The Impact of Access to Electricity on Education: Evidence from Honduras

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Abstract

Worldwide there are over 1.3 billion people who still lack access to electricity which is seen a major hurdle to economic and human development. In this paper I estimate the effect of access to electricity on school attendance and educational attainment. I take advantage of individual level data matched with community level electrification dates, allowing me to study the effect of access to electricity on completed education as well as the age-specific hazard of dropping out of school. Contrary to expectations, I find that access to electricity *reduces* educational attainment. The reduction in education was accompanied by an increase in childhood employment, suggesting that improved labor market opportunities, due to electricity access, led to the increased drop out rates. I also find evidence that increases in adult employment was driving children to stay home to compensate for parents going off to work. Finally, to remove concerns of endogeneity I introduce a new instrument, distance along the distribution grid to the nearest substation, which allows me to instrument for the year of electrification. Using this new instrument I find that my results hold and remain significant.

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1 Introduction

Worldwide there are over 1.3 billion people who still lack access to electricity which is seen a major hurdle to economic and human development. This issue was brought to the forefront of policy discussions in 2014 when President Obama pledged $7 billion dollars to build electrical infrastructure in sub-Saharan Africa. The President said electricity is “the lifeline for families to meet their most basic needs and it’s the connection needed to plug Africa into the grid of the global economy. You’ve got to have power.”

One of the major benefits many proponents of electricity extoll is increased educational attainment. Christine E. Kimes, Acting Head, World Bank Bangladesh said, “Access to energy promotes economic growth and prosperity and has a positive impact on income, expenditure and education.” The European Commission Development Commissioner Piebalgs said, “The benefits of rural electrification are manifold - by connecting people to clean energy, we’ll improve healthcare, education, and opportunities to make a living in the area.” Even though many suggest that greater access to electricity will improve educational attainment, it is not clear theoretically or empirically that this will be true.

The impact of access to electricity on educational attainment is theoretically unclear as there could be multiple mechanisms at work. One possible mechanism is that access to electricity increases demand for low skilled labor. This would increase the opportunity cost for students to stay in school and would lead to a drop in educational attainment. Another could be that access to electricity brings in manufacturing jobs. This would require more high skilled labor increasing the returns to human capital, which would cause students to be more likely to stay in school. There are a myriad of other possible mechanisms, which makes the impact of electricity on educational attainment uncertain.

There is also not a consensus in the empirical literature on the impact of access to electricity on educational attainment. While some papers do find a positive effect, many find no effect. Barron and Torero (2014) and Khandker et al. (2012) find an increase in hours spent studying, but Bensch et al. (2011) finds no effect. As for the impact on enrollment, Barron and Torero (2014) finds no effect while Khandker et al. (2013), Khandker et al. (2012) and Khandker et al. (2009) find increases in both enrollment and attainment.[1]

[1] The research on electricity’s impact on health and income also has conflicting results (Lipscomb et al., 2013; Barron and Torero, 2014). Research on household income is also varied (Barron and Torero, 2014; Chakravorty et al., 2014; Lipscomb et al., 2013; Khandker et al., 2013; Bensch et al., 2011). The labor market outcomes that researchers have focused on are employment, hours worked, and wages (Lipscomb et al., 2013; Dinkelman, 2011; Khandker et al., 2012; Grogan, 2013; Khandker et al., 2012, 2013).

In this paper, I study the electrical expansion in Honduras from 1992 to 2005 in order to estimate the impact of access to electricity on educational attainment. This expansion was instigated by a major energy crisis in 1993, which lead to widespread reform of the electrical industry in 1994. This reform forced the electrical company to expand coverage of electricity to as many people as quickly as possible. I exploit this increase in access to electricity, which occurred at different points in time for each municipality, to estimate the impact of electricity on education.

To measure electricity's impact on education I focus on three measures: attendance, attainment and the hazard of dropping out. Looking first at attendance I find that access to electricity reduced attendance by 4 percentage points. Next, looking at educational attainment I find that the number of years exposed to electricity as a child reduced completed years of schooling by approximately 0.1 years. Finally, by using a hazard approach I can allow for heterogeneity in the dropout rate by year of schooling. I find that access to electricity increased the hazard of dropping out in the first few years of school while actually decreasing the hazard of dropping out in the last few years. Allowing for this heterogeneity by year of education, the number of students in school decreased by 6.5 percentage points with access to electricity while the number of students who finish schooling dropped by 4.5 percentage points. Using each of these measures I find a similar impact of electricity but from the hazard analysis I am able to find heterogeneous results suggesting there may be multiple mechanisms at work. I focus on three possible mechanisms.

The first mechanism I examine is childhood participation in the labor market to see if access to electricity is reducing education through increased employment opportunities for children. I find that access to electricity is associated with a 2.4 percentage point increase in employment for children, which is a similar magnitude to my estimates of the effect of electricity on the number of students dropping out.

The second mechanism I look at is electricity's impact on adult labor markets. I show that with access to electricity there is an increase in employment for women. If more women are being drawn into the labor market, children may need to stay home to take care of younger siblings. I find that having a sibling under the age of 5 reduces the probability that children continue in school. Suggesting that the increased demand for children to stay home may be driving some of the results.

The third mechanism I analyze is access to electricity impact on the demand for human capital. If the demand for completed education is increasing there would be larger returns for individuals near the end of the schooling to stay in school. This might explain why I find a decrease in the hazard of dropping out at the end of individuals schooling. While I do see a return to human capital before access to electricity, I do not find that this return changed with access to electricity.

Finally, to reduce concerns of endogeneity in the year of access to electricity, I introduce a new instrument, distance along the distribution grid from a municipality to the nearest substation. This instrument is an improvement upon previous instruments because I use information on the location of the distribution grid which others have not had. First, I show that distance to the grid is highly correlated with the year municipalities gain access to electricity. Furthermore, distance along the distribution grid is also uncorrelated with population growth, levels or other labor market variables. Finally, using this new instrument I find that my results hold and remain significant.

The rest of the paper is organized as follows: Section 2 provides background information on the education system, electrical grid and electrical company in Honduras. Section 3 describes the data used for the analysis. Section 4 provides information on municipalities gaining access to electricity and the impact it has on education. Section 5 explores the mechanisms at work. Section 6 provides robustness analysis with an instrument for the year of electricity and information on migration patterns. Section 7 concludes.

2 Electrification and Education Background

The electrical network in Honduras is monopolized by the government owned company Empresa Nacional de Energia Electrica (ENEE). ENEE heavily subsidizes electricity to households, such that the main obstacle to having electricity is access to the grid. In 1993, a drought and lack of generation capacity brought about a huge energy crisis in Honduras, causing massive blackouts, and economic and political turmoil. In response to this catastrophe, the government passed a law (Ley marco del subsector eléctrico) in 1994 to create more competition, increase generating capacity, and increase the electrification rate throughout the country. The law succeeded in the last two goals, but the ENEE remains the sole distributor of electricity. The law created the Fondo Social de Desarrollo Eléctrico (FOSODE) which was responsible for increasing electrical access in rural and poor communities. FOSODE along with the ENEE drastically increased access to electricity across a broad swath of the country. The fraction of the population with electricity went from 40% in 1992 to 67% in 2005 (the end of the sample for this paper) and 83% in 2011.

The education system in Honduras is provided by the government and organized as primary, lower secondary and upper secondary. The average years of schooling is 3.57 years in my sample which is lower but similar to the 4.5 years the government found in their 2001 census. Primary school is from ages six to twelve or grades one to six. In my data secondary schooling is almost never observed, less than one percent, therefore I limit the analysis to just primary schooling. The reason that secondary schooling attendance is so low in Honduras is that in many places there is simply no access to secondary schools. Beyond this many secondary schools also charge therefore providing even larger barriers to attendance. While few students go beyond 6 years of education, initial attendance is extremely high, over 95%. On top of this, average attendance in my sample is approximately 75% with around 33% getting 6 years of education.

3 Data

3.1 Household Survey

The individual level data used in this paper is from the Encuesta Permanente de Hogares de Propósitos Múltiples (EPHPM) which is produced by the Instituto Nacional de Estadística (INE) in Honduras. The main objective of the survey is to collect data on labor, housing, education and household composition.[2] On average there are 40,000 individuals per survey with a total of 905,000 individuals over the entire study period from 1992 to 2005. Of the approximately 300 municipalities in Honduras, the survey covered an average of 180 municipalities each year. The municipalities fall into three general categories: municipalities surveyed throughout the entire study period, municipalities surveyed in 1992, 1993, and 2001 onward, or municipalities surveyed from only 2001 onward. The survey has been conducted since 1990 with one or two surveys conducted each year.[3] Beginning in 1992, the survey asked how a household gets its electricity, which will allow me to determine when each household received access to the electrical grid.

