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The Dynamics of Electric Cookstove Adoption: Panel Data Evidence from Ethiopia*

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Abstract

Previous studies on improved cookstove adoption in developing countries use cross-sectional data, which makes it difficult to control for unobserved heterogeneity and investigate what happens to adoption over time. We use robust non-linear panel data and hazard models on three rounds of panel data from urban Ethiopia to investigate the determinants and dynamics of electric cookstove adoption. We find the price of electricity and firewood, and access to credit as major determinants of adoption and transition. Our findings have important implications for policies aiming at promotion of energy transition and reduction of the pressure on forest resources in developing countries.

JEL Classification: Q40, Q41, Q42, Q48.

Keywords: Cookstoves; Electric Mitad; Firewood; Panel data; Random-Effects Probit.

1 Introduction

In this paper, we use rich household-level panel data spanning a decade to investigate the determinants and dynamics of electric cookstove adoption by households in urban Ethiopia. Nearly 2.5 billion people rely on biomass fuel such as firewood and charcoal for cooking (Legros et al. 2009). Such reliance on biomass and forest products has serious health and environmental implications. WHO (2009) documents that solid fuel use is responsible for about 2 million premature deaths per year and 3.3% of the global burden of disease, particularly for women and children. Solid fuels, often burned in inefficient stoves, put significant burdens on women and children who have to divert

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their time from education and income generating activities into cooking and fuelwood collection (Lewis & Pattanayak, 2012). Moreover, the use of firewood for cooking has been a prime cause of deforestation and environmental degradation (Allen and Barnes 1985; Geist and Lambin 2002; Hofstad et al. 2009; Köhlin et al. 2011), very often resulting in loss of biodiversity and disturbance of local ecosystems. Recent studies (e.g., Sagar & Kartha, 2007; Grieshop et al., 2011) also document that, on a per-meal-equivalent basis, burning of biomass fuel in inefficient stoves could contribute more to global warming than fossil fuel using stoves.

One important remedy for achieving the dual objective of improving household outcomes - through reduction of health risks and effort in cooking and energy collection - and protecting the environment is transition to cleaner energy sources such as electricity and solar energy. However, such a transition is not straightforward (Gebreegziabher et al., 2012; Lewis & Pattanayak, 2012) and is conditioned on acquisition of appropriate cooking equipment, which often require substantial financial outlay by poor households. It would therefore be important to understand the factors associated with adoption and the dynamics of modern cookstoves adoption. Specifically, answering the question “what determines adoption and sustained use of clean energy using stoves?” would be useful in providing relevant information to policy makers who aim at promoting energy transition.

A number of previous studies analyzed the determinants of modern and fuel-saving improved cookstoves in developing countries.¹ Lewis & Pattanayak (2012) survey the literature on adoption of improved cookstoves (ICS) and fuel choice in developing countries based on a total of 32 studies. These authors argue that the empirical literature base of adoption studies remains narrow, thin and scattered, failing to take a systematic approach in analyzing the various determinants. We also note that, although the insights generated from these studies are useful, important knowledge gaps exist in the literature. First, almost all of the studies use cross-sectional data, which makes it difficult to control for unobserved heterogeneity (the consequence of which would be biased and imprecise estimation results) and to answer the question “what happens to adoption over time?” Second, most studies focus on rural areas and the adoption of improved biomass cookstoves.² However, given earlier findings that improved biomass cookstoves may not necessarily result in reduction in biomass fuel use due to what is called “rebound effect”,³ and given the rapidly increasing electrification in developing countries, it would be important to understand the determinants of cookstoves that use clean energy (such as electricity) and which variables to target to promote energy transition. Third, most existing studies (with the exception of El Tayeb Muneer & Mohamed, 2003) use household

¹Studies on improved cookstove adoption in developing countries include Amacher et al. (1992) on Rural Nepal; El Tayeb Muneer & Mohamed (2003) on rural and urban Sudan; Edwards & Langpap (2005), rural and urban Guatemala; McEachern & Hanson (2008) on rural Sri Lanka; Beyene & Koch (2012), on urban Ethiopia; Rebane and Barham (2011), on rural Nicaragua; Gebreegziabher et al., (2012) on urban Ethiopia; and Jan (2012) on rural Pakistan.

²Of the mentioned studies on improved cooking appliance adoption, only Edwards & Langpap (2005); McEachern & Hanson (2008); Rebane & Barham (2011); and Gebreegziabher et al., (2012) analyze adoption of stoves and other appliances that use clean energy.

³This is a concept related to the behavioral response of households. Introduction of improved and efficient stoves may reduce the amount of biomass energy used per meal, but households may also respond by increasing the frequency of cooking. In the end, their overall fuel demand may be higher. This is more likely to be the case for households with higher income elasticity of fuel wood (Nepal et al, 2010; Sorrell et al., 2009).

heads' occupational and educational characteristics as major determinants of adoption of ICS. However, in the context of poor households in developing countries, given the fact that acquisition of most modern energy-using cooking appliances requires a relatively substantial amount of cash outlay, it is reasonable to assume that such investment decisions are made by all members of the household, not only by household heads.⁴ In this respect, controlling for the spill-over effects of the socio-economic characteristics of other household members on adoption would be important.

In this paper, we use three rounds of rich panel data from urban Ethiopia to investigate the determinants and dynamics of adoption of "Electric Mitad", the primary cooking appliance used to prepare injera - the main Ethiopian staple - which accounts for 60 percent of household energy consumption (Gebreegziabher et al., 2012). Mitad⁵ is a flat pan about 45 – 60cm in diameter with a 20 – 30mm thick clay griddle operated with either electricity or biomass fuel (mainly firewood) to give fast heat required for a good injera. A typical Ethiopian household uses the appliance on average twice a week, each baking session lasting for about 2 hours. The traditional mitad operated on a three-stone open fire, with about 85-90 percent of the energy wasted, has been one of the prime contributors to the high rate of deforestation and the intensifying shortage of energy in many parts of Ethiopia (Gebreegziabher, 2007). A household using even the most advanced biomass Mitad known as "Mirte" (which reduces biomass consumption by half compared to the traditional three-stone mitad) would need on average 260 kg of wood per year (Bess, 2012).⁶ Therefore, analyzing the determinants of adoption of the Electric Mitad and the corresponding reduction in biomass fuel use would provide useful insights into the magnitude of the impact of energy transition on the biomass stock of the country. In addition, Ethiopia has in recent years been experiencing rapid economic growth (average real GDP growth rate of 11% per annum during 2004-2011), which also included expansion of infrastructure such as roads, schools and hydroelectric power plants (IMF, 2011). Because we use panel data collected on the same households spanning this interesting period of time, we are able to control for unobserved household heterogeneity and estimate the parameters of our models more precisely and consistently using robust non-linear panel data models. We are also able to see transitions of households into and out of adoption of the appliance and to apply a discrete-time proportional hazard model to estimate the hazard functions of entry into and out of adoption over time.

