sum_{i=1}^{N} \Delta y_i D_{im}(T_i) - \frac{1}{N_m}\sum_{i=1}^{N} \Delta y_i D_{il}(T_i)\frac{\hat{r}(m, X_i)}{\hat{r}(l, X_i)} \tag{8}$$

4. Results

Table 10 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 10 are echoed with the decreasing trend of female labor force participation rate for solid fuel users, shown in Table 9.

In Panel 2 of Table 10, 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 10 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. Using the Mexican Family Life Survey and a utility-maximization framework to integrate the household's choice of fuels for cooking and heating with the presence of health issues, Stabridis and Van Gameren (2018) discover that while using firewood keeps women at home, the respiratory issues brought on by it reduce work participation. Burke and Dundas (2015) study household biomass energy drivers using data from up to 175 countries between 1990 and 2010 and discover that female labor force participation is correlated with lower household biomass energy consumption.

Figure 2 - Figure 4 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 2 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 graph (a) of Figure 2. The density distributions of the estimated probability show little mass around zero or one, supporting the overlap assumption. For

Graph (b) of Figure 2, The control group's density, which represents the households that don't change, is skewed to the left. However, there are many households with higher probability of getting treated but who are not actually switching their cooking fuel due to the huge sample size of the comparison group compared to the treatment group (around 21:1).Figure 3 is for switch mixed to solid and modern fuels. Graph (a) and (b) of Figure 3 present no evidence that there is any mass of observations with predicted probabilities close to either 0 or 1. Figure 4 shows the conditional density for switching modern fuels to mixed. There is little mass around o and 1, supporting the overlap assumption.

There is no agreement on the matching procedure, despite the fact that there are numerous ways to compare control and treatment observations. In our paper, we employ kernel matching in the manner of Azam (2018). Each treated observation has a neighborhood defined by kernel matching. It builds the counterfactual using all control observations made nearby, weighting each observation according to how close the treatment and matching control observations are, with the weighting function getting smaller as the distance increases (Azam 2018). According to Blundell and Dais (2009), if we utilize more data per treatment, kernel weights provide less bias than nearest neighbors with many matches and decrease the variability of the estimator when compared to nearest neighbor weights.

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). In order to reduce the influence of career decisions with a significant intertemporal component, including education and retirement, we exclude women households older than 64 and younger than 28. 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.

CHAPTER III

TIME ALLOCATION TREND AND INEQUALITY IN INDIA

1. Introduction

In this paper, we document trends in the allocation of time within India over the last two decades. In particular, we focus our attention on time allocation in leisure, employment, childcare, and domestic service activities. Understanding the time allocation trend is of great importance in general. Just like income, time is a scarce resource that impacts well-being, and individuals with insufficient time to meet their basic needs are considered to be time poor. People who suffer from time poverty do not have the freedom to allocate their time toward activities that maximize their wellbeing (Hirway, 2010). Moreover, Income poverty and time poverty are mutually reinforced. According to Vickery (1977), a household's capacity to convert its free time into spending is reliant on the productivity of both its market and nonmarket labor.

Investigating the time allocation trend over the last two decades towards paid and unpaid activities could deepen our understanding of how gender norms shape individuals' time allocation. According to the database of the World Bank, despite robust economic growth, the labor force participation rate of the female population ages 15 + decreased from 31 percent in 2005 to 21 percent in 2019, and wide gender differences in participation rate also persist. It makes Indian women some of the least employed in the World (ILO 2020).However, almost one-third of Indian housewives still state that they would like to work (Fletcher et al., 2019).The rigid gender norms surrounding job roles, a phenomena common in India and abroad, are likely what prevents so many working-age women from entering the workforce. Many countries believe that if a wife chooses to work outside the home, it will cause her husband social disgrace or humiliation because men should be the major breadwinners (Boudet et al., 2013, Bernhardt et al., 2018). Field et al(2021) analyze the effects of an exogenous rise in women's power over earned income using the canonical collective household model and they show that gender norms originally restricted female employment. The 1991–1994 sex ratio at birth of each person's birthplace served as a proxy for parental gender norms in the study by Hwang et al. (2019) on the influence of parental gender norms on the distribution of household work among the dual-earner couple. According to Hwang et al. (2019), the husband's housework time is unaffected by the couple's province of birth, but both the overall and wife's housework time rise when the husband is from a province with a higher sex ratio at birth. The majority of married men in Saudi Arabia accept their wives' decision to work outside the home (WWOH), according to Bursztyn et al. (2020), who also significantly underestimate the amount of support for WWOH from the broader society, including men in similar socioeconomic contexts.

Analyzing the time allocation trend is necessary considering the evolution of the demographic changes. Since the middle of the 20th century, there have been significant demographic shifts happening all over the world. The age distribution of the population has changed significantly in many countries as a result of declining fertility, rising longevity, and increased mortality. These demographic shifts are causing changes in time allocation. Examining the time allocation trend in leisure, employment, childcare, and home service activities could help us understand India's demographic transition in the past two decades.The demographic shift could have an impact on long-term economic growth (Curtis et al., 2017). As a result of increased life expectancy and declining fertility, India's present population of 1.4 billion is expected to increase to 1.5 billion by 2030 and 1.6 billion by 2050, resulting in major demographic shifts in terms of the age profile of the population (UN, 2019). Between 1999 and 2019, India had a demographic transition that saw its population age from a relatively young to an older age while also raising its level of education. Using a generalized method of moments, Mukherjee et al. (2019) investigate the impact of demographic changes on macroeconomic outcomes in India and come to the conclusion that a rise in the working-age population promotes greater economic growth.

A large number of studies, many of them for individual countries, have documented time allocation trends with time across paid and unpaid activities using various time using surveys. Gammage (2010) uses data from a nationwide household survey conducted in 2000 to assess unpaid work in households in Guatemala using three different methodologies.[12] to estimate a range of values for nonmarket work in the household. This study emphasizes the significance of unpaid work in Guatemalan households from an economic perspective and finds that in 2000, its value was equivalent to about 30% of GDP for that year (Gammage, 2000). Rubiano Matulevich and Viollaz (2019) analyze time use patterns in 19 countries of different income levels and from various regions from 2006 to 2014. They adopt propensity score matching to assess the "penalty" of marriage and parenthood. They find that women perform less market work and more unpaid domestic work than men in every country in the sample. Gimenez-Nadal and Sevilla (2012) also found that men increased the amount of time spent on home duties, using extensive time-use data from the 1970s to 2012 for seven industrialized nations. Contrarily, women spent less time on unpaid household chores and, despite declining fertility rates, more time was spent on childcare in the majority

[12] The three approaches are an opportunity cost method that uses Heckman corrections to value the labor of non-participants in the market economy, a replacement cost method that uses the cost of domestic labor, and a service cost method that distinguishes between activities and applies wage rates of those household services that can be contracted in to replace these discrete activities (Gammage, 2000).

of countries over the period.

Our research advances the field of time allocation literature (Burda and Weil, 2008; Biddle and Hameresh, 1990; Ghez and Becker, 1975). However, our study adds to the body of literature by recording and evaluating the dispersion in leisure, job, childcare, and home service in addition to looking at changes in four separate activities over the past 20 years. Furthermore, instead of reporting unconditional means of these activities, We present time use trends that have been modified for changing demographics. Given the changes in the age distribution, fertility, family structure, and level of education over the past 20 years, this could be significant (Aguiar and Hurst, 2007). To our best knowledge, this is the first paper that combines the length of time series and the cross-sectional dispersion to investigate the trend of time use in India. In addition, we add to a growing body of literature that has primarily concentrated on the long-term durability of cultural characteristics and norms (Fernández, 2007; Giuliano, 2007; Alesina et al., 2013; Voigtländer and Voth, 2015). By examining how time allocation trends have altered over the past two decades in India, our paper contributes to the rich literature on gender and labor markets (Bertrand 2011, Goldin 2014).

The following are the paper's principal conclusions. Both men and women have much more free time, according to our research. We demonstrate that leisure time increased for both men and women by about three to four hours per week for males and by about four to six hours per week for women. The decline in time spent on employment-related activities for both men and women in the six states between 1999 and 2019 is also something we observe. However, the reduction dimension for women, particularly for women in rural regions, is enormous, which widens the gender gap in employment.

Moreover, changes due to different cell means account for most of the unconditional change. We have a relatively stable amount of time allocated to childcare, with a decreasing gender gap allocated to home service since women decrease their time in-home service by about four to seven hours per week. However, women still spend more time than men engaged in childcare and home service activities. Lastly, we document a growing inequality in leisure and employment that is the mirror image of gender discrimination.

The remainder of this paper proceeds as follows. Section 2 describes the data. Section 3 discusses the role of demographics in Mean Trends. Section 4 presents the time allocation inequality. Section 5 concludes.

2. Data

To document the trends in the allocation of time over the last twenty years, we link two time use surveys in India: 1999-2019. The time use survey (TUS) of 1999 is collected by the Social Division of the Central Statistical Organization and covered 18, 591 households spread over six selected states, namely, Haryana, Madhya Pradesh, Gujarat, Orissa, Tamil Nadu, and Meghalaya. Overall, about 70 percent of the respondent were residing in rural areas, and there were a marginally higher number of men (51.7 percent) than women (48.35 percent). The method adopted for the collection of data is interviewing. A reference period of one week was adopted for collecting the data. A one-day recall lapse was used to collect data for each type of there day. Since there was no activity categorization applicable to India, a new activity classification was created to be used in the survey. The TUS 2019 is collected by the Indian National Sample Survey Organization (NSSO). The survey includes 1, 38, 799 households in both rural and urban areas. Data in this survey is collected by diary over 24 consecutive hours and divided into 30-minute intervals. The classification of activities for TUS 2019 is consistent with the international classification of activities.

In order to link the two data sets, we matched the activity categories of the two time use survey and only kept Haryana, Madhya Pradesh, Gujarat, Orissa, Tamil Nadu, and Meghalaya as the six states to ensure a consistent sample. Finally, we have 43 271 total observations from TUS 1999 and 63, 633 observations from the data set TUS 2019. We characterize four major uses of time: Leisure activity, employment activity, childcare activity, and home service activity. Our primary sample consists of respondents aged eighteen to sixty-four who are neither students nor retirees. We drop adults younger than eighteen and adults older than sixty-four to exclude students who are attending school and people who already retired. In order to capture the normal routine of household activities, we only adopt the normal day since collecting the data without loosing much information. We report trends over the last two decades holding constant the demographic composition of the sample. Specifically, we divide the sample into demographic cells defined by five age groups (18-27, 28-37, 38-47, 48-57, 58-64), four education categories (nonliterate, below primary, above primary below secondary, secondary and above), two gender categories, and three castes categories (Schedule Tribe, Schedule Caste and others). The division yields 120 cells. The demographic adjustment is necessary given the significant demographic changes in India over the last twenty years. Since 1999, the average Indian has aged, become more educated, and had few children. All of these changes may affect how an individual chooses to allocate his or her time.