The survey data was not originally designed for matching municipalities across years but rather for creating summary statistics for the national government. Because of this, the surveys have neither consistent variable names (i.e. p4 from one year is p8 in another) nor consistent coding across months and years. To create the dataset used in this paper, I matched all variables across time based on the question asked and recoded all variables for consistency.[4] This unique dataset allows me to follow municipalities across time.

[2]INE website: http://www.ine.gob.hn/index.php/censos-y-encuestas/encuestas-todos-las-encuestas-de-honduras/encuesta-permananente-de-hogares

[3]Survey data is unavailable for 1994 and 2000.

[4]The categories were combined to the smallest number asked and top coding was removed.

3.2 Electrical Grid and Geographic Characteristics

Electrical grid data for Honduras was provided by the ENEE. The ENEE provided an ArcGIS file of the electrical grid for 2012 containing all distribution lines, transmission lines, and substations (Figure 1). They also provided a PDF of the map of transmission lines and substations for 1997 (Figure 2).

The land gradient variable was constructed from the 90-meter Shuttle Radar Topography Mission Global Digital Elevation Model.[5] The average land gradient was calculated for each municipality using GIS software to calculate the gradient (defined in degrees from 0 to 90).

4 Analysis

4.1 Access to the Electrical Grid

The main variable of interest in this paper is whether or not a municipality has access to the electrical grid in a given year. Unfortunately, there is no official record of when a municipality was added to the grid. Therefore, to determine the timing of access, I create a binary variable for each municipality which is based on individual reports of having access to the electrical grid. This variable is defined as one after a municipality gains access and zero before. Once a municipality gains access to electricity they have access for the rest of the sample, regardless of reporting. Figure 3 shows the percentage of the population reporting access to the electrical grid in municipalities before and after I define them as having access to electricity. This graph shows that when a municipality gets hooked up to the electrical grid a significant fraction of the population gets connected.

To generate municipality level access to the electric grid, I must account for individual reporting errors. For example, in one municipality one household reports having electricity while no other household that year or for the next 3 years report having access to electricity. To correct for these errors I can choose a minimum percentage of the population and a minimum number of individuals that are required for a municipality to be defined as having access to electricity.[6] To determine the appropriate cutoffs, I compare the cutoff's effect on the increase in the percentage of the population reporting access to electricity from before I define an area as having electricity to after. Figure 4 shows different percent cutoffs versus the increase in the percentage of the population reporting access to electricity associated with each

[5] http://landcover.org/data/

[6] Both percentage and number of individuals are used for a cutoff because the size of municipalities is extremely heterogeneous. With a percent cutoff large districts might under report electricity while with an amount of people small districts might under report.

cutoff. This graph shows that a cutoff of 5 percent maximizes the difference between the before and after periods. I calculated the difference between before and after for the full set of percent and number of people cutoffs and the values that maximizes the difference are 5 percent and 16 people, as seen in Figure 5.

4.2 Education

As mentioned before, the impact of access to electricity on education is not clear. On one hand, many studies argue that electricity can increase educational attainment by reducing the amount of manual labor needed in the home or by extending the number of daylight hours allowing for more time to study. On the other hand, electricity can reduce educational attainment by increasing the opportunities of students in the labor market, raising the opportunity cost of staying in school. To determine what effect is dominating in Honduras during my time period I look at three outcomes.

First, I estimate the impact of access to electricity on school attendance. I restrict the sample to children between the ages of 7 and 16, because most students have started schooling by age 7 and more than two thirds of the students are no longer in school after age 16. My specification is as follows:

$$attend_{i,m,y} = \delta_0 + \delta_e ect_{m,y} + \delta x X_{i,m,y} + \gamma_m + \sigma_y + \nu_{i,m,y} \tag{1}$$

where *attend* is a binary variable for if students are in school, *ect* is an indicator variable equal to one if that municipality had electricity during that year and zero otherwise, X is a vector of individual characteristics containing sex, age, gender of the household head, and total number of individuals in the household, γ_m is municipality fixed effects, and σ_y is year fixed effects. Table 1 presents the impact electricity had on whether or not children were attending school. I find that electricity had a negative and significant impact on school attendance overall and for males, and no significant effect for females. The decrease in male attendance due to electricity is 4.3 percentage points which is not a small drop in an area that has 75% attendance on average.

Next, I look at the relationship between total years of schooling for individuals and the total number of years with access to electricity during their childhood. In order to get an accurate picture of total years of schooling, I restrict my sample to only those people who were under 24 years of age. The reason for this is that no one over the age of 24 had electricity during their schooling so they are not a good comparison group. Finally, since I am interested in the cumulative impact of electricity, I estimate the impact of the total number of years of electricity during childhood on total years of schooling. The final specification is the following:

$$eduyr_{i,m,y} = \delta_0 + \delta_e ect_{m,y} + \delta_c ectedu_{i,m,y} + \delta x X_{i,m,y} + \gamma_m + \sigma_y + \nu_{i,m,y} \tag{2}$$

where *eduyr* is the number of years of schooling, *ectedu* is the number of years that the person had electricity between the ages of 6 and 12 and all other variables are defined as above. The reason I restrict the sample to ages 6 to 12 is because most of the population starts school at 6 and almost the entire sample gets at most 6 years of schooling. The results of this regression are presented in Table 2. The results show that if an individual had electricity during their entire childhood (6 years) they would have gotten on average a half less year of schooling.

So far, I have assumed that the impact of access to electricity is constant across years of schooling. However, electricity might impact students at the beginning of their education more than students at the end of their education, because students at the beginning of their education have a higher cost to finishing their schooling. Alternatively, it may be the case that access to electricity has a larger effect at the end of an individual's education, when the returns to labor might be higher. To determine whether there were heterogeneous impacts of electricity by year of schooling, I estimate a Cox Proportional Hazard model:

$$h(y, x, ect) = h_0(y) exp(\delta_p ect_{m,y} * YearofSchooling_i + \delta_x X_i + \gamma_m + \sigma_y) \tag{3}$$

where $h(y, x, ect)$ is an indicator variable equal to one in the year that the student drops out of school and zero before, $h_0(y)$ is the hazard rate for dropping out of school for each year of schooling, X is a vector of individual characteristics containing sex, gender of the household head, and total number of individuals in the household, *ect* is an indicator variable equal to one if that municipality had electricity during that year and zero otherwise, and $YearofSchooling$ is an indicator equal to one if the student is in a specific year of school (1-5). The results are presented in Table 3. The coefficients in the earlier years is significant and positive while the coefficients in the later years become negative and significant. This suggests that electricity initially increases the hazard of students to drop out of school but this effect is mitigated in the later years. Directly interpreting the coefficient is extremely difficult due to the non-linearity in the specification but graphical representations make the impact clear.

In Table 4 I present two graphical representations of the coefficients from the analysis above. The first graph is the change in the hazard of dropping out if a location in the sample were to go from having access to electricity to not having access to electricity. These hazards are the predicted value from the Cox regression above, with the values being for the average municipality. By using this hazard, I can calculate the probability that a student would make it to each year. The second graph shows that as students progresses in school the probability they make it to the next year of schooling is lower with electricity. Specifically, with electricity there is a 4.5 percentage point drop in the number of students who finish their education. This would also translate into a 6.5 percentage point decrease in the number of students in school after a location gains electricity.

5 Mechanisms

5.1 Childhood Labor

I have so far shown that gaining access to electricity reduced educational attainment, but I have not yet presented evidence for the mechanism through which this might occur. It seems likely that a change in employment opportunities may have increased students' hazard of dropping out. Atkin (2012), Duryea and Arends-Kuenning (2003), Kruger (2007), and Shah and Steinberg (2013) present evidence that increases in labor market opportunities reduce childhood educational attainment in a wide variety of settings. Honduras in the 1990s struggled with high rates of child labor(Cruz, 2002). These rates are similar to the rates today in many developing countries. Specifically, in Honduras, melon farming is a major industry and a major employer of children. On melon farms "as each fruit nears its maturation workers turn it over a total of three times to guarantee equal exposure in the sun and the appearance that is pleasing to consumers."(Harwood and Mull, 2002, p. 20) This is an easy task for young children who comprise 80 % of the workforce on melon farms. Another common practice in Honduras is to pay workers either for a set quota or by piece. In this situation, it is common for workers to bring their entire family to the worksite to increase the amount collected or to reach the quota in a shorter time. Exacerbating this tradeoff between school and work is that many rural families "reject the importance of their children acquiring a basic education."(Harwood and Mull, 2002, p. 17)

To test if child labor is a driving mechanism behind the increase in drop out rates I compare childhood employment rates before and after electricity.[7] Table 5 shows a significant increase in overall employment and a significant increase in female employment. For male employment, I find a positive effect similar in magnitude but insignificant. These results suggests that there was an increase in child labor market opportunities following electrification and, consequently, an increase in the hazard for dropping out of school.

