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The persistence of energy poverty: A dynamic probit analysis☆

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ABSTRACT

This paper contributes to the growing literature on energy poverty in developing countries. We use a dynamic probit estimator on three rounds of panel data from urban Ethiopia to estimate a model of the probability of being energy poor and to investigate the persistence of energy poverty. We also study the impact of energy price inflation, which Ethiopia experienced during 2007–2009, on energy use and energy poverty. We find strong evidence of state dependence in energy poverty. A household that is energy poor in one round is up to 16% more likely to be energy poor in the subsequent round. Dynamic probit regression results also suggest that an increase in the price of kerosene – the most important fuel for the urban poor – drives households into energy poverty. A fractional response estimator for panel data, which estimates the impact of energy prices on the proportion of energy obtained from clean sources, also supports the finding on the adverse impact of energy price inflation. Households responded to the significant rise in the price of kerosene by consuming a large amount of charcoal, which has been documented to have serious environmental, climate, and health consequences. Our results have significant implications for policies formulated to reduce energy poverty, conserve biomass resources, and promote energy transition in developing countries.

1. Introduction

The countries that adopted the Sustainable Development Goals (SDGs) put universal access to affordable and clean energy as one of the goals to achieve by 2030 (UnitedNations, 2015). Despite the ambitious goal, nearly half of the world's population and about 81% of households in Sub-Saharan Africa (SSA) still rely on wood-based biomass energy (mostly fuelwood and charcoal) to meet their cooking needs (Sander et al., 2011). The use of biomass fuels, often burned in inefficient cookstoves, has serious impacts on the environment, the climate, and human health. Deforestation and forest degradation resulting from efforts to meet cooking energy needs have been the main cause of the loss of irreplaceable biodiversity and destruction of local ecosystems in many developing countries (Allen and Barnes, 1985; Geist and Lambin, 2002; Hofstad et al., 2009; Kohlin et al., 2011). Africa's tropical forests have significant carbon sequestration capacity, but are at greater risk than those in other parts of the world. In fact, they are disappearing three times faster than the world average (Mercer et al., 2011). The use of biomass fuel, often burned in inefficient cookstoves, contributes to climate change through emissions of harmful greenhouse gases, including black carbon and carbon dioxide (Grieshop et al., 2011; Kandlikar et al., 2009; Sagar and Kartha, 2007). Consequently, investigating the energy use behavior of households and the factors that reduce energy poverty and reliance on biomass fuel will have significant implications for environmental and climate policies.

The motivations for this paper are two-fold: first, we want to investigate the impact of energy prices on energy consumption and poverty. Urban Ethiopia is a valuable set-up for investigating the impact of rising energy prices. The country experienced rapid economic growth after 2004, with an average GDP per capita growth rate of 10.6% from 2004 to 2011 (Geiger and Goh, 2012). However, the double digit economic growth was accompanied with double digit inflation. From 2004 to 2009, i.e., the years when the last two rounds of the Ethiopian Urban Socioeconomic Survey (EUSS) panel data used in this paper were collected, the price of cereals increased by 114%. The price of kerosene, the fuel used by a large proportion of the Ethiopian urban poor for cooking, increased by 177% (EUSS). In the 2009 survey, 74% of

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households reported energy price inflation as the second most important shock (after food price inflation) that affected their welfare during the analyzed period. Households in developing countries lack insurance from formal institutions. Instead, they try to cope with risk and shocks using informal mechanisms (Alem and Söderbom, 2012; Behrman et al., 1997; Dercon, 2004; Lim and Townsend, 1998; Rosenzweig and Wolpin, 1993; Skoufias and Quisumbing, 2005; Townsend, 1994). It is therefore highly relevant to investigate the strategies households adopted to cope with the energy price shock and their implications.

We attempt to investigate the behavioral response of households to energy price inflation using the most robust dynamic probit estimator, the Wooldridge Conditional Maximum Likelihood estimator (WCML), on three rounds of the EUSS panel data. The WCML estimator addresses the specific endogeneity problem known in non-linear dynamic estimators as the "initial conditions problem," i.e., endogeneity of the lagged dependent variable, by specifying an approximation for the density of household unobserved heterogeneity conditional on the initial period value of the dependent variable. The detailed energy consumption data in EUSS enables us to convert all energy types into comparable standard units in kilogram of oil equivalent (kgoe) and categorize each household into energy poor or non-poor based on alternative measures. Alternative dynamic probit regression results suggest that an increase in the price of kerosene leads to an increase in the likelihood of being energy poor.

Our results also show that households responded to the rapid increase in the price of kerosene during 2004 to 2009 by reducing their kerosene use and increasing their charcoal use to meet their cooking energy needs. During the period, the price of kerosene - the major cooking fuel for a vast majority of the urban poor - increased by 177% and the average consumption of charcoal increased by 71%. However, the price of electricity, the main cooking energy for the richest 1% of the population did not increase at all, suggesting possible negative distributional consequences. We complement our analysis with results from a fractional response estimator for panel data (Papke and Wooldridge, 2008) that estimates the impact of a rise in energy prices on the proportion of energy derived from clean fuel in actual kgoe. The results confirm the findings from the dynamic probit estimator. An increase in the price of kerosene leads to a statistically significant reduction in the proportion of actual energy derived from clean fuels. Such a shift to solid (biomass) fuel understandably has adverse implications on the health of household members, the climate, and the environment by contributing to deforestation and forest degradation.

Second, we want to investigate the persistence, trends, and correlates of energy poverty. The spatial and temporal distribution of energy poverty and its persistence is important information used by policymakers and other stakeholders aiming to promote transition to cleaner energy sources. Relying on the richness of the panel data at hand, we are able to compute alternative energy poverty measures (Modi, Barnes and the Multidimensional Energy Poverty Index – MEPI) and investigate the persistence of energy poverty and its correlates over time using dynamic probit estimators. We show that 22–60% of urban Ethiopian households have always been energy poor during the decade under analysis (2000–2009). More specifically, dynamic probit regression results suggest that a household that is energy poor in any given round is up to 16% more likely to remain in energy poverty in the subsequent round. The strong state dependence in energy poverty that we document has important implications for the development of policies targeting the persistently energy poor.

The rest of the paper is organized as follows: Section 2 presents the frontier literature on energy poverty. Section 3 describes the panel data and presents descriptive statistics. Section 4 lays out the conceptual framework, which motivates our empirical strategy. Section 5 discusses the initial conditions problem and specifies a dynamic probit model for the probability of being energy poor. This section also motivates and presents the fractional response estimator for fuel substitution. Section 6 presents the results and discusses the associated policy implications. Finally, Section 7 concludes the paper.

2. Related literature

This paper contributes to the limited literature on measuring energy poverty that builds on the work of Sen (1976), Atkinson (1987), and Ravallion (1996) on income poverty; Bourgugnon and Chakravarty (2003) and Alkire and Foster (2011), on multidimensional poverty; and Foster et al. (2000), Pachauri et al. (2004), and Modi et al. (2005) on energy poverty. Foster et al. (2000) offer one of the early contributions in measuring the extent of energy poverty by using the average energy consumption expenditure of households that are below the monetary poverty line in Guatemala. This method assumes that those who are poor in money-metric measures are also energy poor. Pachauri et al. (2004) proposed an alternative measure – the energy access consumption matrix – which gives an indication of the level of access to final energy and the amount consumed by people at the national level. Using this two-dimensional approach, the authors documented that the status of energy poverty in India declined from 1983 to 2000. However, the method is better suited for investigating energy poverty using macro-level data.