Results from a correlated random-effects probit model of adoption suggest that the price of electricity and the alternative energy (firewood) are important determinants of adoption of the Electric Mitad in urban Ethiopia. We also find a strong impact of economic status of households, access to credit and socio-economic characteristics not only of household heads but also of other household members. In order to investigate what determines transition into and out of adoption of the Electric Mitad, we use a discrete-time hazard model and estimate two hazard functions: one for

⁴Previous studies emphasizing the role of other household members' characteristics in household decisions and outcomes include: Stark & Bloom, (1986) viewing migration decision as a household decision; Asfaw & Admassie (2004), modeling agricultural technology adoption as a function of other household members' educational achievement; and more recently, Alem (2011) documenting the role of labor market status of other household members on poverty status of households in urban Ethiopia.

⁵See Fig 1 in the appendix.

⁶In other words, the traditional three-stone mitad requires 520kg wood/year, twice the wood of the Mirte Mitad.

entry into adoption and another for exit from adoption. Our results again show that the price of electricity and firewood, economic status, socio-economic variables and access to credit by not only household heads but also by other household members are important determinants of transition. We argue that reducing the price of electricity and increasing the price of firewood and improving access to credit would encourage households to adopt the appliance and reduce biomass fuel use.

The rest of the paper is structured in the following fashion. In section 2, we provide a brief survey of the literature on improved cookstove adoption. In section 3, we present a theoretical model of stove adoption to provide some rationale for the choice of our main model of adoption. In section 4, we present a description of the correlated random-effects probit and the proportional hazard models. In section 5, we present the panel data and summary statistics of major variables. In section 6, we present and discuss our regression results and, in the final section, we conclude and discuss the policy implications.

2 A Review of literature on improved stove adoption

Most previous studies on stove adoption in developing countries focus to a great extent on adoption of improved biomass cookstoves in rural areas using cross-sectional data. Lewis & Pattanayak (2012) undertake a comprehensive survey of the literature on improved cookstove adoption and fuel choice in developing countries based on 32 studies.⁷ According to these authors, empirical literature on adoption studies in developing countries fails to take a systematic approach in analyzing the various determinants and consequently remains narrow, thin and scattered. In the paragraphs below, we present a brief survey of previous studies focusing on adoption of improved cookstoves and highlight existing knowledge gaps.

An early published study on adoption of improved stoves was undertaken by Amacher et al. (1992). These authors used both theoretical and empirical methods to analyze the adoption and efficient use of improved biomass stoves. In their theoretical analysis, they argued that, even though improved stoves have the potential to reduce fuelwood consumption and exposure to indoor air pollution, these gains are uncertain for households who make decisions considering new technologies. These gains also vary across households depending on their efficient use of the improved stoves. Considering these, households will compare these uncertain gains with the financial cost of improved stoves. Accordingly, the decision to purchase the stove and choice regarding its efficient use depends on household attitudes regarding risk and their expectation of the uncertain gains from adoption. They test some of the results from their theoretical models using a sample of 99 rural households from Nepal and show that households living in high price regions, those expecting greater fuel savings, those with more risky capital, and educated households are more likely to adopt the new technology before the less endowed households.

Using a randomly selected sample of 300 households from Khartoum state, Sudan, El Tayeb Muneer & Mohamed (2003) used a multiple linear regression method to analyze the adoption rate and the factors affecting adoption of improved cookstoves in what they call a “patriarchal society”.

⁷An earlier survey of the literature on diffusion of improved biomass cookstoves was undertaken by Barnes et al., (1994).

During the 1980s and 1990s, improved biomass stoves were one of several programs aimed at testing and disseminating energy-saving technologies implemented in Sudan. Their result suggests that, in a patriarchal society where most of the household decisions are made by the head of the household, men's characteristics are expected to be more important determinants of the households' decision to adopt. However, their empirical result shows that the personal characteristics of the female members of the household are more important, in particular the education of the housewife and other female members. This finding is in line with Kammen (1995) who pointed out that failure to take into consideration the nature of the division of labor and the decision-making process within African households would not help in developing appropriate improved biomass cookstoves at a quick pace nor enhance its adoption at satisfactory rates.

For many households in the developing world, the high fixed cost of improved stoves and limited access to credit are among the factors that impede adoption of improved stoves. Edwards and Langpap (2005) use survey data from rural and urban Guatemala and examine the effect of startup cost and credit constraint in fuel switching. Their analysis shows that the prices of a stove and its complement, fuel, have a negative effect on the adoption of a Liquefied Petroleum Gas (LPG) stove; the effect is more pronounced in rural than in urban areas. The price of wood has a positive effect on stove ownership, indicating that such stoves are normal goods. Access to credit also determines fuel wood consumption indirectly, through its effect on gas-using stove adoption. However, in their simulation result, the effect of credit is small. The authors suggest subsidizing households for the upfront cost of the gas-using stoves as a promising policy for reducing firewood consumption.

In many rural areas of developing countries, access to electricity is low due to the high cost of extending electric grids. In such circumstances, a Solar Home System (SHS) is a potentially important alternative energy-generating technology for households. However, the use of such a technology is constrained by adoption of the appliances of SHS. McEachern and Hanson (2008) and Rebane and Barham (2011) are among few studies investigating the issue in rural areas of Sri Lanka and Nicaragua. The main findings from these studies indicate that: (i) income raises the possibility of adoption (ii) politicians' previous power-grid connection promises reduces SHS adoption (iii) living closer to a dealer (seller) lessens the likelihood of adoption. A possible explanation they provide for this is that, because dealers are close to towns, being close to a dealer is a proxy for being close to an urban area with high expectations of grid extension.