Finally, the hazard model from above gives a prediction of the percent of students who would drop out with and without access to electricity. Comparing the

[7] I restrict the sample to children between the age of 10-15 because children under the age of 10 are not asked labor market questions in many of the surveys and children over 15 are mostly not in school.

overall increase in employment, 2.4 percentage points, I find that this is similar in magnitude but smaller than the drop out rate from above suggesting there may be other mechanisms at work.

5.2 Adult Employment

For adult labor markets, one of the accepted outcomes in the electricity literature is that with access to electricity there is an increase in female labor force participation. [8] I find that access to electricity increased female employment, hours worked and earnings, as shown in Table 6. Increases in female labor force participation would lead to changes in the household dynamics, because household tasks may be redistributed. One of the ways this might impact educational attainment is if a mother goes off to work and requires a child to stay home to take care of a younger sibling. Therefore, I estimate the impact of electricity interacted with the number of toddlers, children under 5, in the household. In Table 7, I find that with access to electricity the number of toddlers in a household increases the probability of dropping out of school.

5.3 Human Capital

The baseline hazard specification demonstrates that access to electricity raised the hazard of dropping out at the beginning of an individual's education but decreases it at the end. So far I have shown evidence for the increase in the hazard of dropping out but not for the decrease. One of the possible explanations for the decrease is that there is an increase in the returns to finishing school. To determine if this is the case, I can look at the returns to education. In Table 8 I show that as schooling increases there is an increase in the wages paid to workers. Next, I can examine whether the returns increased after a municipality received access to electricity. In Table 9, I find that there was not a statistically significant increase in the returns to education for individuals who gained access to electricity. This is unsurprising given that many of the jobs that enter into communities when they gained access to electricity are low skilled manufacturing or agricultural jobs.

6 Robustness

6.1 Instrument

If electricity is endogenously allocated or if the timing of this allocation is endogenous, then the previous estimates will be biased. In this paper, I compare within-

[8] Dinkelman (2011); Grogan (2013); Lipscomb et al. (2013)

municipality changes over time, so endogenous allocation of electricity to certain municipalities will not bias my results. Unfortunately, the timing of access to electricity may still be endogenous. The timing of electrical access in municipalities may be correlated with other public works projects, a powerful politician coming into office, or another major unobservable event. Therefore, I instrument for the year each municipality gained access to electricity with the distance along the electrical network.

Electrical networks provide electricity from power plants to consumers through a four step process. First, power is produced at the power plant. Second, it is transmitted along transmission lines to substations. Transmission lines are extremely high voltage lines and there is no benefit to being near them. Third, at the substation, the voltage is lowered to a level that can be distributed to consumers. Finally, it is distributed along distribution lines from substations to the consumer.[9]

The instrument I propose is distance along the distribution network from the centroid of a municipality to the nearest substation, which I refer to as the "grid distance." The grid distance is calculated for each municipality by first finding the nearest point on the distribution line to the centroid of the municipality. Next, I calculate the distance from the point on the distribution line to the nearest substation, along the grid. An example of this is presented in Figure 6. The location of the substations and distribution lines are based on the 2012 electricity distribution network. One concern with using the 2012 network is that substations might be endogenously placed during the sample. Therefore, I use a map of the network in 1997 to remove any substations or transmission lines built after 1997.[10]

Since the major push to increase access to electricity came with the passage of the 1994 law, mentioned above, the best way to create the instrument would be to use the distance from the end of the grid in 1994 to the centroid of the municipality. Unfortunately, because of the 1994 law, the ENEE stopped keeping records of where their distribution grid was and there are no maps that exist on the location of the distribution network prior to 2012. Therefore by creating the instrument in this way I am making two assumptions. First I am assuming that places that are farther along a distribution line in 2012 were farther from the network in 1994. Second I

[9] The process is actually much more complicated than this with multiple transmission line voltages, substations at intersections of transmission lines and pole transformers to connect to houses. The multiple transmission lines and substations on these transmission lines are ignored for the analysis in this paper. Even though pole transformers are needed to attach to a distribution grid these are assumed to be costless with the majority of the cost of hooking up to electricity being access to a distribution line.

[10] By doing so, only two substation and one transmission line were removed. Although data from 1992 is not available, the small number of substations and lines built after 1997 suggests that few if any substations were built between 1992 and 1997.

am assuming that places were hooked up in the order of their distance from the network in 1994.

Even though I cannot prove either of these there are three pieces of evidence that seem to support these assumptions. First, the law that was passed in 1994 created FOSODE which along with the ENEE were the major drivers of increasing access to electricity. FOSODE was created to give access to poor and rural areas while ENEE was left to increase access to everyone else. Given the information available it seems their incentives would be to hook up places as quickly as possible therefore targeting the closest places first. Second, since distance along the grid is uncorrelated with other outcome variables and population, there is no evidence that access was being targeted at populous or rich regions. Finally, since my instrument strongly predicts the year of electrification it is most likely the case that places that are farther along the line in 2012 were farther from the network in 1994. While none of these proves the assumptions above it does provide strong evidence that they are valid.

Previous research has used a range of instruments for access to electricity but they broadly fall into two categories: geographic based and network based.[11] The most common geographic measure is based on slope or gradient while the most common network characteristic is based on distance to a substation. I create these two other instruments to compare to my instrument. The average slope measure was created following methodology in Dinkelman (2011). The distance to the nearest substation was calculated using straight-line distance for all municipalities, even those without distribution lines, since that is most common in the literature.

To see whether there are any obvious violations of the instrumental variables approach, I first test whether or not the instrument is a good predictor of the endogenous variable, the year of electrification. In Table 10, I regress all three instruments, grid distance, straight distance, and slope, against the year of electrification. Both the grid distance and the substation distance are significant, while the slope variable is insignificant.[12] This is unsurprising since slope was used to estimate which places would gain access to electricity rather than when an area gains access to electricity. Because of this, I concentrate on the other two measures.

The second test compares each instrument to the outcome variables before electricity. If the instrument satisfies the exclusion restriction we would expect it to impact the year a municipality gets electricity, but not the outcome variables before electrification. Table 11 shows that the grid distance does not significantly impact

[11] Dinkelman (2011); van de Walle et al. (2013); Chakravorty et al. (2014); Grogan (2012) and-Khandker et al. (2009)

[12] This is robust to estimation using the average slope and the average slope along the path of the electrical line.

the outcome variables before electrification, but substation distance does significantly impact many of these variables.

The final test checks whether or not the instrument is simply picking up population density or population growth rates. I regress the instruments against various measures of population and population growth, as shown in Table 12. For all four measures, the impact on grid distance is insignificant, while the impact on substation distance is marginally significant for the population growth rate.

Overall these tests suggest that grid distance has a strong first-stage impact on electrification and there is no evidence it fails the exclusion restriction. Also, the evidence suggests that the other two instruments either are not relevant or may fail the exclusion restriction. Therefore, I will use grid distance to instrument for the year of electrification.

My estimation strategy is as follows, I instrument for the year of electrification, $eyear$, with the grid distance, $GridDistance$, while controlling for municipality characteristics, X, average age, percent female, average size of households and percent of households with female heads. The first stage of my analysis is:

$$eyear_m = \beta_0 + \beta_c GridDistance_m + \delta x X_m + \varepsilon_m \tag{4}$$

Next, I predict the year of electrification and generate a variable, $Elect\hat{r}icity$, that is equal to one if a municipality is past the year of electrification and zero if it is before. I use this predicted value in the second stage, as follows:

$$h(y, x, pect) = h_0(y, \alpha) exp(\delta_p Elect\hat{r}icity_{m,y} + \delta_x X_i + \gamma_m + \sigma_y) \tag{5}$$

where the variables are defined as in Section 4.2. The entire process is bootstrapped and the results are robust to bootstrapping each stage.[13]

As done above, I interact electricity with year of schooling. The results, presented in Table 13, show that access to electricity had a positive effect for the first few years of education and decreases to a negative value for later years. Similar to the original estimates but larger. For communities gaining electricity this would reduce the probability of completing schooling by 5 percentage points. Estimating the total effect on attendance, as done above, I find that access to electricity is causing a 15 percentage point drop in the number of students in school. These results are larger but similar in magnitude and direction to the uninstrumented case.

[13] Since this is not the standard two stage set up I am basing the theory on previous literature which has shown that Hazard models are consistent when using a two stage analysis. Beyond this since I am using a generated regressor I simulate the estimation method to show that in the case of an endogenous variable at the municipality level my estimation strategy produces consistent results. Theses simulations are being done now.

