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Residential fuel consumption and technology choices: an application of FGNLS and random effects binary logit model

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Abstract

In this study, Ethiopian households' residential fuel usage and technological preferences are analyzed. For 2524 urban families, we use panel data from two waves of the Ethiopian Socioeconomic Survey (ESS). Households' technology choices and short-run energy consumption behavior are modeled jointly. To estimate the short-run residential fuel consumption behavior, feasible generalized nonlinear least squares (FGNLS) are iterated. Random effects binary logit models are used to predict technology choice. The effective price elasticity of firewood, charcoal, and electricity was found to be negative and less than unity. The effective price of electricity for baking and cooking has a detrimental and considerable impact on technology choice. The choice of traditional baking oven was positively and significantly affected by effective cost of firewood. Traditional cooking stove was also positively and significantly influenced by effective price of charcoal. Technology choice for baking appliance was significantly affected by the dwelling size, and the type of kitchen. Since decisions to choose electric appliances over those that use charcoal and firewood are heavily influenced by housing-related difficulties, energy prices and efficiency of appliances, policy interventions should include house infrastructure installations and efficiency of appliances.

Keywords Fuel consumption, Technology choice, FGNLS, Random effects binary logit

Introduction

Providing affordable and clean energy access has been a global public and political concern over the past decades as reflected in the Sustainable Development Goal 7. Reducing energy consumption and greenhouse gas emissions due to climate change has become a policy option nowadays. Adoption of technologically efficient appliances and energy efficiency has also became a policy priority for increased energy efficiency is recognized as an important mechanism to achieve clean and affordable energy for all (Li and Just 2018; Mondal et al. 2018; Bensch and Peters 2015; Alem et al. 2014; Allcott and Greenstone 2012). Nearly 3 billion people across the world lack access to clean cooking. Solutions and are exposed to a dangerous level of air pollution (U. N. 2020). In sub-Saharan Africa, an estimated 548 million people still lack access to electricity (Pedersen et al. 2020; Group 2020; Kruger et al. 2018). Without electricity, women and girls have to spend hours fetching water, clinics cannot store vaccines for children, many school children cannot do homework at night, and people cannot run competitive businesses. On the other hand, lack of access to clean energy force people to use fuel types with high pollution levels. To address these problems countries, need more investment on renewable energy resources, prioritizing energy efficient practices, and adopting clean energy technologies and infrastructure through policy interventions. Such policies need to be based on analyses of individuals' energy consumption and technology choice behavior.

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Most research related to energy consumption are either related to understanding consumers' behavior or to identify the impact of energy conservation initiatives (Jeuland et al. 2021; Bos et al. 2018; Mondal et al. 2017; Peters and Sievert 2016; Tucho et al. 2014; McDougall et al. 1981). Residential electricity consumption and technology choice have been studied and applied to forecast future energy demands (Mondal et al. 2018; Alem et al. 2016; Christiaensen and Heltberg 2014; Gabreyohannes 2010; Dubin and McFadden 1984). However, the focus on energy efficiency and technology adoption is increasing due to the greater focus on climate policy and climate resilient economies (Mondal et al. 2018; Li and Just 2018; Bensch and Peters 2015; Alem et al. 2014; Christiaensen and Heltberg 2014).

Policy relevance of energy consumption efficiency behavior is growing, and the costs and benefits of policy interventions are more debated especially in developing countries. The energy efficiency gap, potentially explained by market failures, behavioral explanations, and model and measurement errors, is broadly studied in developed countries. Among the studies are Li and Just (2018); Gerarden et al. (2017); Allcott and Greenstone (2012); Anderson and Newell (2004); Helfand and Wolverton (2009); Brown (2001); DeCanio (1998); Howarth et al. (2000). The capital costs for appliances and the expected but uncertain operating costs remain trade-offs for consumers decision (Hassett and Metcalf 1993; Hausman 1979; Train 1985). Market failure, one of the potential reasons for an energy-efficiency gap, has in itself many possible roots including environmental externalities, energy price distortions, innovation spillovers, incomplete information and principal-agent problems (Li and Just 2018; Gillingham et al. 2012; Jaffe et al. 2003).

Modeling and measurement errors are critical issues in energy efficiency gap analysis. Energy consumption and technology choice decisions are made by the same individual based on common preferences and circumstances (Hanemann 1984; Dubin and McFadden 1984; Hausman 1979). This joint and endogenous decision (discrete technology choice and consumption decision) needs to be properly managed (Hanemann 1984; Dubin and McFadden 1984). Studies on joint modeling are limited and lack compatibility of structure with the model by Hanemann (1984).

Using discrete/continuous models, this study adds to the body of literature on household fuel use and technological preferences in less developed nations. The random effects binary logit model is used to model home technology decision, and Iterated Feasible Generalized Nonlinear Least Squares (FGNLS) is utilized to model the short-run residential fuel consumption behavior of households. However, this study differs from Li and Just (2018) in two ways. First, this study examines different energy mix scenario (grid electricity and biomass fuel). Second, this study concerns a less developed countries, where the fuel consumption behavior of households is different from more developed ones. While the study by Alem et al. (2014) looks at adoption and disadoption of cooking stoves in Ethiopia, this study examines both fuel consumption behavior and technology adoption in the same study area. To our knowledge, this is the first study to jointly model the decision-making process for long-term household energy technology choices and short-term energy use in less developed nations. This study also adds to the ongoing policy discussion on environmental policy tools to promote domestic energy efficiency and a decrease in greenhouse gas emissions. However, this study does not do a thorough welfare analysis.

Ethiopia has more than 4500 MW of installed power generation capacity, of which 90 percent is hydropower-based (Kruger et al. 2019). To improve system resilience, the Ethiopian government has made diversification of the country's energy mix with additional clean, renewable energy sources (such as geothermal, solar, and wind) a top priority (Schwab et al. 2014; Kruger et al. 2019; Taka et al. 2020; Hailu et al. 2021). Accordingly, of the installed capacity of the country's power plants, about 3.5 percent of the nation's total electricity is produced using diesel. The rest is produced using clean renewable energy sources, including 88.3 percent from hydropower plants, 7.5 percent from wind turbines, 0.6 percent from biomass, and about 0.2 percent from geothermal plants (Hailu et al. 2021). This makes the country's electricity among the most environmentally friendly in the world.

