

Power to empower: the impact of electricity on women and children in Sub-Sahara Africa

Emile Tenezakis*
Paris School of Economics

Ahmed Tritah†
Le Mans Université, Chaire Energie et Prospérité

January 2019

Abstract

In this paper we investigate the impact of electricity on time-use, labor and human capital outcomes for children and women-spouses. Our analysis consider both household and village-level treatment effects. First, using aggregate data we draw stylized facts regarding the energy-development nexus across the last twenty years in Sub-Sahara Africa. We provide data -driven arguments showing that complementary access to appliances and women empowerment are critical for energy to reach its development potential. In a second part, we quantify the causal relationship between energy, time-use, employment and human capital using a rich and detailed micro-level household survey data from Rwanda. We deal with the endogeneity issue by using a combination of matching and an instrumental variable approach. Matching allows us to carefully choose the control group in a multilevel treatment context (household and village), while the instrument allows to get-rid off unobserved selection bias. Our new instrument is based on the ratio of potential area-to-electrify on potential area of the village under the assumption that households are centered around the road in the village. We show a negative aggregate effect of electricity access at the household level on overall time allocated to chores and a positive effect on overall time allocated to wage job activities. Moreover, the impact of electricity varies across children and spouses. We find strong impact on women propensity to work, and on the number of hours supplied for wage jobs. For children, we find a strong and positive, though insignificant, effect on work propensity and a negative effect on wage-work hours. Among educational outcomes, only repetition seems to be negatively impacted by electricity. This result suggests that accessing electricity is equivalent to a positive shock on household level time endowment which relaxes the usual trade-off between working and studying. Finally, contrasting treatment effects at household and village level reveal a strong spillover effects of electrification which benefits women employment in non-connected households.

Keywords: Labor, Child-labor, Energy, Poverty, Human Capital, Sub-Sahara Africa, Treatment Effects

*Contact: emile.tenezakis@polytechnique.edu

†Contact: ahmed.tritah@univ-lemans.fr

We gratefully acknowledge the Chaire Energie and Prospérité for its support, and particularly Anna Creti and Jean-Pierre Ponssard for their encouragement. We are grateful to participants at the conference Energie Climate and Development at Université Paris Dauphine and particularly to Jörg Peters for their insightful comments

1 Introduction : rural electrification and development

It is widely acknowledged that access to modern energy services is a prerequisite for the economic, and social development of populations in Africa, especially in rural areas. As of 2014, 87% of the population worldwide had access to electricity, whereas 43% Sub-Saharan Africans were able to use electricity at home. For the particular case of Rwanda only roughly 20% of inhabitants have access to electricity. The lack of energy is even more acute in rural areas : in 2014, 17% Rural Sub-Saharan Africans were connected to the grid, and 9% in Rwanda. Because of the low connection rates and their economic status, developing countries have the highest potential for energy consumption growth. As households rise out of poverty they purchase new assets, many of which use substantial amounts of energy: e.g. refrigerators, TVs [Wolfram *et al.* , 2012]. The channels through which access to modern form of energy impacts rural households are numerous and still not well understood and quantified. In this paper we focus on the human capital and labor market channel. An intensive movement of rural electrification projects was launched,¹ in all regions of the developing world, and more recently in SSA. Since 2010, for Africa alone, 38 projects related to rural electrification were approved and supported by the World Bank with a commitment amount of approximately 4 billion USD.

Despite these efforts, knowledge on the consequences remains scarce. At a macroeconomic level, access to electricity is a strong vector of productivity jumps ; factories that acquire electrified capital may decrease their production costs which would eventually decrease prices and enhance manufactured goods consumption [Rud, 2012]. At the micro-economic level, what happens is fuzzier. [Lee *et al.* , 2017] shed light on the lack of micro-founded studies that assess the different impact mechanisms. Since they are theoretically numerous, empirical assessment is challenging. As a matter of fact, for several outcomes such as labor or education, results are highly heterogeneous. Jimenez (2017) [Jimenez, 2017] highlights this and points out the problem of the external validity of each of these works produced in very different contexts. Bernard (2012) [Bernard, 2012] and Lee and al. (2018) [Lee *et al.* , 2018] respectively, summarize the situation. According to the first "No one doubts that RE positively affects household well-being. In addition, if RE is not necessarily a sufficient condition to long-term development of rural areas, it is probably a necessary one." The second authors pointed out that "connecting rural households today is not necessarily an economically productive and high return activity in the worlds poorest countries".