6.2 Migration

One concern with the results presented so far is that there may be differential migration before and after electricity. If families with kids that work are more likely not to move after gaining access to electricity there might be a decrease in education and an increase in childhood labor simply due to migration. To see if there is differential migration I can look at cohorts before and after gaining access to electricity. I generate a dependent variable which is the fraction of individuals in a five age range divided by the number of individuals that were in that cohort 2 years ago. I then compare places that got access to electricity in that time period to places that did not. From the graph of the coefficient on electricity for each regression, Figure 7, there is no significant pattern of migration during the childhood years.

7 Conclusion

With all of the recent investment in electrical grid infrastructure in the developing world, it is important to understand how access to electricity impacts households. I provide substantial evidence suggesting that access to electricity decreases educational attainment. Furthermore, I show evidence that the impact of electricity on attendance is heterogeneous across years of schooling. Specifically, the probability of dropping out of school increases for the first few years of schooling, but decreases for the last few years of schooling. The results of which is a 6.5 percentage point decrease in school attendance and a 4.5 percentage point decrease in students completing their schooling. As a possible mechanism for the decrease in attendance, I show that access to electricity increases the employment of children. Moreover, the magnitude of the increase in childhood employment is similar to the magnitude of the decrease in educational attendance. I provide evidence that another mechanism driving the drop in attendance is an increased draw for students to stay home. This is created by increased job opportunities for adults. Next I show that in the context of Honduras there does not seem to be increases in the returns to education with electricity. Finally, to remove concerns about the endogeneity in the year of electrification, I instrument for the year and find the results hold and are significant.

Even though I find that access to electricity decreases educational attainment this is in no way a reason to decrease or stop programs to increase access to electricity. The key take away is that not all effects of electricity are positive. Therefore policy makers should be aware of the perverse incentives electricity may cause and target programs to try to reverse these incentives.

References

Atkin, David, "Endogenous Skill Acquisition and Export Manufacturing in Mexico," NBER Working Papers 18266, National Bureau of Economic Research, Inc August 2012.

Barron, Manuel and Maximo Torero, "Short Term Effects of Household Electrification: Experimental Evidence from Northern El Salvador," *Job Market Paper*, 2014.

Bensch, Gunther, Jochen Kluve, and Jrg Peters, "Impacts of Rural Electrification in Rwanda," IZA Discussion Papers 6195, Institute for the Study of Labor (IZA) Dec 2011.

Chakravorty, Ujjayant, Martino Pelli, and Beyza Ural Marchand, "Does the quality of electricity matter? Evidence from rural India," *Journal of Economic Behavior & Organization*, 2014, (0), –.

Cruz, Rubn Hernndez, "National report on the results of the child labour survey in Honduras," Technical Report, International Programme for the Elimination of Child Labour 2002.

Dinkelman, Taryn, "The Effects of Rural Electrification on Employment: New Evidence from South Africa," *American Economic Review*, 2011, *101* (7), 3078–3108.

Duryea, Suzanne and Mary Arends-Kuenning, "School Attendance, Child Labor and Local Labor Market Fluctuations in Urban Brazil," *World Development*, 2003, *31* (7), 1165 – 1178. Economic Crises, Natural Disasters, and Poverty.

Grogan, Louise, "Household Electrification, fertility and employment: Evidence from the Colombian censuses," 2012.

— , "Rural Electrification and Employment in Poor Countries: Evidence from Nicaragua," Working Papers 1303, University of Guelph, Department of Economics and Finance 2013.

Harwood, Bill and L. Diane Mull, "Education to Combat Abusive Child Labor: Planning Educational Response Strategies for Working Children in Honduras," Technical Report, Creative Associates International, Inc. 2002. Washington, DC: Creative Associates International, for US Agency for International Development.

Khandker, Shahidur R., Douglas F. Barnes, and Hussain A. Samad, "Welfare impacts of rural electrification : a case study from Bangladesh," Policy Research Working Paper Series 4859, The World Bank March 2009.

Khandker, Shahidur R, Hussain A Samad, Rubaba Ali, and Douglas F Barnes, “Who benefits most from rural electrification? evidence in India,” *Working Paper*, 2012.

Khandker, Shahidur Rahman, Douglas F. Barnes, and Hussain A. Samad, “Welfare Impacts of Rural Electrification: A Panel Data Analysis from Vietnam,” *Economic Development and Cultural Change*, 2013, *61* (3), 659 – 692.

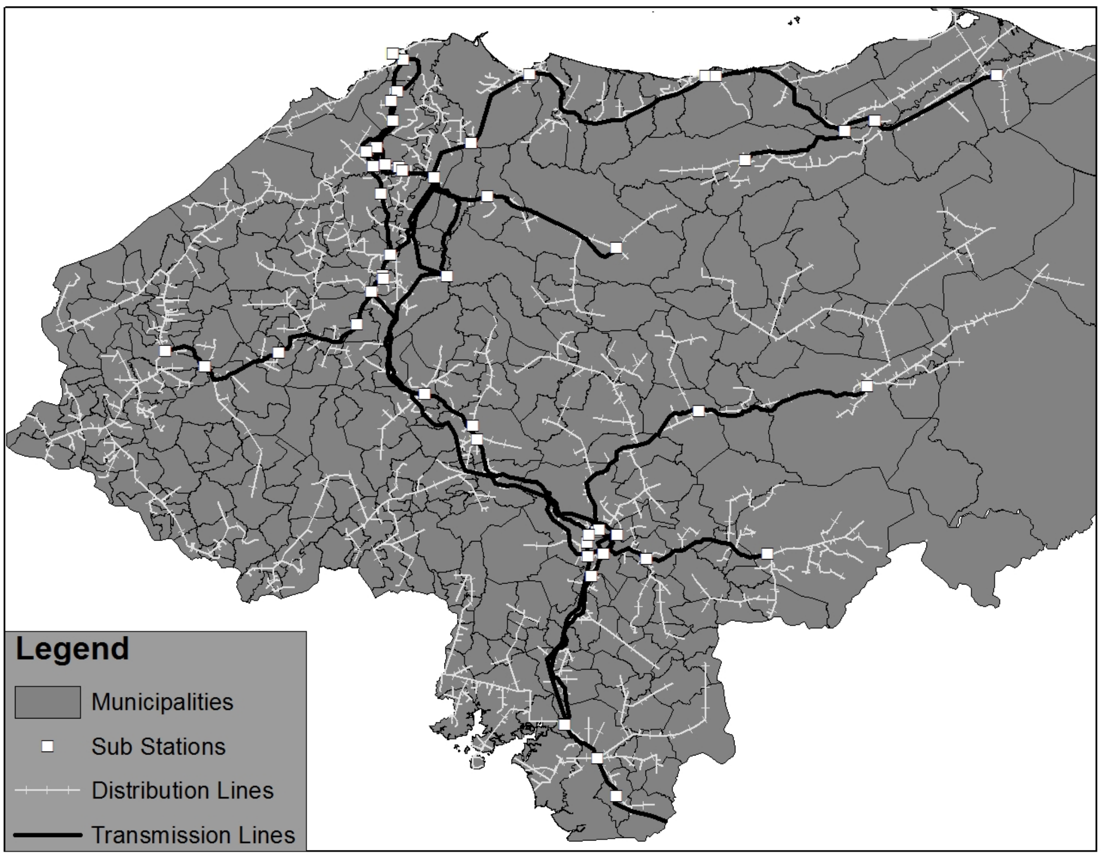
Kruger, Diana I., “Coffee production effects on child labor and schooling in rural Brazil,” *Journal of Development Economics*, 2007, *82* (2), 448 – 463.

Lipscomb, Molly, A. Mushfiq Mobarak, and Tania Barham, “Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil,” *American Economic Journal: Applied Economics*, 2013, *5* (2), 200–231.

Shah, Manisha and Bryce Millett Steinberg, “Drought of Opportunities: Contemporaneous and Long Term Impacts of Rainfall Shocks on Human Capital,” Working Paper 19140, National Bureau of Economic Research June 2013.