We documented four different activities: Employment Activity, Leisure Activity, Childcare Activity, and Home Service Activity. The reasons why we select the four categories are as follows. Changes in leisure time are essential in relation to the evaluation and sustainability of the overall changes in time allocation over prolonged periods. An individual or household is time-poor if their total hours engaged in leisure time is less than a critical threshold. Leisure combines all time spent on "socializing, religious practice, entertainment, travelling and self-care and maintenance activities". These categories include any activity pursued solely for direct enjoyment, such as television watching, playing sports and games, or other cultural activities.

Employment activity is one of the most important parts of people's lives. It means more than just getting paid. It means being able to make your own choices about how you want to live your life. Women are joining the labor force in increasing numbers globally. According to World Bank (2012), the gender gap in labor force participation declined by 6% age points between 1980 to 2009.

India has had a secular fall in women's employment rates during the past few decades, in contrast to worldwide trends. Examining the employment trend across genders could help us understand the decision-making power within the household. In our paper, the employment activity includes employment and related activities and producing goods for final use.

The majority of unpaid care work, such as housework and caring for families without any monetary compensation, is carried out by women globally. The capacity and well-being of humans depend on unpaid caring work. Unpaid care work is crucial for creating and maintaining economic growth because it helps to build human and social capital (Folbre and Nelson, 2000). It is still inconclusive about the economic theory of time allocation. The impact depend on how time spent with children is supposed to be, i.e., whether it is viewed as "preferred leisure" or simply an input in the home production process (Hallberg and Klevmarken, 2002). All the time spent on childcare as a major activity is included in childcare, including feeding and preparing food for kids as well as passive care. Home services for household members include cooking, grocery buying, travel, and other unpaid domestic tasks. The precise content for each category is presented in Appendix 11.

Table 11 shows minutes per day spent in employment, childcare, and home service activities for the total sample, men and women. The average amount of leisure has increased dramatically over the last two decades. The increase is observable across the subsamples. Overall, on average, leisure consumption increased by 40 minutes per day, and the change is more considerable in rural India than in urban areas, especially for women in rural areas. In India, men are the primary breadwinners of the family. However, over the last two decades, the time spent in employment decreased for men and women, except for women in urban areas (increased by two percentage points compared with 1999). Moreover, time spent in childcare is increasing, except for households in urban areas, especially women's households in urban areas. Regarding the home service activity, while women take the most responsibility for unpaid domestic service activity, the trend of time spent in-home service activity is declining, except for the men in rural areas (increased 17 percentage points compared with 1999).

3. The Role of Demographics in Mean Trends

This section will examine the extent to which changes brought on by shifting demographics or shifting cell means can account for the unconditional change in time consumption. Consequently, we employ the Blinder-Oaxaca approach to partition the unconditional mean change in time use into the fraction that can be explained by changing demographics and the portion that can be explained by changing cell methods (within demographic groups).

Following Aguiar and Hurst (2007), we compute the unconditional average amount of time spent in activity j: $\bar{Y}_{j1999}$ from dataset TUS 1999 as $W_{1999}Y_{j1999}$, where $\bar{Y}_{j1999}$ is the vector of mean times of activity j in the TUS 1999 by each demographic group, and W_{1999} is the corresponding vector of demographic weights. Similarly, $\bar{Y}_{j2019} = W_{2019}Y_{j2019}$ represents the average amount of time of each activity in TUS

2019. The change in the unconditional mean between 1999 and 2019 can be decomposed as:$\bar{Y}_{j2019} - \bar{Y}_{j1999} = W_{2019}Y_{j2019} - W_{1999}Y_{j1999} = W_{2019}Y_{j2019} - W_{1999}Y_{j2019} + W_{1999}Y_{j2019} - W_{1999}Y_{j1999} = (W_{2019} - W_{1999})Y_{j2019} + (Y_{2019} - Y_{1999})W_{j1999}$. The expression $(W2019 - W1999)Yj2019$ denotes the contribution to the overall change resulting from changing demographic weights and a fixed-demographic distribution of time allocation, whereas $(Y2019 - Y1999)Wj1999$ denotes the contribution resulting from shifting time allocation within demographic cells with constant weights. An alternative would be to employ the decomposition listed below:

$$(W_{2019} - W_{1999})Y_{j2019} + (Y_{2019} - Y_{1999})W_{j1999} \tag{9}$$

3.1. Leisure Activity

The two decompositions are reported in panel 1 and 2 of Table 12, respectively. The first column of panel 1 in Table 12 shows the unconditional change in time use for leisure activities, employment activities, childcare activities, and domestic service activities. The second column reports the change that is due to changing demographics. The first row shows the unconditional change of time spent in leisure activity is 36.58 minutes per day for the total observation, which translates to about four hours per week. The third column reports the change that changes due to within demographics cells. Shifts in demographics add 12.56 minutes to eight minutes per day to the overall change in leisure activities. This, in part, reflects that more educated and elderly individuals are inclined to spend more time in leisure activities. This is reinforced by an increase in leisure activity within each demographic group.

To gain additional insight into the leisure consumption across genders, we examine the changes in leisure activity across genders. Changes due to changing demographics for both men and women are modest. Much of the trend is due to within-demographic-cell changes rather than evolving demographics, leaving the gender gap of unconditional change is about 1.7 hours per week for the total observations.

The result of Blinder-oaxaca decomposition of mean unconditional change of households in rural India is reported in Table 13. Shifts in demographics add 11.8 to 7.7minutes to the overall change in leisure and the increase in leisure within each demographic group by about 32 minutes to 36 minutes per day, leaving the overall unconditional change at 43.96 minutes per day, which translates to 5 hours per week. This result is echoed with the summary statistics in Table 11 that the increase in time allocation of leisure is mainly comes from rural India. Male and female subsamples is similar. And the main difference origins from the change due to different cell means. However, the unconditional change in leisure in urban area is smaller compared with the rural area. Also observe that panel 1 has a higher shift in leisure as a result of adjusting demographic weights. This illustrates how leisure disparities between demographic groups were larger in 1999 than 2019.

Changes in leisure consumption for the female are more significant than the male, which also implies the inequality of leisure across genders is reduced, even though, men still consume leisure more than women.

3.2. Employment Activity

Table 11 documented a mean decline in total employment activity for men and women over the last two decades. The mean difference from 1999 to 2019 is larger in rural India, which will be echoed in the Blinder-Oaxaca Decomposition analysis in this part. The unconditional change of time spent in employment activity is decreased by about 40 minutes per day, which translates into 4.7 hours per week. Shifts in demographics decrease the overall change in employment by minus 14 to minus six minutes per day. Furthermore, it is reinforced by the changes within demographic cells. The change in employment due to changing the demographic weights is larger in Panel 1, which reflects that employment differences between demographic groups are larger in 2019 than in 1999. The unconditional change is much more significant for females compared with males. Shifts in demographics decrease 14 minutes to two minutes per day, which is reinforced by a decline in employment within each demographic group, leaving the overall unconditional change at minus 44 minutes per day, which translates into 3.6 hours per week (work five days per week).

Compared with the total sample, the unconditional change in rural India is larger than the total observations. The main difference comes from the changes within demographic cells, which reduce the time spent in employment by 47 to 58 minutes per day. The difference in unconditional change in employment across genders in rural India is about 28 minutes per day. The gap due to the changes in demographics is about 10 minutes per day, and the change due to changes within demographic cells is about 18 minutes to 23 minutes per day. The unconditional employment change in urban India is much smaller than in rural India. Furthermore, the change gap across genders is relatively small.

The result reflects that the gap across genders of employment is enlarged significantly in rural India. The result is echoed by the decreasing male labor force participation rate for the men with high secondary and above education levels. The female labor force participation rate remains low and decreases significantly for women below primary education level.

3.3. Childcare Activity

Table 11 shows that women spend most of their time in childcare compared with men. Shifts in demographic reduce the time spent in childcare activity by about 1.5 to 2 minutes per day. This is offset by an increase in childcare activity within each demographic group, leaving the overall unconditional change at minus 1.3 minutes per day. Unlike the overall trend, the unconditional change for men increases by about 1.4 minutes. However, the unconditional change for the female is minus five minutes.

The main change comes from the change due to different demographics. Overall, the unconditional change of childcare is modest. The result of subsamples in the rural and urban area is quite similar. The gap of time allocated to childcare is decreased for households in the urban area, even though the dimension is quite small.

3.4. Domestic Service Activities

The overall unconditional change of time spent in domestic service activities is about minus 22 minutes per day. Much of the trend is due to within-demographic-cell changes rather than evolving demographics. Many studies have documented that the gender imbalance in housework time allocation is a crucial explanatory factor of gender differentials in wages (Amarante and Rossel, 2008; Warren and Fox, 2010). For the overall sample, the overall gap in the unconditional changes between women and men is about 45.79 minutes per day, which can be translated into 5.3 hours per week. Furthermore, the overall unconditional change is small for men. The main change comes from changes within the demographic cells of women. For the unconditional change of time spent in domestic service activity in rural India is smaller compared with the total sample, and the main change is due to different cell means. The overall unconditional change of women follows similar pattern of the total sample but in a smaller dimension, while unconditional change for the men in rural is small.

The overall unconditional change of time allocation in domestic service is significant for urban women, about minus seven hours per week. Moreover, the main change is due to the within-demographic-cell change. This reflects that domestic service differences between demographic groups are larger in 2019 than in 1999.

4. Time Allocation Inequality

We use the decomposition method proposed by Juhn, Murhpy, and Pierce (1993) to investigate the causes of the increasing dispersion in all activities. We follow Aguiar and Hurst (2007) to set up our model. For respondent i in survey year t, Y_{it} represents the amount of time spent on status activities, leisure activities, employment activities, childcare activities, and household service activities. Demographic factors, X, and a residual term, μ_t, can both be used to explain the cross-sectional variation:

$$Y_{it} = X_{it}\beta_t + \mu_{it} \tag{10}$$

X controls include dummy variables for the corresponding interactions between age group, gender, education level, and caste. We specifically include 120 dummy variables that match the 120 demographic cells mentioned in the prior section that were used to calculate our demographically. It indicates the means of the demographic cell. Using data from the time use surveys conducted in 1999 and 2019 individually, we run this model. Changes in the distribution of Y_{it} can be attributed to changes in demographic composition, changes in cell-means β_t, or changes in the residual variation. Suppose ϕ_t represents individual i's percentile in the residual distribution, and F_t the residual distribution function at time t, then $\mu_t = {F_t}^{-1}(\phi_{it}|X_{it})$ We define β to be the mean of the dependent variable by demographic cell for the entire sample. That is is vector of coefficients on the dummy variables from a regression using pool sample. Similarly, $\bar{F}(.|X_{it})$ is the cumulative distribution function for the residuals pooled across all years. Therefore, by definition, we got

$$Y_{it} = X_{it}\bar{\beta} + \bar{F_t}^{-1}(\phi_{it}|X_{it}) + X_{it}(\beta_t - \bar{\beta}) + {F_t}^{-1}(\phi_{it}|X_{it}) - \bar{F_t}^{-1}(\phi_{it}|X_{it}) \tag{11}$$

Note that $Y^1_{it} = X_{it}\bar{\beta} + \bar{F_t}^{-1}(\phi_{it}|X_{it})$. This is the prediction of different activities for the individual with characteristics X_{it} and a relative residual ϕ_{it} using the average cell means $\bar{\beta}$ and the average residual distribution, $\bar{F}$. Changes in the moments of this series over time are driven by changes in observed demographics, X_{it}. The series $Y_{it}^2 = X_{it}\beta_t + \bar{F}_t^{-1}(\phi_{it}|X_{it}) = Y_{it}^1 + X_{it}(\beta_t - \bar{\beta})$ contains the additional variation due to changes in the cell means over time. Finally, the series $F_t^{-1}(\phi_{it}|X_{it}) - \bar{F}_t^{-1}(\phi_{it}|X_{it})$ represents changes in the distribution of unobservables.