In Ethiopia, about 57 percent of households have access to at least one source of electricity either through the grid or off-grid (Padam et al. 2018). However, the principal source of energy in the country is traditional biomass (wood, animal dung, and agricultural residues) which accounts for about 98 percent of the energy supply mix (Tessema et al. 2014). Due to the dependence on biomass for cooking, per capita CO_2 emission in Ethiopia increased from 0.126 metric tons in 2014–0.149 metric tons in 2018 (Gupta and Sharma 2020). Electricity is mostly used in urban areas and small towns. According to the U. N. (2020) report, sectorial electricity consumption in Ethiopia is 39 percent residential, 34 percent industry, and 27 percent commercial and public services. With the highest share of residential electricity consumption, most households use firewood and charcoal for cooking purposes including those who have access to electricity. This makes a study of the short-run fuel consumption and long-run technology choice behavior of households more important.

In this study, household fuel consumption behavior (short-run elasticity) and household technology choice behavior are modeled using the Ethiopian Socioeconomic Survey (ESS) data. Application of joint modeling of household energy technology choice decision (long-run) and short-run energy use is still very limited. Most empirical studies are limited to the effectiveness of alternative energy and environmental policy instruments encouraging the adoption of energy-efficient technology. Results from this study reveal that effective cost of fuel type (which is defined in this study as the average cost of energy output per energy service) is a key determinant factor for fuel consumption decision at household level. This can provide a useful insight into household technology choice based on the efficiency and price of fuel type.

The rest of the paper is organized as follows: Section 2 describes the data. Section 3 presents the theoretical background of household energy demand and technology choice modeling. Section 4 presents estimation strategy for both short-run fuel demand and technology choice. Section 5 discusses summary statistics and the estimation results for short-run fuel demand. The estimation results of technology choice are presented in section 6. Finally, section 7 presents summary and conclusion of the study.

Data description

Panel data for two waves (2013 and 2015/16) collected by the CSA of Ethiopia and the World Bank on socioeconomic household survey of Ethiopia (ESS) which can be found at the data base Agency (2017), and Ethiopia (CSA) accessed 10 October 2019 is used for this study. While data is collected in three waves, this study uses the last two waves (wave 2 (2013) and wave 3 (2015)) because the first wave did not include urban households. The ESS uses a sample of over 5000 households living in rural and urban areas and is nationally representative. The urban areas include both small and large towns.

The Ethiopian Socioeconomic Survey (ESS) is a collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study- Integrated Surveys on Agriculture (LSMS-ISA) team. The project aims at collecting multi-topic, household-level panel data with a special focus on improving agricultural statistics and generating clearer understanding of the link between agriculture and other sectors of the economy. It also aims to build capacity, share knowledge across countries, and improve survey methodologies and technologies (Agency 2017). The data collection was administered by CSA and access conditions is public use files, accessible to all.

A twostage probability sampling is used. A total of 433 enumeration areas (EAs) were selected based on probability proportional to size of total enumeration areas in each region. A total of 43 and 100 EAs were selected for small towns and urban areas, respectively. From the rural sample 290 EAs were selected. Quotas on the number of EA in each region were established for Addis Abeba and the most populous regions (Amhara, Oromiya, SNNP, and Tigray). The second stage sampling was selection of households to be interviewed in each enumeration area. Households were selected randomly from each EA. The response rate was 96.2 percent in the second wave and 85 percent in the third wave. Attrition rate in urban areas is 15 percent due to consent refusal and inability to trace the whereabouts of the sample households. The survey covers a wide range of issues, that includes households' demographic characteristics, housing issues, health, education, labour and time use, households' expenditure on food and non-food items, and land use of households. In this paper, we use data from urban and small-town households.

Theoretical background

The analysis of household energy demand involves both discrete and continuous choices from the same household. The discrete choice is the investment in one or more appliances associated with technologies and fuels. Such investments have long-run implications on both fuel source and quantities needed. The continuous choice is the short-term utilization of the appliances. The two choices should be modeled in a mutually consistent manner using a discrete/continuous choice model.

Starting from the usual utility maximization of an individual household consuming two groups of commodities, composite market commodities (E0) and energy services (E_1,.....E_J).

The utility maximization will be,

$$maxE_0, E_1, ...E_J U(E_0, E_1, ...E_J, \theta) \quad (1)$$

where E_0 is composite market good, represented as a scalar numeraire, E_1, ...E_J is energy use measured in the physical unit of energy output, θ is a k-dimensional vector of household characteristics that influences the consumption of energy (e.g., dwelling size, household size, dwelling type, etc.).

The basic assumption about the utility function is it is increasing and quasi-concave in E_0 and E_J. Maximization of the utility function is also constrained by household budget and energy pro- duction technology. In

producing energy, the efficiency of the appliance used matters. This is measured by the energy service production function,

$$E_j = \varnothing_{ij} x_{l(i)j} \tag{2}$$

where$x_{l(i)j}$, is input fuel l associated with appliance i for household's end use j (for cooking, baking *"Injera"*, and baking bread), $\varnothing_{ij}$, is efficiency of the appliance i used for end user j.

The decision behavior of households here is technology choice which is long-run behavior (discrete) and energy production using fuels which is short-run (continuous). In developing countries, it is reasonable to assume for each energy service there is a single technology. This assumption may be challenged by the fact that when there is construction of new buildings, households may decide to replace an old appliance by a new sophisticated equipment. Since the replacement of appliance is determined by the purchasing power of households, we believe that this challenge is less likely to happen in the less developed countries like Ethiopia. On the other hand, multiple technologies are used to produce the same energy service (e.g., the electric baking oven and the traditional baking oven are used for baking the Ethiopian traditional bread "*Injera*", electric cooking stoves and metal or clay stoves are used for the same energy services using different fuel inputs). In such cases, energy service output will be

$$\mathrm{E}_j = \sum\nolimits_{k=0}^{n} \varnothing_{i(j)j} x_{l(i(j))j.} \tag{3}$$

and household holdings of appliances in the short-run are assumed to be fixed. Given these appliances, the consumer decides on the level of energy services to be consumed, constrained by household income.