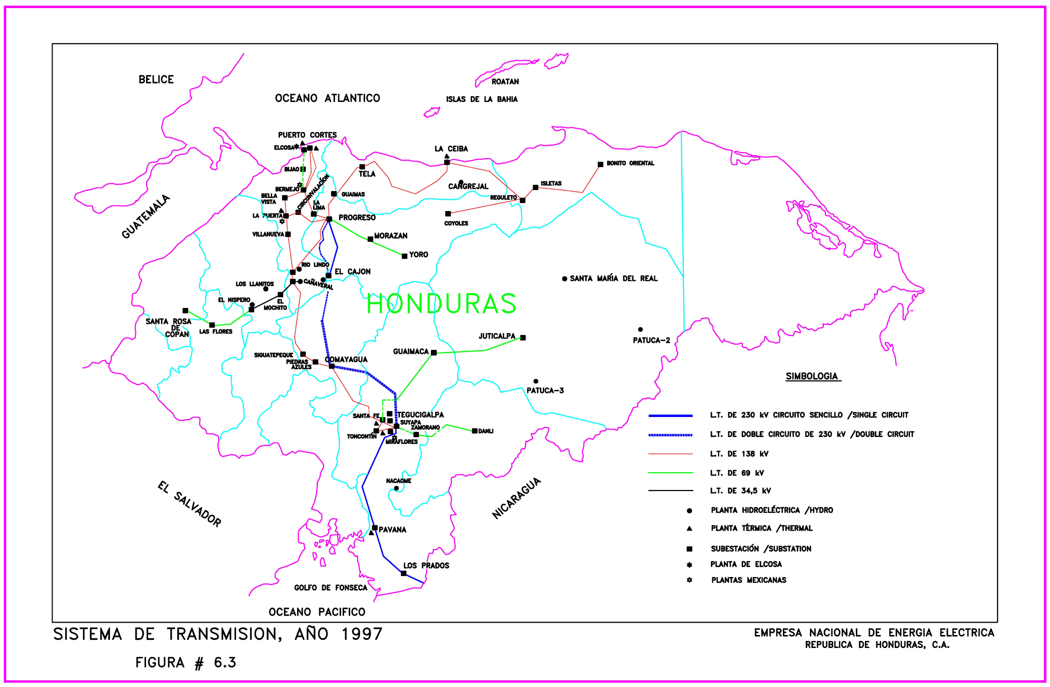
van de Walle, Dominique, Martin Ravallion, Vibhuti Mendiratta, and Gayatri Koolwal, “Long-term impacts of household electrification in rural India,” Policy Research Working Paper Series 6527, The World Bank June 2013.

Figure 1: Honduran Electrical Network in 2012



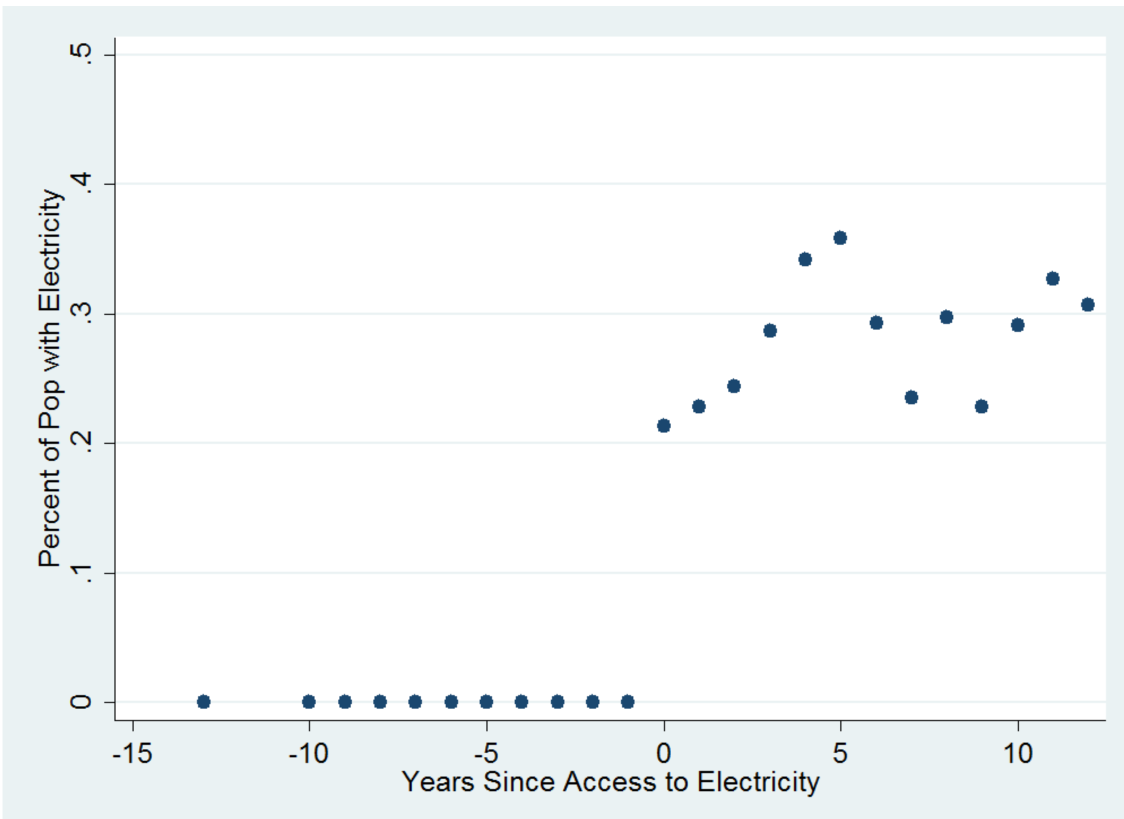
This map represents the electrical grid as it was in 2012.

Figure 2: Honduran Electrical Network 1997



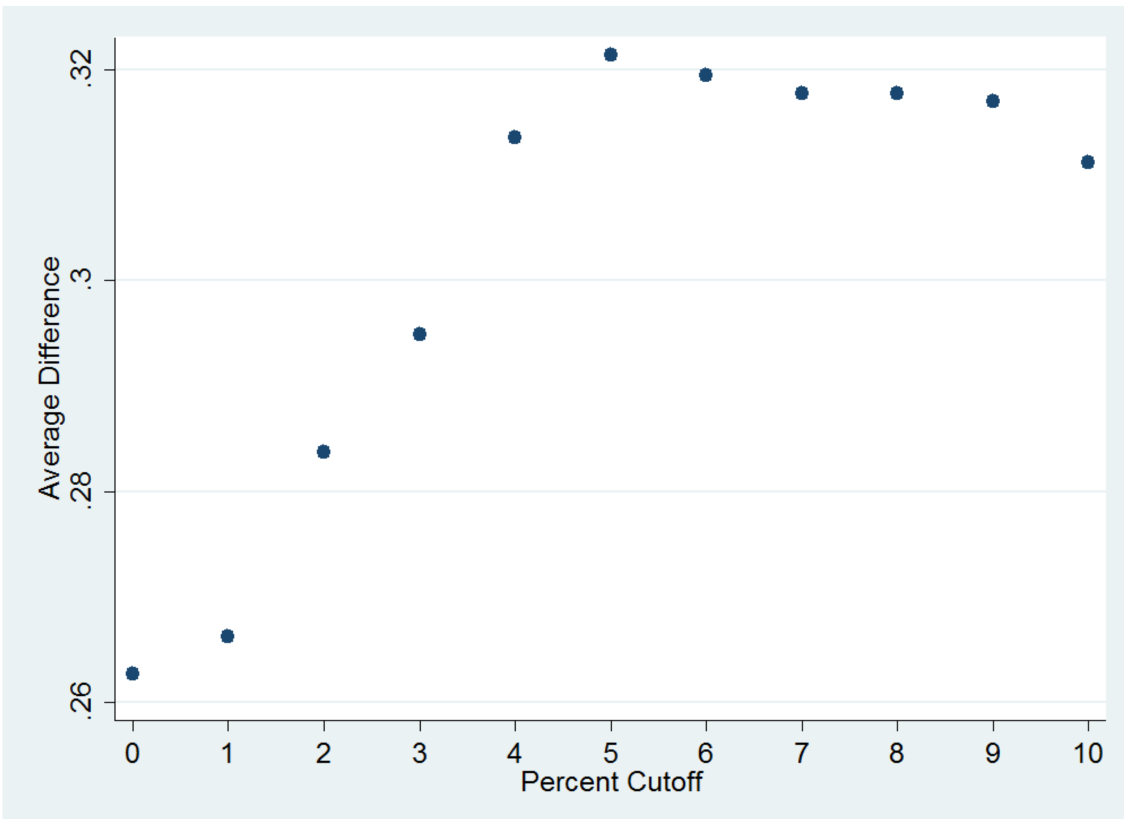
This map represents the electrical grid as it was in 1997. The purple line outlines the country while the light blue line outlines the districts. The thick blue, green and orange lines represent transmission lines, substations are represented by squares and unfortunately distribution lines are not shown. This map was provided by the ENEE in pdf format and is the only other network map available.