Table 15 shows the percentage of the change in the cross-sectional distribution of various activities that each of these components is responsible for. The table shows how the difference between the 90th -10th, 90th -50th, and 50th -10th percentiles changed through time from 1999 to 2019. The first column reports the total change. The second column represents the demographic quantities, which captured by captured by Y_{it}^1 defined earlier. The third column reports the Y_{it}^2 once we subtract the second column's change. The fourth column is the unobservable part that help explain the change.

4.1. Leisure Activity

The first row of Table 15 presents observable and unobservable components of changes in inequality for literature activity, the 90-10 differential increased by 15 minutes per day between 1999 and 2019. Demographics predict a change of two minutes per day, as reported in the second column. The Blinder-Oaxaca decompositions of mean changes illustrated in Table 12 serve as a reminiscent that changes in demographic quantities only partially account for changes in leisure inequality. Four minutes less are added to the dispersion as a result of alterations in the cell means. The majority of the overall change, or the remaining 16 minutes every day, is attributable to unobservables.

For the subsample of males (Panel B of Table 15), the total changes for the time allocated to leisure activity from 90th -10th and 90th -50th of men are 30 minutes per day, which is 3.5 hours per week. The main changes come from the unobservables, similar to Panel A. The inequality for the female is similar to the male sample, the unexplained part of the gap is dominant, but the dimension is smaller than the male. However, for the 90th -50th percentile, the inequality over time is reduced. The demographic quantities have accounted for about 70 percent of the decrease in inequality for those in the 90th-50th percentile. For those below the median, the inequality increase is more significant than for those above the median.

The inequality gap between the 90th-10th and 90th-50th percentile is enlarged in rural India, especially for men. The unobserved component accounts for around 80 percent of the increase in inequality. For females, the inequality is increased for 90th-10th and 50th -10th percentile by about 15 minutes per day, which is 1.8 hours per week. It is mainly attributed to unobservables, representing the bulk of the total change.

Different from rural India, the inequality changes in urban for total observations decreased by10 minutes per day for the 90th-10th and 90th-50th percentile. The decreased dispersion represented from 1999 to 2019 can be attributed to changing demographic-group means. For males in urban India, the observable demographic quantities and unobservables for a slight decrease in overall inequality. The majority of the decrease in inequality is attributed to cell means. For women in urban India, the overall inequality decreased for the 90th-10th and 50th-10th by 20 minutes per day, and the cell means to account for the dominant portion of the decrease in inequality.

4.2. Employment activity

From the percentile distribution of the employment activities, those who belong to the tenth percentile are not working. The 90-10 differential decreased by 30 minutes per day between 1999 and 2019. Demographics predict an increase of four minutes per day, offset by the unobservables' negative effect. The cell means account for the vast majority of the decrease in inequality, accounting for about 90 percent of the reduction in the 90-10 percentile differential. For those 90 - 50 percentiles, the total change of the inequality is 40 minutes per day, and the demographic quantities change is the dominant portion of the increase in inequality. The gap in the inequality decreased dramatically for that 50-10th percentile, 70 minutes per day. Changes in demographic quantities predict a change of 41 minutes per day. The cell means account for 42 percent of the decrease in inequality. The result indicates that those in the 90 − 50th percentile reduced their time allocated to employment activities, considering people in the 10th percentile do not work at all.

The inequality of total change in employment for males is significant for those in 90-10th, 50-10th percentile. The unobservables account for the vast majority of the increase in inequality. This is probably because of the difference in skill and ability in the job market. However, different from men, women in the top 90th and 50th spend less time in employment, reducing the total change of inequality by about 60 minutes and 90 minutes per day, respectively. Following the same pattern of the total observation, for those in the 90-50 percentile, the inequality of time allocated to employment increased by 30 minutes per day. The change comes from 52 percent of demographic quantities and 46 percent of unobservables. This is consistent with the existing literature that the relationship between women's labor force participation rate and economic growth is U-shaped.Women's participation in the job market tends to increase at a certain level of per capita positive connectivity, while it tends to fall during the early stages of economic growth (Lechman and Kaur, 2015). A similar pattern is repeated for the rural sample, but the total change is larger than the total observations. However, the gender gap in time spent in employment in urban India is reduced significantly for women above the mean percentile.

4.3. Childcare Activity

Based on our data set, the time spent in childcare activity for those in the 50th and 10th percentile is zero for all the observations. The inequality in our table shows the change of individuals in the top 90th percentile from 1999 to 2019. People in the top 90th percentile, especially women, increase their time in childcare. There is no change for men. For the total sample, the changes due to cell means account for most of the total change. Nevertheless, for females, changes of unobservables dominate. A similar pattern is repeated in rural areas. Different from the rural area, the total change of childcare in urban India is decreased by 1.8 hours per week, mainly because of the changes in demographic quantities. The total change in the female subsample in urban is the same as the total sample, but the vast majority change is due to changes in unobservables. Men who belong to the 90th percentile in urban India increased their time devoted to childcare by 10 minutes per day, and the changes due to unobservables account for the change.

4.4. Home Service Activity

Time allocation to the home service activity reflects women's and men's gender roles. The Jun-Murphy-Pierce decomposition provides the critical links for understanding the changes in inequality over time. For the overall sample, those in the 10th percentile do not spend time in home service activity. The total change of home service activity is decreased by 70 minutes per day, which translates into eight hours per week. As the table shows, changes in observed quantities account for only about 16 percent of the decrease in home service inequality between the 90th -10th percentile. However, the cell means account for over 60 percent. Similarly, the total change of inequality of those in the 90th-50th has been narrowed by 100 minutes per day, which translates into 12 hours per week. The unobservables represent the bulk of the total change. However, Individuals in the 50th percentile increased their time in home service by about 30 minutes per day.

According to the distribution of the home service activity for men, individuals who belong to the 50th and 10th percentile do not spend any time in home service activity. The result shows that men in the top 90th percentile increased their time in home productivity by 30 minutes per day, which increased the inequality of time allocated to home service. The majority of change comes from the unobservables. For the female in the total sample and other subsamples, the total change decreases mainly because of changes due to unobservable.

5. Discussion and Conclusion

The trend in time allocation for leisure, work, childcare, and housekeeping chores has been examined in this paper. Over the past 20 years, there has been a significant increase in the amount of time spent engaging in leisure activities. This increase can be seen in many subsamples. Women in particular reduced their home service and labor force engagement while increasing their leisure time. Additionally, the period of time when leisure time increased and employment time decreased saw a very stable average for childcare.

Our findings also show a sharp rise in the distribution of leisure and a marked decline in the distribution of employment. However, some of this dispersion can be attributable to variations across educational categories. The majority of this dispersion occurred within demographic groupings. Particularly in the last twenty years, we find that aged and more educated individuals have increased their relative leisure consumption. The total change of time allocated to childcare increases overall due to cell means and unobservables. Men do not change their time devoted to childcare. However, in urban India, the inequality increased for men in the 90th percentile. The overall total change of home service decreases, and the main reason is attributed to changes in cell means. The gender gap increases and the unobservables represent the bulk of the total change.

Our results indicate that over the past two decades, both males and females increased their time spent in leisure activities, coupled with decreasing the time allocated to employment activities. The increasing inequality of employment across genders because the labor market favors higher educated men. Women spend much more time in childcare and home service for household members than men, even though men increased their time devoted to unpaid work such as domestic service activity and childcare activity.