This paper aims at improving this fuzzy knowledge with respect to children and women time use, education and labor outcomes. Its contribution is twofold. Empirically we propose to focus on an analysis of children and women outcomes in the Rwandan context with respect to electrification, an approach that is from our knowledge absent in the literature². Identifying the causal impact of electricity at the household level is challenging, at two levels. First, grid connections are not randomly distributed in the space, some villages are more likely to be connected than other according to characteristics that affect their economic outcomes. Second, while village status is pre-determined, households decide whether to connect or not. This decision may be endogenous to employment and human capital decisions. For instance high wage potential workers may be more likely to connect

¹We will make use of RE as an abbreviation for Rural electrification

²we are inspired by Tanguy and Salmon (2016) [Salmon & Tanguy, 2016] who study jointly wife and husband labor outcome in Nigeria.

than others. We deal with these issues using methods to control for observable characteristics such as classical OLS and Tobit regression for time-use, matching on the propensity score and inverse-probability weighted regression using the propensity scores. We also employed an instrumental variable strategy. We distinguish two level of treatments. The household treatment-level and the village-level treatment. We provide results for an analysis mixing both treatments and an analysis limited to the household-level treatment to provide a message regarding potential spillover effects at the village-level. For the global treatment, the different approaches lead to relatively similar results in various respects. At the household-level, there is clearly a decrease in the aggregated time devoted to chores and an increase in the aggregated time devoted to wage activities, outside of the house. At the individual level, we limit the analysis to the female spouse of monogamous head couples and their children for political economy reasons. Moreover, we show a strong extensive and intensive effect for wage job, for women, in line with expected benefits of electrification for them. What is interesting is that we find also, a positive though non significant effect for children, at the extensive margin. This effect is not found when constraining the analysis to household-level treatment. Furthermore, the effects are all weaker for women in the constrained analysis. This suggests a strong spillover effect and the necessity to distinguish household and village level treatment effect. Overall education outcomes are less impacted, except for repetition that seems to be decreased when household connects, independently of the treatment level suggesting that this outcome is not impacted by a potential spillover effect.

Our IV 2SLS strategy employs a new instrument based on an estimated ratio of areas of the village. We estimate the ratio of the potential to-electrify area of the village to the potential area of the village, under the assumption that households are centered around the road. We expect a higher ratio to diminish the marginal cost of household connection especially in the Rwandan context where land elevation is systematic. There is room for instrument improvement since the IV 2SLS results are less precise.

The rest of the paper is organized as follows. In the second section we provide macroeconomic intuition and motivation for the topic and the mechanisms that we wish to investigate. In the third section we present the Rwandan case study and our underlying theoretical reasoning. In the fourth and fifth, we expose our data, identification issues and empirical strategy. In the sixth we present the main results. The seventh section provides complementary analysis. The last section concludes. Additional results and robustness checks have been relegated into a separate appendix.

2 Macroeconomic intuition and motivations

For both households and firms Electricity is an *enabling energy*. Households don't consume electricity, instead electricity allows them to produce and consume new kinds of goods. Therefore, outcomes depend on the access quality and ultimately on the availability of complementary energy-using assets [Squires, 2015, Wolfram *et al.*, 2012]. For example, in the case of India, for electricity to allow people to save time they must decide to acquire electric stoves to replace their wood-based cooking appliances and thus avoid having to look for wood everyday [World-Bank, 2004]. Impacts differ whether people buy Televisions or electric stoves as a first asset. TV may improve marginal value of leisure time, electric stoves may improve household chores productivity. If household faces financial constraints -

which is systematic in SSA where credit market is underdeveloped - it may be impossible to acquire first assets. Preferences and intra-household decision process may be determinant both for assets purchases and time allocation decisions. In the following we provide a macroeconomic piece of evidence that people do react to supply shocks, that decrease the price of assets, by acquiring more of those assets suggesting that credit constraint on asset acquisition may be important. We use the integration of China to the WTO as an exogenous supply chock triggering the acquisition of energy-complementary assets.

Following the 90s and the entry of China in the WTO in 2001, Chinese global exports surged and especially to Africa. This liberalized trade flows, and particularly import, from China and thus represented for Sub-Saharan African countries a huge positive and exogenous supply shock. This lowers exogenously the cost of imported electronic appliances. Refrigerators are among the items that are first bought by households rising out of poverty in developing countries. Figure 1 shows a strong reaction to the Chinese supply shock in four different SSA countries. As Chinese products became available in the market after 2001, imports of refrigerators from China surged. In 2002, in Kenya which is one of the biggest trade partner of China in the region, it increased by more than 300%. At the firm-level, if companies do connect to the grid and acquire electrified capital requiring labor to be used, then labor demand in the locality should increase. The literature on firm-side effect in poor countries is scarce [Rud, 2012]. Beside low access rate, SSA countries have also a low quality of electricity connection : there is a high variance among countries with respect to number of outages and those with the highest number are typically center-SSA countries.³ In these conditions, as shown by Alby, Dethier and Straub (2013) [Alby *et al.* , 2013], firms may decide not to invest in electrical features from which they get low expected returns given the quality of access.

Second, provided that energy is used by both firms and households, the household-level causality chain is complex. Intuitive effects of electric appliances use are numerous and there is a growing body of literature unequally investigating each path. In developing countries rural areas men and women allocate their time among labor market work, home business, household chores, leisure, and education-devoted time for children. The use of appliances has effect on all these activities returns and costs.