An interesting finding on adoption of improved biomass cookstoves and consumption of biomass fuel was documented by Nepal et al., (2010). Using comprehensive and nationally representative household level data from Nepal, these authors show that improved cookstoves have been followed by increased biomass fuel consumption due to what is called the "rebound effect",⁸ which implies increase in frequency of cooking due to improved efficiency after introduction of improved cookstoves, and consequently increase in biomass fuel consumption. The authors stress the importance of improving availability of cleaner fuels to rural households to reduce biomass energy consumption and the associated adverse consequences. More recently, using household data from rural Pakistan, Jan (2012) confirmed the importance of improving awareness and institutional support by

⁸Sorrell et al. (2009) review the literature on rebound effects in energy use in developing countries.

governments and NGOs to encourage adoption of improved biomass cookstoves.

Relevant studies addressing adoption of improved biomass stoves and modern stoves in urban Ethiopia include Gebreegzabiher et al., (2012) and Beyene and Koch (2012). Gebreegzabiher et al. (2012) use cross-sectional data on a sample of 350 urban households in Tigray, Ethiopia, and find that income (proxied by expenditure), age and education of heads, and family size have positive impacts on electric mitad adoption, while these variables have negative effects on adoption of biomass-using Mitad. Beyene and Koch (2012), on the other hand, used cross-sectional household level data and recall data on duration of stove use among 1577 urban households and investigate the determinants of adoption of two types of improved biomass stoves (“Mirte”, a biomass-using mitad, and “Lackech” a charcoal-using stove) using a duration model. They find that adoption rates of both stoves have been increasing over time, and income and wealth are significant determinants of adoption, while substitute technologies tend to hinder adoption. These authors conclude by highlighting the importance of controlling for unobserved household heterogeneity such as culture and perceptions and the use of panel data that tracks and documents information on the same households over time to better understand the determinants of adoption of improved stoves.

From the foregoing survey of the literature on stove adoption in developing countries, we can draw the following observations. First, almost all previous studies use cross-sectional data, which makes it difficult to control for unobserved heterogeneity and investigate the state of stove adoption over time. Second, most studies focus on rural areas and the adoption of improved biomass cookstoves. However, given earlier findings that improved biomass cookstoves may not necessarily result in reduction in biomass fuel use, due to what is called the “rebound effect”, and given the rapidly increasing electrification in developing countries, it would be important to understand the determinants of adoption of cookstoves that use clean energy (such as electricity) and which variables to target to promote energy transition. Third, most of the studies we surveyed (except El Tayeb Muneer & Mohamed, 2003) use household heads’ occupational and educational characteristics as major determinants of adoption of ICS. However, investment on major household items such as cooking appliances could be made by all household members, not by household heads alone. For this reason, controlling for the spill-over effects of other household members’ socio-economic characteristics would provide more information on the determinants of adopting cooking appliances that use clean energy. In this paper, we attempt to fill these research gaps.

3 Conceptual Framework

Standard microeconomic theory of the consumer postulates that the demand for a durable consumer good arises from the stream of services acquired from the durable commodity. The indirect utility function best characterizes the utility that comes from the durable good. We therefore follow Dubin and McFadden (1984) and specify a utility maximization framework and demand for electricity consistent with discrete appliance choice as follows.

Assume that there are $i = 1, \dots, m$ mutually exclusive, exhaustive cookstove portfolios available to the household with the annualized cost (rental price) of portfolio i being r_i . Consumer i 's conditional indirect utility function can thus be given as

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

where p_i represents price of electricity, p_2 is price of alternative energy sources (biomass fuel in our case), y represents income of the household, s_i and ϵ_i are portfolio i 's observed and unobserved attributes respectively, r_i represents price of portfolio i , and η denotes unobserved characteristics of the household. All prices and income are expressed in real terms. Applying Roy's identity on equation [1] would yield the quantity of electricity and alternative biomass fuel which can be specified as

$$x_1 = \frac{-\partial V(i, y - r_i, p_1, p_2, s_i, \epsilon_i, \eta)/\partial p_1}{\partial V(i, y - r_i, p_1, p_2, s_i, \epsilon_i, \eta)/\partial y} \quad (2)$$

and

$$x_2 = \frac{-\partial V(i, y - r_i, p_1, p_2, s_i, \epsilon_i, \eta)/\partial p_2}{\partial V(i, y - r_i, p_1, p_2, s_i, \epsilon_i, \eta)/\partial y} \quad (3)$$

respectively.

Given the above, household i would choose portfolio i if

$$P_i = Prob\{(\epsilon_1, \dots, \epsilon_m, \eta) : V(i, y - r_i, p_1, p_2, s_i, \epsilon_i, \eta) > V(j, y - r_j, p_1, p_2, s_j, \epsilon_j, \eta) \text{ for } j \neq i\} \quad (4)$$

One can construct a binary choice econometric model for the decision to adopt a cooking appliance provided the indirect utility function satisfies the necessary and sufficient conditions for optimization.

4 Empirical Strategy

Correlated Random Effects Probit Model

We use a random effects probit framework to model the decision to adopt an electric mitad appliance by households in urban Ethiopia. Let the latent model of electric mitad appliance adoption be specified as

$$m_{it}^* = x'_{it}\beta + \varepsilon_{it} \quad i = 1, 2, \dots, N; \quad t = 1, \dots, T \quad (5)$$

$$\varepsilon_{it} = \alpha_i + u_{it} \quad (6)$$

where m_{it}^* is a latent dependent variable; m_{it} is the observed binary outcome variable defined as

$$m_{it} = \begin{cases} 1 & \text{if } m_{it}^* > 0; \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

x_{it} represents a vector of time-varying and time-invariant exogenous variables which influence m^* ; β represents a vector of parameters to be estimated; ε_{it} is a composite error term which can be

decomposed into α_i , a term capturing unobserved individual (household in our case) heterogeneity, and $u_{it} \sim IN(0, \sigma_u^2)$, a random error term. The subscripts i and t refer to households and time periods respectively. One can marginalize the likelihood function by assuming that, conditional on the x_{it} , the unobserved individual heterogeneity term $\alpha_i \sim IN(0, \sigma_\alpha^2)$, is independent of the x_{it} s and u_{it} .⁹