Modi et al. (2005) proposed an approach that is more suitable for analysis at the micro level. These authors defined energy poverty as a lack of the minimum level of energy required for cooking and lighting. Employing a compressive approach, they document the essential role of energy services (such as cooking, heating, and electricity) in achieving the Millennium Development Goals (MDGs). Similarly, using cross-country data, Sovacool (2012) examine the relationship between energy access and MDGs. The study shows that energy poverty – associated with the use of biomass fuel – has dire environmental consequences including deforestation and changes in land use as well as emission of greenhouse gases.

Despite some attempts, less attention has been given to analyzing energy poverty in the world's poorest communities (Birol, 2007). In an attempt to fill the knowledge gap, Barnes et al. (2011) develop a demand-based approach where the energy poverty line is defined as the threshold at which energy consumption begins to rise with an increase in household income. Using cross-sectional data from Bangladesh, the authors show that there are more energy poor than income poor people (58% vs. 45%).

Recently, attention has been given to the multifaceted nature of energy poverty. Nussbaumer et al. (2012) proposed a multidimensional energy poverty index (MEPI) that takes into account the deprivation to modern energy services. They selected five dimension representing basic energy services: cooking, lighting, household appliances, entertainment/education and communication and examined the extent of energy poverty in various African countries. Building on this, Ogwumike and Ozughalu (2016) constructed a simple multidimensional energy poverty index based on three dimensions: cooking, indoor pollution, and lighting. Using a logistic regression on the Nigerian Living Standard Survey data, these authors show that household size, age of household head, proportion of total consumption expenditure spent on food, and general poverty are positively correlated with energy poverty, while being female and being educated are negatively associated.

One key challenge in the existing energy poverty literature is that the results from different studies are not comparable because the energy poverty measures employed in the studies are not uniform. In this regard, Bensch (2013) used a unique household dataset from five sub-Saharan countries and finds that the different measures perform differently in terms of the identification of the energy poor, sensitivities to parameter changes, and data requirements.

Another point in the energy poverty literature worth noting is that, in developed countries, the definition and measures of energy poverty are quite different from those used in developing countries. In Europe, energy-poor households are those that are not able to adequately heat

their homes or that spend more than 10% of their income on energy expenditures. Employing these definitions, Phimister et al. (2015) in Spain and Roberts et al. (2015) in the United Kingdom investigate the dynamics and persistence of energy poverty. Their studies show that there is less persistence in energy poverty than in income poverty, but more energy poverty persistence in urban areas than in rural areas (Roberts et al., 2015).

Our paper contributes to the literature by analyzing the trends and persistence of energy poverty and investigating the impact of energy price inflation using robust panel data estimators on a decade-long panel dataset from a developing country in the process of rapid economic growth. The richness of the panel data enables us to gauge energy poverty using alternative measures and investigate the robustness of our results.

3. Data and descriptive statistics

3.1. Data

We use three rounds of panel data from the Ethiopian Urban Socioeconomic Survey (EUSS) collected in 2000, 2004, and 2009. EUSS is a rich data set containing several socioeconomic variables at the individual and household level. The first two waves of the data used were collected by the Department of Economics of Addis Ababa University in collaboration with the University of Gothenburg, and cover seven of the country's major cities: the capital Addis Ababa, Awassa, Bahir Dar, Dessie, Dire Dawa, Jimma, and Mekelle.[1] Representativeness of the major socioeconomic characteristics of the Ethiopian urban population was taken into consideration when selecting the cities. About 1500 households were distributed over the cities, in proportion to their population, and the sample households were recruited from half of the *kebelles* (the lowest administrative units) in all *woredas* (districts) in each city.

The last wave of the data (EUSS 2009) was collected by one of the authors in late 2008 and early 2009 from a sub-sample of the original sample in four cities (Addis Ababa, Awassa, Dessie, and Mekelle), comprising 709 households.[2] These cities were carefully selected to represent the major urban areas of the country and the original sample.[3] Of the 709 households surveyed, 128 were new, randomly chosen households incorporated into the sample. The new households were surveyed to address the concern that the group of panel households may have become unrepresentative since its formation in 1994. Alem and Söderbom (2012) address this and show that there is no systematic difference between the new households and the old panel households, which implies that the panel households represent urban Ethiopia reasonably well. In addition to a specific module on energy use, the data set contains detailed information on households' living conditions, including income, expenditure, demographics, health, educational status, occupation, production activities, asset ownership, and other individual- and household-level variables.

Since the sample size of EUSS had to be reduced substantially in the most recent wave, it is reasonable to be concerned about bias in the estimation results as a result of attrition. Previous authors (Alem, 2015; Alem et al., 2014) who used the panel dataset for related research attempted to investigate attrition bias using attrition probits (Fitzgerald et al., 1998) and a Becketti, Gould, Lillard, and Welch (BGLW) test (Becketti et al., 1988). Attrition probits represent regression results of binary-choice models for the correlates of attrition in later periods as a function of baseline variables. The BGLW test, on the other hand, investigates the effect of future attrition on the initial period's outcome variable. Based on these tests, the authors conclude that it is less likely that attrition would bias the results for the remaining sample.

3.2. Measures of energy poverty

The energy module of EUSS contains detailed information on household energy purchase and consumption. Some of the fuel types are purchased and consumed in non-standard units. In order to obtain accurate and comparable data, we used carefully constructed conversion factors and converted energy consumed from all energy sources into a common unit of measurement of oil equivalent (kgoe). Besides, energy consumption, the data contains detailed information on income and asset ownership that allowed us to construct the three prominent measures of energy poverty used in the literature.

The first approach employed in the current paper to measuring energy poverty is the *minimum energy consumption threshold approach*. With this method, energy poverty is measured by counting the number of people consuming below the minimum level of energy consumption required to meet basic needs. To determine this level, we follow a procedure proposed by Modi et al. (2005), who construct the energy poverty line based on per capita consumption of energy from modern sources. The modern energy sources used by households in our study are electricity, liquefied petroleum gas (LPG), and kerosene. We classify households based on their per capita modern energy consumption for both lighting and cooking. Following Modi et al. (2005), we use 50 kgoe as the energy poverty line for both cooking and lighting. Although this approach is easy to implement, it is difficult to agree on what a basic "necessity" is, which leads to having different thresholds depending on the country under consideration. Furthermore, this method is very stringent in that a household will be considered energy poor if it relies solely on biomass resources regardless of amount of energy consumed.

The second approach to measuring energy poverty used in the current study is proposed by Barnes et al. (2011). It is an alternative demand-based approach that defines the energy poverty line as the threshold at which energy consumption begins to rise with household income. Hence, it is known as *income-invariant energy demand or the minimum end-use energy (MEE)*. Following this approach, we compute the end-use energy by multiplying the total energy consumed by a conversion factor that is dependent on the type of stove and energy used by households. The Barnes approach identifies energy-poor households in two stages. First, the total end-use energy consumed by households is estimated by including income (wealth) deciles in the regression. Then the income decile at which wealth becomes significant is identified as an energy poverty line.[4] Households that are below the identified income threshold are classified as energy poor. One drawback of Barnes' measure, however, is that it does not encompass the complementary benefit of various energy services.