Home production in developing countries has been exposed to a positive technology shock [Grogan & Sadanand, 2009]. For example, electric stoves or refrigerator allow individuals to save time in home activities. This may either reduce or increase the time allocated to chores : there is a substitution effect because of household chores higher productivity and an endowment effect because of a higher overall time resources [Dinkelman, 2011]. The use of modern form of energy, as electricity, would plausibly decrease time allocated to chores as the home produced goods are bounded from above [Kohlin *et al.* , 2011].

Time allocated to outside work, i.e. to labor market participation, is a key aspect. It has been intensively documented. In particular, Dinkelman (2011) [Dinkelman, 2011] for the case of south Africa, showed an increase in employment for women, only possibly for men, she pointed out new home business opportunities which are possible because of electricity access. Nevertheless, no consensus has emerged on the ultimate impact [Jimenez, 2017]. Although Grogan and Sadanand (2012) [Grogan &

³Source: World Bank enterprise survey

Sadanand, 2012] answer to Dinkelman and found similar result with Nicaraguan data, other authors have shown no effect or even opposite effects.

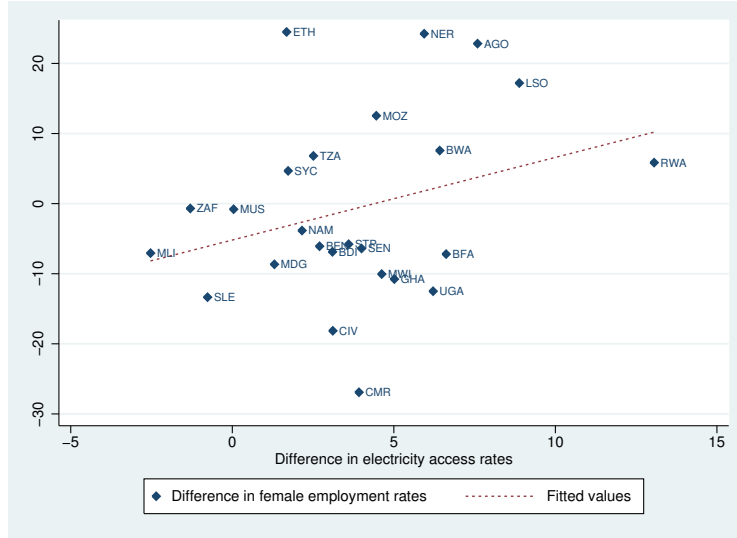


Figure 1: Plotting female employed-to-population ratio difference and electricity access rate difference for 25 countries and the most recent difference observation. Source: World Development Indicators, World Bank.

The macroeconomic insight from figure 2 highlights a clear positive correlation between growth in women employment rate across SSA countries and improvement in access to electricity. Indeed, we expect that the use of modern form of energy will free women-time from some chores allowing them to go working outside, on the other hand the relationship may as well reflect a demand effect instead of a supply effect. In any case interpreting such relationship requires a careful consideration at the micro level. For instance, Salmon and Tanguy (2016) [Salmon & Tanguy, 2016] found effect only for men when taking into account dependence of decision within households. As for home business opportunities, [Kirubi *et al.*, 2009, Dinkelman, 2011] showed that they are indeed stimulated with electricity access.

A second important potential outcome is human capital. With a flavor similar to labor market outcomes, there is no consensus. Some authors do find that education outcomes improve after electrification, some find no effect, and others find that children are worse off with respect to their education outcomes [Jimenez, 2017]. With electric appliances, returns to education may be higher : the daytime is extended with light, the quality of studying is improved with communication technologies, school education is of higher quality. But two other phenomena may occur: substitution of chores between women and children, and opportunity cost of education increases if low-skilled labor demand increases. Numerous works documented the latter phenomena in other contexts than electrification [Atkin, 2016].

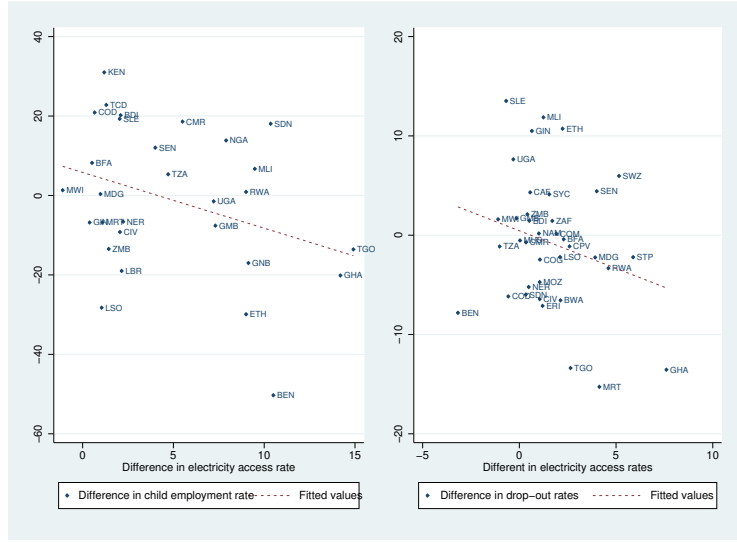


Figure 2: Left: Plotting difference in child employment rates and difference in electricity access rates for 33 countries and the most recent difference observation. Right: Plotting difference in cumulative drop-out rate to the last grade of lower secondary general education and difference in electricity access rates for 34 countries and the most recent difference observation. Source: World Development Indicators, World Bank.

