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

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## Abstract

This paper looks at the effect of energy poverty on income in Nicaragua. Energy poverty, 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, can have wide-ranging impacts on human development and quality of life. Nicaragua is one of the least developed countries in Latin America, and has a high incidence of energy poverty. Almost 28% of households in Nicaragua have no access to electricity. Using Living Standards Measurement Survey panel data from 1998-99 and 2005, and propensity score matching quantile difference-in-difference techniques, this paper investigates energy poverty in Nicaragua and its impact on household off-farm income. We find large and significant effects of electricity on off-farm income.

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# 1 Introduction

Access to modern forms of energy is still absent in many households in the developing world. An estimated 1.2 billion people – 17% of the global population – still do not have access to electricity (WEO, 2015).

Having electricity at the household level affects quality of life through household productivity, education, and health (Khandker et al., 2013; Bridge et al., 2016b). Illumination from electricity effectively lengthens the day, with its positive implications on labor productivity and education. Being able to charge cellular phones enhances communications and enables acquiring information. Replacing candles and fuels for lighting and cooking with electricity reduces time spent foraging for firewood, and reduces indoor pollution. This may have positive implications for health, especially for women and children, who tend to spend more time indoors. Use of electric tools may also improve productivity in cottage industries and farm work. Electricity also allows for home-based, small-scale retail stores common in developing countries that depend on refrigeration.

These gains in time, income, and household productivity may then translate into additional leisure, educational attainment, or in additional labor in the market place. In particular, access to electricity has been shown to create more employment choices, especially for women (Dinkelman, 2011; Grogan and Sadanand, 2013).

This paper looks at the specific effect of electricity on off-farm income in Nicaragua. To address endogeneity issues we use a kernel-based Propensity Score Matching (PSM) difference-in-differences (DiD) approach. We find that the impact of electricity on off-farm income is large and highly significant. In particular, we find a 36 percent increase in per-capita income attributed to electricity during the 1998-2005 period of study. Further, since Nicaragua has large levels of inequality, we examine whether the effects of access to electricity vary at different income levels. To do so, we apply a quantile difference-in-differences approach. We find that the poorest families benefit the most from access to electricity. In particular, the poorest families see an 80 percent increase in per-capita off farm income relative to similar households that do not gain access to electricity.

Though energy poverty impacts the lives of individuals regardless of income, we find that the effects are most acutely felt by the most vulnerable members of society. This makes a strong argument for the importance of including energy poverty in any poverty reduction agenda.

# 2 Data and descriptive statistics

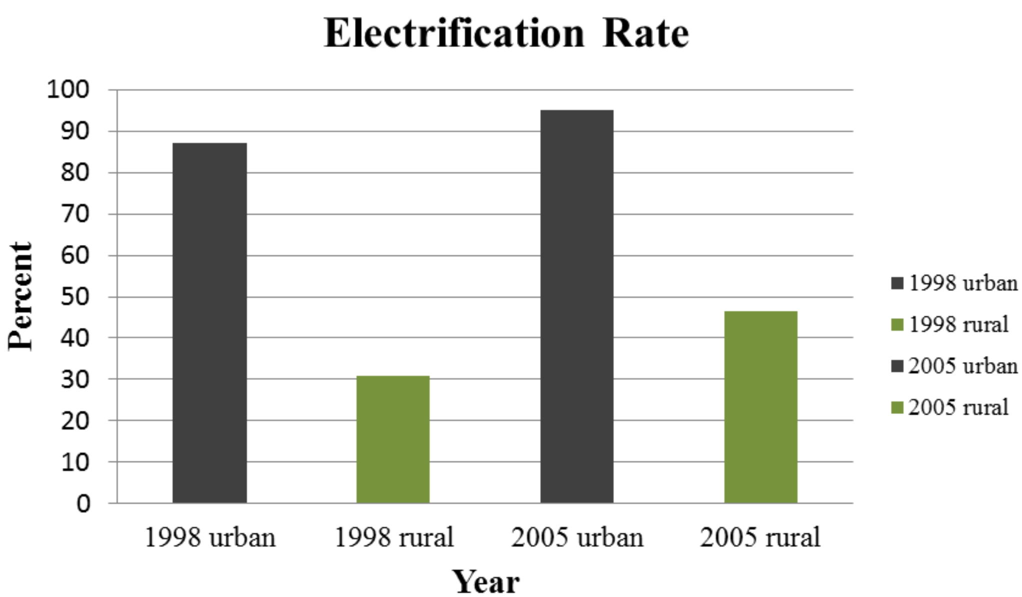
The data used for this analysis is a household panel from Nicaragua's *Encuesta Nacional de Hogares sobre Medición de Nivel de Vida* (EMNV) for 1998 and 2005. These are nationally representative surveys that follow the Living Standards Measurement Survey (LSMS) methodology developed by the World Bank. Our panel data sample size is 3,307 households from 139 municipalities.[1]