Figure 3: Percentage of the Population Reporting Electricity



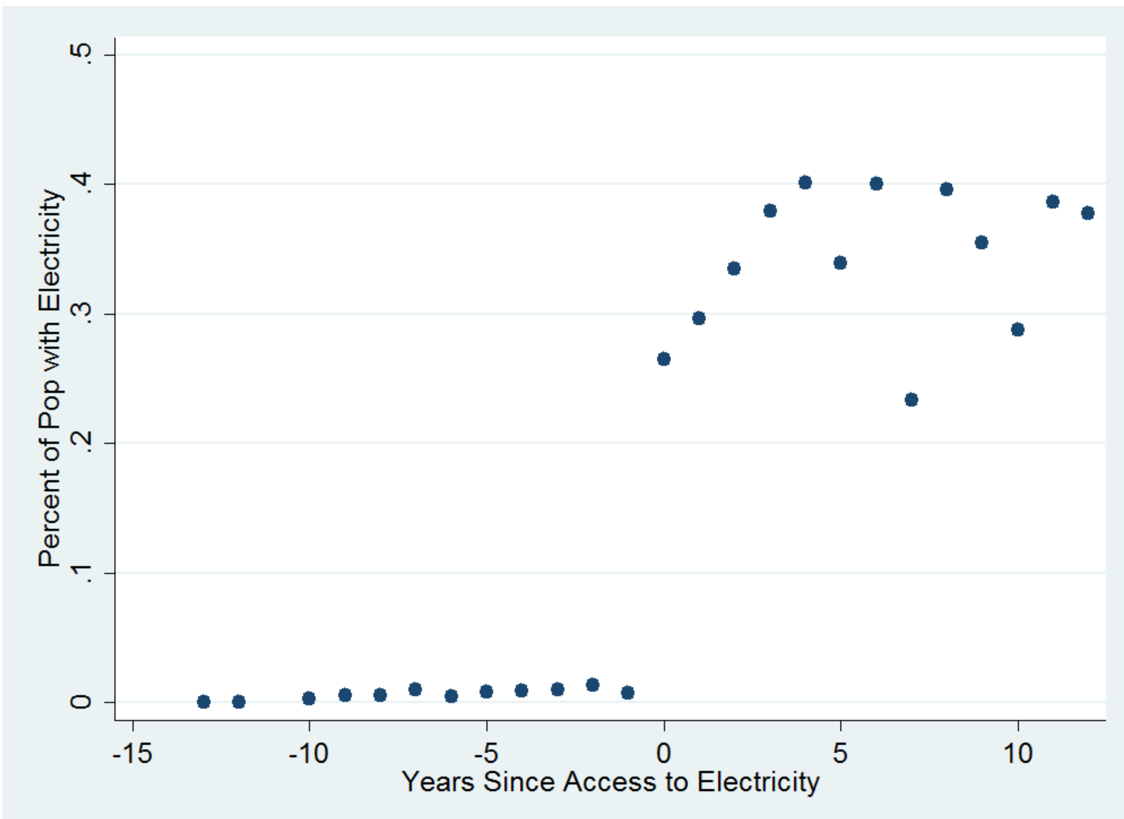
Each point represent the percentage of the population who has access to a electricity. The year of electricity for each individual is defined as the year that the municipality the individual is in had at least one person reporting access to electricity.

Figure 4: Percentage Change in Access



Each point represent the jump in percentage of the population reporting access to electricity given a specific cutoff. The x axis represents the cutoff used to define when a municipality gained access to electricity.

Figure 5: Percentage of the Population Reporting Electricity



Each point represent the percentage of the population who has access to a electricity. The year of electricity for each individual is defined as the year that the municipality the individual is in had at least five percent or 16 people reporting having access to electricity.

Table 1: Educational Attendance

Outcome: School Attendance						
	Full		Women		Men	
Electricity	-0.0386*	-0.0400*	-0.0372	-0.0379	-0.0415*	-0.0428*
	(0.0204)	(0.0203)	(0.0235)	(0.0232)	(0.0222)	(0.0222)
Household Size		-0.00436**		-0.00502**		-0.00370
		(0.00188)		(0.00243)		(0.00236)
Age		0.0127***		0.0110***		0.0148***
		(0.00254)		(0.00357)		(0.00279)
Female Head of Household		0.00720		0.00739		0.00642
		(0.00832)		(0.00987)		(0.0113)
Sex		0.0112*				
		(0.00654)				
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
N	18359	18312	9018	9001	9341	9311

The dependent variable is one if an individual says they are in school and zero otherwise. Electricity is a binary variable with one being if the municipality has electricity and zero otherwise. The sample is limited to children between the age of 7 and 16. The first 2 columns include the entire sample, columns 3-4 limit the sample to only females and columns 5-6 limit the sample to only males. All errors are clustered at the municipality level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Educational Attainment

Outcome: Years of Education			
	Full	Women	Men
Electricity	-0.262*	-0.347**	-0.168
	(0.144)	(0.169)	(0.163)
Years of Childhood Electricity	-0.115***	-0.116***	-0.106***
	(0.0299)	(0.0384)	(0.0334)
Household Size	-0.00860	0.0211	-0.0373**
	(0.0107)	(0.0135)	(0.0145)
Age	-0.0348**	-0.0524***	-0.0170
	(0.0134)	(0.0150)	(0.0164)
Sex	0.292***		
	(0.0644)		
Female Head of Household	-0.0611	-0.0156	-0.111
	(0.0704)	(0.0965)	(0.0886)
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
N	19257	8715	10542

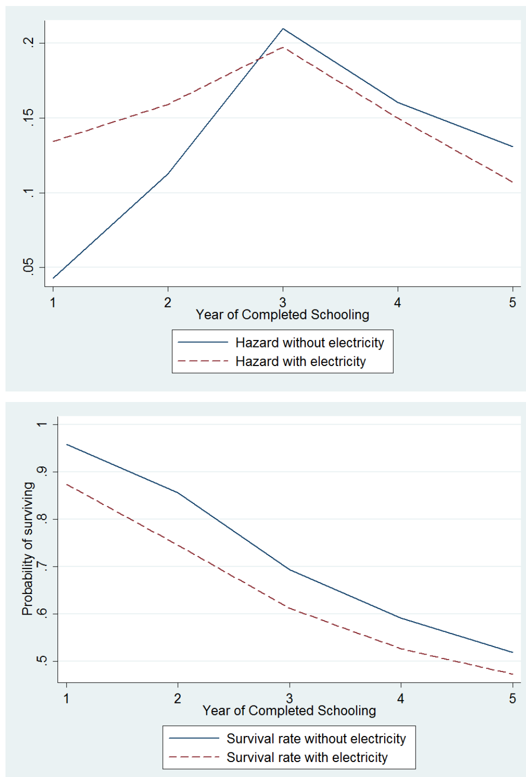
The dependent variable is the number of years of completed schooling an individual has. Electricity is a binary variable with one being if the municipality has electricity and zero otherwise. Years of childhood electricity is the number of years an individual had electricity between 6 and 12. The sample is limited to individuals who have finished schooling, are under the age of 24 and have not moved. Columns 2, 4 and 6 limit the sample to those individuals who had at least one year of electricity as a child. The first 2 columns include the entire sample, columns 3-4 limit the sample to only females and columns 5-6 limit the sample to only males. All errors are clustered at the municipality level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Educational Attainment

Outcome: Hazard of Dropping Out			
	Full	Women	Men
Electricity1	1.139***	1.390***	0.882***
	(0.117)	(0.135)	(0.167)
Electricity2	0.344***	0.297**	0.378***
	(0.0833)	(0.141)	(0.0983)
Electricity3	-0.0606	-0.103	-0.0251
	(0.0640)	(0.0649)	(0.105)
Electricity4	-0.0667	-0.0606	-0.0712
	(0.118)	(0.139)	(0.130)
Electricity5	-0.198*	-0.303**	-0.105
	(0.110)	(0.122)	(0.143)
N	19909	9476	10433
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

The dependent variable is one if an individual drops out of school that year and zero otherwise. Electricity1, Electricity2, Electricity3, Electricity4, and Electricity5 is equal to one if the student is in a specific year of school (1-5) and the year is after the year of electrification and zero otherwise. The model is estimated using a Cox proportional hazard framework. The sample is limited to individuals who have finished their schooling, have non-zero years of schooling and have not moved. The first column includes the entire sample, columns 2 limits the sample to only females and columns 3 limits the sample to only males. All errors are clustered at the individual level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Graph of Heterogeneous Cox Results



These graphs represent different predicted values from the first column of table 3. The hazard with(without) electricity represents the hazard the average individual would face if they did(not) have electricity. Similarly the survival rate with(without) electricity is the probability of completing each year of schooling with(without) access to electricity. To create the hazard without electricity predicted Xb was generated from the previous regression. I then subtracted off electricity times the coefficient on electricity. Finally the hazard displayed is the exponential of this multiplied by the negative of the baseline hazard. For the hazard with electricity I did the same thing except instead of adding electricity times the coefficient I simply added one minus electricity times the coefficient. For the two survival rates I calculated the exponential of the negative baseline hazard for each period and raised that to the hazard with or without electricity. Finally I multiplied each period by the period before to calculate the survivorship.

