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Individual and household-level effects of energy poverty on human development

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ABSTRACT

This study investigates some of the predictors of energy poverty, the interrelationships between different expressions of energy poverty, and the human development impacts of energy poverty on primarily rural individuals and households in an underdeveloped country. It uses data from four rounds of Nicaragua's Living Standards Measurement Survey, and examines the effects of energy poverty on income, education, and health.

Chapter 1 provides background information on energy poverty in general, as well as the specific situation that has developed in Nicaragua. It also provides a modeling framework, both conceptual and mathematical, for the ways in which energy poverty impacts human development on an individual and household-level.

Chapter 2 uses a Two-Stage Least Squares model to account for endogeneity between electricity access and income at the household-level. It is found that electricity has a large and significant effect on income. This chapter also estimates the effect of electricity on income levels by income-quantiles. In estimating the effect of electricity on education and health, no endogenous relationship is found. Thus, probit models are used for those specifications. Evidence is found that electricity has a significant impact on primary school completion, but no significant effect on respiratory ailments.

Chapter 3 focuses on the ways in which energy poverty affects the education and health of individuals in a developing country. The manifestations of energy poverty used are whether an individual has access to electricity, and whether or not they rely primarily on firewood for cooking. Data for this chapter comes from the 2014 Living Standards Measurement Survey. The estimations are performed using varying-intercept multilevel logit models. It is found that electricity has a highly significant impact on education, while firewood has a highly significant impact on health.

Chapter 4 employs a difference-in-differences strategy to estimate the relationship between electricity access and off-farm income in Nicaragua, using panel data from 1998 and 2005. Kernel-based propensity score matching is used in both difference-in-differences and quantile difference-in-differences estimation. It is found that electricity access has a large and significant effect on off-farm income, and that this effect increases with income quantiles. Chapter 5 provides concluding remarks.

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Chapter 1

Introduction and Background of Energy Poverty

Energy use in the modern, developed world is starkly different than that experienced by those residing in developing countries. From its effects on work productivity, to the climate controlled rooms that people sleep in; from the means of transportation people use for going to work or school, to the way people spend their leisure time; energy use impacts the human development of individuals in nearly every moment.

Energy poverty has been defined as "the absence of sufficient choice in accessing adequate, affordable, reliable, high-quality, safe and environmentally benign energy services to support economic and human development" (Masud et al., 2007). The UNDP gives a more narrow definition as the "inability to cook with modern cooking fuels and the lack of a bare minimum of electric lighting to read or for other household and productive activities at sunset" (Gaye, 2007). As of 2010, the UNDP's Human Development Report states that 1.4 billion people around the world suffer from a complete lack of access to electricity. Out of the eight Millenium Development Goals formulated in 2005 (Sachs and McArthur, 2005), seven are made directly more difficult in the face of energy poverty (Modi et al., 2005).

This dissertation investigates some of the predictors of energy poverty, the interrelationships between different expressions of energy poverty, and the welfare impacts of energy poverty on primarily rural households in an underdeveloped country. The aspects of welfare that will be investigated are education, health, and income.

Though energy poverty impacts the lives of individuals regardless of income, the effects are most acutely felt by the most vulnerable members of society. Impoverished households in developing countries spend an inordinately higher proportion of their time and efforts dealing with and suffering the consequences of energy poverty, than those with the means to mitigate some of the associated problems (Birol, 2007).

A predominant aspect of how a lack of access to modern energy may affect human development is through income. Access to modern energy creates more employment choices, primarily for women (Dinkelman, 2011; Grogan and Sadanand, 2013). Electricity may also improve labor productivity, through the the use of modern tools powered by electricity, artificial light may lenghten the working day, and cell phones, which require electricity to charge their batteries, improve communications. Given the importance of this, without widespread, affordable energy, it may be difficult for households to climb out of the cycle of poverty.

Education, both formal and informal, may also be augmented by modern energy. The information age has been made possible by widespread electricity access. In households with no access to electricity, information is much more scarce. Also, individuals must rely on candle light for after-sunset reading and homework excersises. Not only is this inefficient, but it may have negative health consequences. Computers and other audiovisual educational aids are only possible with household electrification, and have been shown to have a positive impact on educational outcomes (Beuermann et al., 2015). Household electricity access specifically has been found to yield positive impacts on years of schooling (Bridge et al., 2016; Khandker et al., 2013). Without modern energy sources, children are often responsible for completing household chores such as fetching water and firewood, to the detriment of school attendance (Gebru and Bezu, 2014; Nauges and Strand, 2013). The mechanisms through which schooling is improved by electricity are varied; though it is generally agreed upon that electricity both provides better access to technology, as well as an extension of the school working day(World World Bank, 2008).

Energy poverty has also been shown to lead to negative health outcomes. The reasons for this are varied, but can be placed into two categories: health problems caused by energy poverty, and health problems that are made more difficult to treat due to energy poverty. The primary health consequence that individuals face as a result of energy poverty is respiratory complications due to indoor air pollution (Bruce et al., 2000; Dasgupta et al., 2006; Ezzati and Kammen, 2002). While air pollution has been shown to have large, negative effects on health and life-expectancy (Pope III et al., 2002), air pollution that results from burning biofuels indoors is one of the greatest health concerns facing the developing world (Dasgupta et al., 2006; Kimemia et al., 2013; Sagar, 2005; Edwards and Langpap, 2012). This indoor air pollution is linked to tuberculosis, lung cancer, and respiratory infections, and is responsible for the deaths of an estimated 1.5 million people per year (WHO, 2006).

This figure is larger than the number estimated to die from the use of drugs, alcohol, and tobacco, unsafe sex, and malaria combined (Sovacool, 2012). A highly problematic aspect of this, is that indoor air pollution may disproportionally affect women and children in developing countries, who spend much of their day gathering fuel and burning it indoors (Dherani et al., 2008; Edwards and Langpap, 2012).

Also, unpredictable and unreliable electricity makes it difficult to power health centers and refrigerate items like vaccines, sterilizations, and medicines, thus greatly affecting the quality of health services available to those suffering from illnesses (Birol, 2007). Electric light for patient care after sunset, as well as electrification for medical devices and tools are necessary for a modern, functioning health facility. Increased electricity access also allows for access to information at the household level. Individuals being more informed of certain health risks may lead to improved health outcomes. For example, Dammert et al. (2014) find that households that own mobile phones have better access to health information, and are therefore less likely to contract dengue fever.

The disparities in access to modern energy that exist across the world have spurred an increase in research in this field. Rubrics have been established to measure and define energy poverty (Gaye, 2007; Masud et al., 2007; Reddy, 1999; Pachauri and Spreng, 2004). Shahbaz et al. (2013) investigate the macro-level relationship between energy use and economic growth. On a micro level, studies have shown how better access to modern energy sources creates more employment choices, primarily for women (Dinkelman, 2011; Grogan and Sadanand, 2013). Studies have been performed to estimate the relationship between indoor air pollution and health outcomes (Edwards and Langpap, 2012; Ezzati and Kammen, 2002), as well as the educational effects of electricity access (Khandker et al., 2013; Bridge et al., 2016), while other papers have studied the health risks and productivity challenges of energy poverty (Birol, 2007; Reddy, 1999; Sagar, 2005; Sovacool, 2012).

While existing research investigates particular aspects of energy poverty, this study seeks to provide a more comprehensive understanding of the effect of electricity on human development outcomes. The present study is novel in several ways. First of all, it examines the effects of multiple manifestations of energy poverty, both electricity access and cooking fuels, on human development. It is also novel in that it estimates the impact of energy poverty on multiple measurements of human development. The measurements utilized are consumption, off-farm income, the likelihood of completing primary school, and the risk of experiencing respiratory ailments. Lastly, the present study does this at both the individual and household-level, while also using quantile regression methods to estimate these effects across the income distribution in a poor country. For that purpose, it uses data from four rounds of Nicaragua's Living Standards Measurement Survey.

1.1 Background

The three regions of the world that suffer the most from energy poverty are Sub-Saharan Africa, Latin America, and South Asia (UNDP, 2014). This study will focus on the situation of Nicaragua, which is the least developed country in Latin America. As of 2014 it was ranked 132 out of 187 countries in the United Nations human development index. Table 1.1 shows some statistics of Nicaragua's development indicators in comparison to the other Central American countries. As seen in Table 1.1, Nicaragua has the lowest GDP per capita of any of the surrounding countries, it is among the least educated, and it has the lowest electrification rate. It is also notable from Table 1.1 that Nicaragua has the second highest incidence of child mortality from indoor air pollution in the region.

This low level of human development stems from many historical, geographical, and political factors. Specifically, the low level of electrification is due to political instability and geographical difficulties. Nicaragua was embroiled in civil war from 1978-1990 which destroyed much of the existing infrastructure and drained the country of resources (Miranda and Ratliff, 1992). Besides war, the country has also experienced several natural disasters which have destroyed much infrastructure. Nicaragua also generates the majority of its electricity by burning oil. As it is not an oil producing country, this makes Nicaragua prone to the high price volatility in international oil markets. This high price volatility has contributed to Nicaragua having the highest electricity costs of any of the other Central American countries (Acevedo, 2005). The highest electricity prices, along with the lowest household incomes in the region, combine to contribute to the lowest electrification rate.

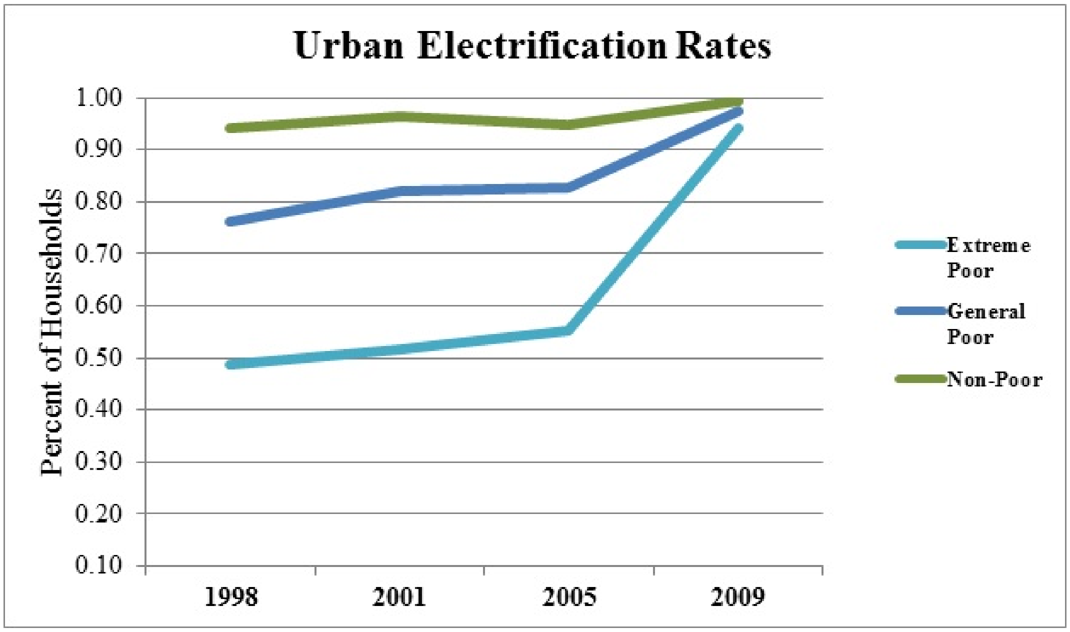
Though only 72% of a population having access to electricity may seem like a bleak situation, it does not give a full understanding of energy poverty in Nicaragua. More information is gained by breaking this statistic down into sub-groups of Nicaragua's population. Figure 1.1 shows the electrification rates for urban residents between the years 1998-2009, using household survey data collected by Nicaragua's National Institute of Development Information (INIDE), and broken down by poverty group. Over the period of 1998-2009 the vast disparity in access to electricity between poverty groups has been largely diminished, with greater than 90% of even extremely poor urban residents sampled having at least some access by 2009.