The third approach to measuring energy poverty that we consider in this paper - the multidimensional energy poverty index (MEPI) - considers energy poverty to be multidimensional. MEPI is a comprehensive measure that takes into account various aspects of energy poverty, specifically based on technological threshold or access to modern energy services. As access to modern energy services is not informative enough about a household's energy poverty status, various aspects beyond ownership of energy appliances should be considered (Nussbaumer et al., 2012).

The multi dimensional poverty measure was first developed and used to study general poverty. In its most recent features proposed by Alkire and Foster (2011), it uses a double cut-off and counting procedure to measure general poverty in a multidimensional aspect. More recently, the approach was adopted in different studies to measure energy

[1] Data from these major urban areas were also collected in 1994 Kohlin et al., 2011, and 1997 (see AAU and UoG (1995) for details on sampling). However, the waves before 2000 did not contain a module on energy use behavior.

[2] Other cities were not covered due to resource constraints.

[3] See Alem and Söderbom (2012) for a detailed description of EUSS - 2008/09.

[4] The energy poverty line is robust to various changes, e.g., the inclusion of household size as one control variable, using real prices instead of nominal prices, including the price of dung cakes and plants.

poverty (See for e.g., Aristondo and Onaindia (2018); Nussbaumer et al. (2012)).[5] In the two cut-off procedures, first the household is identified as deprived or not in each dimension of poverty. Then, either the dimensions in which the household is deprived are counted or a specified weight is attached to the dimension the household is deprived from.

Following Nussbaumer et al. (2012), we construct the index by investigating access to five dimensions. For each dimension, an energy deprivation cut-off was set where corresponding weights are attached to the selected indicator. We attempt to capture energy poverty by considering the type of cooking appliance and the type of fuel used to reflect the fact that cooking is among the very basic needs. Traditional cooking appliances and fuels impose significant cost on households, both in terms of time spent and the negative health effects from indoor air pollution. Hence, the highest weights are attached to exposure to indoor pollution (0.3) followed by the type of modern cooking energy sources (0.2). In our multidimensional index construction, in addition to considering cooking, we look beyond the mere access to light, which is less-relevant in an urban setting and incorporate the burden associated with not having a private electric meter. Not owning a private electric meter can influence the type of appliance that will be used for cooking and other household activities. To this end, we attach a weight of 0.2 for having private electricity meter. Moreover, we capture some of the crucial roles that access to electricity plays in development and quality of life improvement by incorporating information on whether a household has the privilege of enjoying services, such as entertainment, education, and communication. An equal weight of 0.133 is attached to these services: cooling (0.133), electronic media (0.133), and communication (0.133).

In calculating the MEPI, the deprivation matrix is set to be equal to the weight if the household is in the deprivation category (energy-poor) for a specific dimension. If not, it is equal to zero. The MEPI is equal to the sum of weighted deprivation-cut-offs for each household. As in Nussbaumer et al. (2012), the multidimensional poverty line used in our paper is 0.3. Using 0.3 as a cut-off not only offers us a chance to compare our results with previous studies in the literature, but also allows us to classify households as energy poor if they don't have access to critical energy poverty dimensions. For instance, a household is considered to be energy poor if it is exposed to indoor air pollution, which has a weight of 0.3 or if it does not have access to any of the three services discussed above (the total weight for the three services being 0.399).

In a nutshell, we examine energy poverty in urban Ethiopia using three measures that focus on various aspects of energy consumption. Modi's measure is based on the absolute consumption from modern energy sources, while Barnes' measure relies on end-use energy (heat and luminous) obtained from different energy sources. Both of these measures depend on the level of energy consumption, while the third measure, MEPI, uses access to modern energy sources and appliances. Hence, using three measures that focus on different aspects of energy poverty enables us to capture the energy poverty status from different perspectives.

3.3. Descriptive statistics

Fig. 1 presents the incidence of energy poverty during the decade under analysis (2000–2009) using the three measures. The dynamic probit estimator, which we present in detail in Section 5, requires at least three rounds of data for each household. About 434 households were observed in all three rounds, implying a total of 1302 observations. Fig. 1 shows that the incidence of energy poverty measured by all three methods declined from the base year, 2000, to 2009.

Table 1 presents descriptive statistics for the main variables used in the regression. We use real fuel prices, which are adjusted for temporal and spatial variation using price indices carefully constructed from the survey. Comparison with in 2000, the real fuel prices were higher in 2004 and lower in 2009, on average. However, the nominal prices show a significant increase from 2004 to 2009.[6] In 2009, the descriptive statistics also show that the average age of the household heads is 55, and 30% of them did not have formal education. Moreover, the table shows that 72% of the sample come from Addis Ababa, which is the country's capital and also the city that has the largest share of the urban population in the country.

Table 2 reports the number of times that a household has been classified as energy poor. Based on Modi's measure, 60% of the sample have been energy poor in all three rounds while this figure drops to 26% and 22% when using MEPI and Barnes' measure of energy poverty, respectively. On the other hand, the percentage of households that are not classified as energy poor in any of the three rounds varies from 5% using Modi's measure to 40% using Barnes' measure.

4. Conceptual framework

In this section, we provide a theoretical framework that can serve as a basis for the main empirical analysis conducted in this paper. Our outcome variable of interest – energy poverty – has been constructed from consumption levels of the various fuel sources, which originate from the household's fuel choice decision. A household's demand for fuel is a related decision to the demand for durable cooking appliances (Dubin and McFadden, 1984). Therefore, we illustrate that the levels of consumption of energy from different fuel sources can be derived using a simple utility maximization framework once the households adopt an energy appliance. Therefore, we start with the demand functions for appliances, which is shown can be obtained from maximization of a utility function (Dubin and McFadden, 1984).

For simplicity, we focus on a single fuel type, electricity, but the framework can be generalized to all fuel types. In our context, households will have a positive demand for electricity for cooking purposes only if they possesses an electric appliance that can be used for cooking, i.e., either a so-called *electric mitad* or an *electric stove*.[7] Since the utility obtained from an electric appliance originates from the flow services it provides, the utility can only be observed indirectly.

Dubin and McFadden (1984) framework considers a consumer/household that faces a choice of m mutually exclusive appliances, which can be indexed as $i = 1, \ldots .m$, and appliance i has a cost (rental price) of r_i. The conditional indirect utility for appliance i is given as follows:

$$u = V(i, y - r_i, p_1, p_2, s_i, \epsilon_i, \eta) \tag{1}$$

where p_1 is the price of the fuel for appliance i, which is electricity in our case, p_2 represents prices of alternative energy sources for appliance i, s_i and ϵ_i denote the observed and unobserved attributes of the appliance, respectively, and η is unobserved characteristics of the consumer.

The household will choose appliance i over alternative j if

$$V(i, y - r_i, p_i, \mathbf{p}_k, s_i, \epsilon_i, \eta) > V\left(j, y - r_j, p_j, \mathbf{p}_k, s_j, \epsilon_j, \eta\right) \tag{2}$$

Given the indirect utility function specified in Eq. (1), the consumption level for the fuel required for appliance i (electricity) can be obtained using Roy's identity.

$$x_i = -\frac{\partial V(i, y - r_i, p_i, \mathbf{p}_2, s_i, \epsilon_i, \eta)/\partial p_i}{\partial V(i, y - r_i, p_i, \mathbf{p}_2, s_i, \epsilon_i, \eta)/\partial y} \tag{3}$$

[5] See Alkire and Foster (2011) for a brief recap of the vast literature on the evolution of multidimensional poverty measures.