[1] We are not able to use the 2009 and 2014 rounds of the EMNV, as they no longer tracked the households surveyed in 1998 and 2005. As panel data allows us to use methods for addressing endogeneity, we examine the 1998 and 2005 rounds that are compatible with panel estimation techniques. We also restrict our sample

We use off-farm income as our variable of interest. Developing a true measure of consumption in developing countries is not always a straightforward 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 also an important unit of measurement as it affects the household consumption bundle. By working outside of home and agricultural duties, a household will earn currency, which expands their available consumption bundle. Off-farm income is measured in Cordobas (base year 2006), which is the local unit of currency in Nicaragua.[2]

Between 1998 and 2005 the electrification rate in Nicaragua rose in both rural and urban areas, as depicted in figure 1. As of 2005, the electrification rate in urban areas is just above 90%, while over 50% of those living in rural areas live completely without electricity. Figure 2 illustrates off-farm income, which has also risen during this time period, though for rural households in 2005 this figure is approximately 430 US dollars per capita, per year.

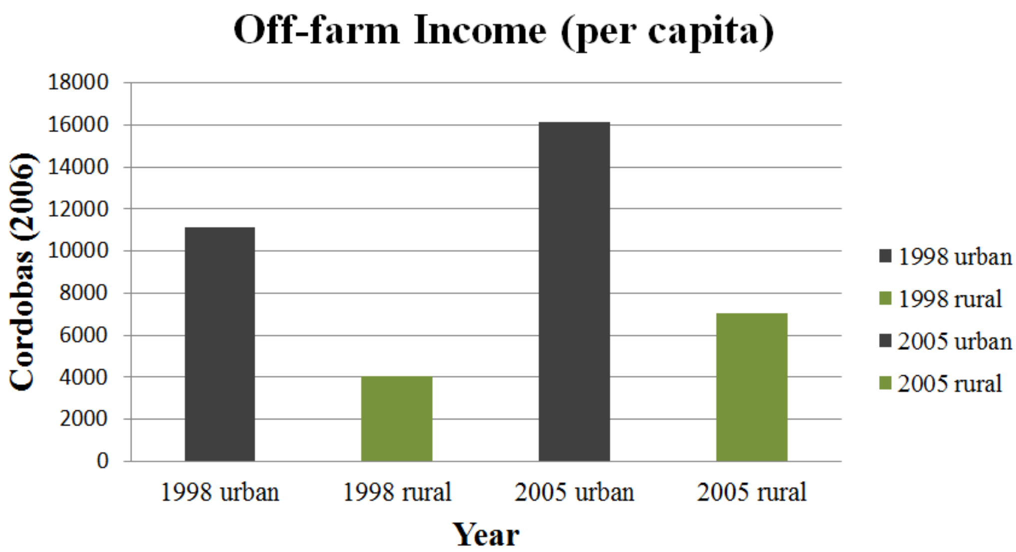
Figure 1: Access to electricity in Nicaragua




to municipalities reporting electrification for 1998-2005, so that a household without electricity has the potential to get connected.

[2] We report the local currency unit, as there were high fluctuations in Cordoba-USD exchange rates in our period of study. As a reference, 1 USD could buy 10 Cordobas in 1998, while in 2005, 1 USD was roughly equivalent to 16 Cordobas.

Figure 2: Off-farm Income (annual, per capita)




We include several variables as controls in our econometric specifications. Income in Nicaragua is correlated with geographical region, gender and education level of the head of household, wether the household uses firewood for cooking, and has an indoor toilet. Also, the history of colonization in Latin America has heavily impacted the current economic landscape in Nicaragua, so we control for indigenous households, which have long suffered from an income gap.

We also account for whether a household has moved between surveys, to control for the potential confounding effects of relocating to an area with better labor markets that also has electricity. Of the 3,309 households in our sample, only 78 households moved from rural to urban areas from 1998 to 2005. With such a low number of households in the sample moving from rural to urban areas, sufficient variation does not exist in the data to use this as a treatment variable.

Table 1 shows the descriptive statistics for our variables used. Note that across the sample, off-farm income in 1998 was, on average, 7,884 Cordobas per person, per household, per year. In 2005 this figure increased to 11,882 Cordobas. The standard deviation of off-farm income is very large, which represents a high degree of inequality with respect to market earnings.