Human Development in Central America

Country	**Life Expectancy**	**Mean Years of Schooling**	**GDP per capita (2011 PPP $)**	**Unemployment Rate (% ages 15 and older)**	**Electrification Rate (% of pop)**	**Death of children under age five due to indoor air pollution (per 100,000)**
Guatemala	72.1	5.6	6990	2.9	80	57
Belize	73.9	9.3	8438	14.4	100	21
El Salvador	72.6	6.5	7445	6.4	91.6	24
Honduras	73.8	5.5	4423	4.3	79.9	49
Nicaragua	**74.8**	**5.8**	**4254**	**7.8**	**72.1**	**49**
Costa Rica	79.9	8.4	13091	7.8	99.2	2
Panama	77.6	9.4	16655	6.5	88.1	16

Source: United Nations Development Program (2014)

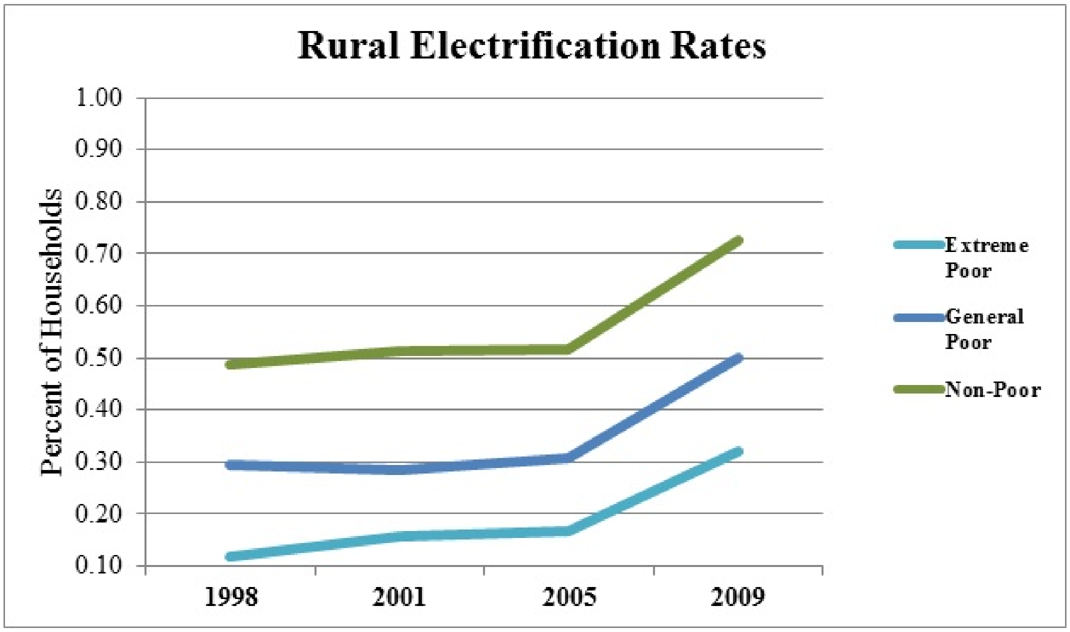
Table 1.1: Human Development in Central America



Source: Nicaragua's Living Standard Surveys, 1998-2009 (INIDE, 1998, 2001, 2005, 2009)

Figure 1.1: Urban Electrification Rates by Poverty Group

Rural populations over the same time period tell a different story. Figure 1.2 displays the electrification rates for rural households between the years 1998-2009, also broken down by poverty group. While an upward trend of household electrification is present between the years 2005-2009, the large electrification inequality persists among poverty groups. Figure 1.2 also shows that only 32% of extremely poor households in rural Nicaragua have even basic access to electricity as of 2009.

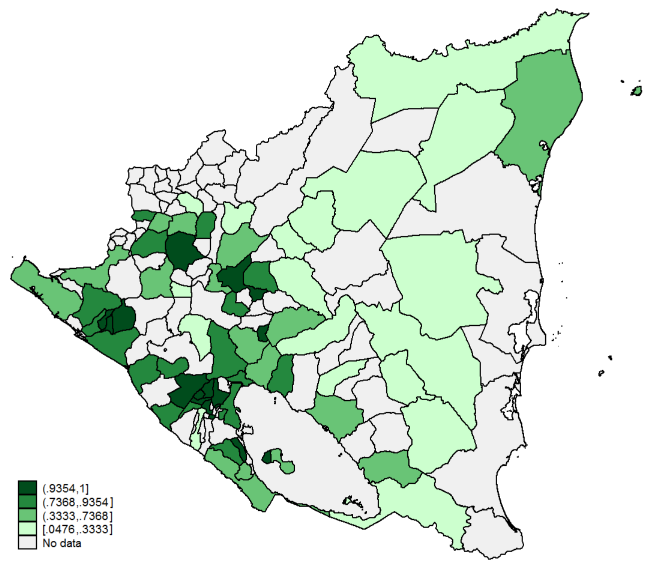


Source: Nicaragua's Living Standard Surveys, 1998-2009
(INIDE, 1998, 2001, 2005, 2009)

Figure 1.2: Rural Electrification Rates by Poverty Group

Figures 1.1 & 1.2 indicate that electricity access depends on more than simply the poverty status of the household. Another notable point from Figure 1.2 is that the general increase in electrification from 2005 to 2009 benefitted the non-poor rural households sampled more so than the extremely poor ones. Non-poor households surveyed went from 51% electrified in 2005 to 73% in 2009, an increase in electrification of 22%. Extremely poor households surveyed over the same time period went from 17% to 32% electrification, an increase of 15%. This would indicate that there are mechanisms affecting electricity access other than rural/urban location and poverty status.

Figure 1.3 looks into the spatial distribution of electricity access in Nicaragua by breaking down rural electrification rates by municipality in 2009. We see that rural electrification is concentrated in the high population municipalities. This seems to indicate that a rural household situated in close proximity to a larger city is more likely to have electricity than a rural household farther removed from metropolitan areas.



Source: Nicaragua's Living Standard Survey (INIDE, 2009)

Figure 1.3: Spatial Distribution of Rural Electrification Rates (2009)

1.2 Modeling Framework

Macro-level GDP growth being correlated with macro-level electricity use has been well documented, as discussed above. However, the specific impacts of access to electricity on the micro-level require further investigation. Our research questions are (1) whether household access to electricity is interrelated with income levels in a statistically-significant way, (2) how exactly electricity access and income levels are interrelated, and (3) what the relevant magnitudes are of these relationships.

The intuitive and anecdotal explanation for electricity's impact on consumption is that electricity improves health, education, and employment outcomes (Birol, 2007). Figure 1.4 displays a conceptual framework for these relationships.

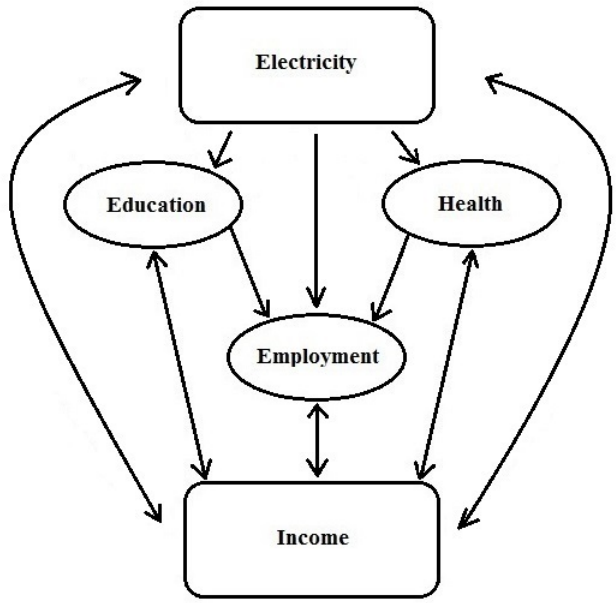


Figure 1.4: Conceptual Model of the Interrelationship Between Electricity Use and Income

Notice in Figure 1.4 that there are several double-sided arrows indicating that causality in theory runs both ways. It is understood, for example that an increase in modern electricity usage will lead to an increase in income through better educational outcomes. It is also true, however, that an increased amount of income enables a household to seek higher qualities of education. Due to this bi-directional causality and others, estimation of these relationships will require an econometric model that accounts for simultaneity.

Most rural households in developing countries engage in some level of home production. The output from these households is both sold in the market and used for own-home consumption (Singh et al., 1986). Also, the factors of production are partly purchased in the market (fertilizer or tools, for example), and partly provided by the household itself (family labor). The theoretical underpinnings of this study are thus presented as a general model of a rural household acting as both producer and consumer, as well as a supplier of labor.

Our model adapts Singh et al. (1986) to show the particular impact of energy use and demand on rural household production and consumption behavior. This model will account for two types of energy use; household energy use (X_e), and energy use as a factor input (F_e) where it is used to augment labor productivity (Barnes and Binswanger, 1986). Thus, total energy (E) is the sum of $X_e + F_e$.

A represetative rural household is assumed to maximize a utility function:

$$U = U\left(X_h, X_m, X_l, X_e\right) \tag{1.1}$$

where (X_h) is household production, (X_m) is a market purchased good, (X_l) is leisure, and (X_e) is household energy. Household energy factors directly into the utility function by potentially providing the household with amenities such as artificial light after dark, cell phones, televisions, etc.

The household faces a production constraint, a time constraint, and a cash constraint. The production constraint shows the relationship between household production inputs and output:

$$Q_h = Q\left(L, F_e, K_H\left(F_e\right), K_v\right) \tag{1.2}$$

where (L) is total labor input, (F_e) is energy as a factor input, (K_H) is the stock of human capital, and $(K_v)$is the fixed stock of manufactured, financial, and natural capital. The stock of human capital $(K_H)$is measured in terms of education and health, and is a function of energy as a factor input (F_e). So energy as a factor input enters our production function directly through augmenting labor productivity, and indirectly through augmenting human capital. The level of rural household production will vary based on many factors such as skill and the quality and availability of inputs, etc. These and many other variables are omitted from this model for ease of exposition. It is assumed that production does not suffer from uncertainty, and that a representative household will have no impact on the prices of inputs or outputs.

The household time constraint is given as:

$$X_l + F_L = T \tag{1.3}$$

where (T) is the total available time for the household, and family labor as a factor of input is given as (F_L). The last constraint faced by the household is the cash constraint:

$$p_m X_m + p_e X_e = p_h\left[Q\left(L, F_e, K_H\left(F_e\right), K_v\right) - X_h\right] - p_l\left(L - F_L\right) - p_e\left(F_e + K_H\left(F_e\right)\right) \tag{1.4}$$

where (p_m) is the price of the market purchased good, (p_e) is the price of energy, and (p_l) is the market wage. As (L) is total labor and (F_L) is family provided labor, if $L - F_L$ is positive then it is equal to non-family hired labor, and if it is negative then it is equal to off-farm family labor. The structure of equation 1.4 is such that the left-hand side is equal to the household cash expenditures, and the right-hand side is equal to total cash income obtained by selling household production and labor.

By collapsing all of the constraints in equations 1.2, 1.3, and 1.4 we get:

$$p_m X_m + p_e X_e + p_h X_h + p_l X_l = \pi + p_l T \tag{1.5}$$

where $\pi = p_h Q\left(L, F_e, K_H\left(F_e\right), K_v\right) - p_l L - p_e\left(F_e + K_H\left(F_e\right)\right)$ is the profit from home production. The left-hand side of equation 1.5 is the total household expenditure, while the right-hand side is the full income constraint. A household maximizes utility in equation 1.1 subject to the full income constraint in equation 1.5. The first order conditions for deriving the input demand functions for labor, energy, and human capital are given as

$$p_h \frac{\delta Q}{\delta L} = p_l \tag{1.6}$$

$$p_h\left(\frac{\delta Q}{\delta F_e} + \frac{\delta Q}{\delta K_H}\frac{\delta K_H}{\delta F_e}\right) = p_e\left(1 + \frac{\delta K_H}{\delta F_e}\right) \tag{1.7}$$

where the standard rule applies that a producer hires factor inputs up to the point where the marginal value productivity of the input is equal to the price of the input.

Solving the first order conditions in equations 1.6 and 1.7 yields the input demand functions shown as

$$L^* = L^*\left(p_l, p_e, p_h\right) \tag{1.8}$$

$$F_e^* = F_e^*\left(p_l, p_e, p_h\right) \tag{1.9}$$

$$K_H^* = K_H^*\left(F_e^*\left(p_l, p_e, p_h\right)\right) \tag{1.10}$$

By substituting the optimal levels L^*, F_e^*, and K_H^* from 1.8, 1.9, and 1.10 into equations 1.5 we get

$$p_m X_m + p_e X_e + p_h X_h + p_l X_l = Y^* \tag{1.11}$$

where Y^* is the value of total household consumption associated with the profit maximizing behavior of

$$Y^* = p_h Q\left(L^*, F_e^*, K_H^*, K_v\right) - p_l L^* - p_e\left(F_e^* + K_H^*\left(F_e^*\right)\right) + p_l T \tag{1.12}$$

Maximizing utility from equation 1.1 subject to this new constraint gives the first order condition of

$$\frac{\delta U}{\delta X_i} = \lambda p_i \,\forall\, i = m, e, h, l \tag{1.13}$$

The solution to equation 1.13 gives the standard demand curve for household energy use

$$X_e^* = X_e^* \left(p_m, p_e, p_h, p_l, Y^*\right) \tag{1.14}$$

which, combined with equation 1.9 gives the total demand for energy as

$$E^* = X_e^* + F_e^* = E^* \left(p_m, p_e, p_h, p_l, Y^*\right) \tag{1.15}$$

Simplifying equations 1.12 and 1.15 to focus primarily on consumption and energy gives

$$Y^* = Y^* \left(E^*, K_H^*, \vec{v_Y}\right) \tag{1.16}$$

$$E^* = E^* \left(Y^*, \vec{v_E}\right) \tag{1.17}$$

where $Y^*$is being expressed as being determined by energy, human capital, and a vector of other covariates ($\vec{v_Y}$)and $E^*$is expressed as being determined by the level of consumption and a vector of other covariates ($\vec{v_E}$). As human capital is measured in terms of education and health, equations 1.16 and 1.17 show the theoretical basis for consumption, energy, education, and health being determined simultaneously. This allows us to examine these relationships by econometric estimation.