The pervasiveness of child labor in the context of SSA can be seen in Figure 3. Child labor is almost systematic, in most countries above 20% children are at work. A difference plot shows a negative relationship between the growth in children employment and improvement in electricity access rate, at the same time a negative relationship emerges between changes in drop-out rates and improvement in access to electricity. It seems that as households get more access to electricity, children are less likely to work, and are also less likely to drop-out of school.

There is a lack of knowledge regarding these two marginal workers: *Women and children*. Children education and women empowerment are acknowledged as priorities for African development [Cabraal *et al.*, 2005, Kohlin *et al.*, 2011] and previous literature indeed calls for deeper research along these two dimensions. In particular, Tanguy and Salmon (2015) [Salmon & Tanguy, 2016] recommended an extension of their approach. They consider interdependence of spouses decisions, but it is very plausible that there is a dependence of the decision affecting children as well. These outcomes depend on the configuration at hand, whether decision is taken by the household head with different weight possibilities of each member's preferences, or if decisions are the product of some bargaining with different powers [Apps & Rees, 2015].

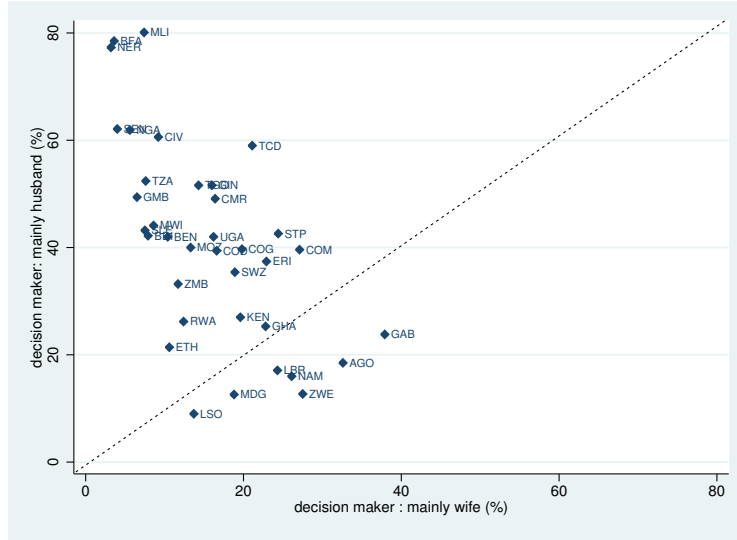


Figure 3: Note: variable is the percentage of 15-49 years old women reporting that the main decision maker for household purchases is mainly husband (y axis) or mainly wife (x axis) in 36 countries for the most recent observation. Source: WDI, World Bank.

The Figure 4 provides insights regarding the importance of the political economy of the household and the culture that defines allocation decision. A large majority of countries have way more women reporting a "dominating" husband than women reporting "dominating" wife. Note that there is a group of country, which are mostly at the left bottom part close to the origin, where women reported in majority a joint decision process. One may do an intuitive comparison between figure 4 and figure 2. Several bottom-left countries from the former figure can be located at the top part of the latter figure in positive areas with respect to the x-axis e.g. Ethiopia (ETH) Angola (AGO) Lesotho (LSO) or Rwanda (RWA). This sheds light on the intuition that in countries where decisions are mostly taken jointly, women are in more favorable position regarding labor market outcomes, when facing an electricity shock.

3 Conceptual Framework

We are interested in women labor outcomes and child labor and education outcomes within rural households. The section above highlighted three major facts for us : the extent to which households can "transform" access to consume further goods, the structure of decision within the household, and the demand-side in the labor market are key aspects for our outcomes of interest. We suggested the effect through higher home-production productivity : but what if one is in a situation where households are even too poor to buy new stoves or fridges? This is precisely the case of rural Rwanda. We use the conceptual framework of Grogan and Sadanand [Grogan & Sadanand, 2012] who show that even in the absence of time-saving appliances, under certain conditions, a time-endowment positive shock pushes women out of home to labor market. We extend the seminal Gronau model [Gronau, 1977], replacing the leisure decision by an education decision and we show that in the presence of home production

and labor market possibilities, the outcomes for children depend on the preference of household for material good consumption and education good consumption ; in certain conditions, more available active time can push children out of the home to the labor market.