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Figures

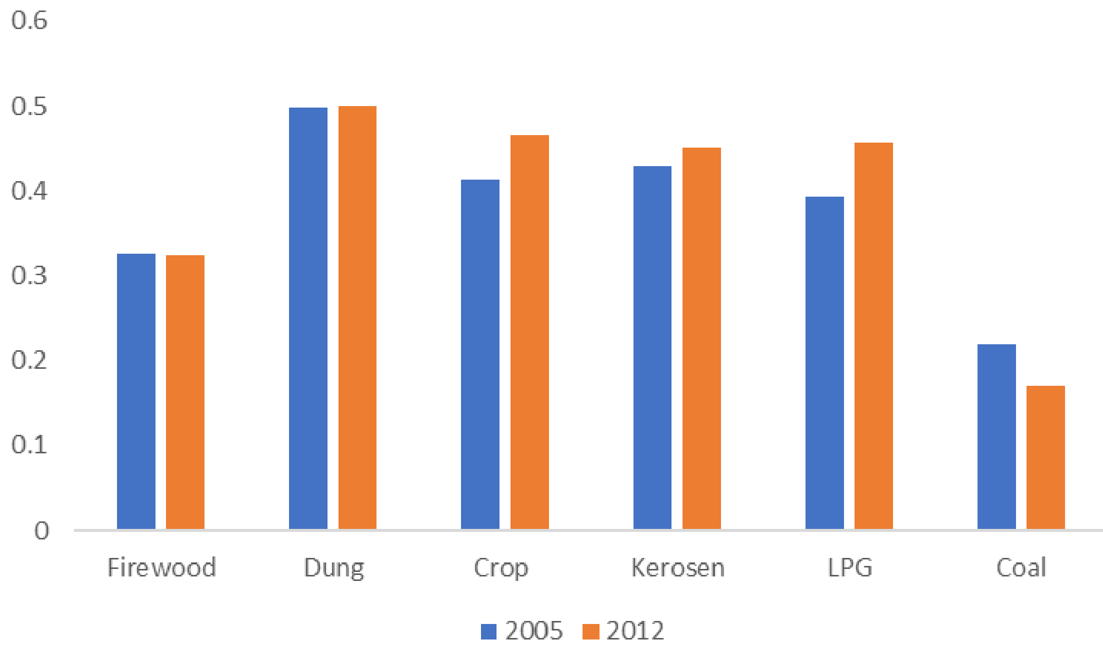
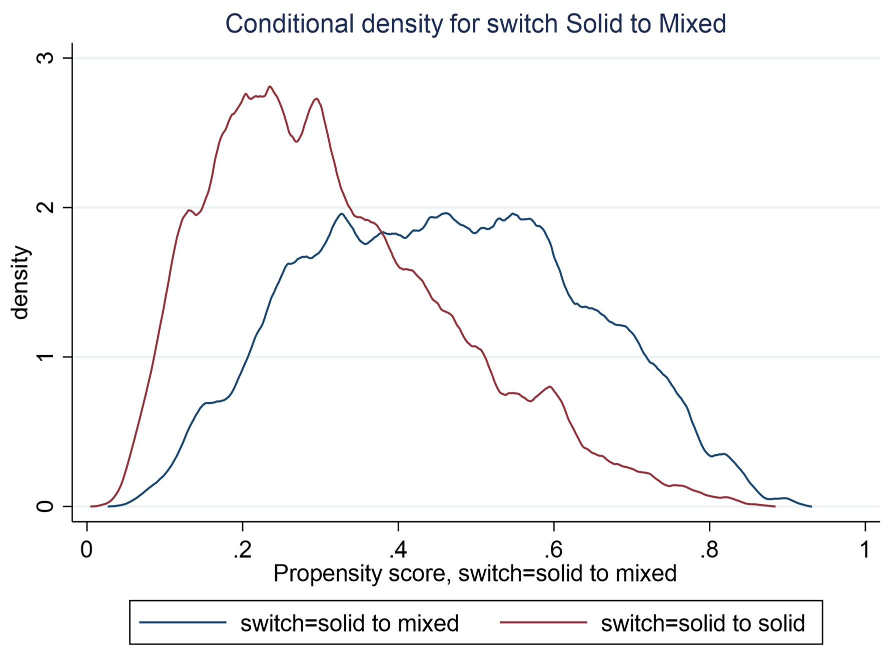
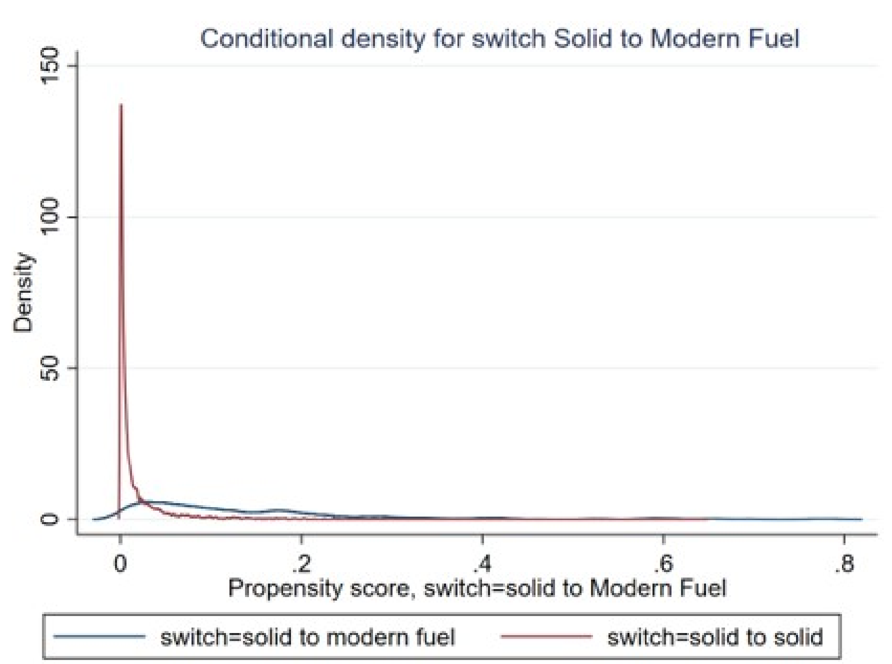


Figure 1: Fuel Use Index in 2005 and 2012

Note: This figure 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 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.



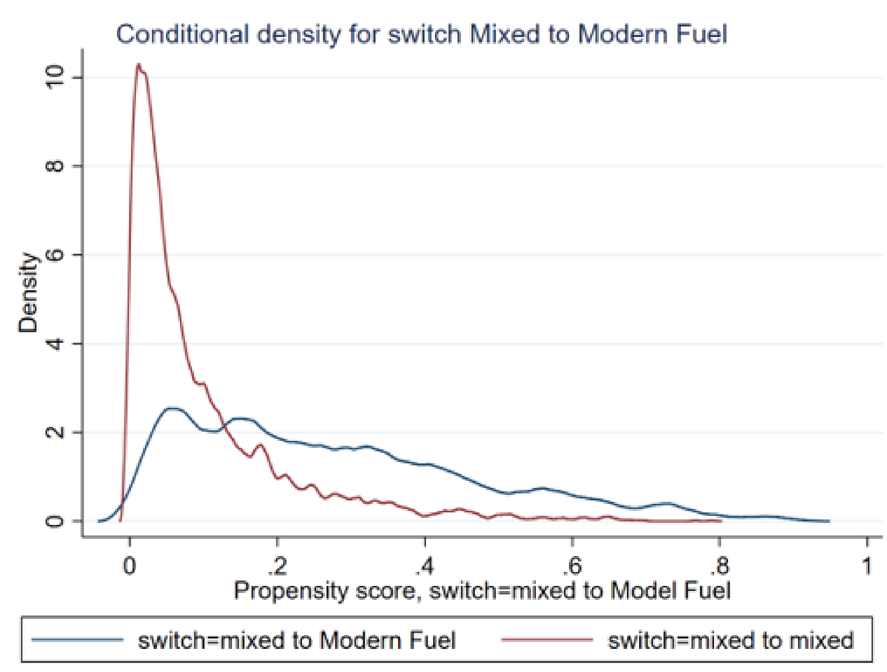
(a) Switching from Solid to Mixed



(b) Switching from Solid to Modern Fuel

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

(a) Switching from Mixed to Solid



(b) Switching from Mixed to Modern Fuel

Figure 3: Conditional Density for Switch Mixed to Solid/Modern fuel

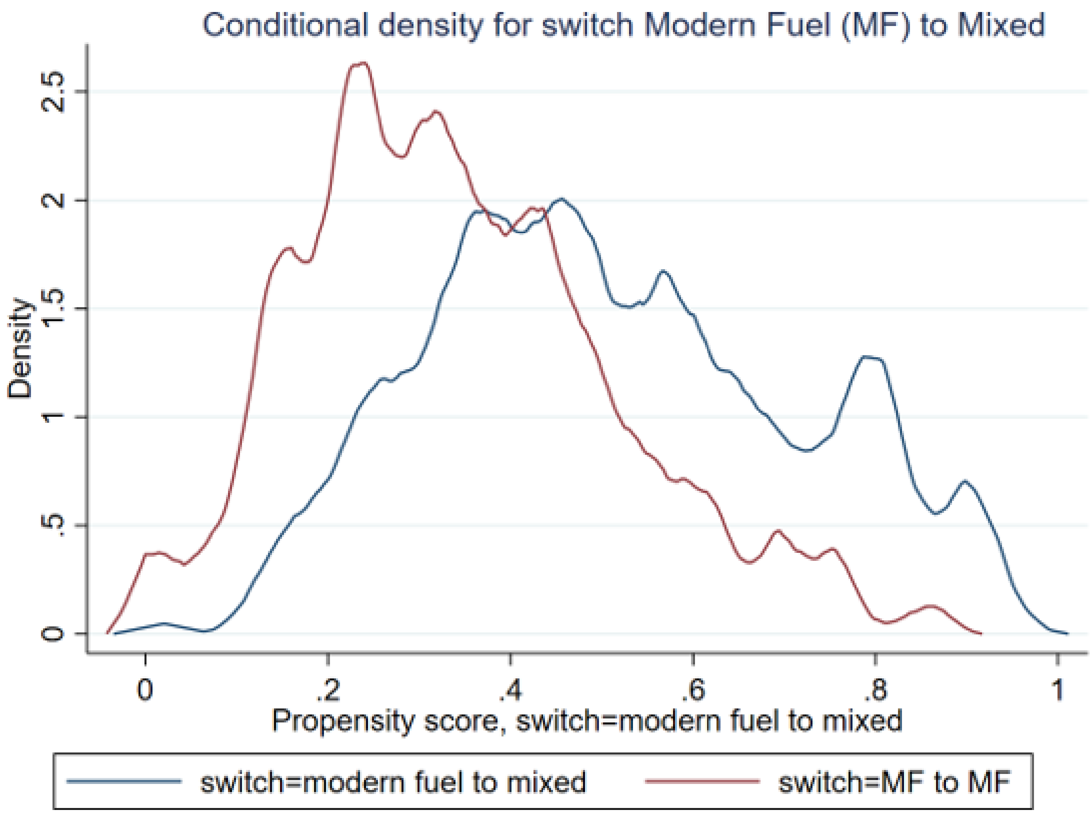


Figure 4: Conditional Density for Switch Modern Fuel to Mixed

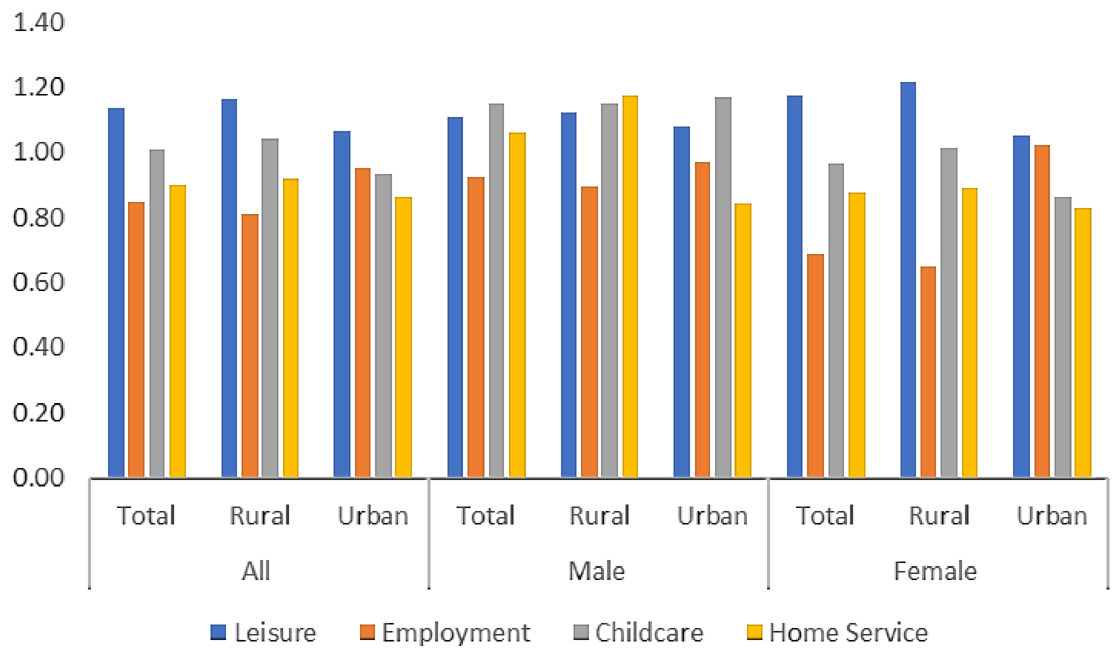


Figure 5: Time Allocation Index

Note: This figure compares time allocation in leisure, employment, childcare, and home service activities in 1999 and 2019. The index is calculated by the mean time of each activity in 2019 divided by the mean time of each activity in 1999. If the value is greater than one, which means compared with 1999, individuals are inclined to spend more time in this activity and vice versa. We also construct the index for our subsample male and female as well.