[6] At the time of collection of the last round of EUSS, i.e., spring 2009, 1 USD = 18.06 Ethiopian Birr (ETB).

[7] An electric mitad is used for baking the staple food injera, while electric stoves are used for preparing stew.

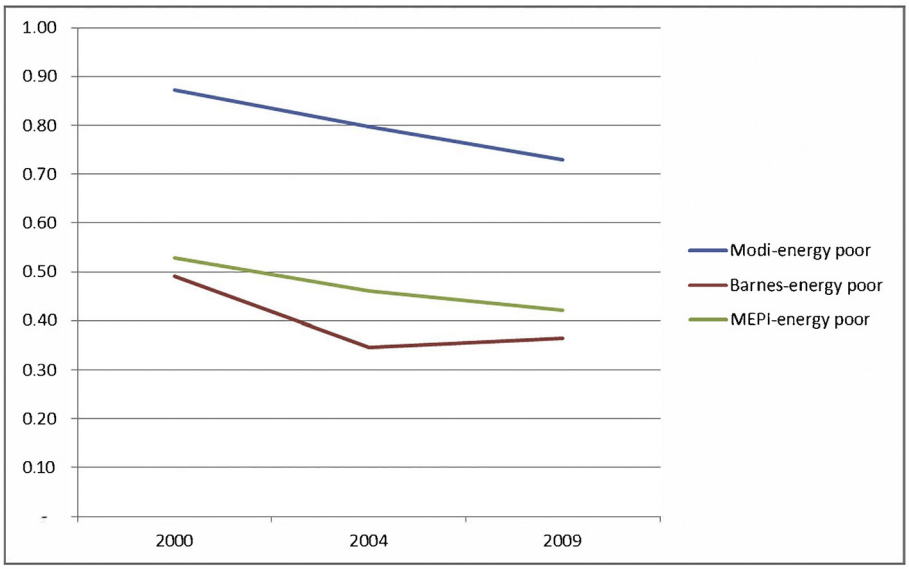

Fig. 1. Trends in energy poverty, 2000–2009.

Table 1
Descriptive statistics of variables, 2000–2009.

	[1]		[2]		[3]	
	[2000]		[2004]		[2009]	
	Mean	SD	Mean	SD	Mean	SD
Real prices of major fuel types						
Firewood (birr/kg)	0.854	0.607	1.111	0.755	0.406	0.222
Charcoal (birr/kg)	1.127	0.488	1.44	0.593	0.691	0.332
Kerosene (birr/l)	2.159	1.002	2.451	0.774	2.444	0.887
Electricity (irr/kwh)	0.38	0.055	0.381	0.055	0.152	0.028
Head characteristics						
Age	50.673	13.278	51.82	13.531	55.447	14.133
Female	0.433	0.496	0.477	0.5	0.495	0.501
No schooling	0.15	0.357	0.357	0.48	0.302	0.46
Primary school completed	0.3	0.459	0.242	0.429	0.297	0.458
Secondary or junior secondary school completed	0.505	0.501	0.32	0.467	0.286	0.452
Tertiary school completed	0.046	0.21	0.081	0.273	0.115	0.32
Out of the labor force	0.3	0.459	0.41	0.492	0.403	0.491
Employer or own-account worker	0.249	0.433	0.24	0.427	0.226	0.419
Civil or public servant	0.184	0.388	0.171	0.377	0.141	0.348
Private sector employee	0.09	0.286	0.078	0.269	0.12	0.325
Casual worker	0.099	0.299	0.065	0.246	0.071	0.258
Household characteristics						
Proportion of females	0.325	0.215	0.335	0.213	0.365	0.233
Number of children members	1.885	1.595	1.498	1.348	1.005	1.123
Number of elderly members	0.053	0.287	0.028	0.178	0.06	0.256
Log of real consumption per adult equivalent	4.631	0.820	4.72	0.746	4.777	0.674
Location						
Addis	0.724	0.448	0.724	0.448	0.724	0.448
Awassa	0.083	0.276	0.083	0.276	0.083	0.276
Dessie	0.099	0.299	0.099	0.299	0.099	0.299
Mekelle	0.094	0.293	0.094	0.293	0.094	0.293
Observations	434		434		434	

Notes: Columns [1], [2] & [3] of this table present summary statistics (means and standard deviations) for key variables from EUSS conducted in 2000, 2004 and 2009. Addis is the capital, where the vast majority of the Ethiopian urban population resides. Awassa and Mekelle are the capitals of the Southern Nations, Nationalities and Peoples' regional state and the Tigray regional state respectively. Dessie is a small city in the Amhara regional state.

Table 2
Persistence of energy poverty.

		[1] Never poor	[2] Poor once	[3] Poor twice	[4] Always poor	[5] Total
Modi poor	Frequency	60	132	336	774	1302
	Percentage	4.61	10.14	25.81	59.45	100.00
Barnes poor	Frequency	522	282	213	285	1302
	Percentage	40.09	21.66	16.36	21.89	100.00
MEPI poor	Frequency	459	198	297	348	1302
	Percentage	35.25	15.21	22.81	26.73	100.00

Notes: Columns [1]–[5] present summary statistics on the number of households that were classified as energy poor across the three rounds based on energy poverty data constructed from EUSS 2000–2009.

Even though one could derive the level of consumption of a particular fuel using adoption models for appliances, such specifications would fail to capture the consumption pattern after the energy appliance has been adopted. In addition, they would not show whether the demand for a specific fuel type is influenced by the price of appliances needed for alternative energy sources.

However, we assume that once a household has adopted a specific appliance, it will decide on the type and amount of fuel it will use for all of its appliances. Consequently, unlike the utility obtained from appliances, the utility from using different fuel sources can be modeled directly.

We consider a household that faces a choice of m mutually exclusive fuel types, which can be indexed as $i = 1, \ldots \ldots m$, and p_i represents the market price of the ith fuel type x. Thus, the household's utility maximization problem can be given as follows:

$$\text{Max } U = f(p_1, p_2 \ldots, p_m, h_i, \eta)$$
$$\text{Subj.} M = p_2 x_2 + \ldots p_m x_m$$

where M is household income, h_i denotes household and household head characteristics, and η represents the economic conditions of the

specific geographical area that may influence fuel choices. Taking the energy appliance that households adopt as given and the utility maximization specified above, the household decides on the consumption level of each fuel type. We use these consumption levels to classify households into energy poor and energy non-poor in the first analysis and to compute the fraction of clean energy used in the second analysis.