Assuming that the distribution of the latent variable m^* , conditioned on α_i , is independent normal (Heckman, 1981), the vector of parameters, i.e, the β s can be estimated easily. Thus,

$$Pr(m_{it} = 1 | \alpha_i, x_{it}) = Pr\left(\frac{u_{it}}{\sigma_u} > \frac{-x'_{it}\beta - \alpha_i}{\sigma_u}\right) = \Phi(v_{it}) \quad (8)$$

where

$$v_{it} = -(x'_{it}\beta + \alpha_i)/\sigma_u \quad (9)$$

and Φ is the distribution function of the standard normal variate. Consequently, the likelihood function to be maximized (which is marginalized with respect to α) is given by

$$\prod_i \left\{ \int_{-\infty}^{\infty} \prod_{t=1}^T [1 - \Phi(x'_{it}\beta^* + \sqrt{\frac{\lambda}{1-\lambda}}\alpha^*)]^{1-m_{it}} \times [\Phi(x'_{it}\beta^* + \sqrt{\frac{\lambda}{1-\lambda}}\alpha^*)]^{m_{it}} \phi(\alpha^*) d\alpha^* \right\}$$

where $\beta^* = \beta/\sigma_u$ and $\alpha^* = \alpha/\sigma_\alpha$. A standard software can be used to estimate β^* and λ , which are normalized on σ_u .¹⁰

However, it is unrealistic in many cases to assume that the time invariant unobserved individual heterogeneity α_i is independent of the observable variables $x'_{it} \forall i$ and t . It is, for example, possible that motivation or ability, which are captured by α_i , would be correlated with some of the observed right-hand side variables such as education or occupational characteristics, which in turn introduce bias in the coefficient estimates. It is possible to estimate more precise β parameters by allowing for correlation following Mundlak (1978) and Chamberlain (1984), which involves including $x_i = (x_{i0}, \dots, x_{iT})$, or alternatively averages of the x -variables over time as additional regressors in the model. The resulting modification would give the more realistic non-linear panel data model called the ‘‘correlated random-effects probit’’ model. In this paper, we allow for correlation and estimate this model.

Discrete-time Proportional Hazard Model

In order to study the transition of households from adoption to disadoption and vice versa, we use a discrete-time proportional hazard model. In the literature of event history models, the length of time spent in a particular state is referred to as a spell (duration or episode). In the context of

⁹A straightforward implication of this assumption is that the correlation between the composite error terms in two successive periods for household i is constant and given by: $\lambda = \text{cor}(\varepsilon_{it}, \varepsilon_{it-1}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2}$.

¹⁰One other applicable binary choice panel data estimator is the fixed effects logit model (Cameron & Trivedi, 2009). However, because it is based on a within transformation (which also drops any time invariant observable variables in x_{it}) and is based on variation in the dependent variable over time (which limits the number of observations to be used for estimation and consequently reduces our sample size significantly) we preferred not to use it.

electric mitad adoption, we focus on the analysis of adoption spells and the estimation of exit from adoption and entry into adoption hazards. Thus, this parametric method of estimating exit from and entry into adoption spells uses the probabilities of ending a spell to model the distribution of adoption spell durations.

Let $d = 1$ for households with completed spells of non-adoption (and hence moved into adoption) and $d = 0$ for those that were still in a non-adoption spell when observed. Thus, the proportion with completed non-adoption spells is the hazard rate for that round. The hazard rate reflects the risk of exit from non-adoption and corresponds to the “survivor rate”, which shows the proportion of households remaining in non-adoption at that time (Jenkins, 1995). Consequently, a discrete-time hazard rate h_{it} can be specified as

$$h_{it} = \text{prob}(T_i = t | T_i \geq t; X_{it}), \quad (10)$$

where X_{it} represents a vector of explanatory variables (either time-variant or invariant) and T_i is a discrete random variable representing the time at which a non-adoption spell ends. Thus, the likelihood of ending a non-adoption spell at $T_i = t$ and at $T_i > t$ can be given by ¹¹

$$\text{prob}(T_i = t) = h_{it} \times \prod_{k=1}^{t-1} (1 - h_{ik}) = [h_{it}/(1 - h_{it})] \times \prod_{k=1}^t (1 - h_{ik}) \quad (11)$$

and

$$\text{prob}(T_i > t) = \prod_{k=1}^t (1 - h_{ik}) \quad (12)$$

respectively. The most common parametric form of the hazard model which has been used to analyze spells - the proportional hazard model - is given by

$$h_{it} = h_0(t) \exp(X'_{it}\beta), \quad (13)$$

where $h_0(t)$ is the baseline hazard function, which is assumed to be the same for all households under analysis, X'_{it} is a vector of explanatory variables ¹², and β is the vector of parameters to be estimated. It is possible to control for unobserved household heterogeneity by incorporating a multiplicative gamma-distributed random error term ν , which is assumed to be uncorrelated with any of the X variables, into the proportional hazard model given in equation (13) as

$$h_{it} = h_0(t) \nu_i \exp(X_{it}) = h_0(t) \exp[X_{it} + \log(\nu_i)]. \quad (14)$$

The corresponding discrete-time hazard function in the j^{th} interval can then be given by

$$h_j(X_{ij}) = 1 - \exp\{-\exp[X'_{ij}\beta] + \gamma_j + \log(\nu_i)\}, \quad (15)$$

¹¹See Jenkins (1995) for detailed derivation of equations (11) and (12).

¹²This implies that with the baseline hazard function h_0 remaining the same for all households, individual household hazard rates depend on the X variables

where γ_j is the parameter of the baseline hazard. The log likelihood of the hazard function presented in (15) is the same as the log likelihood for a generalized linear model of the binomial family with a complementary log-log link (Jenkins, 1995).¹³

5 Data and Description of Variables

The data used in our empirical models comes from three rounds of the Ethiopian Urban Socio-economic Survey (EUSS) collected in the years 2000, 2004 and 2009. The first two waves of the data were collected by Addis Ababa University, Department of Economics, in collaboration with the University of Gothenburg, Department of Economics, from seven major urban areas of Ethiopia: the capital Addis Ababa, Awassa, Bahir Dar, Dessie, Dire Dawa, Jimma, and Mekelle.¹⁴ The cities selected were believed to represent a significant proportion (about 90 percent) of the Ethiopian urban population. Initially, about 1500 households were distributed over the cities in proportion to the cities' population size. Once the sample size for each city had been set, the sample households were recruited from half of the kebelles (the lowest administrative units) in all woredas (districts) in each urban center. The panel data is one of the few African panel data sets which documents detailed socioeconomic information at both the household and individual level for a fairly long period of time.

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.¹⁵ These cities were carefully selected to represent the major urban areas of the country and the original sample.¹⁶ Out of the 709 households covered in the survey, 128 were new households randomly chosen and introduced in the sampling to investigate whether the panel households, which were formed back in 1994, still represent the Ethiopian urban population. Alem & Söderbom (2012) check for this and show that there is no systematic difference between the new households and the old panel households in the key household outcome indicator - welfare measured by per capita consumption expenditure - which implies that the panel households represent urban Ethiopia reasonably well. In estimating our empirical models of adoption and hazard functions, we use information on the unbalanced panel households and 458 households who were surveyed in all three rounds respectively.