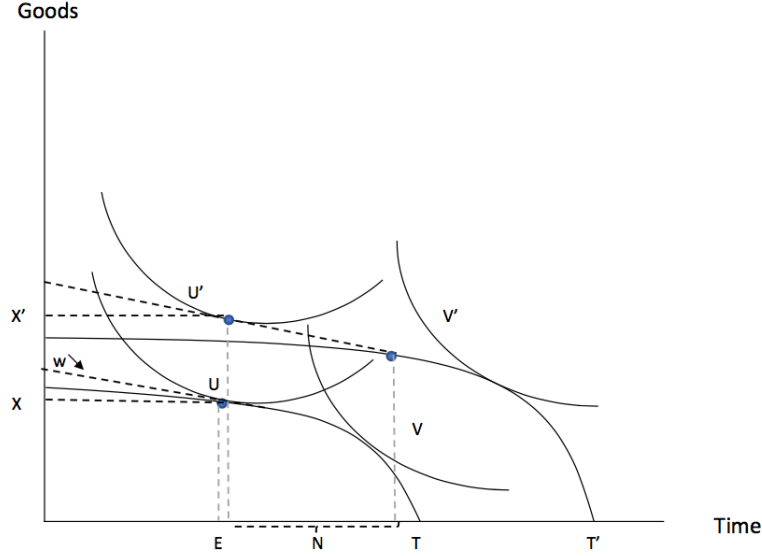
Table 1 provides arguments for the framework of this model. As suggested in the introduction, though we can expect households welfare to be improved because of time-valuing asset acquisition [Fuchs *et al.* , 2016], this will not be the case in Rwanda. Roughly a percent of rural non-electrified households own time-valuing assets (sewing, laundry, cooker, hotplate, freezer), but only 7 percent among those electrified. We explain this by the level of poverty and credit constraint which is prevalent according to our data ; most of the credit amounts are low and built between relatives in an informal way. In this context, we expect electrification impact to occur through a time-endowment shock rather than time-efficiency shock. 97.6% of electrified households use electricity grid for light versus de facto 0 for non-connected households. Grogan and Sadanand showed that if this allows household members to use more active lighted time in the day and work for a wage in labor market, then budget constraint is less tight and household may for example buy wood outside rather than collecting it. This is in line with our empirical evidence. At the same time children get more flexibility in allocating day time between chores, labor and schooling.

Among rural households, a quarter of non-connected households bought wood versus half of those connected. A tenth of non-connected bought coal versus half of the connected, in rural areas only. It means households save time they would use to collect firewood otherwise. Indeed the average number of hours spent foraging is much lower in connected group. It also means they use more efficient source of energy ; coal is indeed a more efficient burnable than wood.

We will therefore investigate our outcomes under the hypothesis of a household-level time-endowment shock. Grogan and Sadanand already provided intuition for women labor supply in this context. We extend this analysis to education. The model is presented in appendix A, we will stick here to a simple graphical intuition in figure 5.

On the y-axis is the amount of good, market or home-produced, that the single household can consume. On the x-axis, is the time the household can allocate to education time consumption, market labor or home production. Let us consider two types of households, type with commodity indifference curve U (see appendix, it corresponds to our Z) and type with V . Type with U has a higher relative preference for material goods consumption. We consider a situation where the total amount of time T increases to T' . This is due to the electrification treatment that allows households to buy light bulbs and to extend their light daytime. Consider type with U . Initially he has T units of time, consumes E for education and $T - E = H$ for home production that allows him to consume only $X = f(H)$ goods since he doesn't work in the market. Type V has initially a higher E and lower H , compared to type U . T increases to T' and the "material-type" chooses the indifference curve U' where $f'(H') = w = MRS$ with H' the new home production time allocation and w the wage rate which is the slope of the tangent lines. He is at a position where he should not allocate the new time in more home production but rather go work in the market for wage w and therefore he supplies $N = T' - E' - H'$ units of labor supply and this allows him to consume $X' > X$ units of material good. Therefore for a material-good loving single-household, a time allocation shock could push the household to work and may or may not decrease education depending on the type. We see that for an

Figure 4: A simple gronau model extended to education and time allocation shock



education-loving single household, this may rather increase mostly education activity.

This is a simple context very similar to Gronau and Sadanand who showed the same theoretical channel but for working women. We can apply indeed a similar reasoning, first because as mentioned above our households all use light as a first asset when they are connected, and second because, since we will restrict our analysis to monogamous couples with children it is very likely that the preference of the household head or decision-maker between education and goods consumption will determine the time allocation of children. Furthermore, we will show hereafter that children seem to work less overall with electricity connection and increase their education time allocation in Rwanda; this is in line with our graph and, we can apply the reasoning to out-of-farm substitution as our data suggests : the decreasing marginal productivity home production function in the graph may well be seen as a decreasing marginal productivity home-farm-production function. In Rwandan rural data indeed, home-farm child labor is rather prevalent.