5. Empirical strategy

5.1. Energy poverty persistence - a dynamic Probit estimator

We draw on the standard poverty transition and persistence literature (Biewen, 2009; Duncan et al., 1993; Oxley et al., 2000) and model energy poverty using a dynamic probit specification. Poverty status is modeled in a dynamic framework because of state dependence, i.e., an individual or household that is poor in any given period is more likely to be poor in the next period. In order to analyze the underlying causes of energy poverty persistence, we therefore specify a general dynamic probit model as follows:

$$g_{it}^{*} = \gamma g_{it-1} + x_{it}'\beta + c_i + u_{it} \tag{4}$$

$(i = 1,\ldots,N; t = 2,\ldots,T)$, where g_{it}^{*} is a latent dependent variable; g_{it} is the observed binary outcome variable defined as

$$g_{it} = 1\left[g_{it}^{*} \geq 0\right], \qquad t = 2, \ldots, T, \tag{5}$$

g_{it-1} represents energy poverty status in the previous period, x_{it} represents a vector of explanatory variables, c_i is a term capturing unobserved household heterogeneity, and u_{it} is a normally distributed error term with mean zero and variance normalized to one. The subscripts i and t refer to cross-sectional units (households in our case) and time periods (rounds), respectively. The number of cross-sectional units, N is assumed to be large, but the numbers of time the cross-sectional units are observed, T is small, which implies that asymptotics depend on N alone. Modeling this relationship in the standard random effects probit framework implicitly assumes that, conditional x_{it}, c_i is normally distributed with mean zero and variance σ_c^2, and independent of u_{it} and x_{it}.

Thus, under the above assumptions, the transition probability for household i at time t, given c_i, is therefore given by

$$Pr(g_{it}|x_{it}, g_{it-1}, c_i) = \Phi\left\{\left(\gamma g_{it-1} + x_{it}'\beta + c_i\right)(2g_{it} - 1)\right\}, \tag{6}$$

where Φ is the cumulative distribution function of the standard normal distribution.

In order to estimate the dynamic probit model specified above, one needs to make assumptions about initial energy poverty status g_{i1}, i.e., the energy poverty status of a household at the start of the panel, and its correlation with the unobserved heterogeneity term c_i. If one assumes that the initial energy poverty status is exogenous, the standard random effects probit estimator can be used to estimate the model. However, such an assumption is unrealistic because the poverty status of households, g_{it}, s not observed from its start, and hence simply assuming it is exogenous and estimating it using the random effects probit estimator would result in biased parameter estimates. This implies that the lagged poverty status, g_{it-1}, will be correlated with c_i. The resulting estimation problem is known in the applied economics literature as the *initial conditions problem*. Estimating the model consistently therefore requires integrating out the unobserved heterogeneity term c_i.

The first estimator that addresses the initial conditions problem encountered in estimating the dynamic probit model specified above was suggested by Heckman (1981),who proposed a two-step maximum likelihood estimator. Heckman's method begins by specifying a linearized reduced form equation for the initial value of the latent variable, which includes exogenous instruments and initial values of the right-hand side variables. The reduced equation can then be incorporated in the likelihood function of each observational unit, and the Guauss-Hermite quadrature approach (Butler and Moffitt, 1982) can be applied to evaluate the integral in the likelihood function. This estimator yields consistent parameter estimates provided the latent equation time-varying error terms are serially uncorrelated (Stewart, 2006). However, Heckman's estimator has not been used much in applied research due to its absence in standard software and huge computational cost.

Later on, Wooldridge (2005) proposed a conditional maximum likelihood estimator, which begins by specifying the joint density for the observed sequence of the outcome variable of interest $(g_2, g_3, \ldots, g_T | p_1)$ as $(g_T, g_{T-1}, \ldots, g_2 | g_1, x, c)$. Next it specifies an approximation of the density of c_i, conditional on the initial value of the outcome variable g_1, which makes it convenient to integrate it out from the main equation. Wooldridge specifically proposes the following specification for the unobserved heterogeneity term, c_i:

$$c_i \mid g_{i1}, z_i \sim N\left(\zeta_0 + \zeta_1 g_{i1} + z_i'\zeta, \sigma_a^2\right), \tag{7}$$

where

$$c_i = \zeta_0 + \zeta_1 g_{i1} + z_i'\zeta + a_i \tag{8}$$

The specification in Eq. (8) takes care of the correlation between g_{i1} and c_i and gives rise to a new unobserved heterogeneity term a_i that is uncorrelated with the initial period outcome variable g_{i1}. Substituting Eq. (8) into Eq. (6) yields

$$\begin{aligned} &Pr(g_{it} = 1|a_i, g_{i1}) \\ &\quad = \Phi\left[x_{it}'\beta + \gamma g_{it-1} + \zeta_0 + \zeta_1 g_{i1} + z_i'\zeta + a_i\right] \qquad t = 2, \ldots, T. \end{aligned} \tag{9}$$

The likelihood function for household i is therefore given by

$$L_i = \int \left\{ \prod_{t=2}^{T} \Phi\left[\left(x_{it}'\beta + \gamma g_{it-1} + \zeta_0 + \zeta_1 g_{i1} + z_i'\zeta + a\right)(2g_{it} - 1)\right] \right\} f^{*}(a) da, \tag{10}$$

where $f^{*}(a)$ is the normal probability density function of the new unobservable term a_i introduced in Eq. (7). Like the two-step estimator proposed by Heckman, this estimator, known as the Wooldridge Conditional Maximum Likelihood (WCML) estimator, can be generalized allow for the error term in the initial period equation to be freely correlated with errors in subsequent time periods. By controlling for period-specific x variables, this estimator, just like Mundlak (1978), also allows for correlation between the explanatory variables, x_{it} and the unobserved heterogeneity term, c_i, an approach, which makes it conveniently implementable in a random effects probit framework. Estimating the WCML estimator in standard software packages is straightforward.[8] We use the estimator to analyze the persistence of energy poverty in urban Ethiopia.

5.2. Fuel substitution – a fractional response estimator

In order to shed light on the channels behind the change in the status of energy poverty following changes in energy prices, we estimate a fractional response model (FRM) (Papke and Wooldridge, 2008). The fractional response model (FRM) enables us to answer the question of how the proportion of clean energy used by households changes in response to price. Our outcome variable of interest is the proportion of energy in kilojoules obtained from clean fuels, namely kerosene, liquefied petroleum gas (LPG), and electricity, run as a function of prices and other covariates. When the dependent variable is bounded between zero and one, as in our case, using linear specifications for the conditional mean might miss important nonlinearities (Papke and Wooldridge, 1996). Even applying a log-odds transformation would fail when one observes corner responses (0 and 1). In addition, not even when the dependent variable is strictly inside the interval is it

[8] We implement this estimator using the *xtprobit* command in Stata.

possible to recover the expected value of the fractional response model unless one makes strong independence assumptions. Papke and Wooldridge (1996) propose an extension of the generalized linear model (GLM) that keeps the predicted value in the unit interval and overcomes the drawbacks associated with using the log-odds transformation. These authors also introduce a Ramsey RESET test for correct specification of the mean function. This is crucial because their model is robust only if the mean function is correctly specified. Moreover, using the fractional logit model in panel data will not provide correct parameter estimates as the standard errors are not robust to arbitrary serial correlation and the conditional variance is misspecified (Papke and Wooldridge, 2008).

Papke and Wooldridge (2008) introduced a quasi-maximum likelihood estimator (QMLE) that extends their fractional response model for cross-sectional data to panel data. In the panel version of FRM, for each random draw of i, we have T observations $t = 1, 2 \ldots T$, and the response variable y_{it}, $0 \le y_{it} \le 1$. We first make a functional form assumption for a set of explanatory variables, x_{it}, a $1 \times K$ vector where

$$E(y_{it}|x_{it,}c_i) = \Phi(x_{it}\beta + c_i), t = 1, \ldots . T \tag{11}$$

where Φ is standard normal cumulative distribution function. This assumption of a probit functional form renders simple estimators in the presence of unobserved individual heterogeneity and endogenous explanatory variables. Even in the case where y_{it} is a binary variable, the conditional logit model would not be suitable to estimate β because there could be serial correlation in the response variable. By employing probit response functions, Papke and Wooldridge (2008)'s approach has the added advantage of readily estimating average partial effects.