1.3 Dissertation Structure

The remainder of this dissertation will be structured as follows. Chapter 2 will examine the household-level effects of energy poverty on income, education, and health. It uses a Two-Stage Least Squares model to account for endogeneity between electricity access and income at the household-level, as well as across the income distribution. The findings of this section are that electricity has a large and significant effect on income (as measured by consumption), and that this effect increases in both significance and magnitude as a household moves along the income distribution. This chapter also estimates the effects of electricity on education and health. As there is no evidence of endogeneity between these variables in the data used, probit models are used for these specifications. Evidence is found that electricity has a significant impact on household primary school completion, but no significant effect on household respiratory ailments.

Chapter 3 focuses on the ways in which energy poverty affects the education and health at an individual level in a developing country. This chapter analyzes two manifestations of energy poverty: whether an individual has access to electricity, and whether or not they rely primarily on firewood for cooking. Whether or not an appropriately-aged child has completed primary school is used as the measurement of educational effects, while whether an individual suffers from a cough, cold, or other respiratory problem is used to measure the impact of energy poverty on health. Data for this chapter comes from the 2014 Living Standards Measurement Survey. The estimations are performed using varying-intercept multilevel logit models. It is found that electricity has a highly significant and positive impact on education, while firewood reliance has a highly significant and detrimental impact on health.

Chapter 4 employs a difference-in-differences strategy to estimate the relationship between electricity access and off-farm income in Nicaragua, using panel data from 1998 and 2005. Kernel-based propensity score matching is used in both difference-in-differences and quantile difference-in-differences estimation. It is found that electricity access has a large and significant effect on off-farm income, and that this effect increases with income quantiles. Chapter 5 provides concluding remarks.

Chapter 2

The effects of electricity on human development: Evidence from Nicaraguan households

The household data for this chapter come from the living standards measurement surveys (LSMS) conducted in Nicaragua in 2009 (INIDE, 2009). This is a nationally-representative survey which follows the methodology developed by the World Bank. The survey contains living standards information from 6,515 households. This household survey data was combined with municipal population density data from the 2005 National Census (INIDE, 2006), as well as geographic data on the mean slope of the land at the municipal level. This geographic data was compiled by Grogan and Sadanand (2013). Finally, we add tree cover data at the department-level (Global Forest Global Forest Watch, 2000) to complete the data set used for this analysis.

In order to econometrically estimate the effects of energy poverty on human development, it is necessary to have exogenous variation in the data with regards to energy use. As seen in Figure 1.3, electricity access is becoming ubiquitous in the large urban areas of Nicaragua. The four largest municipalities that exhibit widespread electrification are Managua, Leon, Granada, and Matagalpa. For this reason, households within these municipalities are excluded from estimation.[1]

The primary household indicators of interest for this study are income (measured by consumption levels), electrification, education levels, and health outcomes. Due to living conditions in developing countries, household consumption is used as a measurement of welfare over the more traditional use of income. This is due to consumption levels exhibiting less fluctuation than income levels in developing countries (Ravallion, 1992). Consumption is also a more reliable and accurate reflection of welfare as it is not distorted by taxation levels. The consumption variable in the data is an aggregated continuous variable that measures per capita yearly costs of food, beverages, and non-food products and services (e.g. housing, health, education, furnishings, transportation, personal expenses, and home maintenance).

[1] The discussion on Table 2.1 will give more detail as to this decision making process

This consumption variable is also used to classify households into three poverty categories; extremely poor, general poor, and non-poor. Extremely poor households were classified as such if their food consumption levels fell below the minimum daily calorie requirements, which have been estimated at 2,268 calories (INIDE, 2011). The cost of meeting this minimum requirement has been estimated at 6,903.08 Nicaraguan Cordobas (C$) per person per year. This is roughly the equivalent of US$ 334.79, in 2009 dollars. The level of extreme poverty for rural households sampled is 15% (256 out of 1,671), and 3% for urban households (123 out of 4,794).

The level of annual per capita consumption required to meet minimum daily caloric requirements plus a sufficient amount for housing, transportation, education, health, and clothing was set at C$ 11,725.09 (US$ 568.65). If a household's consumption level falls between this line and that for extreme poverty then it is classified as general poor. Households with consumption levels higher than the general poverty line are classified as non-poor.

There are two ways for measuring electricity access, dichotomous and continuous. If a household reports its primary light source as coming from the electrical grid, a generator, or a solar panel then it is classified as having access to electricity. There is plausible variation in outcomes however between a household that has just enough electricity to power a single light bulb for one hour per day (not uncommon in Nicaragua), and one that has enough access to power multiple light sources and appliances at any hour of the day or night. To illustrate this concept, in 2009 roughly 35% of households with electricity reported to purchasing fuel, gas, or kerosene as a supplementary light source.

One approach to overcoming this challenge is using the amount paid per month for electric power consumption as a continuous variable. This solution is not without some issues however. First, not every household pays for the electricity they consume. For example, in 2009, 20% of urban and 22% or rural households reported that they did not pay for the electricity consumed. The second issue is more technical in nature, as a continuous variable bounded at zero, with a non-uniform distribution poses difficulties for statistical analysis. For these reasons this chapter will primarily use dichotomous household electricity use for estimating its effects.

Education is measured on the household level as average years of education by those ages six and older, which is an approximation for the household education status (Barro and Lee, 2001). For the health aspect of this chapter, a household variable is included as a dichotomous measurement of whether or not a family member has a cough, cold, or respiratory disease. For a full understanding of the ways in which electrification impacted household health outcomes, more data would be beneficial. For example, health measurements at the municipality-level pertaining to electricity use by hospitals or clinics would be illuminating. The amount of time that households spend purchasing or foraging for electric light substitutes would also likely have repercussions on health outcomes. In the absence of such data, whether a household member suffers from a cough, cold, or other respiratory concern is used as a proxy for the general health status of the household.

In order to investigate the research question at hand, variation in the above mentioned variables is beneficial for statistical analysis. It is therefore important that we use as observations those households that exhibit this variation. Specifically, we want to look at subsections of our data that show variation in electricity access, consumption, educational outcomes, and heath measurements.

For example, even though households in the Managua region exhibit massive variation in consumption, it would prove difficult to estimate the impact of electricity on Managua residents, as it is nearly universal. Table 2.1 reports summary statistics for some of our variables of interest broken down by subsections of the population.

In Table 2.1 we see that over 99% of Managua households have access to electricity, compared with only 78% of all households outside of big urban municipalities. As focusing only on strictly-rural households would reduce the sample size unnecessarily, all households outside of big urban municipalities are included. This way the sample size remains large, while still exhibiting variation in the key measurments.

	All Households (6465 obs)		Households in Managua municipality (3004 obs)		Households not in Managua municipality (3461 obs)		Households outside of big urban municipalities* (3240 obs)		Rural housholds outside of big urban municipalities (1508 obs)	
Variable	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Electricity (% of households)	88.6	31.8	99.6	0.66	79.1	40.6	78	41.1	55.4	49.7
Consumption (2009 C$ per capita)	22616	18513	27501	21021	18376	14767	18268	14294	14241	10698
Average years of education (household)	6.6	3.7	7.9	3.6	5.5	3.4	5.5	3.4	4.1	2.8
Primary school completion rate (% of hh members)	70	34.8	81	28	60.8	36.8	60.7	36.9	45.9	36.5
Cough, cold, or respiratory disease (% of households with an instance of)	58.4	49.3	56.4	49.6	60	48.9	59.3	49.1	64.1	47.9

Table 2.1: Descriptive Statistics by Data Partition

Table 2.2 displays descriptive statistics of the primary variables used in estimating equations 1.16 and 1.17. Consumption is measured in terms of per capita 2009 Nicaraguan Cordobas per household. The indicator "Extreme Poor" is a dichotomous variable indicating whether a household is classified as extremely poor, as previously detailed.

"Age", "Education", and "Gender" refer to the status of those variables of the household head, with Gender equal to one if the household head is male. The regressor "Respiratory Problems" is a dichotomous variable equal to one if a member of the household suffers from a cough, cold, or other type of respiratoy problem. "Toilet" is a dichotomous variable equal to one if the household has a toilet in the home.

The variable "One Room" is equal to one if the household has no dedicated bedrooms in the house. Though only the housseholds outside of the large, urban areas are included in the observations, each household remains classified as "Rural" or "Urban". "Paved Road" is an indicator equal to one if the main access to the household is paved, and equal to zero otherwise.

"Straw Roof" and "Dirt Floor" indicate whether these are characteristics of the household. "Fetch Water" is equal to one if the household has no indoor plumbing and has to fetch their own water supply. "Household Size" is the total number of residents of the household.

Descriptive Statistics: all households besides big urban areas

Variable	n	mean	sd	min	max
Consumption (2009 C per capita)	3240	18268.17	14294.37	1955.024	177535
Extreme Poor	3240	0.0950	0.2933	0	1
Electricity	3240	0.7802	0.414	0	1
Age	3240	46.3	15.8	15	97
Education (head)	3238	5.0688	4.6237	0	22
Gender (head)	3240	0.6895	0.4628	0	1
Years of Education (household mean)	3288	5.47	3.4147	0	18
Respiratory Problem	3240	0.5932	0.4913	0	1
Toilet	3240	0.1963	0.3973	0	1
Forage	3240	0.4096	0.4918	0	1
One Room	3240	0.3552	0.4787	0	1
Rural	3240	0.4654	0.4988	0	1
Paved Road	3240	0.5040	0.5001	0	1
Straw Roof	3240	0.0225	0.1484	0	1
Dirt Floor	3240	0.4383	0.4962	0	1
Fetch Water	3240	0.4006	0.4901	0	1
Household Size	3240	5.15	2.77	1	31

Table 2.2: Descriptive Statistics

2.1 Consumption

The scope of this study is to investigate the ways and mechanisms in which access to modern energy sources impacts quality-of-life for households in the developing world. Tables 1.1-2.1 give an initial impression that modern energy is negatively correlated with poverty in Nicaragua. In order to arrive at a more in-depth understanding of these impacts, we turn to more rigorous methods.

As seen in equations 1.16 and 1.17, human development as measured by education, health, and consumption is co-determined with energy use. Care is required however, in estimating these endogenous relationships. It should be easy to measure, for example, how higher income levels lead to higher degrees of energy use. It should also be fairly obvious that an increase in energy use may result in an increase in income through enhanced labor productivity. This endogenous relationship can reasonably be expected to reveal itself in the estimation procedure.

The codetermination of energy and health, or energy and education may be a bit more complicated. While energy use may have a direct effect on health and education measurements, the inverse effect will likely come indirectly through the income component. Indirect effects often are subject to time horizons that fall outside of the scope of cross-sectional data. This must be kept in mind throughout the proceeding estimation efforts.

We first analyze the interrelationship between consumption and energy poverty. As a preliminary look at the relationship between these two variables, Table 2.3 displays the correlation between per capita consumption and electricity acccess among all households outside of large urban environments.

Correlation		
	Electricity	Consumption
Electricity	1	*
Consumption	0.2564	1

Table 2.3: Correlation between Consumption and Electricity

Table 2.3 verifies the notion from Tables 1.1 through 2.1 that there is a relatively high correlation between income and electricity.

The next aspect to investigate is the endogenous nature of the outcomes. This endogeneity will be addressed through the use of instrumental variables. When estimating two equations simultaneously, the requirements of a valid instrument require that it is correlated with the dependent variable in the first equation while being uncorrelated with the error term in the second equation.

In the current application, this requires that one or more variables is used that is correlated with having access to electricity while being uncorrelated with consumption. In order to meet these requirements, three instrumental variables are included in the following correlation table (Table 2.4). These variables are (1) the mean slope gradient of the land in the municipality, (2) the population density in the municipaluity as measured in 2005 by the Nicaragua census (INIDE, 2006), and (3) the amount of tree cover in the municipality.

	Correlation			
	Electricity	Population Density	Tree Cover	Mean Slope
Electricity	1			
Population Density	0.2962	1		
Tree Cover	-0.4051	-0.2666	1	
Mean Slope	-0.1348	0.1515	0.1161	1

Table 2.4: Correlation between Electricity and Instruments

Table 2.4 displays high positive correlation between electricity and population density, high negative correlation between electricity and tree cover, and moderate negative correlation between electricity and mean land slope. While the correlation of mean slope is lower than the others, it is not so low as to rule out its usage as a valid instrument.