Short-run energy service demand

Following Li and Just (2018) average cost of energy output per energy service i with multiple technology is given by,

$$r_j = \frac{\sum_{j=1}^{J} p_{l(i(j))j} \times x_{l(i(j))j}}{\sum_{j=1}^{J} \phi_{i(j)j} \times x_{l(i(j))j}}, \tag{4}$$

where r_j is average cost of energy output per energy service j, $p_{l(i(j)),j}$ is price of fuel l for technology type i used by household for energy use j, and $x_{l(i(j)),j}$ is amount of fuel l for technology type i used for household's end use j.

On the other hand, for multiple technologies that use the same fuel i, the above Eq. (4) is reduced to,

$$r_j = \frac{p_{l(i(j)),j} \times x_{l(i(j)),j}}{\sum_{j=1}^{J} \phi_{i(j),j} \times x_{l(i)j}} = \frac{p_{l(j),j}}{\sum_{j=1}^{J} \phi_{i(j),j} \times \Psi_{l(i(j)),j}}. \tag{5}$$

where $x_{l(j),j} = \sum_{j=1}^{J} x_{l(i(j)),j}$ and $\Psi_{l(i(j)),j}$ is the share of fuel input l of technology i for energy use j. Equation (4) will be different if the multiple technologies use different fuels,

$$r_j = \frac{\sum_{j=1}^{J} p_{l(i(j)),j} \Psi_{l(i(j)),j}}{\sum_{j=1}^{J} \phi_{i(j)} \Psi_{l(i(j)),j}} \tag{6}$$

In the short-run, the stock of appliances are fixed and the household's utility maximization is based on their derived demands for fuel, but in the long run household decision is based on the capital cost and future flow of operating costs which also depends on the technology choice. In developing countries fuel choice includes firewood, charcoal, gas, and electricity (from the grid or off-grid). The decision to have a stock of appliances depends on the access and price of the fuel type, in addition to the efficiency of the appliance.

There are several popular functional forms to estimate demand functions. Deaton and Muellbauer (1980) introduced the almost ideal demand system (AIDS). The translog system, or the transcendental logarithmic utility function, was introduced by Christensen et al. (1975), while the generalized Leontief method was used by Diewert and Wales (1989) to obtain the system of derived demand equations utilizing the generalized Cobb–Douglas functional form. In order to examine and contrast these three different flexible functional forms, the generalized Leontief, the generalized Cobb–Douglas, and the translog functional form Berndt et al. (1977), and Diewert and Wales (1989) employed Canadian data. They discovered that the translog function was preferred on theoretical and econometric grounds since it was consistent with the asymmetry requirements. However, using data on US demand, Lewbel (1989) found that the elasticity estimates of AIDS and translog were extremely close. Recent research using the translog function produced reliable estimations (Li and Just 2018).

To estimate the short-run demand in this study, we choose a functional form among these popular demand estimation methods. The translog functional form is used in this study as it is more flexible, easier to calculate, and allows to impose linear homogeneity.

$$\omega_i = \frac{x_i p_i}{y^*}, \tag{7}$$

$$\omega_0 = \left(\sum_{j=1}^{J} \Psi\left(x_{i(j),j} > 0\right)\right) \frac{x_{i(j),j} p_{i(j),j}}{y^*}, \tag{8}$$

$$P_{ij} = \frac{\exp\left(-\ln\left(A_0\right) + \ln\left(r_{ij}\right)A_j + H_{ij}\theta\right)}{\sum_{i' \in I} \exp\left(-\ln\left(y_{i'j}\right)A_0 + \ln\left(r_{i'j}\right)A_j + H_{i'j}\theta\right)}. \tag{11}$$

$$\omega_i = \left(\sum_{j=1}^{J} \psi\left(x_{i(j),j} > 0\right)\right) \frac{\alpha_j + 2\sum_{j=1}^{J} \beta_{jj'} \ln\left(\frac{p_{i(j),j}}{\phi_{i(j),j}}\right) - 2\ln\left(y^*\right) \sum_{j'=0}^{J} \beta'_{jj'} + \Gamma_j\theta}{1 + 2\sum_{j''}^{J} \sum_{j'}^{J} \beta_{j''j'} \ln\left(\frac{p_{i(j),j}}{\phi_{i(j),j}}\right) + \sum_{j''=0}^{J} \Gamma_{j''}\theta} + \mu_0, \tag{9}$$

where ω_i is the household monthly budget share for fuel type i, x_i is amount of fuel i use by household per month, p_i price of fuel type i, and $y*$ is total monthly income of household. Γ_j for $j=0,....J$ is row-vector parameters of the indirect utility function, and μ_0 is disturbance in Eqs. (7–9).

For analysis of household energy demand, Eq. (9) consists of four estimable budget share equations, namely electricity, firewood, charcoal, and composite goods. For this study we use engineering energy efficiency for different appliances, $\phi_{(i(j),j)}$ from Ejigu (2016). Assuming single technology energy service, Eq. (9) is estimated for the short-run analysis. We use the coefficients of own effects to estimate the demand elasticities.

Long-run technology choices

Electricity demand estimations that do not include appliance holding decisions of a consumer in addition to electricity consumption lead to biased and inconsistent price and income elasticities (Dubin and McFadden 1984). Even so, some simplifying assumptions are important in modeling household appliance choices. Because appliance usage depends on future price expectations Dubin and McFadden (1984) modeled household technology choice as contemporaneous with utilization decisions. In this study it is assumed that future price and income expectations at each point in time are given by current prices and income. Thus, the probability that technology i provides the highest indirect utility among all possible technologies is given by:

$$P_{ij} = \frac{\exp\left(W_{ij}\beta_j\right)}{\sum_{j=1}^{J}\left(W_{i'j}\beta_j\right)}, \tag{10}$$

where $W_{ij} \cong \{-ln(yij), ln(rij), -2ln(yij)ln(r1), \ldots, -2ln(yij)ln(rj), ln(yij)ln(r1), \ldots\ldots, 2ln(rij)2, \ldots, 2ln(yij)ln(rj), ln(rij)\theta, -ln(yij)\theta, \theta\}$ and

$$\beta_j \cong \left\{1, \alpha_j, \sum_{j=0}^{J} \beta_{j1}, \sum_{j=0}^{J} \beta_{jj,\ldots}, \beta_{j1}, .., \beta_{jj}, \ldots, \Gamma'_j, \sum_{j=0}^{J} \Gamma'_j, H_{i(j),j}\right\}$$

Assuming single technology energy service, we use random effects binary logit model to estimate Eq. (11).