Table 1: Time spent in different activities (*in minutes*)

	(1)			(3)	(4)
				min	max
	LPG	*non-LPG*	All		
Employment and related activities	89.008	79.631	84.556	0	1,260
	(170.895)	(162.023)	(166.806)		
Food management and preparation	206.716	218.910	212.506	0	750
	(109.155)	(114.294)	(111.790)		
Preparing meals/snacks	131.515	141.968	136.479	0	630
	(75.351)	(79.830)	(77.689)		
Serving meals/snacks	24.535	24.050	24.305	0	390
	(33.953)	(32.509)	(33.275)		
Cleaning up after food preparation	40.014	40.243	40.123	0	300
	(36.585)	(37.386)	(36.967)		
Storing, arranging, preserving Food	3.294	3.389	3.339	0	300
	(14.360)	(16.066)	(15.194)		
Other activities of food management	7.358	9.259	8.261	0	360
	(22.372)	(25.991)	(24.177)		
Number of Observation	44770	41200	85,970		

Note: Source: Indian Time Use Survey, 2019. Averages are constructed using sample of women aged 18-60 residing in rural India and accounting for survey weights. Standard deviations are in parenthesis.

Table 2: Summary Statistics

	Mean					
	(1)		(2)		(3)	
Individual level controls	*LPG*	*SD*	*non-LPG*	*SD*	All	SD
Age	37.16	11.678	36.57	12.110	36.88	11.863
Married (1/0)	0.86	0.343	0.86	0.349	0.86	0.346
Primary School (1/0)	0.13	0.342	0.14	0.343	0.14	0.342
Middle School (1/0)	0.16	0.364	0.14	0.352	0.15	0.358
Secondary (1/0)	0.14	0.344	0.08	0.269	0.11	0.312
Higher Secondary (1/0)	0.09	0.291	0.05	0.209	0.71	0.257
Graduate and above (1/0)	0.07	0.259	0.02	0.154	0.50	0.217
self-employed (1/0)	0.13	0.333	0.15	0.355	0.14	0.344
wage or salary employed (1/0)	0.04	0.204	0.02	0.148	0.03	0.180
casual wage labor (1/0)	0.09	0.280	0.09	0.288	0.09	0.284
Household level controls						
LPG	1.00	0.000	0.00	0.000	0.53	0.499
meanLPG (Fraction of household in village with LPG)	0.73	0.270	0.27	0.258	0.51	0.349
Household size	4.35	1.818	4.50	1.996	4.42	1.906
Log of monthly per capita expenditure	8.98	0.521	8.77	0.519	8.88	0.530
Number of age group 0-14	1.13	1.206	1.32	1.352	1.22	1.281
Number of age group 15-64 (male)	1.45	0.875	1.42	0.902	1.44	0.888
Number of age group 15-64 (female)	1.59	0.780	1.59	0.800	1.59	0.790
Muslim (1/0)	0.10	0.305	0.14	0.343	0.12	0.324
Scheduled Tribe (1/0)	0.08	0.267	0.17	0.375	0.12	0.326
Scheduled Caste (1/0)	0.20	0.399	0.22	0.415	0.21	0.407
Other backwards Classes (1/0)	0.46	0.498	0.41	0.492	0.44	0.496
Small family land (1/0)	0.08	0.267	0.07	0.256	0.07	0.262
Medium family land (1/0)	0.05	0.220	0.04	0.191	0.05	0.207
Large family land (1/0)	0.03	0.175	0.02	0.151	0.03	0.165
Semi-pucca house (1/0)	0.26	0.438	0.34	0.472	0.30	0.456
Pucca house (1/0)	0.66	0.473	0.44	0.496	0.55	0.497
Head age	47.23	12.999	46.10	13.246	46.69	13.129
Female head (1/0)	0.14	0.350	0.14	0.345	0.14	0.347
Head education level						
Primary School (head) (1/0)	0.14	0.351	0.16	0.366	0.15	0.358
Middle School(head) (1/0)	0.17	0.374	0.17	0.373	0.17	0.373
Secondary(head) (1/0)	0.15	0.357	0.09	0.283	0.12	0.326

Higher Secondary(head) (1/0)	0.09	0.279	0.04	0.202	0.07	0.246
Graduate and above(head) (1/0)	0.07	0.262	0.02	0.145	0.05	0.216
Self-employed (head) (1/0)	0.48	0.499	0.46	0.498	0.47	0.499
Wage or salary employed (head) (1/0)	0.12	0.329	0.07	0.258	0.10	0.299
Casual wage labor (head) (1/0)	0.24	0.426	0.33	0.471	0.28	0.451
Village Level Controls						
Average log of monthly per capita expenditure	2131.98	816.420	1804.74	658.696	1976.60	763.391
Employment rate	0.38	0.124	0.36	0.119	0.37	0.122
Proportion of high caste in population	0.25	0.302	0.22	0.300	0.23	0.301
Proportion of population with higher secondary or above education	0.14	0.103	0.10	0.080	0.12	0.095
Proportion of population living in mud house	0.11	0.181	0.20	0.248	0.15	0.220
Proportion of households with salaried member	0.19	0.184	0.14	0.164	0.17	0.176
Number of Observation	44770		41200		86,970	

Table 3: Impact of LPG use on women's time allocation in different activities (in minutes), Rural India

	(1)	(2)	(3)					(4)
			(A)	(B)	(C)	(D)	(E)	
	Involved in cooking (1/0)	Food management and preparation	Preparing meals/snacks	Serving meals /snacks	Cleaning up	Storing, arranging preserving Food	Other activities of food manageme nt	Employment and related activities
Panel A: OLS								
LPG	0.001	-1.837**	-0.351	0.980***	-0.981***	-0.303**	-1.111***	1.992**
	(0.002)	(0.755)	(0.537)	(0.235)	(0.280)	(0.121)	(0.186)	(0.878)
Mean	0.899	212.490	136.453	24.319	40.127	3.338	8.252	84.557
Observations	85,969	85,969	85,969	85,969	85,969	85,969	85,969	85,969
R-squared	0.205	0.340	0.308	0.276	0.170	0.088	0.144	0.599
Panel B: IV								
LPG	0.002	-5.730**	-2.419***	2.672***	-1.907**	-0.618***	-3.457***	8.065***
	(0.005)	(1.535)	(1.092)	(0.479)	(0.569)	(0.245)	(0.379)	(1.786)
Observations	85,962	85,962	85,962	85,962	85,962	85,962	85,962	85,962
R-squared	0.206	0.340	0.309	0.276	0.170	0.088	0.143	0.599

Note: The instrument variable used is the fraction of households in village that reported use of LPG as main source of cooking where average is constructed excluding the concerned household. The OLS/IV regressions control for women' age, marriage status, education level, employment status; household demographic composition, religion and caste of household, amount of land owned by household, type of house construction, and monthly per capita consumption expenditure; household head' education, gender, and employment status and day of the week when survey was conducted, village characteristics, and district fixed effects. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Hausman Test for Endogeneity of IV

H0: the variable under consideration (LPG) can be treated as exogenous		
IV= Fraction of household in village with LPG		
	Durbin	WU
Involvement in cooking activities (1/0)	0.063	0.062
	(0.802)	(0.803)
Food management and preparation	8.461***	8.392***
	(0.004)	(0.004)
Preparing meals/snacks	4.718**	4.680**
	(0.030)	(0.031)
Serving meals /snacks	17.849***	17.705***
	(0.000)	(0.000)
Cleaning up after food preparation	3.478*	3.449*
	(0.062)	(0.063)
Storing, arranging preserving Food	2.172	2.154
	(0.141)	(0.142)
Other activities of food management	50.648***	50.260***
	(0.004)	(0.004)
Employment and related activities	15.227***	15.105***
	(0.000)	(0.000)

Note: *p*-values are in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Unconditional Quantile Regression

	(1)	(2)
Quantile(percentile)	Food management and preparation	Food management and preparation (non-zero)
10th	1.975	-7.025***
	(1.704)	(1.214)
25th	-11.530***	-11.317***
	(1.086)	(0.913)
50th	-12.208***	-13.096***
	(0.915)	(0.959)
75th	-15.908***	-14.315***
	(1.101)	(1.090)
90th	-15.506***	-15.360***
	(1.391)	(1.371)

Note: The first Column considered all observations. The second column drops the observations where the reported total time spent in food management and preparation is zero (About 7 percent of the women have reported zero). Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Impact of LPG use on women's time allocation in different activities (in minutes) across Castes, Rural India, IV estimates

IV= Fraction of household in village with LPG and its interaction with Caste indicators								
	(1)	(2)	(3)					(4)
			(A)	(B)	(C)	(D)	(E)	
VARIABLES	Involved in cooking (1/0)	Food management and preparation	Preparing meals/snacks	Serving meals /snacks	Cleaning up	Storing, arranging preserving Food	Other activities of food management	Employment and related activities
LPG	0.009	-14.659***	-2.048	0.643	-6.623***	-1.439***	-5.192***	10.767***
	(0.008)	(2.587)	(1.840)	(0.806)	(0.960)	(0.413)	(0.638)	(3.008)
LPG*ST	-0.028**	4.388	-2.284	1.837	4.163***	-0.175	0.915	5.324
	(0.012)	(3.925)	(2.792)	(1.224)	(1.456)	(0.627)	(0.967)	(4.564)
LPG*SC	-0.019**	3.953	-3.953*	1.042	2.932**	1.154**	2.652***	-5.140
	(0.009)	(3.198)	(2.275)	(0.996)	(1.186)	(0.511)	(0.788)	(3.719)
LPG*OBC	-0.002	16.713***	1.577	3.581***	7.974***	1.315***	2.361***	-4.901
	(0.008)	(2.813)	(2.001)	(0.876)	(1.044)	(0.450)	(0.693)	(3.272)
Mean	0.899	212.490	136.453	24.319	40.127	3.338	8.252	84.557
Observations	85,962	85,962	85,962	85,962	85,962	85,962	85,962	85,962
R-squared	0.206	0.340	0.309	0.276	0.169	0.087	0.143	0.599

Note: The instrument variable used is the fraction of households in village that reported use of LPG as main source of cooking where average is constructed excluding the concerned household and its interaction with Castes. The IV regressions control for women' age, marriage status, education level, employment status; household demographic composition, religion and caste of household, amount of land owned by household, type of house construction, and monthly per capita consumption expenditure; household head' education, gender, and employment status and day of the week when survey was conducted, village characteristics, and district fixed effects. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Impact of LPG use on time allocation in different activities, Rural India, IV estimates