Table 5: Childhood Employment

Outcome: Employment			
	Full	Women	Men
Electricity	0.0238*	0.0289***	0.0143
	(0.0138)	(0.00958)	(0.0245)
Household Size	0.00420***	-0.00165	0.00902***
	(0.00159)	(0.00160)	(0.00213)
Age	0.0819***	0.0326***	0.127***
	(0.00191)	(0.00267)	(0.00301)
Female	-0.288***		
	(0.0125)		
Female Head of Household	-0.00761	0.0332***	-0.0474***
	(0.00981)	(0.0109)	(0.0130)
N	22923	11090	11833
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes

The dependent variables is whether an individual is employed. Electricity is a binary variable with one being if the municipality has electricity and zero otherwise. The controls are household size, age, age squared, sex, and the gender of the head of the household. The first column includes the entire sample, column 2 limits the sample to only females and column 3 limits the sample to only males. All errors are clustered at the municipality level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Female Employment

	Employed	Hours Worked	Log(Earnings)	Log(Wage)
Electricity	0.0564***	4.088***	0.150**	0.0311
	(0.0161)	(1.038)	(0.0736)	(0.0643)
Household Size	-0.0105***	-0.212*	-0.0250***	-0.0175***
	(0.00141)	(0.115)	(0.00750)	(0.00637)
Age	0.0200***	-0.108	0.0410***	0.0487***
	(0.00104)	(0.0978)	(0.00849)	(0.00862)
Age Squared	-0.000242***	0.0000167	-0.000549***	-0.000561***
	(0.0000105)	(0.00111)	(0.0000935)	(0.0000940)
Female Head of Household	0.189***	0.161	-0.0288	-0.0389
	(0.00991)	(0.658)	(0.0429)	(0.0409)
N	31168	9615	8663	8369
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes

The dependent variables are whether an individual is employed, the hours an individual worked, the log of one plus labor earnings, and the log of one plus wage. Electricity is a binary variable with one being if the municipality has electricity and zero otherwise. The sample is limited to only females above the age of 18. All errors are clustered at the municipality level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Impact of Childcare

Outcome: Hazard of Dropping Out			
	Full	Women	Men
Electricity1	1.011***	1.149***	0.903***
	(0.131)	(0.175)	(0.180)
Electricity2	0.256**	0.275*	0.239*
	(0.106)	(0.166)	(0.138)
Electricity3	-0.128*	-0.137	-0.124
	(0.0714)	(0.0919)	(0.129)
Electricity4	-0.117	-0.145	-0.0979
	(0.134)	(0.191)	(0.154)
Electricity5	-0.215	-0.330*	-0.122
	(0.137)	(0.187)	(0.152)
Electricity1*Toddler	0.101	0.173*	-0.0323
	(0.0748)	(0.0939)	(0.116)
Electricity2*Toddler	0.0733	0.00866	0.124*
	(0.0607)	(0.0945)	(0.0724)
Electricity3*Toddler	0.0602	0.0206	0.102
	(0.0514)	(0.0555)	(0.0828)
Electricity4*Toddler	0.0491	0.0700	0.0314
	(0.0484)	(0.0904)	(0.0713)
Electricity5*Toddler	0.0169	0.0225	0.0211
	(0.0886)	(0.112)	(0.0948)
Toddler	0.0712***	0.0858***	0.0569***
	(0.00916)	(0.00980)	(0.0125)
N	89246	42887	46359
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

The dependent variable is one if an individual drops out of school that year and zero otherwise. Electricity1, Electricity2, Electricity3, Electricity4, and Electricity5 are equal to one if the student is in a specific year of school (1-5) and the year is after the year of electrification and zero otherwise. Toddler is equal to the number of children under five in a household. The model is estimated using a Cox proportional hazard framework. The sample is limited to individuals who have finished their schooling, have non-zero years of schooling and have not moved. The first column includes the entire sample, columns 2 limits the sample to only females and columns 3 limits the sample to only males. All errors are clustered at the individual level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Returns to Education

Outcome: Log of Wage			
	Full	Women	Men
Years of Schooling 1-2	0.220***	0.284**	0.215**
	(0.0766)	(0.117)	(0.0879)
Years of Schooling 3-4	0.262***	0.368**	0.232***
	(0.0506)	(0.154)	(0.0472)
Years of Schooling 5-6	0.503***	0.753***	0.433***
	(0.0704)	(0.131)	(0.0646)
Household Size	-0.00347	-0.00675	-0.00378
	(0.00812)	(0.0186)	(0.00929)
Age	0.0531***	0.0403**	0.0570***
	(0.00650)	(0.0162)	(0.00642)
Age Squared	-0.000538***	-0.000373*	-0.000589***
	(0.0000751)	(0.000198)	(0.0000709)
Female	-0.205***		
	(0.0654)		
Female Head of Household	-0.0788	-0.121	-0.0369
	(0.0517)	(0.0880)	(0.0797)
N	4490	978	3512
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes

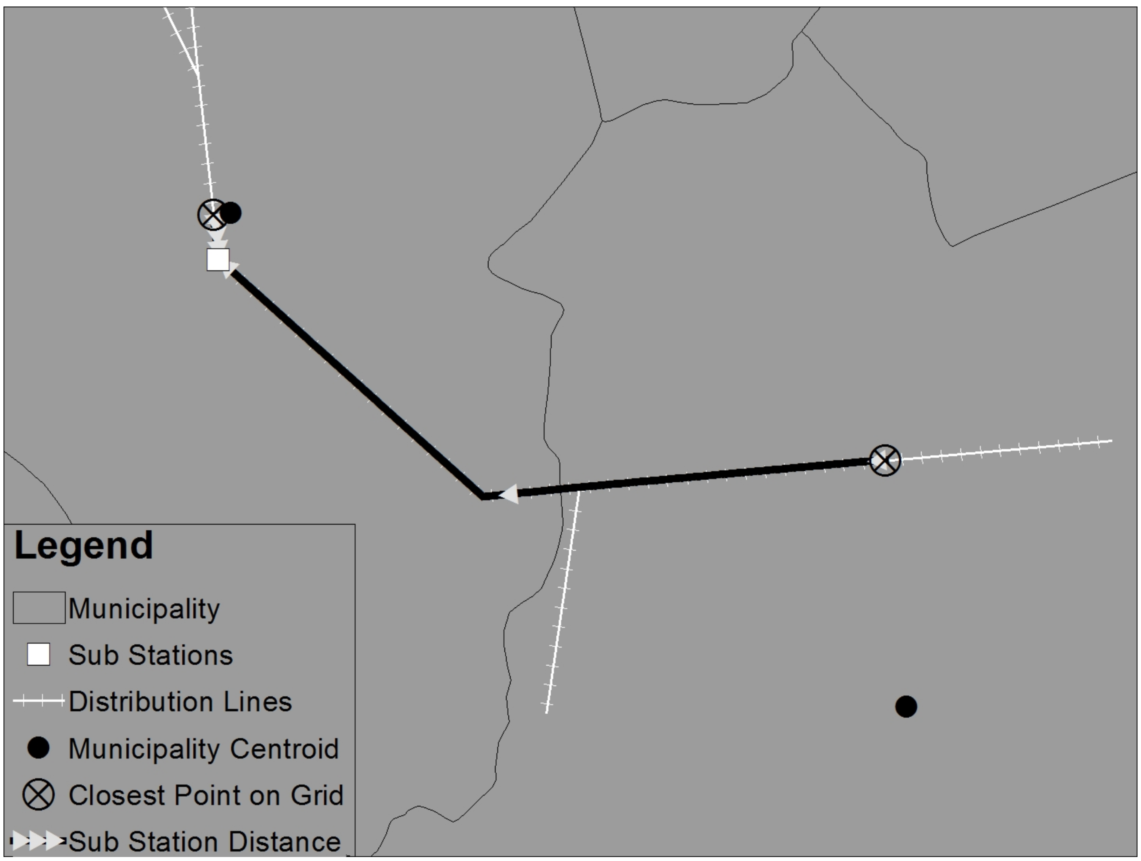
The dependent variables is the log of one plus an individuals wage. Years of Schooling 0, 1-2, 3-4, and 5-6 are binary variables which are one if an individuals maximum years of schooling is equal to the number and zero otherwise. The sample is limited to places before they gain access to electricity. The first column includes the entire sample, column 2 limits the sample to only females and column 3 limits the sample to only males. All errors are clustered at the municipality level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Returns to Education with Electricity