Estimation strategy

Energy demand involves both long-run and short-run phenomena. It has a system of simultaneous equations with continuous demand and discrete technology choice. Maximizing jointly both continuous and discrete equations using log-likelihood can result in multiple roots of the normal equations, and is infeasible since the global maximum is not guaranteed (Abel and Blanchard 1983; Hanemann 1984). The two-step approach with limited maximum likelihood utilized by e.g. Dubin and McFadden (1984), and Li and Just (2018) is therefore used for this study. In the first step, the continuous demand estimation is made and in the second step, discrete technology choice is estimated. This is mainly because energy consumption depends on the availability of appliances but not vice versa. It is also reasonable to assume no disturbance correlation for the discrete choice because decisions for appliances are made at different periods in time. Separate estimations are for the second step. The statistical package we used for the estimation is Stata 17.

The effective cost of fuel[1] is calculated based on the annual fuel consumption of households in Ethiopia studied by Ejigu (2016) for different types of fuels in kWh per year. In addition the energy efficiency for appliances is used from the same study.

In the first step, four equation systems are jointly estimated. Equation (12) and is for composite goods and Eq. (13) is for i (electricity, firewood, and charcoal). For identification purpose, we drop equation for kerosene.

$$\omega_{n,0} = \frac{\alpha_0 + 2\sum_{j=0}^{5} \beta_{0j} \ln\left(\frac{p_{i(j),j}}{\phi_{i(j),j}}\right) - 2\ln\left(y^*\right) \sum_{j'=0}^{5} \beta'_{jj'} + \Gamma_j\theta}{1 + 2\sum_{j''=0}^{5} \sum_{j'=0}^{5} \beta_{j''j'} \ln\left(\frac{p_{i(j),j}}{\phi_{i(j),j}}\right) + \sum_{j''=0}^{5} \Gamma_{j''}\theta} + \mu_0, \tag{12}$$

for $j = 0, 1, \ldots.., J$.

[1] Effective cost of fuel refers to the effective price of fuel use per KWh. It is the ratio of a unit price of fuel per efficiency of the appliance used.

$$\omega_{n.i} = \sum_{j=1}^{5} \Psi(x_{i(j),j} > 0) \frac{\alpha_0 + 2\sum_{j=1}^{5} \beta_{0j} \ln\left(\frac{p_{i(j),j}}{\phi_{i(j),j}}\right) - 2\ln(y^*) \sum_{j'=0}^{5} \beta'_{jj'} + \Gamma_j \theta}{1 + 2\sum_{j''=0}^{5} \sum_{j'=1}^{5} \beta_{j''j'} \ln\left(\frac{p_{i(j),j}}{\phi_{i(j),j}}\right) + \sum_{j''=0}^{5} \Gamma_{j''} \theta} + \mu_0, \tag{13}$$

where $\omega_{n,0}$ is the household's budget share for the numeraire, and $\omega_{n,i}$ is the household's bud- get share for ($i=1$ for electricity, $i=2$ for firewood and $i=3$ for charcoal) and ($j=0$ for numeraire, $j=1$ for electric baking stove, $j=2$ for electric cooking stove, $j=3$ for traditional cooking stove, $j=4$ index of all other energy services).

In the second step, household's technology choices are estimated separately. Electric baking oven, electric cooking stoves, traditional baking oven, and traditional cooking stoves are energy technology choice equations. The dependent variable here is whether the household chooses the specific technology or not. This leads the method of estimation to be a logit model. The model is estimated using maximum likelihood to maximize the likelihood function. The choice probability a household will choose technology j for energy use i will be,

$$P_{ij,n} = \frac{\exp\left(-\ln(A_0) + \ln(r_{ij})A_j + H_{ij}\theta\right)}{\sum_{i' \in I} \exp\left(-\ln(y_{i'j})A_0 + \ln(r_{i'j})A_j + H_{i'j}\theta\right)}, \tag{14}$$

where n represents for household. A_0, A_j, $H_{i,j}$, and $\theta_{j,n}$ are defined in equation (11).

However, the factors that influence households to purchase a cooking appliance are not only observed but also unobserved. In order to overcome the unobserved heterogeneity, we use random effects binary logit model. This is mainly because typical random effects approach enables every estimated parameter in the model to potentially fluctuate across observations and account for the heterogeneity between one data observation and the next (Greene 2020).

Estimations and result

We use the discrete–continuous model developed in Sect. 4 which consists of energy demand, the discrete technology choice, and other variables like prices of fuel types, the income of the household, and household characteristics. In the first case where a system of continuous equations are estimated assuming the energy consumption of household depends on their observed appliance choice.

The system of equations is budget share for electricity, budget share for charcoal, budget share for firewood and budget share for composite goods. We drop equation for kerosene for identification (Greene 2020) and iterated feasible generalized non-linear least squares (FGNLS) is applied to get consistent estimates.

The technology choice equation (Eq. 14) is then estimated using the random effects binary logit model. Four different cooking appliances are considered. Power saving traditional baking oven (Ps stove), electric stove, electric baking oven (locally *"electric Mitad"*), and power saving traditional cooking stove. Because the decisions of households to purchase appliances are made separately at different periods, it is reasonable to estimate the choice equations separately. Hence the random effects binary logit model is used for the technology choice. Finally, the marginal effects are estimated from the random effect binary logit output.