We investigate the determinants of adoption of electric mitad appliance under four headings: economic variables, head's characteristics, household-level variables, and city and time dummies. The economic variables include real per capita consumption expenditure and price of electricity¹⁷

¹³A logistic form of a non-proportional hazard specification is also common in empirical research. However, in most cases, given the fact that the logistic model converges to a proportional hazard model as the hazard rates become smaller, the two specifications yield similar estimates (Jenkins, 1995).

¹⁴Data was also collected from these cities in 1994, 1995, and 1997. However, detailed information on energy use and prices was not collected in these earlier waves. Refer to AAU & GU (1995) for details on sampling.

¹⁵Resource constraints prevented the author from surveying households in the other cities.

¹⁶See Alem & Söderbom (2012) for detailed description of EUSS-2009.

¹⁷Having access to electricity could be a source of bias in analyzing the determinants of any electricity- using appliance. In our case, however, because all the households are located in major urban areas, 99 percent of the households had access to electricity.

and alternative fuels (in our case, firewood). We computed aggregate household consumption expenditure by adding up reported household expenditure on food and non-food items. The non-food component of consumption includes expenditures on items such as clothing, footwear, energy, personal care, utilities, health and education. To correct for spatial and temporal price differences, we divided nominal consumption expenditure by carefully constructed price indices from the survey, and computed real consumption expenditure. We then divided real household level consumption expenditure by adult equivalent units to adjust for difference in needs and economies of scale in consumption.¹⁸

Electricity, the energy required to operate an Electric Mitad, is provided by the government-owned monopoly, Ethiopian Electric Power Corporation (EEPCo). Hydropower constitutes over 90 percent of electricity production in Ethiopia, the rest coming from self-contained systems generating electricity using diesel. The country has more than 45,000 megawatt (MW) potential of hydropower. However only 3.3 percent (around 1494MW) of the total potential has been used so far (EEPCo, 2011). Currently, the Ethiopian government is going through major investments to build dams that can generate around 10,000 MW in the coming few years. The largest dam which is under construction, “Grand Millennium Dam,” is expected to generate around 6000MW electricity by the year 2014. Access to electricity in the country has increased over the last five years to 46%; however, currently, only around 1.9% of households use electricity for cooking (EEPCo, 2011; CSA, 2011). EEPCo implements progressive pricing on electricity, where per-unit price increases with increased electricity usage. It is therefore obvious that this price regime discourages increased utilization of modern electric cooking appliances such as the Electric Mitad. We computed average price of electricity by dividing the monthly bill paid for electricity used by the amount of kilowatt hours (kwh).

The household-head variables constitute conventional variables used in previous adoption literature: age and its square, education, gender, and occupation of the household head. In this paper, we view acquisition of a major cooking appliance as an investment decision that requires a relatively substantial cash outlay by poor households.¹⁹ Thus, we consider the decision to buy an electric mitad as a household decision (rather than the decision of only the household head) and control for the characteristics of other household members residing in the same dwelling. Most previous studies on the topic consider the characteristics of the household head and use them as proxies for the underlying ability of the household to generate income. However, in the context of developing countries, where there is intra-household heterogeneity in socio-economic characteristics of household members, it may be important to consider the role of other household members’ characteristics in major household level decisions. In view of this, we control for education, occupational structures, and access to credit by all members. Because there is strong evidence that the high startup cost and lack of access to credit prevents households in developing countries from adopting clean-energy stoves (Edwards & Langpap, 2005), we use membership in a credit association by any member of

¹⁸Refer to Alem & Söderbom (2012) for details on computation.

¹⁹The average price of a standard electric mitad in urban Ethiopia and the median per capita consumption expenditure in 2009 computed from the survey in nominal prices were about \$95 and \$18.80 (339.88 Ethiopian Birr) respectively.

the household as a proxy for access to credit. Finally, we introduce city dummies to capture any lifestyle and other spatial differences in access to energy and information by households. Table 1 presents summary statistics of our variables for both adopters and nonadopters of electric mitad in urban Ethiopia over the study period.

Table 1 about here

Table 2 presents the percentage of the panel households adopting electric mitad in the four cities over time. It can be noted that the proportion of electric mitad adopters is larger in the capital (Addis Ababa) than in all the other cities in all rounds. This is expected, because living in the capital could offer better access to information about modern cooking appliances. Between the years 2000 and 2009, we observe 12% 14%, 3% and 9% increases in the proportion of electric mitad adopters among the sampled households living in Addis Ababa Awassa, Dessie and Mekelle, respectively. However, one can see from the table that the majority of households outside the capital still use biomass stoves for baking injera.

Table 2 about here

Table 3 depicts stove adoption transition of households in the sample over the study period. It can be seen that 76.03 and 82.18 percent of non-adopters and adopters, respectively, never show any transition over the study period. However, 17.82 percent of households who adopted the stove before 2009 become non-adopters, and 23.97 percent of the non-adopters transition to electric stoves in 2009. This makes the analysis of what determines transition important.

Table 3 about here

6 Empirical Results

Adoption of Electric Mitad Appliance

Table 4 shows regression results and the corresponding marginal effects for the determinants of electric mitad adoption as presented in equation [5]. As stated in the preceding section, we examine the correlates of electric mitad appliance adoption under four headings: economic variables, head's characteristics, household-level variables, and city and time dummies. To test for the robustness of the different correlates of adoption, we estimate the model using three alternative nonlinear specifications: pooled probit, random effects probit and correlated random-effects probit models. Comparison of results in table 4 reveals that our regressions from all the estimators provide similar results indicating the robustness of our findings. The coefficient for ρ , which indicates the important role of unobserved heterogeneity, is significantly different from zero and is large in magnitude in both the random effects and correlated random-effects probit models (0.53 and 0.55 respectively). This clearly indicates the need to use panel data models in estimating the cookstove adoption model. Since the correlated random-effects probit model is based on an appealing formulation of allowing for correlation between some of the explanatory variables and the unobserved individual heterogeneity term, we refer to the results from this estimator in our discussion below.