Table 1: Electricity access and time in Rwandan rural areas : descriptive statistics

	Mean	Min	Max
Household without electricity			
uses electricity for light	0.000	0	0
purchased wood	0.238	0	1
purchased coal	0.089	0	1
purchased bulbs	0.065	0	1
amount spent to purchase coal	1583.148	10	11500
amount spent to purchase wood	1235.560	50	25000
amount spent to purchase bulbs	411.151	50	5000
owns leisure-valuing asset	0.562	0	1
owns time-saving asset	0.014	0	1
hours spent foraging wood	1.965	0	42
Household with electricity			
uses electricity for light	0.976	0	1
purchased wood	0.487	0	1
purchased coal	0.525	0	1
purchased bulbs	0.475	0	1
amount spent to purchase coal	3058.108	100	14000
amount spent to purchase wood	2172.232	100	33000
amount spent to purchase bulbs	909.761	50	2100
owns leisure-valuing asset	0.823	0	1
owns time-saving asset	0.068	0	1
hours spent foraging wood	0.954	0	28
Observations	12144		

Rural areas only. No zero purchase amounts.

4 Data and Variables

Our data source is the EICV4, the cross-sample of the integrated household living conditions survey provided by the national institute of statistics of Rwanda. It is the fourth round of a household survey conducted every five years, across two years. The EICV4 was implemented in 2013-2014. It contains a wide range of socio-economic information including labor and education for 66'081 individuals in 14'419 households in 1'230 villages in 30 districts. There are four levels of information: district, village, household, and individual. We restrict our analysis to rural households composed of monogamous couple and at least one children. The reason we focus on rural households is twofold: first in urban areas electrification rates are very high and an exogenous variation in access is more plausible in rural areas; second, developing access in rural areas is more costly and therefore knowledge of impacts is necessary. The reason we focus on this particular kind of households is the following: we are interested in outcomes for children and women that are interrelated at the household unitary-level because children and women specialize in home production activities. Even though we yet proceed with independent estimation, our ultimate goal is to provide an analysis of interdependence between children and women outcomes. Thus focusing on a framework with monogamous parents and children is more relevant. Therefore our household-level analysis will be limited to those households and our individual outcomes analysis will be limited, for women adults to the female spouse of the household-head couple and for children to the children of that couple. We loose 6'415 households and 22'533 individuals who are not in our type of households - note that those lost households were mostly single-female-headed households. We further loose 6'711 individuals and 1'174 households from in-rural restriction. Our final sample is composed of 36'837 individuals in 6'830 households in 1'013 villages.

Summary statistics of key household characteristics for our final sample are provided in table 2, by treatment group - i.e. for electrified and non-electrified households. Because of our household restrictions, Household head is almost systematically male. Household head in electrified houses is slightly younger in average, 38.728 years old versus 40.043 years old. As expected, a variety of developing rural areas wealth indicators vary across groups. Households are bigger in terms of number of adults and very slightly bigger in terms of all-age children in connected dwellings. The floor area is in average way higher in connected dwellings as well as the probability of having a cement-based floor. Electrified households are also more educated. Head is literate in 68.9% of non-connected houses versus 88.9%. Connection to piped water is also a strong predictor: Half a percent of connected houses are piped versus 22.9%. These figures provide intuition for the selection bias issue we will deal with hereafter: connected households are wealthier in diverse aspects. We also provide household-level summary statistics for aggregated time use. We sum the hours spent during the last 7 days in a variety of activities, jobs and chores, over all members. In this more restricted sample we find the same figure as in Table 1 regarding wood foraging time, which is way lower in average among electrified dwellings.

Table 3 and 4 provide summary statistics and mean-comparison tests for individual outcomes of interest, i.e : participation to wage job during last 12 months, total paid hours if individual had one job in the last 7 days and if dropped-out of school between 2012 and 2013 - i.e. was in class in 2012 but not anymore in 2013 or repeated a class between 2012 and 2013. A children is defined as an individual younger than or 18 years old and who is the kid of the head couple. The female spouse is the female member of the couple. For job outcomes, samples are restricted to individuals older than six years

old. For education outcomes, sample is restricted to children who were in class in 2012 in a primary or secondary school. For the drop-out variable we exclude those who were in the last year of the primary or secondary school in 2012, because they may just have finished the curriculum, which is not properly verifiable in our dataset.

In a preliminary overview, overall children tend to work less among electrified households. I.e. child labor seems to be smoothened by electrification. For human capital outcomes, the overview suggest that both repetition and drop-out decrease with electricity. When it comes to women, the tables suggest a strong impact on women work propensities and hours of work. Of course these figures should not be interpreted as causality analysis and should be taken with caution considering the strong selection bias in our context that will be detailed hereafter.