Table 1: Descriptive statistics

| Variable | Description | Obs | Mean | Std Dev | Min | Max |
|---|---|---|---|---|---|---|
| Off-farm Income | household annual per capita off-farm income, 2006 Cordobas | | | | | |
| 1998 | | 4,207 | 7,884 | 23,499 | 0 | 863,587 |
| 2005 | | 3,307 | 11,882 | 34,457 | 0 | 1,006,523 |
| Electricity | household has electricity (Yes = 1, No = 0) | | | | | |
| 1998 | | 4,209 | 0.613 | 0.487 | 0 | 1 |
| 2005 | | 3,309 | 0.723 | 0.448 | 0 | 1 |
| Rural | household is in rural area (Yes = 1, No = 0) | | | | | |
| 1998 | | 4,209 | 0.461 | 0.498 | 0 | 1 |
| 2005 | | 3,309 | 0.472 | 0.499 | 0 | 1 |
| Indigenous | household is indigenous (Yes = 1, No = 0) | | | | | |
| 1998 | | 4,209 | 0.021 | 0.144 | 0 | 1 |
| 2005 | | 3,299 | 0.027 | 0.162 | 0 | 1 |
| Education | Years of education of head of household | | | | | |
| 1998 | | 4,209 | 4.862 | 2.943 | 0 | 17 |
| 2005 | | 3,309 | 5.849 | 3.065 | 0 | 17 |
| Firewood | household uses firewood for cooking (Yes = 1, No = 0) | | | | | |
| 1998 | | 4,209 | 0.721 | 0.449 | 0 | 1 |
| 2005 | | 3,309 | 0.651 | 0.477 | 0 | 1 |
| Toilet | household has an indoor toilet (Yes = 1, No = 0) | | | | | |
| 1998 | | 4,209 | 0.180 | 0.384 | 0 | 1 |
| 2005 | | 3,309 | 0.238 | 0.426 | 0 | 1 |
| Never moved | household did not move between 1998 and 2005 (Yes = 1, No = 0) | | | | | |
| 2005 | | 3,309 | 0.726 | 0.446 | 0 | 1 |

# 3 Econometric model

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

$$Y_{it} = \alpha_0 + \alpha_1 E_{it} + \boldsymbol{\beta'}\mathbf{X_{it}} + \varepsilon_{it} \tag{1}$$

where $Y_{it}$ denotes off-farm income for household $i$ at time $t$, $E_{it}$ is access to electricity, $\mathbf{X_i}$ is a vector of control variables, and $\varepsilon_i$ is the error term.

Equation (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 (Bridge et al., 2016a), and the significant impact of income on access to electricity (Louw et al., 2008; Pachauri and Spreng, 2004). We correct this endogeneity problem by estimating this relationship through a propensity score matching difference-in-differences approach.

The difference-in-differences evaluates the effect of a treatment (access to electricity) on an outcome $Y$ over a population of individuals (household off-farm income). The sample is broken down into two groups of households indexed by the treatment variable $E$, which is binary, i.e., $e \in \{0,1\}$, 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. The time variable is given as $T$, where two time periods are observed $t \in \{0,1\}$. Period 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 be modeled by the following equation:

$$Y_i = \alpha + \beta_1 \mathbf{X_i} + \beta_2 e_i + \beta_3 t_i + \beta_4 (e_i * t_i) + \varepsilon_i \tag{2}$$

where $\beta_2$ is the treatment group specific effect, $\beta_3$ is the time trend common to both the control and treatment groups, and $\beta_4$ is the true treatment effect of gaining access to electricity.

Off-farm income can be indexed by the treatment and time-period variables as $Y_t^e$, indicating the off-farm income that would be realized given certain values of $e$ and $t$. The difference-in-differences 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, so that

$$\hat{\beta}_{DD} = \left(\bar{Y}_1^1 - \bar{Y}_0^1\right) - \left(\bar{Y}_1^0 - \bar{Y}_0^0\right) \tag{3}$$

Running this regression alone would yield reasonable estimates 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. We account for this 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 the covariates $\mathbf{X_i}$ summarized in the data section above.

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 $\mathbf{X_i}$.