Table 4 about here

It is evident from all the regression results that most of the economic, household head, household-

level, and city-level variables are important in explaining adoption of electric mitad appliances in urban Ethiopia. We begin with economic variables. One can see from table 4 that the economic status of the households as measured by per capita consumption expenditure is a positive and significant determinant of adoption of an electric mitad appliance. This is consistent with findings from earlier studies (e.g., Amacher et al., 1992; Arthur et al., 2010; Beyene and Koch, 2012; Gebreegziabher et al. 2012; Jan 2012) who document the importance of economic status in explaining adoption of modern cookstoves. Increase in the price of electricity reduces adoption of electric mitads and increase in the price of the substitute fuel (firewood) increases adoption. The marginal effects presented in column 4 indicate that, other factors held constant, a one percent increase in the price of electricity reduces adoption by 9.6 percent, and a one percent increase in the price of firewood increases the adoption of electric mitad appliances by 3.8 percent. This indicates the role that, for instance, reduction in the price of electricity (say through subsidy) and increase in the price of firewood (through tax) could play in encouraging households to switch to cleaner energy sources. We further explore the impact of the price of electricity by testing the null hypothesis that adopters and non-adopters fall in the same electricity price regime. We specifically test whether the cumulative distributions of electricity prices of adopters and non-adopters are “far apart” at any point of the distributions using the Kolmogorove-Smirnov two-sample test.²⁰ We rejected the null hypothesis (p-value 0.000) that adopters and non-adopters have similar distribution of prices, which implies that the the two groups of households do not fall in the same price regime. This indicates that reduction in average price of electricity would encourage non-adopters to adopt electric mitads.

Consistent with earlier findings, household heads’ characteristics are important correlates of modern cookstove adoption. Households with heads who are aged, educated and working in the formal sector are correlated positively with adoption of electric mitad appliances, while those with heads working as self-employed and casual worker are not. Earlier studies (e.g., Beyene & Koch) find differences in adoption based on gender of the household head. We don’t find a gender difference in adoption, as can be seen from the insignificant coefficient on the “Female” variable. The sign is, however, negative, implying that female headed households are less likely to adopt electric mitads. Detailed investigation of the difference sections of our panel data indicates that about 32.02 percent of the female headed households in urban Ethiopia engage in small-scale traditionally female business activities such as preparing and selling food and drinks. Thus, they appear to have a lower tendency of adopting an electric mitad appliance for a number of possible reasons, such as low opportunity cost of time which could be used to collect and buy traditional biomass fuel.

Because of our interest in the role of other household members in making the decision to adopt an electric mitad, we control for the educational and occupational characteristics of other household members. All the three nonlinear models presented in table 4 suggest that, in addition to household heads’ characteristics, other household members’ educational and occupational characteristics have a significant effect on the adoption of electric mitads. Consistent with our discussion above, households with more members earning a living as self-employed or casual workers have a lower

²⁰This is a two-sample nonparametric test used to check whether two data samples come from the same distribution. The null hypothesis is that the two samples under analysis are drawn from the same distribution which implies that the two samples are not different with respect to the variable of interest (see Conover, 1971) for details.

likelihood of adopting electric mitads, while those with more members working in the formal sector have a higher likelihood. We also note that maximum education of females and a larger proportion of educated household members are positively associated with adoption of electric mitads, most probably indicating the positive spill-over effects of education in the household. We also note that households with a larger number of children are more likely to invest in electric mitads. This is probably due to awareness on the adverse consequences to the health of children of using biomass energy.

Because acquisition of modern cooking appliances is constrained by lack of access to credit (Edwards & Langpap, 2005), we control for access to credit and for savings by any household member by using membership in credit associations and “equbs” as proxies.²¹ The results in table 4 suggest that access to credit by any member of the household positively affects the ability to purchase and adopt electric mitads. The reported marginal effects indicate that membership in a credit association by any member of the household increases the probability of adoption by 8.4 percent. This reinforces earlier findings on the importance of access to financial resources in enabling households to adopt improved cookstoves and make a transition to cleaner energy sources. We do not find access to a traditional savings institution to be a significant factor.

Finally, the coefficients on the city dummies indicate a clear spatial difference in adoption of electric mitads, with strongly statistically significant coefficient estimates. Compared to households in the reference city, Mekelle, households in the capital Addis are more likely to adopt electric mitads, while households in the city of Awassa are less likely to adopt. Households living in the capital have about a 28.8% higher probability of adopting electric mitads compared to households in Mekelle. On the other hand, households in the city of Awassa have about a 17.8% lower probability of using an electric mitad. This could probably be explained by better biomass fuel availability and the relatively lower level of awareness about the implications of using biomass fuel in the city of Awassa (Reynolds, et al., 2010).

Transitions into and out of adoption

In order to answer the question “which households adopt and disadopt electric mitad appliance over time in urban Ethiopia?” we use discrete-time hazard models and estimate two hazard functions: one for entry into and another for exit from electric mitad adoption. To check for the robustness of the impact of the different variables on the hazards of entry into and exit from adoption, we estimated the models using both non-proportional and proportional hazard models.²² The regression results presented in Table 5 reveal no significant difference between the non-proportional and proportional hazard models. Both models are estimated with unobserved household heterogeneity.

Table 5 about here

The results in columns [1] and [3] of table 5 suggest that the transition from the state of no adoption to adoption of electric mitad is strongly determined by the price of electricity (negative)

²¹Equbs are informal Rotating Saving and Credit Associations commonly used by households in urban Ethiopia. See Kedir et al. (2005) for definitions and institutional arrangement of equbs.

²²We estimated the non-proportional hazard model using the logit specification, which is a widely used discrete-time non-proportional hazard model (Jenkins, 1995).

and the price of firewood (positive). This is consistent with findings from the correlated random effects probit model and implies that increase in the price of electricity and decrease in the price of firewood over time may hinder households from moving from not-adopting to adopting an electric Mitad. We don't find per capita consumption expenditure as an important determinant of entry into adoption in the proportional hazard model.²³ Consistent with results from the model of adoption, households with educated heads are more likely to enter into adoption. None of the other household head related variables are important in explaining the hazard of entering into adoption. Results also confirm the importance of household-level variables in entering into adoption. The number of children, access to credit by any member of the household, the number of household members employed in the formal sector, and proportion of educated members all positively determine transition into adoption.