As Φ is strictly monotonic, ignoring the subscript i, the partial effects are given as follows. In the case where$\times_{tj}$ continuous,

$$\frac{E(y_t|\mathbf{x}_{t,}c)}{\times_{tj}} = \beta_j \phi(\mathbf{x}_t\beta + c) \tag{12}$$

And a discrete change in the explanatory variable is given as:

$$\Phi\left(\mathbf{x}_t^{(1)}\beta + c\right) - \Phi\left(\mathbf{x}_t^{(0)}\beta + c\right) \tag{13}$$

where $\mathbf{x}_t^{(0)}$ and $\mathbf{x}_t^{(1)}$ are two different values.

However, as shown in Eqs. (12) and (13), the average partial effects (APEs) are not identified as they depend on the unobserved heterogeneity (c). In order to identify both β and the APEs, two additional assumptions are required.

Assumption 1. Conditional on c_i, $[\mathbf{x}_{it} : t = 1,\ldots.T]$ is strictly exogenous

$$E(y_{it}|\mathbf{x}_{i,}c_i) = E(y_{it}|\mathbf{x}_{it,}c_i), t = 1, \ldots T. \tag{14}$$

Assumption 2. The conditional normality assumption proposed by Chamberlain (1980)

$$c_i \mid \mathbf{x}_{i1,}\mathbf{x}_{i2,\ldots.}\mathbf{x}_{iT} \sim N(\psi + \overline{\mathbf{x}}_i\xi, \sigma_a^2) \tag{15}$$

where $\overline{\mathbf{x}}_i = T^{-1}\sum_{t=1}^{T} x_{it}$ is a $1 \times K$ vector of time averages. Having made the above assumptions, the partial effects are identified under no assumption of serial dependence in the response function while allowing the endogenous explanatory variables to be correlated with unobserved shocks in other time periods. In addition, Papke and Wooldridge (2008)'s approach allows for correlation between the time-invariant unobserved effects and the explanatory variables, which is the main concern while using a probit response function with panel data. Instead of treating the unobserved effects as parameters to be estimated, the authors combine Mudlak-Chamberlain's approach of modeling unobserved heterogeneity with the control function method, which produces consistent parameter estimates.

Table 3
Correlates of energy poverty – marginal effects from random effects probit regressions.

Variables	[1]	[2]	[3]
	Modi_poor	Barne's_poor	MEPI_poor
Lagged poverty	0.088***	0.280***	0.249***
	(0.029)	(0.023)	(0.024)
Firewood log price	0.048**	0.042*	0.023
	(0.024)	(0.024)	(0.025)
Charcoal log price	−0.013	0.016	−0.034
	(0.030)	(0.033)	(0.034)
Kerosene log price	0.121***	0.180***	0.189***
	(0.044)	(0.046)	(0.047)
Electricity log price	−0.067	0.094	−0.010
	(0.072)	(0.080)	(0.081)
Head, age	−0.001	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)
Head, female	−0.049	−0.021	−0.053
	(0.031)	(0.033)	(0.034)
Head, primary school completed	−0.083**	−0.051	−0.099***
	(0.037)	(0.033)	(0.034)
Head, secondary or junior secondary school completed	−0.163***	−0.165***	−0.204***
	(0.043)	(0.040)	(0.041)
Head, tertiary school completed	−0.271***	−0.205***	−0.251***
	(0.068)	(0.053)	(0.054)
Head, employer and own account-worker	0.037	0.019	−0.025
	(0.032)	(0.035)	(0.036)
Head, civil or public servant	0.046	0.022	−0.008
	(0.035)	(0.048)	(0.048)
Head, private sector employee	0.041	0.074	−0.008
	(0.042)	(0.053)	(0.053)
Head, casual worker	0.143***	0.097	−0.021
	(0.044)	(0.059)	(0.058)
Proportion of females	−0.002	−0.017	−0.052
	(0.061)	(0.067)	(0.070)
Number of children members	0.045***	−0.032**	−0.025*
	(0.013)	(0.013)	(0.013)
Number of elderly members	0.023	0.085	−0.009
	(0.051)	(0.059)	(0.068)
Log of real cons. Per adult equivalents	−0.201***	−0.129***	−0.099***
	(0.019)	(0.022)	(0.022)
Round Fixed Effects	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
Observations	868	868	868

Notes: Columns [1], [2] & [3] of this table presents marginal effects from random effects probit estimators for the correlates of energy poverty measured by the three indicators (Modi's, Barnes' and Multidimensional Poverty Index (MPI)) respectively with real energy prices. Standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

6. Results and discussions

Based on the three types of energy poverty measures, Table 3 presents marginal effects for a model of the probability of being energy poor as given by Eq. (1). All marginal effects are computed from a random effects probit model, which controls for unobserved household heterogeneity but treats initial conditions as exogenous. In all regressions, we control for round and city fixed effects. The results suggest that there is strong state dependence on energy poverty. Columns [2] and [3] show that a household that is energy poor in any given round is about 8.8%, 28%, and 24.9% likely to be energy poor in the subsequent round according to the Modi, Barnes, and MEPI measures, respectively. The results also suggest that an increase in the price of kerosene – the most commonly used fuel type by urban Ethiopian households – leads to a rise in energy poverty in all regressions. Given that the random effects estimator does not correct for the initial conditions problem and very likely overestimates the persistence of energy poverty, we do not discuss this findings further.

Table 4 presents marginal effects from the WCML estimator for the three energy poverty measures. The WCML estimator addresses the

Table 4
Correlates of energy poverty - marginal effects from WCML estimator.

Variables	[1]	[2]	[3]
	Modi_poor	Barne's_poor	MEPI_poor
Lagged Poverty	0.040	0.164**	0.098***
	(0.035)	(0.080)	(0.037)
Initial poverty status (2000)	0.092**	0.148**	0.211***
	(0.037)	(0.070)	(0.037)
Firewood log price	0.050**	0.042*	0.030
	(0.024)	(0.025)	(0.025)
Charcoal log price	−0.012	0.016	−0.036
	(0.030)	(0.034)	(0.033)
Kerosene log price	0.117***	0.179***	0.176***
	(0.044)	(0.047)	(0.046)
Electricity log price	−0.056	0.112	−0.025
	(0.072)	(0.080)	(0.080)
Head, age	−0.001	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)
Head, female	−0.048	−0.023	−0.061*
	(0.031)	(0.034)	(0.033)
Head, primary school completed	−0.082**	−0.038	−0.081**
	(0.037)	(0.034)	(0.034)
Head, secondary or junior sec. School completed	−0.164***	−0.159***	−0.183***
	(0.043)	(0.041)	(0.042)
Head, tertiary school completed	−0.270***	−0.196***	−0.211***
	(0.068)	(0.055)	(0.058)
Head, employer and own account-worker	0.037	0.016	−0.024
	(0.032)	(0.036)	(0.035)
Head, civil or public servant	0.048	0.025	−0.030
	(0.035)	(0.048)	(0.047)
Head, private sector employee	0.039	0.079	−0.023
	(0.042)	(0.053)	(0.051)
Head, casual worker	0.143***	0.092	−0.009
	(0.044)	(0.059)	(0.057)
Proportion of females	−0.007	−0.020	−0.038
	(0.061)	(0.068)	(0.068)
Number of children members	0.046***	−0.035***	−0.023*
	(0.013)	(0.013)	(0.013)
Number of elderly members	0.026	0.087	−0.015
	(0.051)	(0.060)	(0.067)
Log of real cons. Per adult equivalents	−0.197***	−0.123***	−0.091***
	(0.019)	(0.022)	(0.021)
Round Fixed Effects	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
Observations	868	868	868