The estimation of propensity scores can be done through a binary model as follows:

$$P(E_i = 1 \mid \mathbf{X_i}) = G(\gamma_0 + \boldsymbol{\gamma_1} \mathbf{X_i}) \tag{4}$$

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

$$G(\gamma_0 + \boldsymbol{\gamma_1} \mathbf{X_i}) = \exp(\gamma_0 + \boldsymbol{\gamma_1} \mathbf{X_i}) / [1 + \exp(\gamma_0 + \boldsymbol{\gamma_1} \mathbf{X_i})] \tag{5}$$

The Epanechnikov kernel-based propensity score for household $i$ is then given as:

$$\hat{P}(E_i = 1 \mid \mathbf{X_i}) = G(\hat{\gamma}_0 + \hat{\gamma}_1 \mathbf{X_i}) = \widehat{PS}_i \tag{6}$$

The last step prior to estimating the difference-in-differences estimator assigns weights to untreated households based on propensity scores. That is, greater weights are assigned to the matched control households based on their propensity scores given by equation (6). This satisfies the common support assumption for proper identification of a difference-in-difference estimator (Lechner et al., 2011), which is given as:

$$P\left[TE=1|\mathbf{X}=x,(T,E)\in\left\{(t,e),(1,1)\right\}\right]<1;\forall(t,e)\in\left\{(0,1),(0,0),(1,0)\right\};\forall x\in\mathbf{X} \quad (7)$$

In addition, given the large variation of income across households, we are interested in whether the effects of access to electricity vary at different levels of income. To do so, we apply the propensity score matching quantile difference-in-differences approach (Villa et al., 2016). In particular, we consider our outcome variable that depends on all covariates $\mathbf{Z_i}$ as detailed in equation (2), and where $\gamma(\tau)$ is a vector of regression coefficients for the $\tau$th conditional quantile of off-farm income, as in:

$$Q_{Y_i}(\tau|\mathbf{Z_i})=\gamma(\tau)\mathbf{Z_i},\ 0\leq\tau\leq1 \quad (8)$$

# 4 Results

Table 2 displays a simple OLS model for the vector of control variables $\mathbf{X_i}$ that impact off-farm income, in order to establish their relevance as covariates in our propensity score matching below. All of the explanatory variables have the expected sign, and with the exception of being an indigenous household, all covariates show significance.

Table 2: OLS estimation of Covariates

| Dep. Var: Off-farm Income | Coefficient | Robust Standard Error | t-stat | p-value | Lower limit | Upper limit |
|---|---|---|---|---|---|---|
| Rural | 2,380.23*** | 776.03 | 3.07 | 0.002 | 859.01 | 3,901.46 |
| Indigenous | -2,367.81 | 2,098.64 | -1.13 | 0.259 | -6,481.72 | 1,746.11 |
| Education | 2,311.77*** | 132.73 | 17.42 | 0.000 | 2,051.58 | 2,571.96 |
| Firewood | -4,557.85*** | 923.83 | -4.93 | 0.000 | -6,368.82 | -2,746.88 |
| Toilet | 5,022.24*** | 984.21 | 5.10 | 0.000 | 3,092.92 | 6,951.56 |
| Never Moved | -2,485.94*** | 666.62 | -3.73 | 0.000 | -3,792.71 | -1,179.18 |
| Constant | 57.84 | 1,261.49 | 0.05 | 0.963 | -2,415.03 | 2,530.70 |

*** $p<0.01$; ** $p<0.05$; * $p<0.1$

Table 3 displays the results of the logistic estimation as modeled by equations (4)-(5). It shows that all the predictors of electricity have the expected signs and significance. The results from this specification are then used to create a propensity score based on equation

(6), in order to assign corresponding weights to the control households for the DiD estimation below.

Table 3: Logit Model for Propensity Score Matching

| Dep. Var: Electricity | Coefficient | Standard Error | z-stat | p-value | Lower limit | Upper limit |
|---|---|---|---|---|---|---|
| Rural | -1.798*** | 0.0919 | -19.54 | 0.000 | -1.978 | -1.617 |
| Indigenous | -2.102*** | 0.3398 | -6.19 | 0.000 | -2.768 | -1.435 |
| Education | 0.391*** | 0.0226 | 17.24 | 0.000 | 0.346 | 0.435 |
| Firewood | -1.568*** | 0.1819 | -8.62 | 0.000 | -1.925 | -1.212 |
| Toilet | 2.761*** | 0.4765 | 5.79 | 0.000 | 1.827 | 3.694 |
| Never Moved | 0.467*** | 0.0892 | 5.24 | 0.000 | 0.293 | 0.642 |
| Constant | 0.779*** | 0.2073 | 3.76 | 0.000 | 0.374 | 1.186 |

*** $p<0.01$; ** $p<0.05$; * $p<0.1$

Table 4 shows the results of the kernel-based propensity score matching difference-in-difference estimation. Notice that across the distribution, there is no statistical difference between the households in the treatment group and those in the control group before the treatment is applied (bottom-left difference cell), as a consequence of the PSM procedure. In contrast, the difference between treatment and control groups after treatment is a large 4,586.14 Cordobas, and significant. Finally, the DiD estimator, the corner bottom-right cell, is significant and large in magnitude. That is, a household gaining access to electricity during our period of study is estimated to receive an increase in per-capita off-farm income of 3,000.75 Cordobas per year, relative to an ex-ante similar household that did not gain access to electricity. This represents approximately a 36 percent increase in annual per-capita income attributed to electricity over our period of study.