	(1)	(2)	(3)					(4)
			(A)	(B)	(C)	(D)	(E)	
	involved in cooking	Food management and preparation	Preparing meals/snacks	Serving meals /snacks	Cleaning up	Storing, arranging preserving Food	Other activities of food management	Employment and related activities
Panel A: Married Women								
LPG	-0.005	-6.988***	-3.625***	2.718***	-2.096***	-0.584***	-3.401***	10.002***
	(0.004)	(1.612)	(1.146)	(0.526)	(0.613)	(0.262)	(0.402)	(1.841)
Mean	0.93	225.158	144.704	26.49	42.12	3.448	8.397	74.446
Observations	73,678	73,678	73,678	73,678	73,678	73,678	73,678	73,678
R-squared	0.155	0.306	0.280	0.274	0.161	0.093	0.154	0.579
Panel B: Single Women								
LPG	0.043***	0.702	4.862	1.472	-1.216	-1.382*	-3.034***	-4.893
	(0.020)	(4.620)	(3.308)	(1.011)	(1.517)	(0.715)	(1.105)	(5.990)
Mean	0.706	134.18	85.45	10.899	27.813	2.66	7.358	147.054
Observations	12,284	12,284	12,284	12,284	12,284	12,284	12,284	12,284
R-squared	0.255	0.277	0.256	0.235	0.208	0.120	0.166	0.668

Note: The instrument variable used is the fraction of households in village that reported use of LPG as main source of cooking where average is constructed excluding the concerned household. The IV regressions control for women' age, education level, employment status; household demographic composition, religion and caste of household, amount of land owned by household, type of house construction, and monthly per capita consumption expenditure; household head' education, gender, and employment status and day of the week when survey was conducted, village characteristics, and district fixed effects. Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: 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 59.67	3,779 37.48	287 2.85	10,082 100
	Mixed Fuels	3,035 35.83	4,627 54.62	809 9.55	8,471 100
	Modern Fuels	82 7.94	398 38.53	553 53.53	1,033 100
	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 9: 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: This table presents the female labor force participation rate for women household in rural India aged 28-64 in 2011.

Table 10: 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: This table 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.

Table 11: Minutes Per Day Spent in leisure, employment, childcare, and home service activities for Full Sample, men, and women

	Total			Rural			Urban		
Time-use Category	1999	2019	Difference	1999	2019	Difference	1999	2019	Difference
Panel1: Full Sample									
Leisure	295.69	336.46	40.77	284.82	332.03	47.21	323.38	345.18	21.80
Employment	340.38	288.42	-51.96	354.45	287.39	-67.06	304.57	290.44	-14.12
Childcare	26.32	26.53	0.21	25.86	27.00	1.15	27.49	25.60	-1.88
Home Service	166.87	150.52	-16.35	164.85	151.54	-13.31	171.99	148.50	-23.49
Panel 2: Men									
Leisure	309.33	342.49	33.16	308.90	346.45	37.55	310.38	334.89	24.51
Employment	481.73	444.58	-37.15	478.60	428.85	-49.75	489.28	474.75	-14.53
Childcare	7.94	9.14	1.20	8.14	9.35	1.21	7.46	8.73	1.27
Home Service	21.97	23.34	1.37	22.22	26.10	3.88	21.36	18.04	-3.33
Panel 3: Women									
Leisure	281.84	330.56	48.72	261.10	318.15	57.05	337.64	355.57	17.93
Employment	196.87	135.71	-61.16	232.17	151.29	-80.88	101.89	104.33	2.43
Childcare	44.97	43.54	-1.44	43.30	43.98	0.68	49.46	42.64	-6.82
Home Service	313.99	274.89	-39.10	305.33	272.23	-33.11	337.28	280.26	-57.02
Sample Size	43,271	63,633	20,362	29,386	38,049	8,663	13,885	25,584	11,699

Note: Source: Indian Time Use Survey, 1999 and 2019. The mean value is constructed using sample of individuals aged 18-64 in six states (Haryana, Madhya Pradesh, Gujarat, Orissa, Tamil Nadu, and Meghalaya) of India using fixed demographic weights, as described in the text. Students are excluded from the sample.

Table 12: Blinder-Oaxaca Decomposition Of Mean Unconditional Changes In Time Use

Time use category(years)	Unconditional Change	Change due to different demographics	Change due to different cell means	Unconditional Change	Change due to different demographics	Change due to different cell means	Unconditional Change	Change due to different demographics	Change due to different cell means
	$W_{2019}Y_{2019} - W_{1999}Y_{19}$	$(W_{2019} - W_{1999})Y_{2019}$	$(Y_{2019} - Y_{1999})W_{1999}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{2019}$	$(Y_{2019} - Y_{1999})W_{1999}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{2019}$	$(Y_{2019} - Y_{1999})W_{1999}$
Panel 1: Decomposition evaluated at 1999 demographic weights and 2019 cell means									
	Sample A: Total			**Sample B: Male**			**Sample C: Female**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Leisure	36.58	7.91	28.66	29.59	4.49	25.11	43.76	11.48	32.28
Employment	-40.52	-5.82	-34.70	-31.07	-3.22	-27.85	-44.11	-2.47	-41.64
Childcare	-1.32	-2.05	0.73	1.35	-0.09	1.45	-4.67	-4.67	0.00
Home Service	-22.14	-0.47	-21.67	-1.77	-0.20	-1.57	-47.56	-5.48	-42.08
	$W_{2019}Y_{2019} - W_{1999}Y_{19}$	$(W_{2019} - W_{1999})Y_{1999}$	$(Y_{2019} - Y_{1999})W_{2019}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{1999}$	$(Y_{2019} - Y_{1999})W_{201}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{1999}$	$(Y_{2019} - Y_{1999})W_{20}$
Panel 2: Decomposition evaluated at 2019 demographic weights and 1999 cell means									
	Sample A: Total			**Sample B: Male**			**Sample C: Female**		
Leisure	36.58	12.56	24.02	29.59	8.92	20.67	43.76	16.46	27.30
Employment	-40.52	-14.15	-26.37	-31.07	-8.31	-22.76	-44.11	-14.35	-29.77
Childcare	-1.32	-1.46	0.140	1.35	1.09	0.26	-4.67	-4.68	0.01
Home Service	-22.14	-0.11	-22.03	-1.77	-0.37	-1.40	-47.56	-5.23	-42.33

Note: This table reports two alternative Blinder-Oaxaca decompositions of trends in the allocation of time to leisure, employment, childcare, and home service. The first column of each panel represents the overall unconditional change between 1999 and 2019 for each activity. The second and third columns decompose the total change into components due to different weights on demographic cell means ($W_t, t = 1999, 2019$)and to different cell means ($Y_t, t = 1999, 2019$), respectively. Panel 1 evaluates the effect of the change in demographic weights using the cell means of 2019, while Panel 2 evaluates the change in weights at the cell means of 1999. Correspondingly, Panel 1 evaluates the change in cell means at the demographic weights of 1999, and Panel 2 evaluates the change in cell means at the demographic weights of 2019. The restriction of samples is illustrated in the text.

Table 13: Blinder-Oaxaca Decomposition Of Mean Unconditional Changes In Time Use (Rural)

Time use category(years)	Unconditional Change	Change due to different demographics	Change due to different cell means	Unconditional Change	Change due to different demographics	Change due to different cell means	Unconditional Change	Change due to different demographics	Change due to different cell means
	$W_{2019}Y_{2019} - W_{1999}Y_{19}$	$(W_{2019} - W_{1999})Y_{2019}$	$(Y_{2019} - Y_{1999})W_{1999}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{2019}$	$(Y_{2019} - Y_{1999})W_{1999}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{201}$	$(Y_{2019} - Y_{1999})W_{1999}$
Panel 1: Decomposition evaluated at 1999 demographic weights and 2019 cell means									
	Sample A: Total			**Sample B: Male**			**Sample C: Female**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Leisure	43.96	7.67	36.29	34.07	2.72	31.36	54.48	13.17	41.31
Employment	-63.83	-5.58	-58.25	-47.44	-0.85	-46.59	-75.16	-5.09	-70.06
Childcare	1.74	-2.01	3.75	2.08	-0.12	2.19	0.77	-4.55	5.32
Home Service	-13.16	-0.29	-12.87	3.88	0.01	3.82	-35.14	-5.31	-29.83
	$W_{2019}Y_{2019} - W_{1999}Y_{19}$	$(W_{2019} - W_{1999})Y_{1999}$	$(Y_{2019} - Y_{1999})W_{2019}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{1999}$	$(Y_{2019} - Y_{1999})W_{2019}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{199}$	$(Y_{2019} - Y_{1999})W_{201}$
Panel 2: Decomposition evaluated at 2019 demographic weights and 1999 cell means									
	Sample A: Total			**Sample B: Male**			**Sample C: Female**		
Leisure	43.96	11.80	32.15	34.07	8.26	25.81	54.48	16.09	38.39
Employment	-63.83	-16.08	-47.76	-47.44	-8.96	-38.46	-75.16	-18.55	-56.60
Childcare	1.74	-1.06	2.80	2.08	1.19	0.89	0.77	-3.88	4.65
Home Service	-13.16	1.12	-14.28	3.88	-0.06	3.93	-35.14	-2.81	-32.33

Note: This table reports two alternative Blinder-Oaxaca decompositions of trends in the allocation of time to leisure, employment, childcare, and home service in rural India. The first column of each panel represents the overall unconditional change between 1999 and 2019 for each activity. The second and third columns decompose the total change into components due to different weights on demographic cell means ($W_t, t = 1999, 2019$)and to different cell means ($Y_t, t = 1999, 2019$), respectively. Panel 1 evaluates the effect of the change in demographic weights using the cell means of 2019, while Panel 2 evaluates the change in weights at the cell means of 1999. Correspondingly, Panel 1 evaluates the change in cell means at the demographic weights of 1999, and Panel 2 evaluates the change in cell means at the demographic weights of 2019. The restriction of samples is illustrated in the text.