Notes: Columns [1], [2] & [3] of this table presents marginal effects from the Wooldridge Conditional Maximum Likelihood (WCML) estimator on the correlates of energy poverty measured by the three indicators (Modi's, Barnes' and Multidimensional Energy Poverty Index – MEPI), respectively, with real energy prices. Standard errors in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels, respectively.

initial conditions problem robustly using the time-varying *x* variables in the *z* vector. The coefficient of the energy poverty persistence variable (the lagged dependent variable) declines from 0.08 to 0.04 in the case of the Modi measure, from 0.28 to 0.16 in the case of the Barnes measure, and from 0.25 to 0.09 for the MEPI measure. This corresponds to a decrease in the marginal effects of about 50%, 42%, and 64% for the three energy poverty regressions, respectively. However, the lagged poverty is not statistically significant in the Modi measure. Consequently, we focus on the dynamic probit regression results from using Barnes' and the MEPI measures (columns [2] & [3]). The initial energy poverty status is not only statistically significant but also large in magnitude, in fact even larger than the coefficient of the lagged dependent variable in the case of the MEPI measure. This provides strong evidence in favor of controlling for endogeneity of the initial conditions problem.

We observe a large state dependence in energy poverty in urban Ethiopia. Columns [2] and [3] of Table 4 indicate that a household that is energy poor in a given period has a 16% and 10% likelihood of remaining energy poor in the subsequent period. This is consistent with existing literature on poverty persistence in both developed and

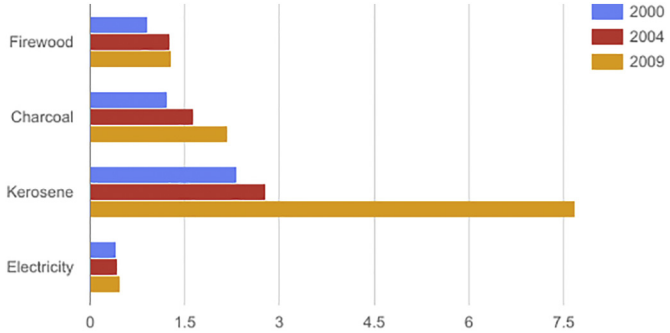

Fig. 2. Trends in mean nominal energy prices.

developing countries. The high purchase price for modern cooking appliances and lack of access to micro-credits (Alem and Ruhinduka, 2020; Edwards and Langpap, 2005) for acquiring them are likely the two key obstacles to adoption of modern energy appliances that use clean energy sources. Consequently, a large majority of households continue to use cheap and inefficient cookstoves that use solid (biomass) fuel. Such energy use behavior, directly contributes to the persistence of energy poverty.

The results also reveal the strong impact of energy prices on energy poverty.[9],[10] Energy prices are exogenous to households as they are determined by market forces, and by international prices in the case of kerosene – the most important cooking energy source for households in urban Ethiopia.[11] All the dynamic probit regression results reported in Table 4 show that a rise in the price of kerosene leads to an increase in energy poverty. Although the three measures of energy poverty differ in their construction, the coefficient of kerosene price is statistically significant at 1% for all of them (and the coefficients in the Barnes and MEPI dynamic probit regressions are almost identical). More specifically, a 10% increase in the price of kerosene leads to an increase of about 1.8% in energy poverty measured by the Barnes and MEPI measures. These results have important implications for policies aimed to reduce energy poverty and promote energy transition. EUSS shows that from 2004 to 2009, the average price of kerosene increased by 177%. Consequently, in the 2009 survey, around 74% of urban Ethiopian households reported it to be the *se*cond most important shock (after food price inflation) to adversely affect their welfare.

We further investigate the consequences of the large increase in the price of kerosene in urban Ethiopia. Fig. 2 shows the average nominal price of all four fuel types in urban Ethiopia for the three rounds of panel data collected. The average price of firewood, charcoal, and electricity did not change significantly during the period of analysis. However, the average price of kerosene increased from around 2.7 birr to around 7.6 birr in 2009. This corresponds to an increase of about 177%.[12] In Fig. 3, we investigate the implications of rising kerosene prices on energy use by households in Ethiopia. As can be seen, there was a rapid increase in the amount of charcoal used during the period of inflation. The average quantity of charcoal consumed by households grew from around 14 kg/month in 2004 to around 24 kg/month in 2009, corresponding to a 71% increase. The rapid increase in charcoal consumption during the period suggests that households in urban

[9] There is large temporal and spatial variation in energy prices across Ethiopia. Appendix Figure A.1 presents the price variation in Addis Ababa.

[10] Results reported in Appendix B show that the findings do not change when we use nominal prices instead.

[11] Ethiopia almost exclusively buys petroleum products from the international market. In 2008/09 alone, Ethiopia imported 1971.9 million metric ton of petroleum products (NBE, 2009). The value of petroleum import is comparable to 60–160% of the total export earning between 2000/01 and 2009/10 (Andualem et al., 2014).

[12] A similar pattern is observed when we use median prices in each year. The figures are presented in Appendix A.2 and A.3

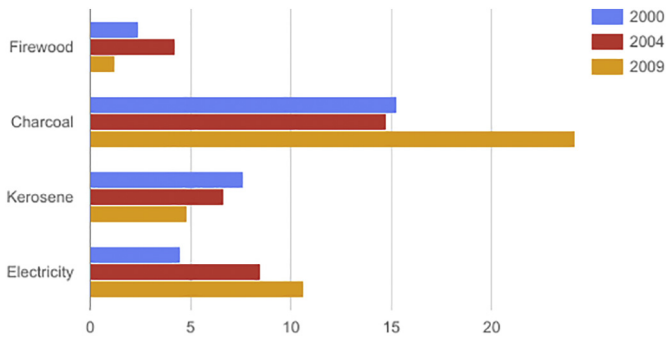

Fig. 3. Trends in mean energy consumption in standard units.

Ethiopia responded to the unprecedented increase in the price of the key fuel, kerosene, by consuming more charcoal to meet their increased energy needs. The use of charcoal to meet the cooking energy needs is one of the prime causes of deforestation and forest degradation in Africa (Allen and Barnes, 1985; Geist and Lambin, 2002; Hofstad et al., 2009; Kohlin et al., 2011).

A closer look at the price differences between the different fuel sources and their consumption offers striking insights. In 2009, 1 kgoe of energy from electricity cost around 6 birr, while the same amount of energy from kerosene cost 9 birr. In addition, the real price of electricity halved from 2004 to 2009, while it remained fairly constant for kerosene. Despite these glaring differences, the observed increase in consumption of electricity in 2009 was not significant. One factor explaining this situation is the significant difference in purchase price between a kerosene stove and an electric stove. Electric cookstoves cost much more than kerosene stoves, which likely explains the lack of a significant shift to electricity.[13] The phenomenon of a large increase in the price of kerosene, but almost no increase in the price of electricity has significant income distribution implications. Only the rich, who constitute less than 5% the urban population, are able to acquire expensive cooking appliances and benefit from lower electricity prices. In contrast, the rapid increase in the price of kerosene has forced the population in the lower part of the income distribution to shift to harmful biomass fuels, such as charcoal.