The estimation technique that will be followed is an instrumental variable approach. Equations 2.1 and 2.2 show this estimation strategy, drawing from Eqs. 1.16 and 1.17:

$$Y_i = \alpha_0 + \alpha_1 E_i + \vec{\beta}' \vec{X_{ci}} + \epsilon_{ci} \tag{2.1}$$

where Y_i is per capita consumption for household i, α_0 is an intercept, E_i is a dichotomous variable equal to one if household i has access to electricity and equal to zero otherwise, $\vec{X}_{ci}$ is a vector of regressors relating to the consumption of household i, while ϵ_{ci} is error term. The electricity equation is given as:

$$E_i = \gamma_0 + \vec{\gamma}' \vec{z}_i + \vec{\delta}' \vec{X}_{ei} + \epsilon_{ei} \tag{2.2}$$

where γ_0 is an intercept, $\vec{z}_i$ is a vector of instrumental variables, $\vec{X}_{ei}$ is a vector of regressors relating to the electricity access of household i, while ϵ_{ci} is an error term. This estimation will take place in two stages. First, equation 2.2 will be estimated using OLS, as a linear probability model. Once this is estimated, the predicted value of electricity $(\hat{E}_i)$ will be used to replace the regressor for electricity in equation 2.1, with equation 2.1 becoming

$$Y_i = \alpha_0 + \alpha_1 \hat{E}_i + \vec{\beta}' \vec{X_{ci}} + \epsilon_{ci} \tag{2.3}$$

The results of equations 2.3 and 2.4 are found in Table 2.5.[2] A Hansen's J-test for overidentifying restrictions returns a p-value of 0.9834, failing to reject the null hypothesis of valid overidentifying restrictions. It is also shown in Table 2.5 that the three instruments chosen are highly statistically significant in the electricity equations, with the anticipated signs. An increase in population density will likely result in an increase in availability of electricity access. Whereas higher levels of tree cover and land slope would likely make extension of the electrical grid more challenging.

High R-squared and Adjusted R-squared measurements (0.487 and 0.484) suggest that the instruments used are not weak. Also, the nominal size of a 5% Wald test for this model is 22.30, which is exceeded both by the Robust F-Statistic (24.3792) and the minimum Eigenvalue statistic (26.9277). Thus, the null hypothesis of weak instruments is firmly rejected.

Using instrumental variables, it is observed that a household accessing electricity consumes 38.4% per capita more than a household without. The magnitude of this effect is quite large, especially in light of the magnitudes of the other regressor coefficients. For example, these results suggest that the impact that electricity has on household consumption is equivalent to roughly seven more years of education per person in the household. While this result is certainly very large, it is a testament to the multitude of ways that modern energy has the ability to transform life in a developing country.

Other significant results from the model that show an increase in household per capita consumption are average years of education, having a male head of household, and residing in a rural area. This last indicator may at first glance appear counterintuitive. It is a reasonable result however,when considered in light of everything else that is held constant. This could be an indication of land ownership or a greater means of transportation to and from a rural residence.

An increase in household size is seen to reduce per capita consumption. This is expected as it signifies a greater number of people consuming the same amount of resources. Households that forage for firewood are associated with a reduction in per capita consumption as well. Having a dirt floor is correlated with reduced consumption, as could be expected.

Pacifico, Central, Atlantico, and Managua are the four main departments of the country. For this analysis, Managua is excluded while the other three departments are included as measurements against Managua. It appears that, holding all else constant, a household in the Atlantico department experiences an increase in consumption over a household in the Managua department.

It is important to note that while the households residing within the municipality of Managua are not included in the observations, there remain 1,164 households within the larger department of

[2]As a robustness check, equations 2.3 and 2.4 are estimated using a number of various techniques. We find that our results remain qualitatively the same. Results available upon request.

Managua that are included in the sample.

	Two-Stage Least Squares	
	Consumption (ln)	**Electricity**
Electricity	0.3841**	
	(0.1573)	
Household Size	-0.0822***	0.0045**
	(0.0039)	(0.0018)
Years Education (mean)	0.05264***	0.0091***
	(0.0033)	(0.0017)
Paved Road	0.0319	0.0955***
	(0.0263)	(0.0132)
Age	0.0015	-0.0027
	(0.0028)	(0.0018)
Age Squared	-0.0001	0.0001
	(0.0001)	(0.0001)
Gender (head)	0.0527***	-0.0077
	(0.0173)	(0.0110)
Fetch Water	0.05125	-0.1724***
	(0.0352)	(0.0162)
Forage	-0.1736***	-0.1602***
	(0.0356)	(0.0165)
Straw Roof	0.0409	-0.2593***
	(0.0650)	(0.0325)
Dirt Floor	-0.1644***	-0.0626***
	(0.0201)	(0.0134)
Rural	0.0784***	-0.0884***
	(0.0280)	(0.0145)
One Room	-0.1125	-0.0315**
	(0.0182)	(0.0130)
Pacifico	-0.0196	-0.0197
	(0.0199)	(0.0140)
Central	0.0005	0.0419**
	0.0255	(0.0205)
Atlantico	0.1361***	-0.0078
	(0.0429)	(0.0369)
Population Density (log)		0.0459***
		(0.0058)
Tree Cover		-0.3958***
		(0.0855)
Mean Slope		-0.0054***
		(0.0014)
Constant	9.474198***	0.9593***
	(0.1645)	(0.0694)

Source: Nicaragua LSMS 2009. Households outside of large, urban municipalities included. Robust standard errors are in parentheses.
*, **, ***: Significant at 10%, 5%, and 1% level, respectively.

Table 2.5: Electricity access and consumption in Nicaragua

Table2.5 shows the positive and significant effect of electricity on household per capita consumption across the sample. It gives little detail however, about how electricity affects consumption within the various levels in the distribution of wealth. In order to better understand how electricity affects the households in various income levels, quantile regression is used.

Where standard linear regression explains the average relationship between a set of covariates and the dependent variable based on the conditional mean function $E(y|x)$, quantile regression summarizes the relationship between a set of covariates and the dependent variable based on the conditional median function $Q_q(y|x)$ where the median is quantile q of the empirical distribution (Koenker, 2005). The quantile $q\epsilon(0,1)$ is the value of the dependent variable (y) which divides the data into proportions q below and $(1-q)$ above.

The optimization of a quantile regression uses linear programming methods. The $q'th$ quantile regression estimator $\hat{\beta}_q$ minimizes over β_q the objective function

$$Q(\beta_q) = \sum_{i:y_i \geq x_i'\beta}^{N} q|y_i - x_i'\beta_q| + \sum_{i:y_i < x_i'\beta}^{N} (1-q)|y_i - x_i'\beta_q| \tag{2.4}$$

where $0 < q < 1$, and β_q is used rather than β to emphasize the fact that different levels of q estimate correspondingly different values of β (Cameron and Trevedi, 2009).

Table 2.6 displays the results of a quantile regression of the predicted values of electricity from equation 2.2 and the other covariates on the log of per capita consumption. There are several interesting aspects of the results found in Table 2.6. First of all, there is now a more clear picture of how electricity impacts households of different consumption levels. In households under the 25th consumption percentile, electricity has no significant effect on increasing consumption.

At the 50th percentile there begins to appear significance, but only at the ten percent level. It is seen that at the upper end of the consumption distribution electricity has an increasingly large and increasingly significant impact on consumption. This may be explained by levels of human capital. Electricity acts as an augmenter of productive capacity. Households living in levels of poverty or extreme poverty are likely to have very low levels of education and productive capacity, giving electricity very little to augment. At the higher ends of the income distribution, households will likely have the human capital to use electricity to its fullest extent. This will have compounding impacts on consumption levels.

Quantile Regression

	Quantile				
Consumption (per capita)	0.10	.025	0.50	0.75	0.90
Electricity	-0.0622	0.2295	0.3464*	0.4722**	0.7980***
	(0.2032)	(0.1841)	(0.1925)	(0.2116)	(0.2498)
Household Size	-0.1001***	-0.0791***	-0.0836***	-0.0796***	-0.0782***
	(0.0048)	(0.0037)	(0.0033)	(0.0048)	(0.0044)
Years Education (mean)	0.0578***	0.0573***	0.0542***	0.0501***	0.0521***
	(0.0036)	(0.0036)	(0.0038)	(0.0040)	(0.0051)
Paved Road	0.0889***	0.0494*	0.0558**	0.0396	-0.0332
	(0.0267)	(0.0301)	(0.0284)	(0.0329)	(0.0404)
Age	0.0047	0.0015	0.0020	0.0020	0.0060
	(0.0039)	(0.0041)	(0.0033)	(0.0042)	(0.0046)
Age Squared	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Gender (head)	0.0468**	0.0475**	0.0528***	0.0530**	0.0830***
	(0.0198)	(0.0200)	(0.0195)	(0.0208)	(0.0280)
Fetch Water	-0.0404	0.0240	0.0191	0.0582	0.0774
	(0.0428)	(0.0392)	(0.0400)	(0.0434)	(0.0515)
Forage	-0.2397***	-0.2085***	-0.1958***	-0.2343***	-0.2417***
	(0.0431)	(0.0389)	(0.0382)	(0.0413)	(0.0515)
Straw Roof	-0.0453	0.0295	0.0552	0.0364	0.1397
	(0.1766)	(0.0998)	(0.0784)	(0.0627)	(0.1794)
Dirt Floor	-0.1747***	-0.1624***	-0.1580***	-0.1922***	-0.1474***
	(0.0254)	(0.0260)	(0.0247)	(0.0273)	(0.0338)
Rural	0.0308	0.0749**	0.0746	0.1072***	0.1108**
	(0.0340)	(0.0324)	(0.0327)	(0.0341)	(0.0435)
One Room	-0.1371***	-0.1386***	-0.0970***	-0.0718***	-0.0718**
	(0.0233)	(0.0234)	(0.0222)	(0.0239)	(0.0294)
Pacifico	-0.0152	-0.0144	-0.0478**	-0.0290	-0.0035
	(0.0220)	(0.0244)	(0.0225)	(0.0256)	(0.0300)
Central	-0.0707**	-0.0145	-0.0033	0.0201	0.0507
	(0.0304)	(0.0322)	(0.0311)	(0.0320)	(0.0432)
Atlantico	0.0308	0.0992*	0.1224**	0.1636***	0.3000***
	(0.0610)	(0.0514)	(0.0542)	(0.0590)	(0.0692)
_cons	9.3781***	9.2846***	9.4375***	9.6122***	9.4446***
	(0.2227)	(0.2079)	(0.2085)	(0.2346)	(0.2723)

Source: Nicaragua LSMS 2009. Households outside of large, urban municipalities included. Robust standard errors are in parentheses.
*, **, ***: Significant at 10%, 5%, and 1% level, respectively.

Table 2.6: Electricity access and consumption quantiles

An interesting outcome of Table 2.6 is that the education coefficient remains highly significant throughout the consumption distribution. This result is meaningful as even a household in extreme poverty will benefit from an increase in education in a statistically significant way. A visual representation of the results from Table 2.6 can be seen in Figure 2.1.

Impacts on Per Capita Houshold Consumption by Quantile

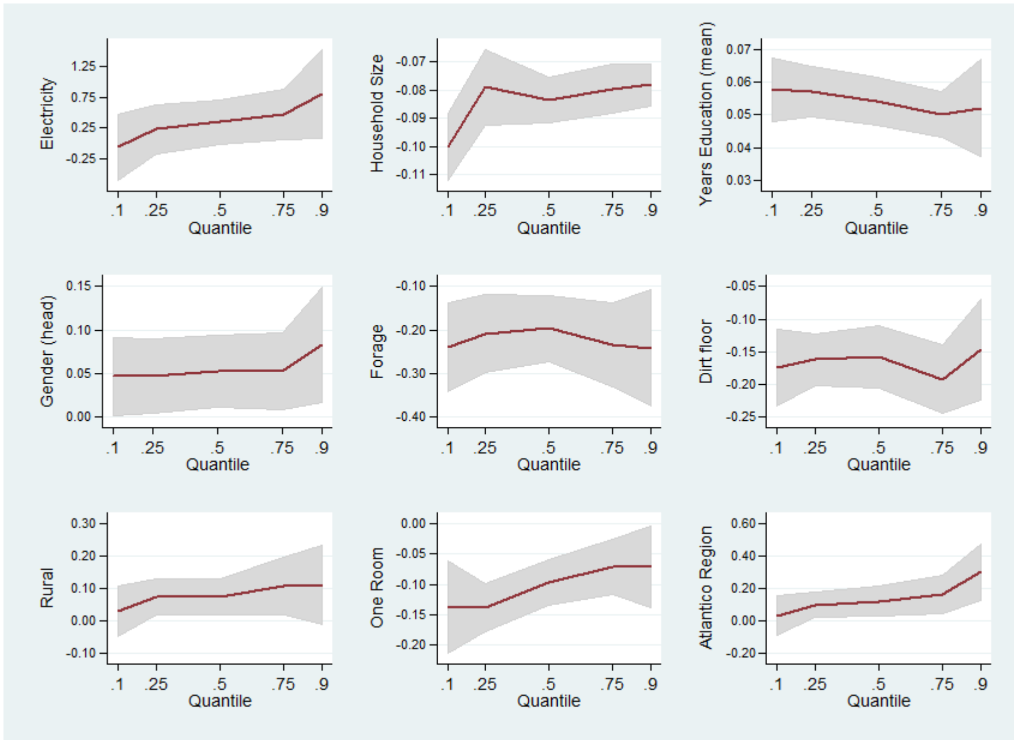


Figure 2.1: Consumption quantiles

2.2 Education

As mentioned above, electricity access and educational outcomes will likely be simultaneously determined in the long run, but this impact may be indirect. In other words, a household obtaining access to electricity will not immediately experience an increase in average years of education. These effects will take time. For these reasons, endogeneity when measuring the impact on education is less of a concern.