Table 1 Primary types of ovens used for baking "Injera" or bread by year

Types of oven	(1) 2013	(2) 2015	(3) Pooled
Traditional oven removable	60.00	61.41	60.64
Traditional oven not removable	19.10	20.30	19.64
Improved oven energy saving	3.34	3.19	3.27
Electric Baking ("*Mitad*")	9.20	8.98	9.10
None	8.36	6.12	7.35
Kitchen type			
No kitchen	29.76	25.67	27.90
Inside house traditional	23.00	29.03	25.73
Outside house traditional	43.00	39.77	41.53
Inside house modern	2.37	3.27	2.78
Outside house modern	1.88	1.93	1.90
Others		0.34	0.15
N	1143	1192	2335

Table 2 Sources of cooking fuels by year

	(1) 2013	(2) 2015	(3) Pooled
Collecting firewood	10.35	9.66	10.05
Purchase firewood	29.37	33.67	31.24
Charcoal	26.20	25.36	25.83
Electricity	23.35	21.24	22.43
Crop residue/leaves	0.65	0.84	0.73
Dung/manure	1.35	1.76	1.53
Sawdust	0.32	0.42	0.37
Kerosene	1.88	1.68	1.80
Butane/gas	0.78	0.84	0.80
None	5.75	4.53	5.22
N	1190	1191	2331

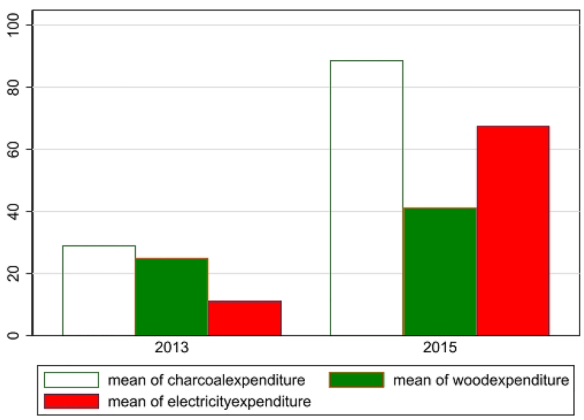

Fig. 1 Mean urban fuel expenditure by fuel types and by Year

Table 3 Summary statistics of variables

	(1) Mean/2013	(2) Mean/2015	(3) Mean/Pooled
Panel A budget share			
Electricity	0.01	0.03	0.02
Charcoal	0.03	0.06	0.04
Firewood	0.02	0.03	0.02
Composite	0.94	0.88	0.92
N	1382	1142	2524
Panel B effective cost (ETB/KWH)			
Charcoal (traditional stove)	0.48	1.65	1.01
Electricity (electric stove)	0.17	1.21	0.64
Electricity (electric baking)	0.11	0.81	0.43
Firewood (Traditional baking)	1.38	2.62	1.96
Panel C: household characteristics			
Household head age	45.40	43.27	44.45
Male headed	0.66	0.58	0.62
Household size	3.52	3.80	3.65
Number of rooms	1.68	2.17	1.90
Modern Kitchen	0.047	0.055	0.051
N	1102	1142	2224

Descriptive results

Types of ovens and kitchen used

Even though the data are not reflecting a major change in energy technology, with a longer panel during a period of rapid urban growth and the erection of new buildings, one would of course expect more significant results from our analysis. Already from the descriptive statistics we can see that not much changed in these two years. We believe, however, that the approach that we use will be useful as soon as more data come online.

Table 1 shows the main types of ovens used by households in Ethiopia to bake *"Injera"* or bread, and the types of kitchens owned by households by year and pooled. According to Table 1, the percentage of urban households using traditional ovens (removable) increased from 60 percent in 2013 to about 61 percent in 2015. Additionally, it showed that traditional oven (not removable) users increased from 19 percent in 2013 to 20 percent in 2015 and about 20 percent when combined. Improved ovens (which save energy) usage account for a lower percentage of around 3 percent. Electric baking, often known as electric *"Mitad"* accounts about 9 percent as their primary kind of oven for baking. Households without kitchens make up roughly 26 percent of all homes in 2015, down from about 30 percent in 2013. More people have a typical kitchen inside their homes, which increases from 23 to 29 percent. In 2013, families owned 43 percent of traditional kitchens outside the home by 2015 that percentage had dropped to 40 percent. While the percentage of contemporary kitchens outside the home stays at around 2 percent, the percentage of modern kitchens inside the home rises from 2 to roughly 3 percent.

Table 2 presents the primary sources of various types of cooking fuels by year. In both 2013 and 2015, firewood dominated fuel usage. Once again, it is important to note the bigger picture, from a energy transition perspective,

Table 4 Short-run energy demand estimation results

	(M1) With efficiency	(M2) Without household variable	(M3) Without efficiency
Own effects			
Baking oven(wood)	−1.43e-5*** (−3.77)	−1.75e-6*** (−13.42)	−8.73e-6** (−2.71)
Cooking stove (charcoal)	−5.19e-6*** (−3.75)	−1.97e-7*** (−14.82)	−6.30e-7*** (−4.44)
Electric baking	−2.81e-10 (−1.64)	2.47e-11*** (3.30)	−2.05e-10 (−1.60)
Electric cooking	−4.55e-08 (−1.91)	−1.65e-09** (−2.63)	−4.00e-08 (−1.68)
N	2224	2224	2224
R^2 Numeraire	0.80	0.73	0.81
R^2 Charcoal	0.22	0.20	0.22
R^2 Firewood	0.13	0.11	0.13
R^2 Electricity	0.12	0.09	0.12
Log Likelihood	8971.17	8970.89	7571.831

t statistics in parentheses

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

that Ethiopia is still at the early stages. There seem to be a significant increase in purchased firewood, and that can be seen as a first step toward a more market-based energy demand. The real penetration of modern fuels is yet to be seen.

Figure 1 illustrates after controlling for inflation in 2015, how the average urban household expenditure on electricity, firewood, and charcoal grew between 2013 and 2015. The average monthly household expenditure on charcoal has increased from about 30 Birr in 2013 to about 90 Birr in 2015.[2] The average monthly cost of firewood rises from roughly 24 Birr in 2013 to about 40 Birr in 2015. The average expenditure of electricity also rose significantly, from approximately 11 Birr in 2013 to about 68 Birr in 2015.