Table 2: Household descriptive statistics

	Mean	Std. Dev	Min	Max
Household without electricity				
HH is male	0.996	0.061	0	1
HH age	40.043	11.804	18	94
HH is literate	0.689	0.463	0	1
size of household extended	5.364	1.780	3	15
number of literate	2.380	1.588	0	9
nb children below 6 yo	1.219	0.896	0	6
nb children above 6 and below 12 yo	0.976	0.971	0	4
nb children above 12 and below 18 yo	0.629	0.879	0	4
nb children	2.824	1.508	1	9
nb adults	2.277	0.744	0	8
uses piped water (home or public)	0.226	0.418	0	1
uses electricity for light	0.000	0.000	0	0
cement	0.080	0.272	0	1
Floor area of the dwelling	36.669	16.920	5	560
Number of rooms occupied by HH	3.683	1.101	1	11
distance to road in meters	622.507	1286.281	0	15000
distance to cellule office in meters	2437.755	2265.271	8	72000
hours spent foraging wood	6.807	8.119	0	84
hours spent cooking	21.569	10.386	0	122
hours spent fetching water	9.746	9.548	0	126
hours spent searching fodder	17.557	19.232	0	210
hours spent going to market	3.475	4.298	0	112
hours spent for other chores	13.934	15.445	0	165
work hours wage out-of-farm	12.686	24.534	0	196
work hours wage-in-farm	10.379	19.434	0	206
work hours in-house out-of-farm	0.710	5.213	0	111
work hours in-house-in-farm	18.860	21.359	0	178
Household with electricity				
HH is male	0.999	0.038	0	1
HH age	38.728	9.381	22	74
HH is literate	0.889	0.314	0	1
size of household extended	5.721	2.011	3	18
number of literate	3.285	1.724	0	12
nb children below 6 yo	1.210	0.872	0	4
nb children above 6 and below 12 yo	0.969	1.017	0	4
nb children above 12 and below 18 yo	0.655	0.967	0	4
nb children	2.835	1.585	1	9
nb adults	2.453	0.852	1	8
uses piped water (home or public)	0.517	0.500	0	1
uses electricity for light	0.978	0.146	0	1
cement	0.515	0.500	0	1
Floor area of the dwelling	54.900	35.318	10	613
Number of rooms occupied by HH	4.417	1.216	1	10
distance to road in meters	197.806	513.267	0	5850
distance to cellule office in meters	1728.826	1641.260	10	15000
hours spent foraging wood	3.183	5.661	0	53
hours spent cooking	21.739	11.561	0	81
hours spent fetching water	8.015	11.666	0	94
hours spent searching fodder	10.776	15.517	0	129
hours spent going to market	3.651	3.599	0	21
hours spent for other chores	16.196	16.194	0	140
work hours wage out-of-farm	34.561	49.043	0	305
work hours wage-in-farm	3.074	11.987	0	112
work hours in-house out-of-farm	3.598	13.057	0	91
work hours in-house-in-farm	12.417	19.128	0	146
Observations	6830			

Note : sampling weights used to compute means. Size of household is extended to all members of the household, not only the female and male head spouses and children. Aggregated time use is computed according to this extended membership to get an intuition of the input to household production and overall supply of labor to the market.

Table 3: Individual summary statistics

	Without electricity	
	Mean	Std. Dev
Children		
paid non-farm job	0.059	0.236
total paid hours non-farm job	20.920	17.648
dropped-out	0.032	0.176
repeted	0.265	0.442
Women		
paid non-farm job	0.571	0.495
total paid hours non-farm job	26.686	18.932
Observations	23524	
	With electricity	
	Mean	Std. Dev
Children		
paid non-farm job	0.021	0.144
total paid hours non-farm job	10.913	10.876
dropped-out	0.018	0.135
repeted	0.183	0.387
Women		
paid non-farm job	0.415	0.493
total paid hours non-farm job	41.184	21.051
Observations	2299	

Note: households with monogamous couple with children included in the sample. Children are the children of the head couple below or equal to 18 yo and Women are female spouses of the head couple.

Table 4: OLS with a single control

Variables	Children			
	(1) extensive	(2) intensive	(3) drop-out	(4) repetition
elec	-0.0382*** (0.00562)	-10.01** (4.013)	-0.0135** (0.00678)	-0.0825*** (0.0154)
Observations	12,185	382	7,773	7,773
	Women			
	(5)	(6)		
elec	-0.207*** (0.0203)	18.32*** (1.850)		
Observations	6,832	1,498		

Note: same note as Table 3. Here OLS is used as a way to implement a mean-difference test between electrified and non electrified sample. Each block corresponds to a different demographic groupe - children and female spouses. Each column corresponds to an outcome and corresponding sub-sample. For example column (2) includes only individuals with a job within the demographic group.

5 Empirical Strategy

5.1 The Multi-level Treatment Issue

A typical issue that we noticed in the literature is that the authors almost never distinguish at which level the electrification effect they identify occurs. We are in the situation of multi-level data with multi-level treatment. A household is electrified because her village is electrified. But a household can be non-electrified while the village, is. In that case, is that household different with respect to labor or education, from a household in a non-electrified village, all other things being equal? We expect the answer to be positive. For example the labor market effect of electrification can be separated into a labor demand effect that must arise at the village-level - neighbors in the village get electrified, business develop and labor demand rises in the locality - and a labor supply effect that arises at the household level : thanks to lighting the members have more time and they may supply more hours of work. We can distinguish three treatments effects as shown in the next table: (1) being electrified in an electrified village (first line) w.r. being in a non electrified village that we call the combined effect because treated households take benefit from both effects; (2) being electrified in an electrified village w.r. to being non-electrified in an electrified village (second line) - all households take benefit from spillover effects so that we estimate only household-level effect. (3) Finally, considering only non-electrifying households within electrified areas as a treatment w.r. to household outside grid catchment areas (line 3); so that no household take benefit from household-level effect.