These reasons also make it necessary to examine the effect of electricity on education through a different measurement. One standard measurement of education in the developing world is primary school completion rates (UNESCO, 2009). This chapter will look at whether all of the appropriately aged children in a household completed primary school.

To identify the impact of electricity on educational outcomes, the following equation is estimated by using a probit model:

$$PR(PRIMARY)_i = \beta_0 + \beta_1 * E_i + \vec{\eta} * \vec{X}_i + \epsilon_i \tag{2.5}$$

where i refers to the household in question. Household controls in $\vec{X}_i$ are similar to those in Eqn. 2.3, with the addition of the number of school-aged children in the home (N_sch), the adult literacy rate (Literacy), and the consumption status of the home (Not Poor) which is a dichotomous variable indicating whether or not a household is considered poor as discussed in section 3.1. The results of Eqn. 2.5 are shown in Table 2.7.

	Probit: Full Primary School Completion
Electricity	0.0572**
	(0.0252)
N_sch	0.0940***
	(0.008)
Literacy	0.1695***
	(0.0303)
Not Poor	0.0955***
	(0.0191)
Rural	0.0012
	(0.0246)
Age	0.0153***
	(0.0025)
Age Squared	-0.0001***
	(0.0000)
Gender (head)	-0.0276
	(0.0212)
Fetch Water	-0.0616***
	(0.0219)
Straw Roof	-0.0347
	(0.0752)
Dirt Floor	0.0035
	(0.0235)
One Room	-0.0663***
	(0.0165)
Paved	-0.003
	(0.0171)
Pacifico	0.0015
	(0.0187)
Central	0.0067
	(0.0230)
Atlantico	-0.0954***
	(0.0342)
N	3233

Source: Nicaragua LSMS 2009. Households outside of large, urban municipalities included. Marginal effects reported. Clustered standard errors by municipality are in parentheses.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 2.7: Educational outcomes

Here it is shown that there is a positive and significant relationship between a household having electricity and all of the children completing primary school. The number of school-aged children in the home is also positively related with primary school completion. This is expected as more children are likely to complete primary school, controlling for all the other covariates. The adult literacy rate in the household, along with the household not being labelled as poor, both havestrong positive effects on primary school completion.

One interesting outcome of this model is that if the household has to fetch its water supply, the children are less likely to all finish primary school. Having controlled for poverty status, this would suggest that the children are needed to fetch the water at the expense of going to school.

2.3 Health

The last of the human development indicators that will be investigated is health. The health measurement that will be used is whether a household member suffers from a cough, cold, or other respiratory problem, as discussed in section 3.1. This will also be estimated through the use of a probit model given as:

$$PR(RESP)_i = \beta_0 + \beta_1 * E_i + \vec{\nu} * HHCO\vec{N}TRL_i + \epsilon_i \tag{2.6}$$

where i refers to the household in question. Household controls include whether the household resides in a rural area, whether the household is poor, the age (and age squared) of the household head, the gender of the housheold head, whether the household fetches water, straw roof, one room, and regional controls. The sample of households included are again those residing outside of large urban areas.

The results of equation 2.6 are included in Table 2.8. It is seen that electricity, as measured here, does not have a statistically significant effect on health. This is likely due to the available measurements in the data, which motivates further inquiry into the interrelationships between electrification and health. It is shown that living in rural areas increases negative health outcomes. This is likely due to unobservables in the data that affect health. Poverty level has a highly significant impact on health, with a household not being classified as poor exhibiting a 13.97% decrease in the probability of a household member suffering from a cough, cold, or other respiratory problem. The last two items of note are “Gender” and “Straw Roof”. Table 2.6 showed that having a male head of household is associated with increased consumption, so it is likely that this variable is picking up wealth effects outside of just poverty classification. The inverse is true of “Straw Roof”, where it is a proxy for other unobserved characteristics which will negatively influence health outcomes.

Probit: Cough, Cold, or Other Respiratory Problem	
Electricity	0.0180
	(0.0259)
Rural	0.0784**
	(0.0274)
Not Poor	-0.1397***
	(0.0152)
Age	0.0039
	(0.0030)
Age Squared	-0.0001**
	(0.0000)
Gender (head)	-0.0360**
	(0.0166)
Fetch Water	-0.0141
	(0.0228)
Straw Roof	0.1210**
	(0.0519)
One Room	-0.0001
	(0.0202)
Pacifico	0.0142
	(0.0504)
Central	-0.0495
	(0.0492)
Atlantico	-0.0306
	(0.0481)
N	3240

Source: Nicaragua LSMS 2009. Households outside of large, urban municipalities included. Marginal effects reported. Clustered standard errors by municipality are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

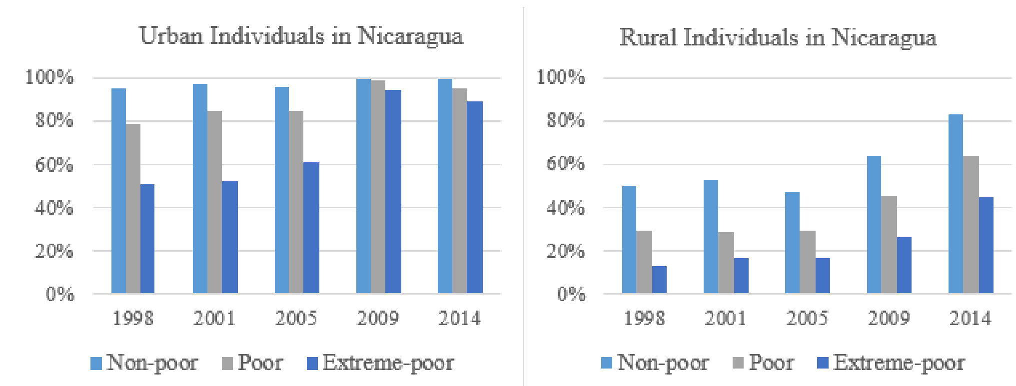
Table 2.8: Health Outcomes

Chapter 3

Individual-level effects of energy poverty on education and health

Table 3.1 shows the electrification rates for urban and rural residents for the years 1998-2014, broken down by poverty group. Over this period the vast disparity in access to electricity between poverty groups in urban areas has been largely diminished, with around 90% of even extremely poor urban individuals sampled having at least some access by 2014.

Individual Electrification Rates

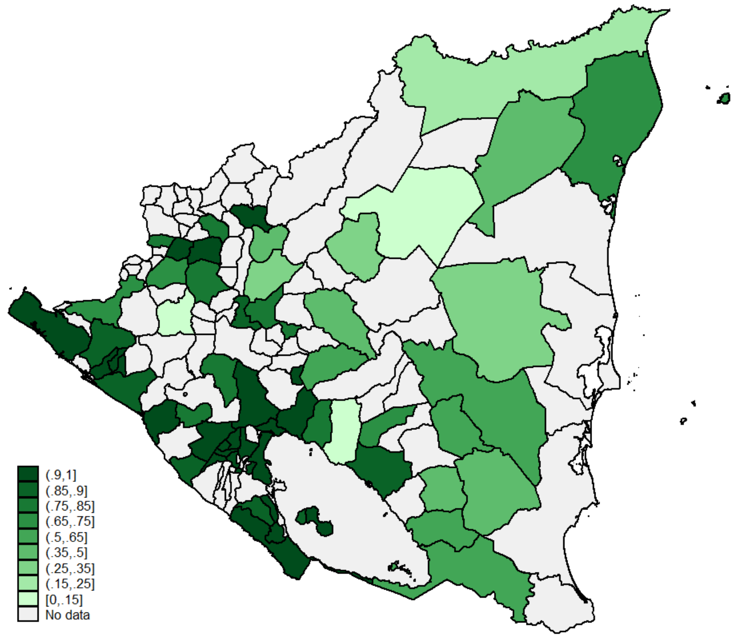


Source: (INIDE, 1998, 2001, 2005, 2009, 2014)

Table 3.1: Electrification Rates by Poverty Group

Rural populations however, are still largely energy poor. Table 3.1 shows that while electrification is increasing through the years, a large proportion of poor and extremely-poor individuals are still lacking even a minimum amount of electrification. Only 45% of extremely poor individuals sampled in rural Nicaragua have basic access to electricity as of 2014.

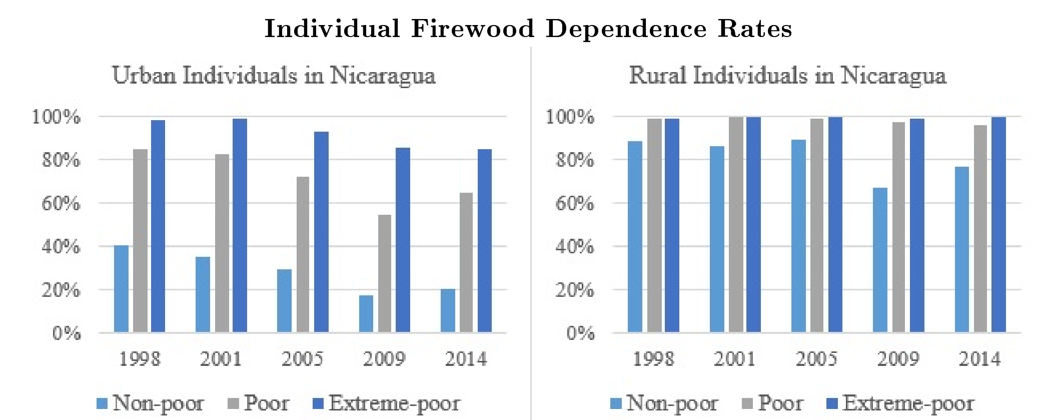
Figure 3.1 displays the rural electrification rates by municipality. We can see that the increases in electricity access shown in Table 3.1 were primarily experienced by rural individuals residing close to large urban municipalities. Figure 3.1 also shows that the more remote municipalities sampled displayed the lowest rates of individual electricity access in 2014.



Source: Author's calculation using Nicaragua EMNV 2014 data (INIDE, 2014)

Figure 3.1: Spatial Distribution of Individual Rural Electrification Rates (2014)

The cooking fuels that individuals rely on is the second main aspect of energy poverty that will enter into this analysis. Table 3.2 shows urban and rural firewood use as a percentage of individuals surveyed between the years of 1998-2014, broken down into poverty groups. As with electrification, we see that firewood dependence decreases in an almost uniform manner for urban residents across poverty groups between the years 1998 and 2014. Contrary to electrification however, is that the majority of poor and extremely-poor individuals in urban areas still depend primarily on firewood for cooking fuel.

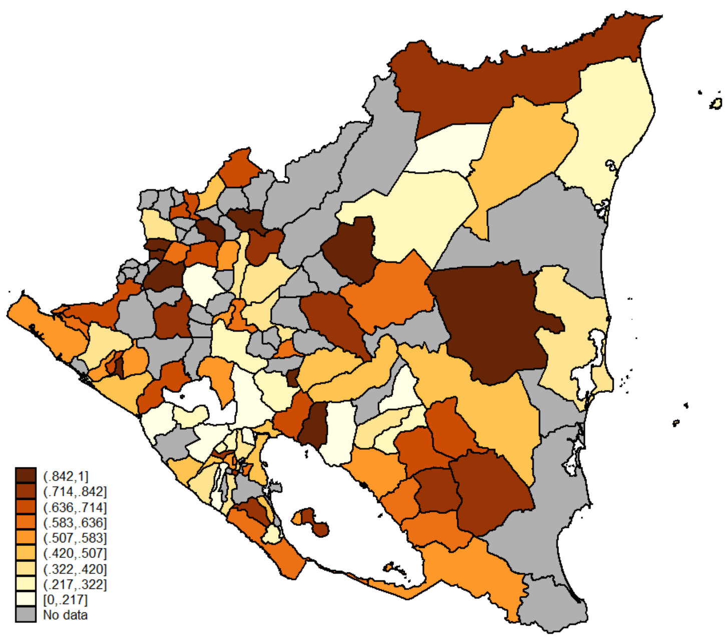


*Source:*Author's calculation using Nicaragua EMNV 1998-2014 data(INIDE, 1998, 2001, 2005, 2009, 2014)

Table 3.2: Firewood Use by Poverty Group (2014)

The rural section of Table 3.2 displays the proportions for rural individuals relying on firewood over the same time period, displayed by poverty group. While non-poor individuals in rural areas experienced roughly a 10% reduction in firewood dependence over the 16 year period, the rural poor and extremely-poor individuals sampled realized almost no change in firewood reliance. Table 3.2 does show some reduction in firewood dependence among rural non-poor individuals sampled between the years of 2005-2014. Other than this, the reduction for poor or extremely poor rural individuals is slight to non-existent, with an average prevalence of 98.3%of households depending on firewood for cooking. This sheds some light on the issue of indoor air pollution related health problems in Nicaragua.