Columns [2] and [4] of table 5 present discrete-time non-proportional and proportional hazard estimation results, respectively, for exiting the state of adoption over time. The results suggest that economic status as measured by per capita consumption expenditure has a negative impact on the hazard of exit from adoption. This is consistent and intuitive given the fact that households may decide to stop using the appliance and move to a biomass-using stove as their economic conditions worsen. The price of electricity, on the other hand, has a significant positive effect on the hazard of exit from adoption. We don't find a statistically significant effect of the price of firewood on exit from adoption of the electric mitad. This could be due to the fact that, once households have started adopting the electric mitad, a change in the price of firewood (say a decrease) would not give them the incentive to switch into biomass-using stoves, because using a biomass stove imposes other costs on the household, such as health hazards from smoke. Finally, one can see from columns [2] and [4] that almost all the significant household head and household-level variables in the hazard of entry into adoption reveal the opposite effect on the hazard of exit from adoption.

7 Conclusions and Policy Implications

In order to combat the adverse consequences of biomass fuel use, such as deforestation, indoor air pollution and emission of greenhouse gasses in developing countries, reducing the intensity of biomass fuel use and transitioning to cleaner energy sources has been discussed as one important step. However, previous studies document that such a transition is conditioned by adoption of improved cookstoves. For this reason, analyzing the determinants and dynamics of adoption of improved cookstoves that use clean energy provides useful information to policy makers. This paper, probably the first to use panel data in a study of clean-energy stove adoption in developing countries, investigates the determinants and dynamics of electric cookstove adoption in urban Ethiopia, using data spanning 2000-2009.

Results from a correlated random-effects probit model, which controls for unobserved household heterogeneity, suggest that adoption of electric mitad appliances in urban Ethiopia is strongly determined by economic status, price of electricity and price of firewood (the alternative fuel). A

²³The variable is slightly significant (10%) in the non-proportional hazard model.

one percent reduction in the price of electricity increases the likelihood of adopting an electric mitad by about 9.6 percent. We also show that access to credit and socio-economic characteristics of not only household heads but also other household members are important determinants of adoption. For instance, marginal effects from our correlated random-effects model show that, compared to households headed by an uneducated individual, households with a head who completed at least primary education have a 16.9 percent higher probability of adopting an electric mitad appliance. However, not only the education of the head matters, but also that of other household members. Having one more household member with at least a primary level of schooling increases the likelihood of adopting an electric mitad by 7.9 percent. This reinforces our hypothesis that adoption of a major cooking item such as an electric mitad appliance is made by all household members jointly and that there may be trickle-down effects from education and labor market status of other household members within the household.

We also used discrete-time non-proportional and proportional hazard models to estimate the likelihood of entering into and exiting from adoption by households in urban Ethiopia. Economic status (positive), price of electricity (negative), and price of firewood (positive) determine the likelihood of transition from the state of adoption to non-adoption. Socio-economic characteristics of all household members and access to credit have also been found to be important determinants of such transitions. Most of the explanatory variables that positively determine transition of households into adoption negatively determine transition out of adoption, with the exception of the price of firewood, which positively determines entry into adoption but has no statistically significant effect on exit from adoption. This could possibly be due to the fact that, once households invest in the appliance and develop a taste for using it, reduction in the price of firewood alone may not be a sufficient condition to make them exit from adoption.

Our use of robust non-linear panel data econometric models on data spanning a fairly long period of time adds useful insights to the growing literature on improved cookstove adoption. Our findings that prices of electricity and firewood and access to credit are important determinants of adoption and dis-adoption support the idea that increasing the price of biomass fuel (for example, by introducing a tax), reducing the price of electricity (for example, through subsidy or reduction in the average price electricity through investment in hydroelectric power production) and improving access to credit would result in more adoption of modern stoves and transition into using cleaner energy sources. In addition, the fact that the socio-economic characteristics of other household members are also important determinants of adoption indicates the trickle-down effects of factors such as education and labor market status within the household. This could be important information for policy makers and stakeholders such as NGOs that aim to promote the adoption of modern cookstoves and reduction of the pressures on forest resources by households in developing countries.

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Figure 1: Electric Mitad.

Table 1: Descriptive Statistics of Variables 2000-2009

Variables	[All Households]		[Adopter Households]		[Nonadopter Households]	
	Mean	SD	Mean	SD	Mean	SD
Household adopts electric mitad	0.492	0.500	1.000	0.000	0.000	0.000
<i>Economic Variables</i>						
Real per capita cons. (log)	4.733	0.763	4.990	0.698	4.484	0.740
Real price of electricity (log)	-1.200	0.425	-1.235	0.436	-1.173	0.417
Real price of firewood (log)	-0.467	0.803	-0.337	0.723	-0.597	0.853
<i>Household head variables</i>						
Age of head/100	0.511	0.139	0.521	0.135	0.502	0.143
Age of head squared	0.281	0.147	0.289	0.143	0.273	0.151
Head female	0.459	0.498	0.411	0.492	0.505	0.500
Head male	0.541	0.498	0.589	0.492	0.495	0.500
Head educated	0.717	0.450	0.845	0.362	0.593	0.491
Head uneducated	0.278	0.448	0.155	0.362	0.407	0.491
Head casual worker or self employed	0.318	0.466	0.228	0.420	0.406	0.491
Head formal sector employee	0.295	0.456	0.366	0.482	0.226	0.418
Head out-of-labor-force	0.380	0.485	0.407	0.491	0.368	0.482
<i>Household-level variables</i>						
Number of children	1.487	1.436	1.409	1.408	1.562	1.460
Maximum female education	2.243	1.214	2.595	1.137	1.898	1.188
Member of a credit association	0.075	0.264	0.101	0.302	0.050	0.218
Not member of a credit association	0.902	0.297	0.884	0.320	0.921	0.269
Member of equb	0.178	0.382	0.198	0.398	0.160	0.367
Not member of equb	0.803	0.398	0.789	0.408	0.815	0.389
Number of casual/self-employed members	0.346	0.715	0.265	0.586	0.425	0.813
Number of formal sector employee members	0.633	0.968	0.887	1.116	0.387	0.717
Proportion of educated members	1.122	0.521	1.221	0.480	1.028	0.537
<i>City and time variables</i>						
Addis Ababa	0.719	0.449	0.867	0.340	0.577	0.494
Awassa	0.090	0.286	0.039	0.195	0.139	0.346
Dessie	0.097	0.297	0.045	0.207	0.148	0.356
Mekelle	0.093	0.291	0.048	0.215	0.136	0.343
Observations	2934		1444		1490	

Notes: * Denotes reference group.