Table 4 also shows that education is negatively associated with the probability of being energy poor. Compared with household heads with no formal education, those who have primary, *sec*ondary, or tertiary education have a lower likelihood of being energy poor and the difference is statistically significant. Households with a higher economic status as measured by the log of real consumption expenditure per adult equivalents are also less likely to be energy poor. However, it is important to note that all these variables – unlike the energy prices – are likely to be endogenous. Consequently, these associations (correlations) should not be considered to be causal.

Table 5, which reports regression results from a fractional response estimator, offers additional insights on how the increase in key energy prices, most importantly in the price of kerosene, has influenced the proportion of clean energy used by households. The results suggest that, among all studied fuel sources, the price of kerosene has the largest impact on the proportion of energy obtained from clean energy sources. More specifically, a 10% increase in the price of kerosene led to a 1.4% decline in the proportion of clean energy used by households. This is intuitive and consistent with the descriptive results presented in the preceding sections, because the increase in the price of kerosene – a relatively clean energy source, at least compared with biomass fuel sources – prompts households to switch to biomass fuel sources, all other factors constant. This reduces the proportion of energy obtained from clean sources and increases the proportion from dirty sources. The results also show that the increase in the prices of firewood and charcoal leads to a statistically significant increase in the proportion of energy obtained from clean sources, because households will likely switch to cleaner energy sources such as kerosene.

Table 5
Energy prices and household energy use: results from a fractional response estimator.

Variables	[1]	[2]
	OLS	GLM Marginal effects
Firewood log price	0.059***	0.050***
	(0.012)	(0.012)
Charcoal log price	0.103***	0.107***
	(0.019)	(0.018)
Kerosene log price	−0.158***	−0.141***
	(0.028)	(0.027)
Electricity log price	−0.072	−0.089**
	(0.047)	(0.044)
Head, age	−0.001	−0.001
	(0.001)	(0.001)
Head, female	−0.026	−0.034
	(0.020)	(0.021)
Head, primary school completed	0.038*	0.028
	(0.023)	(0.024)
Head, secondary or junior sec. School completed	0.062***	0.044*
	(0.024)	(0.024)
Head, tertiary school completed	0.142***	0.112***
	(0.035)	(0.036)
Head, employer and own account-worker	−0.041*	−0.047**
	(0.022)	(0.022)
Head, civil or public servant	0.015	0.016
	(0.027)	(0.030)
Head, private sector employee	−0.037	−0.041
	(0.030)	(0.031)
Head, casual worker	−0.073**	−0.070*
	(0.034)	(0.036)
Proportion of females	0.109**	0.088*
	(0.045)	(0.046)
Number of children members	−0.004	−0.005
	(0.007)	(0.008)
Number of elderly members	0.013	0.005
	(0.035)	(0.031)
Round Fixed Effects	Yes	Yes
City Fixed Effects	Yes	Yes
Observations	1302	1302

Notes: Columns [1] & [2] of this table present regression results from a fractional response estimator on the correlates of the proportion of energy in kilogram oil equivalent units obtained from clean energy sources, with real energy prices. Robust standard errors in parentheses. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

Consistent with the findings for the WCML estimator reported in Table 4, the fractional response estimator results reported in Table 5 show that higher education level of the household head, higher economic status as measured by the log of real consumption per adult equivalent and having a larger proportion of females in the household are all associated with a larger proportion of clean energy use. In contrast, being headed by a self-employed worker or a casual worker are both negatively associated with the proportion of clean energy use. These results are intuitive because the variable captures better awareness of the different fuel types available and stronger financial capacity to acquire and use clean energy sources and appliances. However, the results should be interpreted with caution as these variables are likely to be endogenous.

7. Conclusions

This paper investigates the persistence of energy poverty and the impact of energy price inflation on energy poverty in urban Ethiopia. Taking advantage of detailed panel data that spans a decade, namely

[13] The average market price of a standard electric mitad (stove) used to cook the staple food Injera cost about USD 97 in 2009. The equivalent biomass fuel mitad cost only 7.8% of the cost of the electric mitad, i.e., only about USD 8.

the Ethiopian Urban Socioeconomic Survey (EUSS), we convert all energy consumed by households to comparable kilogram oil equivalents (kgoe) and compute energy poverty based on three popular measures: Modi's, Barnes', and Multidimensional Energy Poverty Index (MEPI). We then estimate a dynamic probit model, the Wooldridge Conditional Maximum Likelihood (WCML) estimator, for the probability of being energy poor, which is defined based on three measures. WCML addresses the initial conditions problem encountered in non-linear dynamic models in a robust manner and identifies the coefficient of energy poverty persistence. During the period under analysis, energy prices, in particular the price of kerosene, soared. The contributions of the paper therefore lie in investigating the impact of a rise in the price of energy on household energy use behavior and energy poverty, and in exploring the correlates of energy poverty over time.

We find strong state dependence on energy poverty in urban Ethiopia. A household that is energy poor in any given period is 10–16% more likely to be energy poor in the subsequent period. This provides evidence of the presence of an energy poverty trap, an equilibrium level of energy poverty that is difficult to exit from without external interventions. Regression results from Wooldridge's conditional maximum likelihood estimator show that increase in the price of kerosene increases energy poverty significantly. Drawing on a fractional response estimator, we augment the analysis and show that the rapid increase in the price of kerosene, which Ethiopia experienced 2004–2009, resulted in a significant decline in the ratio of clean energy used by households measured in kilogram oil equivalents. This is mainly attributed to the large increase in the quantity of charcoal consumed by households in urban Ethiopia in response to the unprecedented sharp increase in the price of kerosene.

Our findings have important policy implications. First, the fact that there is a great deal of energy poverty persistence implies that households likely lack the capacity to acquire modern and relatively costly cooking appliance and switch to clean energy sources. During the period under analysis, the price of electricity in real terms declined by half, but households did not switch to using electricity for cooking, possibly because of the high purchase price of electric cookstoves. An electric stove used for baking the staple food injera costs almost 10 times as much as an improved biomass stove in the capital, where a large majority of the households reside. This clearly points to the need for micro-finance opportunities to enable poor households to acquire costly cookstoves. This is indeed what previous studies (Edwards and Langpap, 2005; Alem and Ruhinduka, 2020) conclude as well. Second, the price of kerosene soared at an unprecedented level from 2004 to 2009, causing households to increase their consumption of charcoal. The use of charcoal has large adverse effects on the environment, the climate, and the health of household members. Consequently, careful policies addressing the increased use of charcoal should be implemented. Third, the rapid increase in the price of kerosene, which is mostly consumed by the poor, coupled with cheap electricity has noticeable distributional implications. More specifically, the rich, who already have the capacity to use expensive cooking appliances, benefit significantly, while the poor experience significant welfare loss. Policy makers should therefore consider alternative approaches to protect the welfare of the poor during times of energy price inflation.

CRediT authorship contribution statement

Yonas Alem: Conceptualization; Formal analysis; Funding Acquisition; Data curation; Writing - original draft; Writing review & editing. **Eyoual Demeke:** Conceptualization; Formal analysis; Writing - original draft.

Declaration of Competing Interest

None.

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