Table 14: Blinder-Oaxaca Decomposition Of Mean Unconditional Changes In Time Use (Urban)

Time use category(years)	Unconditional Change	Change due to different demographics	Change due to different cell means	Unconditional Change	Change due to different demographics	Change due to different cell means	Unconditional Change	Change due to different demographics	Change due to different cell means
	$W_{2019}Y_{201} - W_{1999}Y_{1}$	$(W_{2019} - W_{1999})Y_{2019}$	$(Y_{2019} - Y_{1999})W_{199}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{2019}$	$(Y_{2019} - Y_{1999})W_{1999}$	$W_{2019}Y_{2019} - W_{1999}Y_{199}$	$(W_{2019} - W_{1999})Y_{2}$	$(Y_{2019} - Y_{1999})W_{1999}$
Panel 1: Decomposition evaluated at 1999 demographic weights and 2019 cell means									
	Sample A: Total			**Sample B: Male**			**Sample C: Female**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Leisure	29.21	8.17	21.04	25.12	6.27	18.86	33.05	9.80	23.25
Employment	-17.22	-6.06	-11.15	-14.68	-5.58	-9.11	-13.09	0.14	-13.23
Childcare	-4.38	-2.09	-2.29	0.64	-0.06	0.70	-10.09	-4.78	-5.32
Home Service	-31.11	-0.65	-30.46	-7.42	-0.47	-6.95	-60.00	-5.66	-54.34
	$W_{2019}Y_{201} - W_{1999}Y_{1}$	$(W_{2019} - W_{1999})Y_{1999}$	$(Y_{2019} - Y_{1999})W_{201}$	$W_{2019}Y_{2019} - W_{1999}Y_{1999}$	$(W_{2019} - W_{1999})Y_{1999}$	$(Y_{2019} - Y_{1999})W_{201}$	$W_{2019}Y_{2019} - W_{1999}Y_{199}$	$(W_{2019} - W_{1999})Y_{1}$	$(Y_{2019} - Y_{1999})W_{2}$
Panel 2: Decomposition evaluated at 2019 demographic weights and 1999 cell means									
	Sample A: Total			**Sample B: Male**			**Sample C: Female**		
Leisure	29.21	13.31	15.90	25.12	9.59	15.52	33.05	16.79	16.26
Employment	-17.22	-12.22	-5.00	-14.68	-7.65	-7.03	-13.09	-10.08	-3.01
Childcare	-4.38	-1.86	-2.52	0.64	1.01	-0.37	-10.09	-5.47	-4.62
Home Service	-31.11	-1.34	-29.77	-7.42	-0.69	-6.73	-60.00	-7.69	-52.31

Note: This table reports two alternative Blinder-Oaxaca decompositions of trends in the allocation of time to leisure, employment, childcare, and home service in urban India. The first column of each panel represents the overall unconditional change between 1999 and 2019 for each activity. The second and third columns decompose the total change into components due to different weights on demographic cell means ($W_t, t = 1999, 2019$)and to different cell means ($Y_t, t = 1999, 2019$), respectively. Panel 1 evaluates the effect of the change in demographic weights using the cell means of 2019, while Panel 2 evaluates the change in weights at the cell means of 1999. Correspondingly, Panel 1 evaluates the change in cell means at the demographic weights of 1999, and Panel 2 evaluates the change in cell means at the demographic weights of 2019. The restriction of samples is illustrated in the text.

Table15: Observable and Unobservable Components of Changes in Inequality (total observations)

Distribution percentile Comparison	Total Change	Decomposition: Changes due to Demographic Quantities	Decomposition: Changes due to Cell means	Decomposition: Changes due to Unobservables	Total Change	Decomposition: Changes due to Demographic Quantities	Decomposition: Changes due to Cell means	Decomposition: Changes due to Unobservables	Total Change	Decomposition: Changes due to Demographic Quantities	Decomposition: Changes due to Cell means	Decomposition: Changes due to Unobservables
	Panel A: Total				Panel B: Male				Panel C: Female			
Leisure	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
90-10	15.00	2.22	-3.58	16.36	30.00	5.19	-7.92	32.73	17.50	3.45	-3.34	17.39
90-50	5.00	-0.02	-2.10	7.13	30.00	2.69	-0.71	28.01	-12.50	-8.79	-5.61	1.90
50-10	10.00	2.24	-1.47	9.23	0.00	2.50	-7.22	4.72	30.00	12.25	2.27	15.49
Employment												
90-10	-30.00	3.54	-28.52	-5.02	50.00	-9.07	-18.09	77.16	-60.00	-11.79	-48.66	0.45
90-50	40.00	45.40	1.69	-7.09	20.00	14.44	5.36	0.20	30.00	15.63	0.56	13.82
50-10	-70.00	-41.87	-30.21	2.08	30.00	-23.51	-23.45	76.96	-90.00	-27.42	-49.21	-13.37
Childcare												
90-10	7.50	-5.31	7.95	4.86	0.00	-4.01	-3.34	7.35	12.50	2.25	1.91	8.34
90-50	7.50	-4.82	8.02	4.30	0.00	-3.05	-2.90	5.95	12.50	0.34	8.75	3.41
50-10	0.00	-0.50	-0.06	0.56	0.00	-0.96	-0.44	1.40	0.00	1.91	-6.83	4.93
Home Service												
90-10	-70.00	-10.77	-42.45	-16.78	30.00	6.35	-1.19	24.84	-90.00	1.53	-26.25	-65.27
90-50	-100.00	-29.73	-28.72	-41.56	30.00	6.49	-0.04	23.55	-57.50	-2.60	-6.40	-48.50
50-10	30.00	18.96	-13.74	24.78	0.00	-0.14	-1.15	1.29	-32.50	4.13	-19.85	-16.77

Note: This table reports the change in the cross-sectional distribution of leisure, employment, childcare and home service between 1999 and 2019 for the total observations (Panel 1), Male (Panel 2), and Female (Panel 3). The cross-sectional distribution is measured by the 90–10 percentile difference (row 1 in each panel), the 90–50 percentile difference (row 2), and the 50–10 percentile difference (row 3). The changes in these percentile comparisons, not adjusting for any demographics, are shown in column (1). The portion of the unadjusted change attributed to changing demographic quantities is reported in column (2). The portion of the unadjusted change attributed to changing demographic cell means is reported in column (3). The last column is the remaining change attributed to unobservables. The details of the methodology are described in the text.

Table 16: Observable And Unobservable Components Of Changes In Inequality (Rural)

Distribution percentile Comparison	Total Change	Decomposition			Total Change	Decomposition			Total Change	Decomposition		
		Changes due to Demographic Quantities	Changes due to Cell means	Changes due to Unobservables		Changes due to Demographic Quantities	Changes due to Cell means	Changes due to Unobservables		Changes due to Demographic Quantities	Changes due to Cell means	Changes due to Unobservables
	Panel A: Total				Panel B: Male				Panel C: Female			
Leisure	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
90-10	25.00	0.41	-7.06	31.65	60.00	9.12	0.93	49.95	15.00	4.35	-12.47	23.11
90-50	25.00	0.91	-1.38	25.47	50.00	6.16	2.95	40.89	0.00	-4.74	-4.92	9.66
50-10	0.00	-0.50	-5.68	6.18	10.00	2.96	-2.02	9.06	15.00	9.09	-7.54	13.45
Employment												
90-10	-40.00	-12.85	-19.39	-7.75	90.00	21.20	-7.87	76.67	-45.00	-16.64	-26.43	-1.93
90-50	45.00	35.90	-6.25	15.35	20.00	5.66	2.84	11.50	85.00	34.87	-1.92	52.04
50-10	-85.00	-48.76	-13.14	-23.10	70.00	15.54	-10.72	65.18	-130.00	-51.51	-24.51	-53.98
Childcare												
90-10	15.00	-3.50	13.17	5.34	0.00	-5.13	-1.49	6.62	10.00	3.44	-4.18	10.74
90-50	15.00	-3.89	13.87	5.01	0.00	-4.42	-0.84	5.26	10.00	-0.79	9.35	1.44
50-10	0.00	0.39	-0.71	0.32	0.00	-0.71	-0.65	1.36	0.00	4.22	-13.53	9.31
Home Service												
90-10	-60.00	-12.69	-35.73	-11.58	30.00	-0.56	0.10	30.46	-110.00	-3.03	-23.88	-83.09
90-50	-80.00	-27.66	-24.58	-27.77	30.00	0.59	1.08	28.33	-70.00	-6.55	-0.46	-62.99
50-10	20.00	14.97	-11.15	16.18	0.00	-1.15	-0.98	2.14	-40.00	3.52	-23.41	-20.10

Note: This table reports the change in the cross-sectional distribution of leisure, employment, childcare and home service between 1999 and 2019 for the total observations (Panel 1), Male (Panel 2), and Female (Panel 3) in rural India. The cross-sectional distribution is measured by the 90–10 percentile difference (row 1 in each panel), the 90–50 percentile difference (row 2), and the 50–10 percentile difference (row 3). The changes in these percentile comparisons, not adjusting for any demographics, are shown in column (1). The portion of the unadjusted change attributed to changing demographic quantities is reported in column (2). The portion of the unadjusted change attributed to changing demographic cell means is reported in column (3). The last column is the remaining change attributed to unobservables. The details of the methodology are described in the text.

Table 17: Observable And Unobservable Components Of Changes In Inequality (Urban)

		Decomposition				Decomposition				Decomposition		
Distribution percentile Comparison	Total Change	Changes due to Demographic Quantities	Changes due to Cell means	Changes due to Unobservables	Total Change	Changes due to Demographic Quantities	Changes due to Cell means	Changes due to Unobservables	Total Change	Changes due to Demographic Quantities	Changes due to Cell means	Changes due to Unobservables
	Panel A: Total				Panel B: Male				Panel C: Female			
Leisure	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
90-10	-10.00	2.63	-16.45	3.81	-25.00	-4.16	-19.06	-1.78	-20.00	2.55	-16.38	-6.17
90-50	-10.00	-7.61	-8.14	5.75	-30.00	-12.44	-18.10	0.54	0.00	-3.14	-1.07	4.21
50-10	0.00	10.24	-8.31	-1.94	5.00	8.27	-0.96	-2.31	-20.00	5.68	-15.31	-10.37
Employment												
90-10	-30.00	-0.88	-46.30	17.18	-30.00	72.00	-107.17	5.17	30.00	-14.54	-6.27	50.81
90-50	-30.00	3.46	-34.49	1.03	0.00	22.19	-7.17	-15.02	30.00	-6.44	-6.11	42.55
50-10	0.00	-4.34	-11.81	16.15	-30.00	49.81	-100.00	20.19	0.00	-8.10	-0.16	8.26
Childcare												
90-10	-15.00	-9.68	-3.66	-1.66	10.00	0.56	0.49	8.95	-15.00	-4.25	-4.36	-6.39
90-50	-15.00	-8.99	-3.98	-2.03	10.00	1.56	-0.81	9.25	-15.00	-1.73	3.61	-16.88
50-10	0.00	-0.69	0.32	0.37	0.00	-1.00	1.30	-0.30	0.00	-2.52	-7.97	10.49
Home Service												
90-10	-80.00	-7.25	-66.53	-6.22	0.00	4.00	-6.58	2.59	-65.00	-4.77	-21.19	-39.04
90-50	-80.00	-18.52	-52.05	-9.43	0.00	3.46	-4.51	1.05	-25.00	5.92	-14.04	-16.88
50-10	0.00	11.28	-14.48	3.20	0.00	0.54	-2.07	1.54	-40.00	-10.69	-7.15	-22.16

Note: This table reports the change in the cross-sectional distribution of leisure, employment, childcare and home service between 1999 and 2019 for the total observations (Panel 1), Male (Panel 2), and Female (Panel 3) in urban India. The cross-sectional distribution is measured by the 90–10 percentile difference (row 1 in each panel), the 90–50 percentile difference (row 2), and the 50–10 percentile difference (row 3). The changes in these percentile comparisons, not adjusting for any demographics, are shown in column (1). The portion of the unadjusted change attributed to changing demographic quantities is reported in column (2). The portion of the unadjusted change attributed to changing demographic cell means is reported in column (3). The last column is the remaining change attributed to unobservables. The details of the methodology are described in the text.