An examination of the spatial distribution of firewood dependence shows a high concentration of use in areas that are far from large metropolitan centers, as seen in Figure 3.2. In fact, a close comparison of Figures 3.1 and 3.2 will show that areas of high electrification display relatively low firewood dependence, and vice versa. The reasoning for this will be investigated further in section 4.



Source: Author's calculation using Nicaragua EMNV 2014 data (INIDE, 2014)

Figure 3.2: Spatial Distribution of Individual Firewood Usage (2014)

3.1 Data

The individual-level data for this study come from the living standards measurement surveys (LSMS) conducted in Nicaragua in 2014 (INIDE, 2014). This is a nationally-representative survey which follows the methodology developed by the World Bank, which contains living-standards information from 30,489 individuals. For more precise estimation of the statistical effects of energy poverty on individual quality of life, this survey data was combined with two other data sets. The first of these is a municipal population density data set from the 2005 National Census (INIDE, 2006). It is assumed that individuals residing in locations with higher population density will be more likely to have access to electricity. The last data set that was combined with the survey data is a forest-density measurement at the department-level (Global Forest Watch, 2000). This is assumed to impact electrical distribution and access as relatively more-thick jungles and forests are an impediment to electrical infrastructure expansion.

In order to econometrically estimate the effects of energy poverty on human development, it is necessary to have exogenous variation in the data with regards to energy use. As seen in Table 3.1, electricity access is becoming ubiquitous in the urban areas of Nicaragua. For this reason, we only use observations of rural individuals outside of the capital department of Managua when estimating the impacts of electricity on education. Table 3.2 and Figure 3.2 however, show that firewood usage is still highly prevalent among all but the non-poor, urban individuals. This high level of variation among individual firewood reliance rates motivates using all of the observations in the sample when estimating the effects of indoor air pollution on health outcomes.

The main indicators of interest for this study are electrification, cooking fuels, education levels, and health outcomes. Electricity is a dichotomous variable measuring whether or not an individual has access to electricity in the home. Firewood is also given as a dichotomous variable, and is used to indicate whether or not an individual resides in a household which relies primarily on firewood for cooking its food. Whether or not the individual forages for this firewood is also included in the data. When estimating the impact of electricity and firewood use on education, a dichotomous variable is used indicating whether or not an individual over the age of twelve has completed primary school.

To better understand the effects of indoor air pollution and health, it would be desirable to have data such as the amount of firewood burned, length of time per day exposed to indoor smoke, eye problems, heart and lung problems, and duration of illnesses. Presently the survey only reports on whether or not an individual suffers from a cough, cold, or respiratory disease, which is used here as a dichotomous variable. Another variable of interest to estimating the health effects of energy poverty is whether the individual lives in a one-room dwelling. A one-room dwelling will likely exhibit higher levels of indoor air pollution, thus creating a potentially more harmful environment for respiratory problems.

Other characteristics that are used in this analysis include: number of household members, whether the individual lives in a dwelling with a dirt floor and/or straw roof, whether the individual fetches his/her own water, whether the main access to the community or neighborhood is a paved road, as well as the gender, age, indigenous status, and education level of the head of household.

Table 3.3 gives descriptive statistics of the primary variables used in our estimations. "Primary School Completion" is measured for rural individuals that are aged 12 or higher, and is equal to one if the individual has completed primary school, and zero otherwise."Respiratory Problem" is a dichotomous variable equal to one if the individual suffers from a cough, cold, or respiratory problem. The indicator "Extreme Poor" is a dichotomous variable indicating whether an individual is classified as extremely poor according to **?**, which gives the full explanation of the classification of poverty groups. "Forage" indicates whether or not the individual surveyed is tasked with collecting the primary amount of fuel wood for the household. The indicator labled "One Room" is a measurment equal to one if the individual resides in a one-room dwelling. This is included in the analysis as it is an indicator of wealth status, but also because one room dwellings carry a greater risk of detrimental health impacts from indoor air pollution.

Descriptive Statistics

Variable	n	mean	sd	min	max
Primary School Completion (rural: age 12+)	4201	0.559	0.497	0	1
Respiratory Problem	30489	0.295	.0456	0	1
Firewood	29443	0.386	0.0.487	0	1
Electricity (rural)	5793	0.729	0.444	0	1
Age	29443	27.9	20.0	0	97
Education (head)	29421	6.769	5.067	0	22
Gender (head)	29440	0.602	0.489	0	1
Indigenous (head)	30489	0.015	0.119	0	1
Years of Education (age 5+)	25742	7.05	4.87	0	22
Extreme Poor	30489	0.038	0.191	0	1
Forage	29443	0.206	0.404	0	1
One Room	30489	0.209	0.406	0	1
Rural	30489	0.196	0.397	0	1
Dirt Floor	29443	0.271	0.445	0	1
Fetch Water	29443	0.216	0.412	0	1
Household Size	30464	5.19	2.62	1	21

Table 3.3: Descriptive Statistics

3.2 Econometric Methodology

The purpose of this chapter is to analyze the mechanisms through which access to modern energy sources impacts the quality of life for individuals in the developing world. Tables 3.1-3.2 give an initial impression that modern energy is negatively correlated with poverty in Nicaragua. And poverty is assumed to be correlated with education and health.

In order to observe high variation in electricity access and educational outcomes, only those individuals residing in rural areas outside of the capital department are used in estimating electricity access impacts on quality of life. This leaves 5,758 observations. Out of these individuals, 73% have access to electricity. Firewood dependence is far more widespread however, with 39% of all individuals sampled relying primarily on this fuel source. Thus, when estimating the impacts of cooking fuel on quality of life, the entire sample population is used, resulting in 29,443 observations.

Human development as measured by education, health, and income is codetermined with energy use. The codetermination of energy and health, or energy and education may be complicated. While energy use may have a direct effect on health and education measurements, the inverse effect will likely come indirectly through the income component. Indirect effects often are subject to time horizons that fall outside of the scope of cross-sectional data. This must be kept in mind throughout the proceeding estimation efforts.

Educational outcomes and energy poverty are likely simultaneously determined in the long run, but this impact will be indirect. In other words, an individual that obtains access to electricity or clean cooking fuels will not immediately experience an increase in the quantity or quality of their education. Rather this effect will happen over time and possibly in the next generation. Thus, when measuring the impact of energy poverty on education, endogeneity is likely not present in cross-sectional data. Also, as a true measurement of an individuals "education" is latent, it is necessary to examine the effect of electricity on education through a dichotomous measurement. Primary school completion is a standard measurement of education in the developing world (UNESCO, 2009). This chapter will look at whether an individual older than the age of twelve has completed primary school. As a preliminary look at the relationship between energy poverty and education, Table 3.4 shows the correlation between primary school completion, electricity access, and firewood reliance among rural individuals above the age of primary school.

Correlation

	Electricity	Firewood	Primary School Completion
Electricity	1		
Firewood	-0.1880	1	
Primary School Completion	0.2282	-0.1745	1

Table 3.4: Correlation between energy use and primary school completion

In Table 3.4 it is observed that electricity access is negatively correlated with firewood use and positively correlated with primary school completion, while firewood use is negatively correlated with primary school completion.

Regarding health, Nicaragua shows a high incidence of child death due to indoor air pollution, as seen in Table 1.1. The primary cause of indoor air pollution is cooking with firewood. The hypothesis is that energy poverty will impact health primarily through the means of cooking fuel. Table 3.5 shows the correlation between energy poverty and the health outcome as measured in the data, where electricity and respiratory problems are negatively correlated while relying on firewood is positively correlated with this health outcome. Testing for endogeneity, both Durbin (chi-squared) and a Wu-Hausman (F) tests between electricity, firewood, and primary school completion; as well as between electricity, firewood, and respiratory problems, fail to reject the null hypothesis of exogenous variables in each case.

	Correlation		
	Electricity	Firewood	Respiratory Problem
Electricity	1		
Firewood	-0.3011	1	
Respitatory Problem	-0.0415	0.0666	1

Table 3.5: Correlation between energy use and having a cough, cold, or other respiratory problem

The outcome of interest here is how the probability of completing primary school, or having a resporatory problem, is affected by electricity acces and firewood use, as seen in Equation 3.1.

$$P(y=1|\overrightarrow{x})_i = P\left(y=1|x_1, x_2, ..., x_k\right), \tag{3.1}$$

where i refers to the individual in question, $y=1$ indicates individual i completing primary school, and $(x_1, x_2, ..., x_k)$ are the explanatory variables. When estimating the educational impacts of energy poverty, there are many unobserved characteristics that influence the probability of primary school completion. Many of these unobservables are likely to be location specific. A multilevel regression model is used to address this variation in regional impacts, where a separate regression is fit within each municipality. The individual-level regression and the municipality-level regression are the two levels in the multilevel model. The regressions have the same slopes in each of the municipalities, while the intercepts are permitted to vary. In this instance, a multilevel logit model is used, as shown in Eqn. 3.2

$$P(y=1|\vec{x})_i = G\left(\alpha_{j[i]} + \overrightarrow{\beta}\overrightarrow{X_i} + \epsilon_i\right)\ for\, individual\, i = 1, ..., n$$

$$\alpha_j = a + \overrightarrow{b}\overrightarrow{u_j} + \eta_j \tag{3.2}$$

where $j[i]$ indicates municipality j wherein individual i resides. The vectors $\vec{X_i}$ and $\overrightarrow{u_j}$ are predictors at the individual and municipality levels respectively, and ϵ_i and η_j are independent error terms at each of the two levels. The function G is the logistic function:

$$G\left(\alpha_{j[i]} + \overrightarrow{\beta}\overrightarrow{X_i} + \epsilon_i\right) = exp\left(\alpha_{j[i]} + \overrightarrow{\beta}\overrightarrow{X_i} + \epsilon_i\right) / \left[1 + exp\left(\alpha_{j[i]} + \overrightarrow{\beta}\overrightarrow{X_i} + \epsilon_i\right)\right] \tag{3.3}$$

3.3 Education and Health Results

The results of Eqn. 3.2 are shown in Table 3.6. The covariates in Eqn. 3.2 are the log of the distance to the nearest public primary school, electricity access, firewood reliance, the number of years of education of the household head, whether or not the individual lives in extreme poverty, gender, whether the individual fetches water, has a straw roof, has a dirt floow, resides in a one-room dwelling, the log of municipal population density, and regional controls. The four regions in Nicaragua are Managua, Central, Pacifico, and Atlantico. As this model only uses rural observations outside of the Managua region, Pacifico and Atlantico are included in the regression results in reference to the Central region. An interaction term is also included for the gender and indigenous status of the household head. For robustness verification, the regressors are added to the estimation in groups. Bootstrapped standard errors are given in the parentheses of Table 3.6.