Table 2: Percentage of panel households adopting electric mitad over time, 2000-2009

Cities	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-Adopters
Addis Ababa (%)	58	42	56	44	70	30
Awassa (%)	17	83	17	83	31	68
Dessie (%)	19	81	27	73	22	77
Mekelle (%)	26	74	29	71	35	65
Observations	216	239	216	242	268	191

Table 3: Transition into and out-of adoption - percentage of households

	[Transit to]	
	Disadopter	Adopter
Disadopter	76.03	23.97
Adopter	17.82	82.18

Table 4: Determinants of Electric Mitad adoption: Results from alternative non-linear models

	[1-POP]		[2-REP]		[3-CREP]		[4-CME]	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
<i>Economic variables</i>								
Real per capita cons. (log)	0.677***	0.044	0.871***	0.069	0.403***	0.098	0.086***	0.020
Real price of electricity (log)	-0.356***	0.071	-0.447**	0.226	-0.454**	0.231	-0.096**	0.049
Real price of firewood (log)	0.150***	0.044	0.161**	0.063	0.181***	0.065	0.038***	0.014
<i>Household head variables</i>								
Age of head/100	4.010***	1.144	4.261**	1.708	4.826***	1.763	0.460***	0.077
Age of head squared	-2.357**	1.093	-2.127	1.635	-2.628	1.684	-	-
Head female	-0.047	0.061	-0.081	0.094	-0.062	0.097	-0.013	0.021
Head educated	0.663***	0.070	0.811***	0.101	0.796***	0.103	0.169***	0.021
Head casual worker or self employed	-0.236***	0.073	-0.314***	0.107	-0.276**	0.110	-0.059**	0.023
Head formal sector employee	0.161**	0.079	0.261**	0.117	0.275**	0.120	0.058**	0.025
<i>Household-level variables</i>								
Number of children	0.100***	0.021	0.147***	0.032	0.165***	0.034	0.035***	0.007
Maximum female education	0.157***	0.025	0.206***	0.037	0.187***	0.038	0.040***	0.008
Member of a credit association	0.212*	0.110	0.365**	0.157	0.396**	0.161	0.084**	0.034
Member of equb	-0.034	0.074	-0.080	0.107	-0.090	0.110	-0.019	0.023
Number of casual/self-employed members	-0.180***	0.041	-0.246***	0.060	-0.219***	0.062	-0.047***	0.013
Number of formal sector employee members	0.171***	0.033	0.216***	0.047	0.215***	0.048	0.046***	0.010
Proportion of educated members	0.266***	0.059	0.375***	0.088	0.371***	0.090	0.079***	0.019
<i>City and time variables</i>								
Addis Ababa	0.813***	0.102	1.257***	0.178	1.358***	0.187	0.288***	0.035
Awassa	-0.610***	0.140	-0.790***	0.233	-0.839***	0.241	-0.178***	0.050
Dessie	-0.216	0.135	-0.350	0.225	-0.308	0.233	-0.065	0.049
2004	-	-	0.123	0.088	0.156*	0.090	0.033*	0.019
2009	-	-	0.128	0.238	0.213	0.243	0.045	0.052
Intercept	-6.780***	0.426	-8.809***	0.700	-10.692***	0.833	-	-
Pseudo R-squared	0.307	-	-	-	-	-	-	-
Rho	-	-	0.536	0.043	0.557	0.043	-	-
Log-likelihood	-1374.316	-	-1312.944	-	-1290.801	-	-	-
Observations	2863	-	2863	-	2863	-	2863	-

POP: is the Pooled Probit Estimator. *REP*: is the Random Effects Probit Estimator.

CREP: is the Correlated Random Effects Probit Model. *CME*: shows the Marginal Effects from the CREP.

Table 5: Entry into and exit from electric mitad adoption: Results from proportional hazard models

	[1-ENNP]		[2-EXNP]		[3-ENP]		[4-EXP]	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
<i>Economic variables</i>								
Real per capita cons. (log)	0.188*	0.109	-1.604***	0.410	0.131	0.084	-1.351***	0.323
Real price of electricity (log)	-0.266**	0.128	0.609**	0.293	-0.255**	0.102	0.527**	0.249
Real price of firewood (log)	0.724***	0.104	-0.019	0.240	0.598***	0.084	-0.046	0.207
<i>Household head variables</i>								
Age of head/100	4.139	3.207	-1.511	8.096	3.494	2.474	-1.319	6.996
Age of head squared	-3.091	3.021	-1.815	7.492	-2.770	2.322	-1.405	6.463
Head female	0.250	0.156	-0.230	0.429	0.197	0.122	-0.211	0.370
Head educated	1.187***	0.182	-4.393***	1.087	0.965***	0.153	-3.935***	0.872
Head casual worker or self employed	-0.153	0.198	-0.272	0.458	-0.092	0.157	-0.277	0.393
Head formal sector employee	-0.040	0.180	-0.904	0.551	-0.016	0.138	-0.797*	0.478
<i>Household-level variables</i>								
Number of children	0.142**	0.057	-0.403**	0.197	0.110**	0.043	-0.360**	0.163
Maximum female education	0.134*	0.068	-0.073	0.162	0.123**	0.056	-0.067	0.139
Member of a credit association	1.369***	0.175	-1.732	1.141	0.991***	0.126	-1.594	0.992
Member of equb	0.013	0.185	1.034*	0.607	-0.014	0.142	0.836	0.513
Number of casual/self-employed members	-0.048	0.104	-0.193	0.257	-0.043	0.084	-0.164	0.215
Number of formal sector employee members	0.143**	0.067	-0.905***	0.329	0.084	0.051	-0.819***	0.283
Proportion of educated members	1.269***	0.400	-1.872**	0.820	0.985***	0.334	-1.651**	0.663
<i>City and time variables</i>								
Addis Ababa	0.382	0.293	0.591	0.752	0.396	0.247	0.532	0.647
Awassa	-0.789*	0.409	0.348	1.056	-0.487	0.344	0.384	0.921
Dessie	0.206	0.406	-0.554	0.971	0.195	0.353	-0.468	0.848
Intercept	-6.415***	1.126	8.632***	3.058	-5.580***	0.880	6.874***	2.490
Log-likelihood	-594.964		-158.959		-596.508		-158.828	
N	1340		1340		1340		1340	

EN-NPH: Entry into adoption - Non-proportional Hazard Model. *EX-NPH*: Exit from Adoption - Non-proportional Hazard Model.

EN-PH: Entry into adoption - Proportional Hazard Model. *EX-PH*: Exit from Adoption - Proportional Hazard Model.