Table 4: Kernel-based Propensity Score Matching Difference-in-Differences

| | Off-Farm Income | | |
|---|---|---|---|
| | Before Electricity (1998) | After Electricity (2005) | Difference |
| Gets Electricity (Treatment) | 8,238.69 | 11,836.90 | 3,598.21 |
| Does not get Electricity (Control) | 6,653.29 | 7,250.76 | 597.47 |
| Difference | 1,585.39 | 4,586.14** | 3,000.75** |
| | (993.52) | (1,794.66) | (1,788.65) |

Clustered Standard Errors in Parenthesis. Means and Clustered Standard Errors are estimated by linear regression. *** p<0.01; ** p<0.05; * p<0.1

The income distribution in our sample shows a high degree of skewness to the right, consistent with the existing high degree of income inequality in Nicaragua. where the vast majority of the population is poor. In fact, median income is roughly half mean income. Given this, we are interested in whether the effects of access to electricity vary across the income distribution, and especially if access to electricity affects the poor different from the rich. To do this we turn to a quantile approach. Table 5 displays the results from the kernel-based PSM quantile DiD estimations. We report the results of the 20th, median, and 80th quantiles.

Results are consistent with the above means-reporting estimation, showing large income gains attributed to access to electricity across all quantiles. Further, in absolute terms, the magnitude of the treatment-effect increases with each earnings quantile. However, in percentage terms, the gains are actually higher for the bottom quantiles. That is, the poorest families that gain access to electricity see an 80% increase in per-capita off farm income relative to the families that do not gain access to electricity. The gains for the median and wealthier households are 58% and 47%, respectively.

It is also interesting to notice that control households in the 50th and 80th quantiles experience an actual decrease in off-farm income after the treatment period. This is visible only after adjusting for inflation, as income for those households actually increased in nominal terms. A potential explanation for the real-term decrease is that in a modernizing economy, a lack of even the most basic of access to electricity may actually harm the prospects of earning income outside of the home.

Table 5: Kernel-based Propensity Score Matching Quantile Difference-in-Differences

| | Off-Farm Income | | |
|---|---|---|---|
| 0.20 Quantile | Before Electricity (1998) | After Electricity (2005) | Difference |
| Gets Electricity (Treatment) | 1,476.92 | 2,791.91 | 1,314.99 |
| Does not get Electricity (Control) | 1,032.97 | 1,166.67 | 133.70 |
| Difference | 443.96 | 1,625.25*** | 1,181.28** |
| | (276.50) | (443.19) | (5232.37) |
| 0.50 Quantile | Before Electricity (1998) | After Electricity (2005) | Difference |
| Gets Electricity (Treatment) | 4,566.15 | 6,733.33 | 2,167.18 |
| Does not get Electricity (Control) | 4,123.07 | 3,656.79 | -466.28 |
| Difference | 443.08 | 3,076.54*** | 2,633.47*** |
| | (467.36) | (489.86) | (677.04) |
| 0.80 Quantile | Before Electricity (1998) | After Electricity (2005) | Difference |
| Gets Electricity (Treatment) | 10,748.71 | 14,511.11 | 3,762.40 |
| Does not get Electricity (Control) | 9,846.15 | 8,546.67 | -1,299.48 |
| Difference | 902.56 | 5,964.44** | 5,061.88* |
| | (1547.42) | (2462.76) | (2979.33) |

Clustered Standard Errors in Parenthesis. Means and Clustered Standard Errors are estimated by linear regression. *** $p<0.01$; ** $p<0.05$; * $p<0.1$

# 5 Conclusion

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, this paper examines the effect of obtaining access to electricity on a household's per capita off-farm income. We find a 36 percent average increase in annual per-capita income attributed to electricity. Further, this effect varies greatly at different income levels. We find that the poorest families benefit the most from access to electricity. In particular, the poorest families see an 80% increase in per-capita off farm income, while median and wealthier households benefit by 58% and 47%, respectively.

These results are meaningful 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. Energy poverty impacts individuals regardless of income, but the benefits of gaining access to electricity are felt the largest by the poorest members of society. This makes a strong argument for the importance of including energy poverty in any poverty reduction agenda, especially as an estimated 1.2 billion people in the world still do not have access to electricity.

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