Budget share of fuels, effective cost, and household characteristics

Panel A of Table 3 shows the budget share for different types of fuels. Using total annual consumption expenditure and annual expenditure on fuel type, in 2013 the mean household budget share for electricity was 0.01(1 percent), 3 percent for charcoal, 2 percent for firewood, and the rest 94 percent was for composite goods. In 2015 households spent 3 percent of their total expenditure on electricity, 6 percent on charcoal, another 3 percent on firewood, and the remaining 88 percent on composite goods. This implies that household's budget share for fuel types of electricity, firewood, and charcoal has increased.

Panel B of Table 3 shows the effective cost of different fuel type. Whereas the effective cost for charcoal (traditional stoves) was 0.48ETB/KWH, the effective cost of electricity (for electric stoves) was 0.17ETB/KWH in 2013. These effective fuel prices increase to 1.65ETB/KWH for traditional stoves and 1.21ETB/KWH for the electric stove in 2015. When the data is pooled the mean effective cost for charcoal (traditional stoves) was about 1ETB/KWH which is higher than the effective cost of electricity (for electric stove), 0.64ETB/KWH. This implies electric stoves are more cost-effective than traditional stoves. The mean effective cost for firewood (traditional baking oven) was about 2ETB/KWH which is higher than the effective cost of electricity (for electric baking oven) which was 0.43ETB/KWH. This implies that electric baking ovens are more cost-effective than traditional baking stoves.

Panel C of Table 3 shows household head characteristics. The mean age of the head of the family was approximately 45 years. The mean family size was about 4 when the data is pooled. On average a household own two rooms. About 5 percent of the households have modern kitchen and around 66 percent of the household heads are male.

Short-run energy demand estimation

The ESS data set lacks some important variables like unit price of energy. But the monthly fuel expenditure for different fuel types is available. We use the block tariff prices for electricity from Ethiopian electric utility for the

[2] Expenditure for the Year 2015 are deflated by the average annual inflation rate of Ethiopia.

Table 5 Estimation results for elasticity of demand

	(Budget share of fuel type) Variable	(2) Elasticity
Budget share for firewood	Effective cost of firewood	− 0.975*** (− 1.8e + 04)
Budget share for charcoal	Effective cost of charcoal	− 0.958*** (− 1.1e + 05)
Budget share for electricity	Effective cost of electricity (baking)	− 0.979*** (− 6.2e + 05)
Budget share for electricity	Effective cost of electricity (cooking)	− 0.979*** (− 6.2e + 05)

z statistics in parentheses

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

Table 6 Marginal effects of baking and cooking

	(1) Traditional baking	(2) Electric baking	(3) Electric stove	(4) Traditional stove
Consumption expenditure (ln)	0.0028 (0.45)	0.079* (2.35)	0.020* (2.05)	−4.64e-3 (−0.54)
Effective cost firewood	0.0119** (2.84)	0.0043 (0.90)		
Effective cost electricity (baking)	−0.027 (0.19)	−0.1328* (−2.17)		
Effective cost electricity (stove)			0.466*** (11.05)	−0.210*** (−4.02)
Effective cost of charcoal (stove)			−3.4e-3 (−0.61)	0.013** (2.61)
Number of rooms	−5.55e-3 (−1.30)	0.0366*** (8.16)	−7.37e-4 (0.12)	6.02e-3 (1.14)
Modern kitchen	−0.064*** (3.35)	0.1977*** (12.63)	−8.49e-3 (−0.27)	0.0311 (1.19)
Male headed	−0.023* (−2.25)	−0.0023 (-0.25)	−0.012 (−0.87)	0.013 (0.99)
Household size	4.0e-4 (0.019)	−0.0084** (−2.8)	−3.4e-3 (−0.94)	−0.011** (−2.92)
Head's age	−2.96e-4 (1.10)	2.2e-4 (0.63)	−1.07e-3* (−2.10)	−2.8e-4 (−0.72)
N	2488	2488	2488	2488

z statistics in parentheses

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

years of study. Based on the reported monthly electricity expenditure of households, we link them to their respective marginal price. These marginal prices and the specific efficiency of appliances[3] were then used to get the effective cost of electricity. For firewood and charcoal, we use the reported household's expenditure for the fuel type and the average annual household consumption of fuel type [4] to get the average price per kilogram of firewood or charcoal. Using these average prices and the efficiency of the specific appliances, we get the effective cost for firewood and charcoal. For the short-run energy demand estimation, we estimate equations (12) and (13) simultaneously.

Column M1 in Table 4 is estimation result for our main model. Whereas M2 is M1 without household characteristics variables, a log likelihood ratio test between the two models rejects the null hypothesis that households demand own effects are jointly zero with $p < 0.001$. Also, the statistical test for each of the household characteristics are statistically significant. M3 is M1 without using the efficiency of appliances. Similarly, the log likelihood ratio test rejects the null hypothesis that households demand own effects are jointly zero with $p < 0.001$. This implies our main model is inclusive of determinant variables. In addition to the effective cost of fuel type and

[3] The efficiency as calculated by Ejigu (2016) for electric baking is 75 percent, the electric cooking stoves is 50 percent, power-saving traditional stoves (firewood) is 26 percent, and power saving traditional stove (charcoal) is 35 percent.

[4] Ejigu (2016), report on average annual household fuel consumption in Ethiopia.

annual consumption expenditure, variables like dwelling size, household size, oven type, kitchen type and age of household head determines the demands for energy.

The first column of Table 4 shows the estimation results of own effects for firewood, charcoal, and electricity using iterative FGNLS. The efficiency of appliances is used to get the effective cost of energy output. In addition, household income and demand interaction variables like kitchen type, household size, gender of household head, age of the head, and dwelling size are included. The second column of Table 4 shows the results for households' demand for firewood, electricity, and charcoal. Column 3 is column 1 without taking the efficiency of appliances into consideration. The estimation is done by clustering at the household level.[5] The coefficient estimates of M1 are used for subsequent interpretations and to get elasticity. The coefficients are used to estimate the elasticity of the effective cost of fuel type using *nlcom* command in stata and the results are presented in Table 5. In addition, we use these values to estimate the maximum likelihood estimators *A*0 and *Aj* of common parameters in the technology choice section.