Outcome: Log of Wage			
	Full	Women	Men
Electricity*Years of Schooling 0	-0.0189	-0.0205	0.00373
	(0.0544)	(0.0770)	(0.0621)
Electricity*Years of Schooling 1-2	0.0679	0.155	0.0312
	(0.0593)	(0.103)	(0.0657)
Electricity*Years of Schooling 3-4	0.0699	0.128	0.0435
	(0.0690)	(0.125)	(0.0686)
Electricity*Years of Schooling 5-6	0.0256	-0.0674	0.0430
	(0.0617)	(0.0856)	(0.0619)
Years of Schooling 1-2	0.208***	0.242**	0.217**
	(0.0752)	(0.114)	(0.0845)
Years of Schooling 3-4	0.284***	0.379***	0.267***
	(0.0490)	(0.140)	(0.0476)
Years of Schooling 5-6	0.508***	0.733***	0.466***
	(0.0619)	(0.112)	(0.0597)
Household Size	-0.0137***	-0.0111*	-0.0142***
	(0.00358)	(0.00627)	(0.00408)
Age	0.0519***	0.0514***	0.0505***
	(0.00344)	(0.00794)	(0.00311)
Age Squared	-0.000515***	-0.000521***	-0.000498***
	(0.0000353)	(0.0000833)	(0.0000328)
Female	-0.0586*		
	(0.0312)		
Female Head of Household	-0.0824***	-0.0378	-0.122***
	(0.0228)	(0.0408)	(0.0251)
N	30145	8161	21984
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes

The dependent variables is the log of one plus an individuals wage. Ect is a binary variable with one being if the municipality has electricity and zero otherwise. Years of Schooling 0, 1-2, 3-4, and 5-6 are binary variables which are one if an individuals maximum years of schooling is equal to the number and zero otherwise. The first column includes the entire sample, column 2 limits the sample to only females and column 3 limits the sample to only males. All errors are clustered at the municipality level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 6: Instrument Creation



The instrument was created in two steps. First the nearest point, on the distribution line, to the centroid of the municipality was determined. Second the distance to the nearest substation from this point was calculated. All municipalities without a distribution line were removed and the final value is in kilometers.

Table 10: Test 1: Relevance

Outcome: Year of Electrification			
Grid Distance	0.0340***		
	(0.0108)		
Straight Distance		0.0439***	
		(0.0129)	
Average Slope			-0.0527
			(0.141)
Age	-0.0849	-0.103	-0.117
	(0.129)	(0.128)	(0.129)
Sex	-19.12**	-14.87*	-14.71*
	(7.921)	(8.190)	(8.535)
Household Size	-0.383	-0.652	-0.439
	(0.451)	(0.473)	(0.452)
Female Head of Household	-0.8897	-3.535	-2.776
	(3.692)	(3.756)	(3.928)
N	85	87	87

The dependent variable is the year each municipality got electricity. Grid distance is the distance along the distribution line from a substation to the closest point to the centroid of a municipality. Straight distance is the distance from the centroid of a municipality to the nearest substation. Average slope is the average slope in the municipality. The control variables, age, sex, household size, and gender of household head are the average for the municipality in the first year that data is available. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Test 2: Exclusion Restriction

	Employment	Hours Worked	Log Earnings	Log Wage	School Attendance	Years of Schooling	Log of Household Income
Grid	0.0000145	-0.0208	0.000887	0.00132	0.000762	0.000718	-0.000514
Distance	(0.000202)	(0.0176)	(0.00204)	(0.00163)	(0.000513)	(0.00135)	(0.00146)
N	10505	6159	5336	5272	6185	6185	3838
Straight	0.000521***	0.0108	0.00657***	0.00594***	0.00113***	0.000656	0.00478***
Distance	(0.000108)	(0.00718)	(0.000858)	(0.000695)	(0.000229)	(0.000607)	(0.000797)
N	10617	6226	5397	5333	6262	6262	3880

The dependent variables are whether an individual is employed, the number of non-zero hours worked, the log of non-zero earnings, and the log of non-zero wages respectively averaged over individuals in a municipality. Grid distance is the distance along the distribution line from a substation to the closest point to the centroid of a municipality. Straight distance is the distance from the centroid of a municipality to the nearest substation. The sample is limited to observations before the municipality had electricity. All errors are clustered at the municipality level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Test 3: Population Density and Growth

	Population 1988	Population 2001	Population Growth 1974-1988	Population Growth 1974-2001	Population Growth 2001-2010
Grid	-0.0627	-0.125	-0.00238	-0.00416	0.0000701
Distance	(0.0935)	(0.117)	(0.00409)	(0.00286)	(0.00380)
Straight	-0.0897	-0.155	-0.00303	-0.00621^{*}	0.00987^{**}
Distance	(0.114)	(0.139)	(0.00657)	(0.00316)	(0.00428)
Sample	All	All	All	All	Post 2001

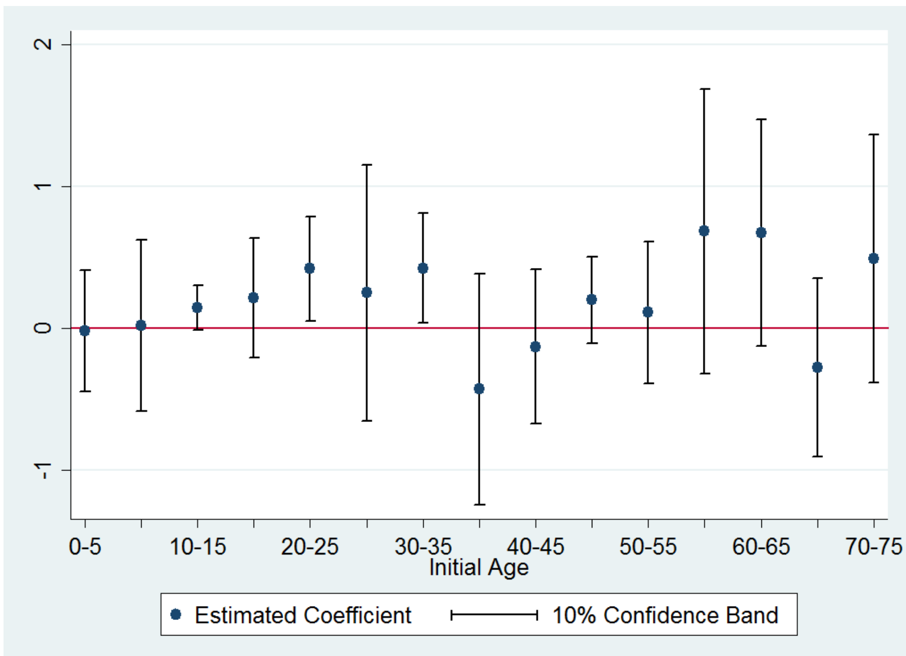
The dependent variables are population and population growth rates by municipality. Rid distance and straight distance were run in seperate regressions. Grid distance is the distance along the distribution line from a substation to the closest point to the centroid of a municipality. Straight distance is the distance from the centroid of a municipality to the nearest substation. In column four the sample is limited to municipalities that get electricity post 2001. All errors are clustered at the municipality level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Instrumented Educational Attainment

Outcome: Hazard of Dropping Out			
	Full	Women	Men
$\hat{Electricity1}$	1.628***	1.8271***	1.3879***
	(0.0987)	(0.1299)	(0.1549)
$\hat{Electricity2}$	0.5922***	0.7523***	0.4340***
	(0.0881)	(0.1197)	(0.1303)
$\hat{Electricity3}$	0.0511	0.0271	0.0598
	(0.0802)	(0.1265)	(0.1052)
$\hat{Electricity4}$	0.0154	0.02847	-0.0041
	(0.0926)	(0.1333)	(0.1300)
$\hat{Electricity5}$	-0.17998*	-0.2258	-0.1560
	(0.1015)	(0.1511)	(0.1390)
N	37302	18240	19062
		First Stage	
Grid	0.0340***	0.0340***	0.0340***
Distance	(0.0105)	(0.0105)	(0.0105)
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Bootstrapped	Yes	Yes	Yes

The dependent variable is one if an individual drops out of school that year and zero otherwise. $\hat{Electricity1}$, $\hat{Electricity2}$, $\hat{Electricity3}$, $\hat{Electricity4}$, and $\hat{Electricity5}$ is equal to one if the student is in a specific year of school (1-5) and the year is after the predicted year of electrification and zero otherwise. The predicted year of electrification is created by instrumenting for the year a municipality got electricity with Grid distance. The model is estimated using a Cox proportional hazard framework. The sample is limited to individuals who have finished their schooling, have non-zero years of schooling and have not moved. The first column includes the entire sample, columns 2 limits the sample to only females and columns 3 limits the sample to only males. All errors are clustered at the individual level and the entire two stage process is bootstrapped. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 7: Migration



This graph represents the coefficient on electricity in a regression of electricity on the ratio of ages in a municipality. The ratio is ages 2 years divided by ages today. For example the amount of individuals who are 2-7 in two years divided by the number who are 0-5 today. Electricity is defined as 1 if a municipality gained access to electricity in those two years and zero if they did not have electricity in those two years.