Table 3.6: Multilevel Logit: Primary School Completion

	(1)	(2)	(3)	(4)	(5)
Completed primary school					
Electricity	0.761***	0.747***	0.658***	0.580***	0.494***
	(0.138)	(0.169)	(0.115)	(0.144)	(0.134)
Firewood	-1.234***	-1.312***	-0.542***	-0.432***	-0.328**
	(0.148)	(0.215)	(0.149)	(0.160)	(0.139)
Dist to school (log)		-0.0993**	-0.0649*	-0.0604*	-0.0622
		(0.0465)	(0.0359)	(0.0361)	(0.0391)
Extreme poor		-1.087***	-0.856***	-0.836***	-0.856***
		(0.154)	(0.115)	(0.138)	(0.125)
Male		-0.295***	-0.376***	-0.370***	-0.371***
		(0.0929)	(0.115)	(0.121)	(0.0965)
Age		-0.0704***	-0.0817***	-0.0819***	-0.0822***
		(0.0055)	(0.0050)	(0.0055)	(0.0054)
Age squared		0.0001*	0.0003***	0.0003***	0.0003***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
HH head yrs educ			0.362***	0.358***	0.356***
			(0.0234)	(0.0204)	(0.0204)
Head male=0 × Head indig.=0			0	0	0
			(0)	(0)	(0)
Head male=0 × Head indig.=1			-0.0709	-0.136	-0.00293
			(0.334)	(0.316)	(0.405)
Head male=1 × Head indig.=0			-0.0015	-0.0071	0.0148
			(0.124)	(0.116)	(0.111)
Head male=1 × Head indig.=1			0.872	0.841	0.911
			(0.699)	(0.738)	(0.784)
Fetch water				-0.0610	-0.0049
				(0.115)	(0.133)
Straw roof				-0.344	-0.278
				(0.266)	(0.249)
Dirt floor				-0.204*	-0.221*
				(0.116)	(0.118)
One room				-0.173	-0.240*
				(0.115)	(0.125)
Pop. density (log)					0.0411
					(0.0814)
Atlantic					-0.334
					(0.237)
Pacific					0.202
					(0.195)
Constant	0.716***	3.209***	1.092***	1.339***	1.141**
	(0.203)	(0.335)	(0.277)	(0.296)	(0.531)
lnsig2u					
Constant	-1.987***	-1.233***	-1.813***	-1.812***	-2.299**
	(0.314)	(0.240)	(0.409)	(0.453)	(1.070)
Observations	3316	3306	3293	3293	3293

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Here it is shown that there is a positive and significant relationship between an individual having electricity and completing primary school, with electricity access predicting an approximate 11% increase in the probability of completion. As expected, these results estimate an extremely poor individual is significantly less likely to complete primary school. Firewood, in this estimation, is only a significant predictor of school completion at the 10% level, though is negatively correlated as assumed. An interesting result is that rural males are less likely to complete primary school than females. This could be due to males being more likely to be engaged in agricultural labor at younger ages. Age is negatively correlated with primary school completion above the age of 12. This could be due to the increases in primary school completion rates over time, with the older population less likely to have completed primary school as children. The household head's level of education is a highly positive and significant predictor of primary school completion, as might be assumed. Interestingly, the head of household's gender and indigenous status do not seem to have a significant impact on the outcome of interest in this specification.

In Table 3.3 it was shown that over 38% of individuals sampled rely primarily on firewood for their cooking fuel. The health measurement that will be used is whether the individual suffers from a cough, cold, or other respiratory problem. Again, there are many potential unobserved variables at the municipal-level that can impact the respiratory health of an individual. For this reason, this is also estimated as a varying-intercept multilevel logit model as in Eqn. 3.3. Additional controls include the distance that the individual lives from the nearest health facility, and an interaction term of firewood use and living in a one-room dwelling. This is done to more specifically control for the situations where indoor air pollution would presumably be the most concentrated.

Health results are included in Table 3.7, with bootstrapped standard errors in parentheses. It is observed that in this model, electricity does not have a statistically significant effect on the health measurement. The main results of interest from this model are the coefficients and significance levels of the permutations of the interaction term. Each permutation between firewood reliance and living in a one-room dwelling increase the probability of having a cough, cold, or other respiratory disease in a highly significant way. It is of note as well that the coefficient with the highest magnitude and significance level is that of the interaction term of firewood and one-room being equal to one. This situation increases the probability of an individual having a cough, cold, or other respiratory disease by almost 8%.

Table 3.7: Multilevel Logit: Cough, Cold, or Other Respiratory Problem

	(1)	(2)	(3)	(4)	(5)
Health					
Electricity	-0.205**	-0.198**	-0.193*	-0.151	-0.159*
	(0.0950)	(0.0922)	(0.113)	(0.0967)	(0.0943)
Firewood=0 × One room=0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)
Firewood=0 × One room=1	0.307***	0.202***	0.191***	0.171***	0.169***
	(0.0540)	(0.0558)	(0.0579)	(0.0558)	(0.0573)
Firewood=1 × One room=0	0.231***	0.220***	0.192***	0.159***	0.165***
	(0.0632)	(0.0463)	(0.0519)	(0.0537)	(0.0541)
Firewood=1 × One room=1	0.478***	0.389***	0.355***	0.306***	0.300***
	(0.0848)	(0.0731)	(0.0687)	(0.0784)	(0.0695)
Dist to health (log)		0.0208	0.0204	0.00921	0.00977
		(0.0156)	(0.0192)	(0.0185)	(0.0179)
Extreme poor		-0.185	-0.193	-0.220*	-0.213
		(0.131)	(0.133)	(0.127)	(0.132)
Male		0.00202	0.00194	0.00210	0.00207
		(0.0227)	(0.0268)	(0.0254)	(0.0220)
Age		-0.0136***	-0.0135***	-0.0135***	-0.0135***
		(0.0009)	(0.0009)	(0.0008)	(0.0008)
Age squared		-0.0000**	-0.0000***	-0.0000***	-0.0000***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
HH head yrs educ			-0.0069*	-0.0054	-0.0055
			(0.0039)	(0.0039)	(0.0041)
Head male			-0.0121	-0.0186	-0.0183
			(0.0474)	(0.0393)	(0.0459)
Head indig.			-0.0647	-0.0706	-0.0619
			(0.163)	(0.175)	(0.181)
Fetch water				0.133**	0.132**
				(0.0635)	(0.0667)
Straw roof				-0.0759	-0.0883
				(0.358)	(0.264)
Dirt floor				0.0571	0.0584
				(0.0433)	(0.0407)
Pop. density (log)					-0.0436
					(0.0452)
Atlantic					-0.281
					(0.210)
Pacific					0.127
					(0.121)
Central Region					-0.382***
					(0.137)
Constant	-0.823***	-0.349***	-0.269**	-0.357***	-0.00952
	(0.110)	(0.103)	(0.123)	(0.116)	(0.303)
lnsig2u					
Constant	-1.538***	-1.507***	-1.501***	-1.512***	-1.717***
	(0.188)	(0.189)	(0.195)	(0.187)	(0.187)
Observations	29443	29378	29359	29359	29359

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Chapter 4

Household-level effects of electricity access on off-farm income

The data used for this analysis come from Nicaragua's Living Standards Measurement Surveys, which were performed by the Encuesta Nacional de Niveles de Vida (EMNV) between 1998-2005. These are nationally representative surveys that follow the Living Standards Measurement Survey (LSMS) methodology developed by the World Bank (INIDE, 2005).The panel data sample size for the is 3,299 households from 139 primary sampling units.

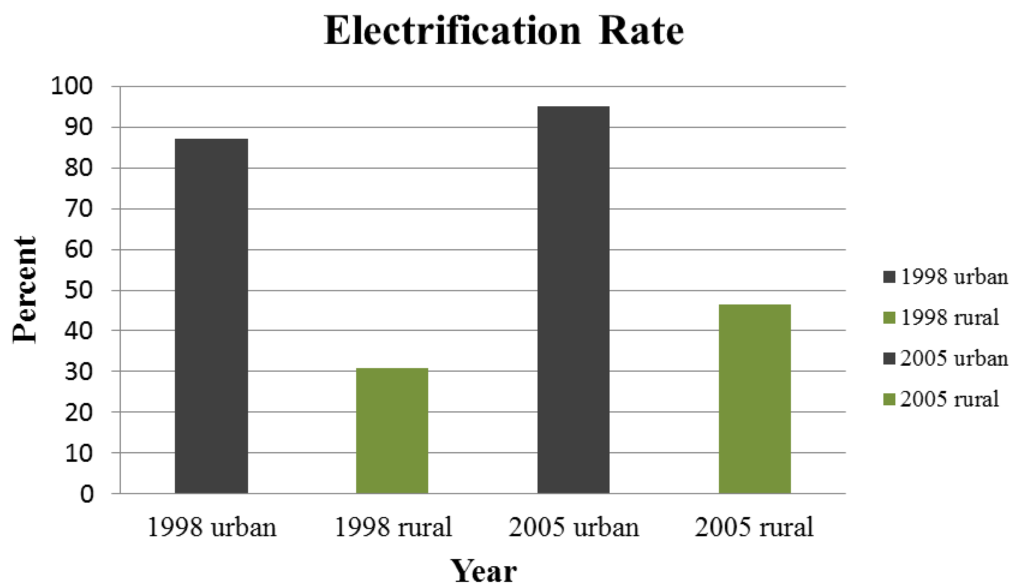
Our level of analysis for this study is a household. Household poverty, and hence income and consumption levels in Nicaragua, are correlated with geographical region, household size, gender of the head of household, ethnicity, and education level. Therefore, these variables are included as controls in our econometric specification. As indigenous populations have long suffered from an income-gap, whether a household is indigenous is controlled for in the estimation strategy.

Between 1998 and 2005 the electrification rate in Nicaragua rose in both rural and urban areas. This can be seen in Table 4.1. As of 2005 the electrification rate in urban areas is just above 95%, while over half of those living in rural areas live completely without electricity. In Table 4.2 we see that off-farm income has also risen during this period, though for many households in rural areas this figure is very low at US$ 450 per year.

Off-farm income is used as the variable of interest in this study for several reasons. First, developing a true measure of consumption in developing countries is not always a straight forward task. This is due to the nature of agriculture-based societies that consume some of their own production, engage in barter and trade with neighbors, and often receive in-kind payments for work performed (Ravallion, 1992). These aspects create difficulties when constructing a measurement of how much a household consumes. Off-farm income is none-the-less an important unit of measurement as it affects a household consumption bundle. By working outside of household and agricultural duties, a household can access goods that cash can more easily purchase, such as clean cooking fuels.

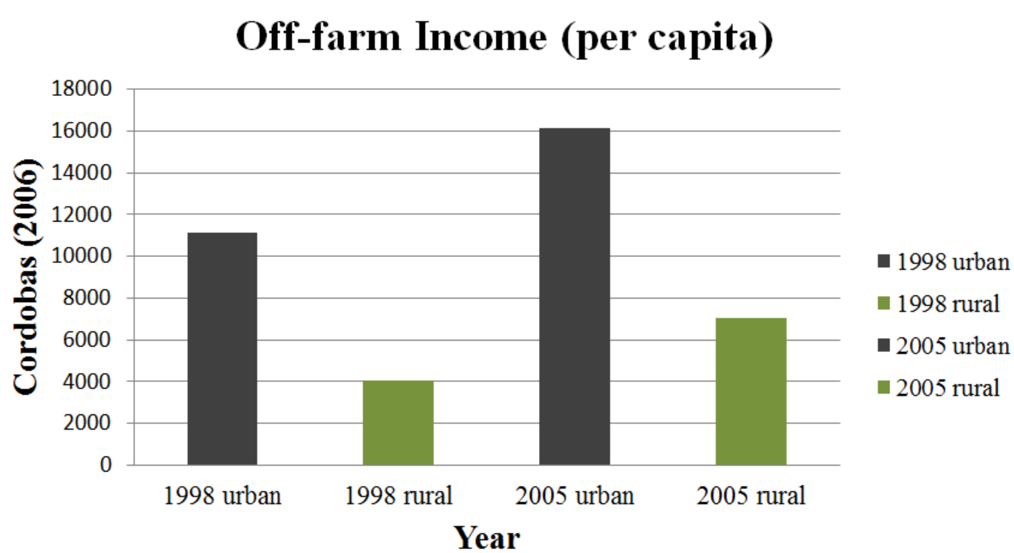
Off-farm income is measured in Cordobas (base year 2006), which is the local unit of currency in

Nicaragua. Local currency units are reported in this study as opposed to their conversion to USD. This is due to the high fluctuations of exchange rates throughout the period. As a reference, 1 USD could buy 10 Cordobas in 1998, while in 2005, 1 USD was roughly equivalent to 16 Cordobas.



Source: Author's calculation using Nicaragua EMNV 1998 & 2005 data (INIDE, 1998; 2005)

Table 4.1: Electrification Rates



Source: Author's calculation using Nicaragua EMNV 1998 & 2005 data (INIDE, 1998; 2005)

Table 4.2: Off-farm Income (household-level, per capita)

Table 4.3 shows the descriptive statistics for the rest of the variables of interest. Note that across

Variable	Description	Variable Type	Obs	Mean	Std Dev	Min	Max
Off-farm Income '98 '05	Per year, per capita 2006 Cordobas	Continuous	 4207 3307	 7883 11847	 23499 34457	 0 0	 863587 1006523
Electricity '98 '05	If the hh has electricity	Dichotomous (Yes = 1, No = 0)	 4209 3309	 0.613 0.723	 0.487 0.448	 0 0	 1 1
Rural '98 '05	If the hh is in rural area	Dichotomous (Yes = 1, No = 0)	 4209 3309	 0.461 0.472	 0.498 0.499	 0 0	 1 1
Residents '98 '05	Number of people in hh	Continuous	 4038 3309	 5.788 5.516	 2.981 2.682	 1 1	 15 14
Indigenous '98 '05	If hh is indigenous	Dichotomous (Yes=1, No=0)	 4209 3299	 0.021 0.027	 0.144 0.162	 0 0	 1 1
Education '98 '05	Ave. years by hh	Continuous	 4209 3309	 4.862 5.849	 2.943 3.065	 0 0	 17 17
Gender '98 '05	Gender of head of hh	Dichotomous (Male=1, Female=0)	 4209 3299	 0.739 0.684	 0.439 0.465	 0 0	 1 1
Age '98 '05	Age of head of hh	Continuous	 4207 3299	 45.42 51.13	 15.739 14.856	 15 17	 97 97
Firewood '98 '05	If household uses firewood	Dichotomous (Yes=1, No=0)	 4209 3309	 0.721 0.651	 0.449 0.477	 0 0	 1 1

Source: Author's calculation using Nicaragua EMNV 1998 & 2005 data (INIDE, 1998; 2005)

Table 4.3: Descriptive Statistics

the sample, off-farm income in 1998 was, on average, 7,883 Cordobas per person, per household, per year. In 2005 this figure had risen to 11,847 Cordobas. The standard deviation of off-farm income is very large, which represents a high degree of inequality with respect to market earnings.