Table 5 shows the estimated own-price elasticity of firewood, charcoal, and electricity when used with different devices. Price elasticity measures the sensitivity of quantity demanded to change in price. The result revealed that the sign of effective price elasticity is negative for the three fuel types. A one percent increase in effective cost of firewood decreases the budget share for firewood by 0.975 percent. For charcoal, a one percent increase in the effective cost of charcoal decreases the budget share for charcoal by 0.958 percent. These implies that, in Ethiopia, the price elasticities of demand for firewood and charcoal are inelastic. Households' response to effective price changes in electricity was also like elasticity of firewood and charcoal. The estimated short-run price elasticities are less than unity implying demand is inelastic. Hence electricity, firewood, and char- coal are necessity goods.

Long-run technology choice results

Households' technology choice is dependent on the type of fuel their appliances use. We expect that; households would be less likely to use an appliance associated with a higher effective fuel price. Subsequently, we expect that a higher effective fuel price would decrease the demand for a particular appliance. However, our results presented in Table 6 for electric stoves, traditional stoves, and traditional baking ovens does not conform to this expectation. At the end of this section, and in the conclusion, we will return to some potential reasons for the counter-intuitive results.

We apply a binary random effects logit model for the technological choices on traditional baking oven, traditional cooking stove, electric baking, and electric cooking stoves individually after estimating the maximum likelihood estimators A_0 and A_j of common parameters. The Estimation results for the binary random effects logit are presented in Table 8 of the appendix. The estimates are made through clustering at the household level, and Table 6 reports the marginal effects. The first and second columns are for baking using the traditional baking oven and electric baking oven, while the third and fourth columns are for cooking using traditional cooking stoves, and electric cooking stoves.

Surprisingly, the first (1) specification of Table 6 indicate that; the effective cost of firewood has a positive and significant effect on the likelihood that a traditional baking stove is used. Similarly, the effective cost of electricity has a non-expected negative, but not significant effect, on the prob- ability to use traditional baking oven. In the second (2) specification of the same table, higher effective cost of electricity decreases the likelihood of using electric oven for baking, albeit with a weak significance at 10 percent.

The results of households' technology choice for cooking are shown in columns 3 and 4 of Table 6. once again, the results are unexpected with an increase in effective price of electricity having positive and significant effect on the probability of using electric cooking stoves, while the effect on the probability of using traditional cooking stoves is negative and statistically significant. Similarly, traditional cooking stove choice is also positively affected by an increase in effective prices of charcoal.

These counter-intuitive results could be related to several factors. First, as we noted in the descriptive statistics, the two years from 2013 to 2015 did not represent a period with rapid changes in terms of choice of energy source and technology. The period was also characterized by rapid inflation and changing relative prices while nominal prices for certain fuels, such as electricity were constant. This means that the price signals could have been blurred to many consumers. A more fundamental reason is that these appliances are long-lived and there are no data on when they were acquired. The results might therefore pick up a confounding effect from old acquisitions with recent price changes. At the same time, the results show

[5] The full estimation result of the models is shown in Annex A.1 table 7. The results of demand interaction variables are reported.

other factors like the number of rooms and modern kitchen are also determinant factors for technology choice. Having modern kitchen increases the probability to use electric baking oven, while it decreases the probability to use traditional baking oven. Households with a greater number of rooms are more likely to use electric baking oven than those with a smaller number of rooms. This implies that energy transition in the country is related to technology choice, where the latter is determined by the housing infrastructures rather than relative prices.

Summary and conclusion

Residential fuel consumption and technology choice behavior of households is becoming a prominent issue for climate policy in building a climate resilient economy. In this study, residential fuel consumption and technology choice behavior of households are modeled using Ethiopia socio eco- nomic household survey. The short-run analysis of fuel consumption behavior is modeled using feasible generalized nonlinear least squares (FGNLS) and the technology choice analysis is modeled using a random effect binary logit model. Panel data from two waves (2013 and 2015/16) collected by CSA and the World Bank on socioeconomic household survey of Ethiopia was used in this study. The data show that not even in the towns of Ethiopia, the energy transition has come very far, and there is not much change in the short period covered by the study. The main sources of fuel for cooking in medium and large towns are purchased firewood, charcoal, and electricity. About 31 percent of households use purchased firewood for cooking and only 10 percent use collected firewood for cooking. About 28 percent of the households use charcoal as a fuel source for cooking and about 22 percent use electricity for cooking, other sources include crop residue/leaves, dung, sawdust, kerosene, and butane gas.

The estimated short-run own price elasticities in the three models are negative and less than unity. A 1 percent increase in the effective cost of firewood decreases the budget share for firewood by 0.975 percent. A one percent increase in effective cost of charcoal decreases the budget share for charcoal by 0.958 percent. Households' responses to effective price changes in electricity was also like elasticities of firewood and charcoal. The price elasticities are less than unity which implies relatively inelastic demand and that these types of fuels (electricity, firewood, and charcoal) are necessities. The estimation of the longer-term technology choice led to a series of counter-intuitive results when it comes to the impact of effective prices on appliance use. There could be many reasons behind these results. The most fundamental could be that the time span of the data is not enough to elicit long-term investment behavior. While the estimation approach is still valid, it is recommended to be applied on longer-term panel data where relative price changes could affect long-term investment behavior affecting energy transition.

The validity of the approach is also strengthened by the significance of other determinant factors affecting household's decision on technology choice such as dwelling size and type of kitchen they own. Not surprisingly, owning a dwelling with more rooms and a modern kitchen make people use modern appliances. It of course broadens the set of policies available for a sustainable energy transition. While households' demand is inelastic in the short run for the three fuel sources examined in this study, long-term decisions on the choice of appliances are also affected by the infrastructure now created in the rapidly growing cities of Africa.

While this study has made a methodological contribution in the joint estimation approach, there are certain limitations to the study too. The first limitation is the limited time captured by the two rounds of panel data available. The second limitation is that, the impact of power outages on appliance usage and electricity consumption habits is not taken into account. Power outages, a typical occurrence in the research area, may influence households' choices of appliance and, consequently, fuel type. Third, rather than using the specifications of each appliance used by a home, we used the study's average technology type efficiency to calculate the true cost of energy use. Future studies are recommended to consider and address these constraints.