APPENDIX

Table A1: Distribution of households by cooking fuels

	Rural	Urban	Total
Firewood and chips	42.82	6.62	31.35
LPG	51.53	86.18	62.51
Other natural gas	0.23	1.14	0.51
Dung cake	3.83	0.23	2.69
Kerosene	0.19	0.74	0.36
Coke or coal	0.25	0.34	0.28
Gobar gas	0.07	0	0.05
Other biogas	0.01	0	0.01
Charcoal	0.21	0.22	0.21
Electricity	0.03	0.17	0.08
No cooking	0.46	3.63	1.47
Others	0.38	0.73	0.49

TableA2: First Stage Regression for IV Estimates

VARIABLES	LPG
Instruments	
MeanLPG	0.835***
	(0.005)

Note: The first stage regression controls women' age, marriage status, education level, employment status; household demographic composition, religion and caste of household, amount of land owned by household, type of house construction, and monthly per capita consumption expenditure; household head' education, gender, and employment status and day of the week when survey was conducted, village characteristics, and district fixed effects. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Regression Results for the Cooking Time

	(1)	(2)	(3)
	Number of times cooked per day	Cooked more than 3 times per day	Average time spent per cooking activity
Panel A: OLS			
LPG	0.039***	0.013***	-1.247***
	(0.008)	(0.003)	(0.176)
Mean	2.726	0.208	57.566
Observations	77,117	77,117	77,117
R-squared	0.243	0.209	0.365
Panel B: IV			
LPG	0.062***	0.019***	-3.005***
	(0.016)	(0.003)	(0.359)
Observations	77,110	77,110	77,110
R-squared	0.243	0.209	0.364

Note: The instrument variable used is the fraction of households in village that reported use of LPG as main source of cooking where average is constructed excluding the concerned household. The IV regressions control for women' age, marriage status, education level, employment status; household demographic composition, religion and caste of household, amount of land owned by household, type of house construction, and monthly per capita consumption expenditure; household head' education, gender, and employment status and day of the week when survey was conducted, village characteristics, and district fixed effects. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.

Table A4: Hausman Test for Endogeneity of IV (Castes)

H0: The variable under consideration can be treated as exogenous		
IV= Fraction of household in village with LPG		
	Durbin	WU
Involvement cooking activities	4.293	1.064
	(0.368)	(0.372)
Food management and preparation	36.188***	8.975***
	(0.000)	(0.000)
Preparing meals/snacks	11.470**	2.844**
	(0.021)	(0.022)
Serving meals /snacks	22.216***	5.509***
	(0.000)	(0.000)
Cleaning up after food preparation	50.031***	12.411***
	(0.000)	(0.000)
Storing, arranging preserving Food	17.267***	4.282***
	(0.002)	(0.002)
Other activities of food management	56.880***	14.111***
	(0.000)	(0.000)
Employment and related activities	20.344***	5.045***
	(0.000)	(0.000)

Note: *p*-values in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Impact of LPG use on women's time allocation in different activities (in minutes) across castes, Rural India, OLS

	(1)	(2)	(3)					(4)
			(A)	(B)	(C)	(D)	(E)	
VARIABLES	Involved in cooking (1/0)	Food management and preparation	Preparing meals/snacks	Serving meals /snacks	Cleaning up	Storing, arranging preserving Food	Other activities of food management	Employment and related activities
LPG	0.005	-4.523***	0.721	-0.181	-2.684***	-0.652***	-1.727***	2.798*
	(0.004)	(1.426)	(1.015)	(0.444)	(0.529)	(0.228)	(0.351)	(1.658)
LPG*ST	-0.019***	-2.420	-2.877*	0.331	0.255	0.423	-0.552	2.711
	(0.007)	(2.442)	(1.738)	(0.761)	(0.906)	(0.390)	(0.602)	(2.841)
LPG*SC	-0.008	1.274	-2.258	0.315	1.719**	0.473	1.026**	-3.023
	(0.006)	(1.955)	(1.391)	(0.609)	(0.725)	(0.313)	(0.482)	(2.274)
LPG*OBC	-0.002	5.917***	-0.630	2.198***	2.897***	0.450*	1.002**	-0.958
	(0.005)	(1.691)	(1.203)	(0.527)	(0.627)	(0.270)	(0.417)	(1.967)
Mean	0.899	212.490	136.453	24.319	40.127	3.338	8.252	84.557
Observations	85,969	85,969	85,969	85,969	85,969	85,969	85,969	85,969
R-squared	0.206	0.341	0.309	0.277	0.170	0.088	0.144	0.599

Note: The OLS regressions control for women' age, marriage status, education level, employment status; household demographic composition, religion and caste of household, amount of land owned by household, type of house construction, and monthly per capita consumption expenditure; household head' education, gender, and employment status and day of the week when survey was conducted, village characteristics, and district fixed effects. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Impact of LPG use on women's time allocation in different activities (in minutes), OLS

	(1)	(2)	(3)					(4)
			(A)	(B)	(C)	(D)	(E)	
	involved in cooking (1/0)	Food management and preparation	Preparing meals/snacks	Serving meals /snacks	Cleaning up	Storing, arranging preserving Food	Other activities of food management	Employment and related activities
Panel A: Married Women								
LPG	0.000	-1.705**	-0.307	1.067***	-1.078***	-0.313**	-1.074***	1.898**
	(0.002)	(0.801)	(0.569)	(0.261)	(0.305)	(0.130)	(0.200)	(0.914)
Mean	0.93	225.158	144.704	26.49	42.12	3.448	8.397	74.446
Observations	73,684	73,684	73,684	73,684	73,684	73,684	73,684	73,684
R-squared	0.155	0.307	0.280	0.274	0.162	0.093	0.156	0.580
Panel B: Single Women								
LPG	0.000	-3.670*	-0.703	-0.711	-1.015	-0.305	-0.936*	2.675
	(0.009)	(2.185)	(1.564)	(0.478)	(0.717)	(0.338)	(0.522)	(2.833)
Mean	0.706	134.18	85.45	10.899	27.813	2.66	7.358	147.054
Observations	12,285	12,285	12,285	12,285	12,285	12,285	12,285	12,285
R-squared	0.256	0.277	0.257	0.237	0.208	0.121	0.167	0.668

Note: The instrument variable used is the fraction of households in village that reported use of LPG as main source of cooking where average is constructed excluding the concerned household. The IV regressions control for women' age, education level, employment status; household demographic composition, religion and caste of household, amount of land owned by household, type of house construction, and monthly per capita consumption expenditure; household head' education, gender, and employment status and day of the week when survey was conducted, village characteristics, and district fixed effects. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Hausman Test for Endogeneity of IV (Married & Single Women)

H0: the variable under consideration can be treated as exogenous				
IV= Fraction of household in village with LPG	*Married Women*		*Single Women*	
	Durbin	WU	Durbin	WU
Involvement cooking activities	2.030	2.011	6.126**	5.781**
	(0.154)	(0.156)	(0.013)	(0.016)
Food management and preparation	14.214***	14.080***	1.136	1.071
	(0.000)	(0.000)	(0.287)	(0.301)
Preparing meals/snacks	11.107***	11.002***	3.590	3.387
	(0.001)	(0.001)	(0.058)	(0.066)
Serving meals /snacks	13.041***	12.918***	5.923**	5.589**
	(0.000)	(0.000)	(0.015)	(0.018)
Cleaning up after food preparation	3.644*	3.609	0.022	0.021
	(0.056)	(0.057)	(0.881)	(0.885)
Storing, arranging preserving Food	1.417	1.403	2.876	2.713
	(0.234)	(0.236)	(0.090)	(0.010)
Other activities of food management	44.420***	44.020***	4.580**	4.321**
	(0.000)	(0.000)	(0.032)	(0.038)
Employment and related activities	25.681***	25.443***	2.025	1.910
	(0.000)	(0.000)	(0.155)	(0.167)

Note: *p*-values in parentheses *** p<0.01, ** p<0.05, * p<0. 1.

Table A8. Baseline, 2005 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

Table A9: The Education distribution across Years

Education Level	1999	2019	Total
non literate	15,255	13,954	29,209
	35.25	21.93	27.32
below primary	5,811	5,372	11,183
	13.43	8.44	10.46
primary to secondary	11,393	19,828	31,221
	26.33	31.16	29.2
secondary and above	10,812	24,479	35,291
	24.99	38.47	33.01
Total	43,271	63,633	106,904
	100	100	100

Note: This table shows the number of observations in each education level. The second row in each category is the percentage.

Table A10: The age group distribution across years

age group	1999	2019	Total
18-27	13,462	14,971	28,433
	31.11	23.53	26.6
28-37	12,223	17,647	29,870
	28.25	27.73	27.94
38-47	8,877	14,132	23,009
	20.51	22.21	21.52
48-57	6,090	10,792	16,882
	14.07	16.96	15.79
57-64	2,619	6,091	8,710
	6.05	9.57	8.15
Total	43,271	63,633	106,904
	100	100	100

Note: This table shows the number of observations in each age level. The second row in each category is the percentage.

Table A11: TIME-USE CLASSIFICATION

Classification	Activities that included
Employment	Employment in corporations, government and non-profit institutions Employment in household enterprises to produce goods Employment in household enterprises to provide services Ancillary activities and breaks related to employment Training and studies in relation to employment Seeking employment Setting up a business Travelling and commuting for employment Agriculture, forestry, finishing and mining for won final use Making and processing goods for won final use Construction activities for own final use Travelling, moving, transporting or accompanying goods or persons related to own-use production of goods
Leisure	Socializing and communication Participating in community cultural/social events Religious practices Travelling time related to socializing and communication, community participation and religious practice Other activities related to socializing and communication, community participation and religious practice Attending/visiting cultural, entertainment and sports events/venues Cultural participation, hobbies, games and other pastime activities Sports participation and exercise and related activities Mass media use Activities associated with reflecting, resting, relaxing Travelling time related to culture, leisure, mass-media and sports practices Other activities related to culture, leisure, mass-media and sports practices Personal hygiene and care Receiving personal and health/medical care from others Travelling time related to self-care and maintenance activities Other self-care and maintenance activities
Childcare	Caring for children including feeding, cleaning, physical care Providing medical care to children

	Instructing, teaching, training, helping children Talking with and reading to children Playing and sports with children Minding children (passive care) Meetings and arrangements with schools and childcare service providers Other activities related to childcare and instruction Accompanying own children
Home Service	Food and meals management and preparation Cleaning and maintaining of own dwelling and surroundings Do-it-yourself decoration, maintenance and repair Care and maintenance of textiles and footwear Household management for own final use Pet care Shopping for own household members Travelling, moving, transporting or accompanying goods or persons related to unpaid domestic services for household members Other unpaid domestic services for household members

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