4.1 Econometric methodology

Our main objective in this chapter is to study the effect of electricity access on off-farm income. Based on this, we need to estimate the following equation

$$off-farm\,income_i = \alpha_0 + \alpha_1 electricity_i + \overrightarrow{\beta}'\overrightarrow{X_i} + \epsilon_i \tag{4.1}$$

where $\overrightarrow{X_i}$ is a vector of control variables, and ϵ_i is an error term.

Equation 4.1 could be estimated using Ordinary Least Squares (OLS) if there was not potential endogeneity between off-farm income and electricity. The presence of endogeneity is suspected on the basis of studies which reveal the significant impact of electricity on both income and consumption (Khandker et al., 2013), and the significant impact of income on access to electricity (Louw et al., 2008; Pachauri and Spreng, 2004).

One way of solving the endogeneity problem is to estimate this relationship through a difference-in-difference approach. This approach evaluates the effect of a treatment (in this case, receiving electricity) on an outcome Y over a population of individuals (or in this case, off-farm income of households). The sample is broken down into two groups of households indexed by treatment status T = [0, 1] where 0 indicates households in the control group that do not gain access to electricity, and 1 indicates households in the treatment group that do gain access to electricity. Two time periods are observed, t = [0, 1] where 0 indicates a time period before the treatment group receives access to electricity, and 1 indicates the time period after the treatment group receives electricity.

Off-farm income for household i would then modeled by the following equation.

$$Y_i = \alpha + \beta_1 \overrightarrow{X} + \beta_2 T_i + \beta_3 t_i + \beta_4 \left(T_i * t_i\right) + \epsilon_i \tag{4.2}$$

where Y is annual per capita off-farm income in Cordobas, $\overrightarrow{X}$ is a vector of regressors, β_2 is the treatment group specific effect, β_3 is the time trend common to both the control and treatment groups, and β_4 is the true treatment effect of gaining access to electricity.

The difference-in-difference estimator is the difference in average outcome in the treatment group before and after treatment minus the difference in average outcome in the control group before and after treatment

$$\hat{\beta}_{DD} = \overrightarrow{Y_1^T} - \overrightarrow{Y_0^T} - \left(\overrightarrow{Y_1^C} - \overrightarrow{Y_0^C}\right) \tag{4.3}$$

Running this regression alone would yield reasonable estimates however, only in the event that those households treated with electricity were treated at random. As there are many factors influencing whether or not a household becomes connected to electricity, it cannot be assumed that the treatment is random.

A method of overcoming this assumption violation is through the use of propensity score matching, where treated households are compared to non-treated households with similar observed characteristics. The propensity score is the probability of receiving treatment, conditional on X_i. This approach has the following requirements. First, there can be no systematic differences between treated households and untreated households. Second, in both the treated and untreated groups there are households with similar propensity scores. Lastly, similar propensity scores must be based on similar values of X_i. The estimation of propensity scores can be done through a binary model as follows:

$$P\left(T_i = 1|\overrightarrow{X_i}\right) = G\left(\gamma_0 + \overrightarrow{\gamma_1}\overrightarrow{X_i}\right) \tag{4.4}$$

where *G(.)* is the logistic function:

$$G\left(\gamma_0 + \overrightarrow{\gamma_1}\overrightarrow{X_i}\right) = exp\left(\gamma_0 + \overrightarrow{\gamma_1}\overrightarrow{X_i}\right) / \left[1 + exp\left(\gamma_0 + \overrightarrow{\gamma_1}\overrightarrow{X_i}\right)\right] \tag{4.5}$$

The propensity score for household i is then given as:

$$\hat{P}\left(T_i = 1|\overrightarrow{X_i}\right) = G\left(\hat{\gamma_o} + \hat{\gamma_1}\overrightarrow{X_i}\right) = P\hat{S}_i \tag{4.6}$$

The last step prior to estimating the difference-in-differences estimator is to make certain to compare only households with similar propensity scores. In order to verify this, those households that are treated with electricity that have no similar propensity score match in the control group are dropped from the sample.

4.2 Estimation Results and Discussion

Table 4.42 displays a simple OLS model of the household regressors that impact off-farm income. All of the explanatory variables have the expected sign and significance except the indicator for whether a household resides in a rural or urban environment. This is most likely due to the very large standard deviation of off-farm income for rural households.

Table 4.5 displays the results of the propensity score estimation. It is shown that all of the predictors of electricity have the expected signs and significance.

Table 4.2 shows the results of the kernel-based propensity score matching difference in difference estimator (bottom right cell of table 4.2). We see that a household receiving the treatment is estimated to see an increase in off-farm income of over 4,000 Cordobas per person, per year. While this effect is large, it is only significant at the 10% level, and there appears to be non-random selection into the treatment group. Notice the significant difference between the average treatment household before receiving the treatment and the average control household.

This may be interpreted as higher earning households being more likely to gain access to electricity over the course of the time period. In order to more accurately observe the true effect of electricity access on off-farm income we turn to a quantile regression approach.

Off-farm Income	β	se*	t	pvalue	ll	ul
Rural	334.2609	407.7431	0.819783	0.412	-465.033	1133.555
Residents	-464.431***	65.23664	-7.11918	0.000	-592.314	-336.549
Indigenous	-2012.18**	897.9723	-2.2408	0.025	-3772.46	-251.894
Education	1933.517***	284.0718	6.806437	0.000	1376.654	2490.379
Gender	2891.32***	610.9289	4.732663	0.000	1693.724	4088.917
Age	207.0211**	95.16384	2.175418	0.030	20.47255	393.5697
Age^2	-1.95527**	0.826416	-2.36596	0.018	-3.57528	-0.33526
Firewood	-4283.71***	479.4541	-8.93455	0.000	-5223.57	-3343.84
_cons	-4133.53	2861.962	-1.4443	0.149	-9743.8	1476.741

Source: Author's calculation using Nicaragua EMNV 1998 & 2005 data (INIDE, 1998; 2005). *robust standard errors

Table 4.4: Ordinary Least Squares

Electricity	β	se*	z	pvalue	ll	ul
Rural	-1.7380***	0.0944	-18.420	0.0000	-1.92294	-1.55303
Residents	-0.0209	0.0152	-1.380	0.1690	-0.05069	0.008885
Indigenous	-2.0799***	0.3405	-6.110	0.0000	-2.74722	-1.41261
Education	0.4150***	0.0235	17.630	0.0000	0.368836	0.461085
Gender	-0.1912*	0.1075	-1.780	0.0750	-0.40191	0.019585
Age	0.0486***	0.0157	3.090	0.0020	0.017801	0.079457
Age^2	-0.0004**	0.0002	-2.380	0.0170	-0.00066	-6.5E-05
Firewood	-1.4812***	0.1819	-8.140	0.0000	-1.8378	-1.12467
Toilet	2.6303***	0.4830	5.450	0.0000	1.683624	3.576891
Constant	-0.2810	0.4222	-0.670	0.5060	-1.10844	0.546418

Source: Author's calculation using Nicaragua EMNV 1998 & 2005 data (INIDE, 1998; 2005). *robust standard errors

Table 4.5: Propensity Score Logit Model

	Before Electricity (1998)	*After Electricity (2005)*	*Difference*
Gets electricity (Treatment)	10963.192 (571.357)	14287.714 (774.613)	3324.522
Does not get electricity (Control)	7676.992 (1310.065)	6907.864 (1400.127)	-769.128
Difference	3286.200** (1429.238)	7379.850*** (1600.119)	**4093.649* (2145)**

Means and robust standard errors are estimated by linear regression
Inference: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 4.6: Kernel-based Propensity Score Matching Difference-in-Difference Estimation Results

Tables 4.7-4.9 display the results from the kernel-based propensity score matching quantile difference-in-difference estimations. Three quantiles are analyzed to arrive at a more true understanding of the difference that electricity has on a household in a developing country.

One outcome of interest is that in the three quantiles estimated, there is no statistical difference between the households in the treatment group and those in the control group before the treatment is applied. The difference in difference estimator in all cases is significant at the 1% level and large in magnitude. We also notice that the magnitude increases with the earning quantile. This result is to be expected through the mechanics of this effect.

There are several plausible ways that gaining electricity may result in an increase in off-farm employment. First, having electricity lengthens the effective day in developing regions. With an increase in day time comes an increase in either work, leisure, or both. This additional work time may be used to provide labor in the market place, increase educational attainment, or engage in a home-based enterprise. All of these options will likely result in an increase in income, and higher earning individuals will see a greater increase in income than lower earning individuals.

Another outcome of interest is that households in the control group are earning less off-farm income after the treatment period and after accounting for inflation. This could mean several things. It is likely that in a modernizing economy, a lack of even the most basic of access to electricity will harm your prospects of earning income. No electricity means a complete lack of cell phone communication, also no computer or internet connectivity, among other impacts.

	Before Electricity (1998)	*After Electricity (2005)*	*Difference*
Gets electricity (Treatment)	2276.923 (74.055)	3661.111 (76.965)	1384.188
Does not get electricity (Control)	1846.154 (293.099)	1587.302 (271.530)	-258.852
Difference	430.769 (302.310)	2073.810*** (282.227)	**1643.040*** (413.574)**

Values are estimated at the .25 quantile
Inference: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 4.7: Kernel-based Propensity Score Matching Quantile Difference-in-Difference Estimation Results (.25)

	Before Electricity (1998)	*After Electricity (2005)*	*Difference*
Gets electricity (Treatment)	5050.256 (91.615)	7348.571 (95.191)	2298.315
Does not get electricity (Control)	5000.000 (565.480)	3656.790 (368.316)	-1343.21
Difference	50.256 (572.854)	3691.781 *** (380.418)	**3641.525*** (687.662)**

Values are estimated at the .50 quantile
Inference: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 4.8: Kernel-based Propensity Score Matching Quantile Difference-in-Difference Estimation Results (.50)

	Before Electricity (1998)	*After Electricity (2005)*	*Difference*
Gets electricity (Treatment)	10660.235 (232.973)	14185.186 (242.128)	3524.951
Does not get electricity (Control)	9846.154 (1609.238)	6666.667 (1226.363)	-3179.487
Difference	814.081 (1626.015)	7518.519 *** (1250.037)	**6704.438*** (2050.979)**

Values are estimated at the .75 quantile
Inference: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 4.9: Kernel-based Propensity Score Matching Quantile Difference-in-Difference Estimation Results (.75)

Chapter 5

Concluding remarks

Energy poverty in the developing world is a factor in nearly all of the human development indicators. Nicaragua is one area of the world with high levels of energy poverty and relatively low levels of human development. The aim of this dissertation is to investigate how electrification and cooking fuels impact three key human development indicators in Nicaragua: consumption, education, and health.

Controlling for endogeneity through a Two-Stage Least Squares model, it is found that electricity has a highly significant effect on consumption levels. Using Probit models, this model found that education is significantly impacted by electricity access, while health outcomes as measured in the data are not directly impacted by household electricity. These results are significant as they show the important role that energy plays in acheiving the primary goals of policy makers in developing countries: increasing education, improving health outcomes, and increasing income levels.

Using multilevel logit models, this study found evidence that primary school completion is significantly impacted by electricity access, while health outcomes are heavily impacted by energy poverty through cooking fuels. These results are significant as they show the important role that energy plays in acheiving the primary goals of policy makers in developing countries: increasing education, improving health outcomes, and increasing income levels.

Nicaragua is a country that faces many development challenges. Particularly in the rural areas of the country, low incomes, poor health, and low education levels are problems that affect the majority of Nicaragua's inhabitants. Using a difference in difference model, the effect of obtaining electricity on a household's per capita off-farm income was investigated. A very large and statistically significant effect is found when the sample is examined by quantiles. In particular, it is worth noting that obtaining access to electricity is about twice as impactful on off-farm income than an additional year of average education for the household. These results are illuminating in that they highlight the importance of electricity on off-farm earning potential, a development indicator of particular importance to the more vulnerable segments of society in this region.

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