Appendix

See Tables 7 and 8

Table 7 Short-run Energy Demand Estimation Results

	(1) With efficiency	(2) Without household variable	(3) Without efficiency
Intercepts			
Firewood		6.33e-5*** (15.60)	
Charcoal		8.44e-5*** (18.40)	
Own effect			
(f1)			
Baking Oven (Wood)	−1.43e-5*** (−3.77)	−1.75e-7*** (−13.42)	−8.73e-6** (−2.71)
(g1)			
Cooking stove (charcoal)	−5.19e-6*** (−3.75)	−1.97e-7*** (−14.82)	−6.30e-6*** (−4.44)
(b1)			
Electric baking	−2.81e-10 (−1.64)	2.47e-11*** (3.30)	−2.05e-10 (−1.60)
b2			
Electric cooking	−4.55e-08 (−1.91)	−1.65e-09** (−2.63)	−4.00e-08 (−1.68)
Cross effect (numeraire)			
h1			
Electric baking	−7.28e-6*** (−9.86)	−1.66e-6*** (−6.12)	1.77e-6 (0.96)
h2			
Electric stove	1.32e-5*** (11.70)	1.37e-6***	
h3			
Cooking stove	−8.85e-7* (−2.43)	2.72e-7* (2.19)	1.34e-6*** (3.94)
h4			
Baking oven	−2.02e-7 (−0.68)	−6.47e-7*** (−4.85)	−1.80e-6*** (−7.01)
N	2244	2244	2244
Budget wood			
Dwelling size	−1.79e-6 (−1.31)		−2.00e-6 (−0.69)
f5			
Household size	−1.74e-6* (−2.50)		−5.05e-7 (−0.86)
f8			
Kitchen type	−8.51e-6 (−1.48)		−8.28e-6* (−2.39)
f9			
Oven type	−5.89e-6 (−0.79)		−1.60e-6 (−0.05)
f10			
Household head age	1.14e-6*** (4.21)		3.98e-7* (2.14)
f11			
Male headed	1.54e-5*** (3.96)		7.25e-7 (0.13)
Budget charcoal			
g4			
Dwelling size	−7.59e-7 (−1.02)		−3.86e7 (−0.60)
g5			
Household size	−1.17e-6*** (−3.59)		−1.07e-6*** (−3.64)
g8			
Kitchen type	−5.19e-6*** (−4.02)		−7.32e-6*** (−4.26)
g9			
Oven type	−2.27e-6** (−2.63)		−3.43e-6*** (−3.47)
g10			
Household head age	4.79e-7*** (3.71)		4.39e-7*** (3.76)
g11			
Male headed	6.34e-6* (2.54)		2.92e-6 (1.24)
N	2244	2244	2244

Table 7 (continued)

	(1) With efficiency	(2) Without household variable	(3) Without efficiency
Budget numeraire			
h5			
	(8.22)		(3.88)
h6			
Household size	−6.39e-6 (-1.17)		4.69e-6 (1.11)
h8			
Kitchen type	1.07e-5*** (5.13)		1.61e-4*** (8.08)
h9			
Oven type	−1.70e-4*** (−9.25)		−1.88e-4*** (−11.18)
h10			
Household head age	−6.26e-6*** (−8.70)		−3.66e-6*** (−6.18)
h11			
Male headed	3.34e-4*** (10.58)		1.12e-4*** (3.69)
Budget electricity			
b5			
Dwelling size	−9.15e-7* (−2.30)		−9.13e-7* (−2.30)
b6			
Household size	−3.40e-7** (−2.69)		−3.35e-3** (−2.65)
b8			
Kitchen type	−9.34e-7** (−2.60)		−8.69e-7* (−2.42)
b9			
Oven type	5.85e-7 (1.54)		5.33e-7 (1.42)
b10			
Household head age	4.77e-08* (2.81)		4.70e-08** (2.77)
b11			
Male headed	2.04e-5** (2.77)		2.04e-5** (2.76)
N	2224	2224	2224
R^2 Numeraire	0.80	0.73	0.81
R^2 Charcoal	0.22	0.20	0.22
R^2 Firewood	0.13	0.11	0.13
R^2 Electricity	0.12	0.09	0.12
Log Likelihood	8971.17	8970.89	7571.831

t statistics in parentheses

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

Table 8 Binary Random Effects Estimation Result for Technology Choice

	(1) Traditional oven	(2) Electric oven	(3) Electric stove	(4) Traditional stove
Consumption expenditure(ln)	0.0792 (0.45)	0.298* (2.33)	0.223* (2.05)	−0.0554 (−0.54)
Effective cost traditional oven	0.337** (2.93)			
Effective cost electric"*Mitad*"	−0.776 (−0.71)	−2.276* (−2.18)		
Effective cost electric stove			4.979*** (8.72)	−2.510*** (−3.96)
Effective cost of traditional stove		0.0703 (1.03)	−0.0237 (−0.45)	0.151* (2.57)
Male headed	−0.659* (−2.27)	−0.0413 (−0.22)	−0.131 (−0.87)	0.154 (0.99)
Household size	0.0120 (0.19)	−0.139** (−2.78)	−0.0379 (−0.95)	−0.128** (−2.92)
Head's age	−0.00835 (−1.09)	0.00386 (0.66)	−0.0116* (−2.12)	−0.00338 (−0.71)
Number of rooms	−0.156 (−1.38)	0.608*** (7.57)	−0.00731 (−0.11)	0.0718 (1.14)
Type of kitchen	−1.802** (−3.24)	3.278*** (8.98)	−0.0919 (−0.28)	0.371 (1.18)
2015.Year	0.0340 (0.13)	−0.0801 (−0.42)	1.284*** (6.40)	1.179*** (6.21)
Constant	3.570* (1.99)	−5.706*** (−4.72)	−7.570*** (−7.23)	−0.328 (−0.37)
lnsig2u	−0.727 (−0.36)	−0.753 (−0.64)	−1.084 (−0.99)	−10.82 (−0.00)
N	1839	2209	2209	2209

t statistics in parentheses

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

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Author contributions
NJM undertook data analysis and prepared the manuscript. GK and AM participated in data analysis and editorial comments on the draft manuscript. All authors read and approved the final manuscript.

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Declarations

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