Note that this embedded treatment structure magnifies identification issues we will highlight hereafter. In line three, we may conclude that labor demand is higher in connected localities just because of program placement - authorities choose more dynamic villages, villages already endowed with better infrastructure for grid expansion. In line two, we may conclude that labor supply is higher in connected households just because those households have preferences that make them both working more and more likely to connect, or simply because, given their other observable characteristics they have higher wage potential and/or lower reservation wages.

Table 5: Double treatment issue: separating sub-samples

Treated	Control	Variation level
$H = 1$ and $V = 1$	$H = 0$ and $V = 0$	village and household
$H = 1$ and $V = 1$	$H = 0$ and $V = 1$	household
$H = 0$ and $V = 1$	$H = 0$ and $V = 0$	village

5.2 Control methods

5.2.1 Tobit and OLS

Our core outcomes of interest are the wage-work employment and hours for spouses and children. Educational outcome is measured by grade repetition, and school drop out among school age children. Additionally we also have secondary-level results to analyze the time substitutions at stake, namely other activities participation (wage farm work and in-house farm work propensity) and time-use related to household chores.

Note that in the main results, for all strategies, we discard individuals from non-electrified households in electrified villages i.e. those who had the choice to connect but did not, to avoid unobserved spillover effects. We will consider those effects in a further section.

In the vein of Grogan and Sadanand [Grogan & Sadanand, 2012] we use a Tobit model (Table 5) to estimate the electrification effect on household-level aggregated time allocated to chores, wage non-farm jobs, wage farm jobs and in-house farm job and to account for 0-hours value of time allocation. We also use a Tobit model for individual time allocated to chores, for female spouses, male spouses and children of this couple. Furthermore, we use an OLS regression to estimate the effect of electrification on individual employment and binary education outcomes, as well as intensive margin for all types of work ; the use of a Tobit is unnecessary for the individual work hours given that there are almost no 0 hours of work. For both Tobit and OLS we control for household wealth, composition, and education characteristics. For individual outcomes we additionally control for age and gender.

5.2.2 Propensity score matching

As an additional control method we use average treatment effect estimation through propensity score matching. The advantages of this method are twofold. First it does not rely on functional form assumption for our outcome variable and household observed characteristics as in the OLS or Tobit. As shown by Imbens and Wooldridge (2008) specification bias may be important in the context of high heterogeneity between treated and control groups, as it is the case in our context. Second, for our samples which have sufficient number of observations we can conduct meaningful heterogeneity analysis.

Let us introduce the basic evaluation problem with a brief intuition of the Roy-Rubin model (see also Caliendo and Kopeinig (2005)). Let $D_i = \{0, 1\}$ denote the binary treatment status for individual i . $D_i = 1$ if the individual is treated, electrified in our case, and 0 otherwise. The key concept is the

potential outcome. Let $Y_i(D_i)$ be the potential outcome for individual i given his treatment status D_i . Then the treatment effect is $\tau_i = Y_i(1) - Y_i(0)$. The problem of evaluation is that we don't observe both potential outcomes for each i , so we must rely on population averages. The parameter of interest in our context is the *average treatment effect on the treated*, τ_{ATT} :

$$\tau_{ATT} = \mathbb{E}(Y_i(1)|D_i = 1) - \mathbb{E}(Y_i(0)|D_i = 1) \quad (1)$$

But we don't observe the second term, the counterfactual outcome for the treated. Using the expectation for the untreated, $\mathbb{E}(Y_i(0)|D_i = 0)$ is not a good solution because of self selection bias :

$$\mathbb{E}(Y_i(1)|D_i = 1) - \mathbb{E}(Y_i(0)|D_i = 0) = \tau_{ATT} + B \quad (2)$$

The term B is the bias : the dependence of potential outcomes on treatment status. It must be equal to 0 for τ_{ATT} to be identified. In our context it is presumably the case that, absent access to electricity, those electrified household would have had different education and labor market outcome than those that are observed non electrified. There are two source of selection bias. One is at the placement i.e village level, the grid is not randomly allocated across villages. The second selection issue is at household level, households choose whether to connect or not ; that is, connected households are not random sample of those that have access to grid connection. With matching, as in OLS and Tobit we assume we have a set of observable characteristics X that explain both dimensions of selection and we can invoke the following two assumptions to reach an identification strategy :

$$Y(0), Y(1) \perp\!\!\!\perp D|X, \forall X \text{ (Unconfoundedness assumption)}$$

$$0 < \mathbb{P}(D = 1|x) < 1 \text{ (Common support)}$$

The former means that, given X a vector of observable covariates, whether i is treated or untreated, potential outcomes are independent of a person treatment status. Rather than controlling for the whole X vector (with regression or matching), one may control only for a uni-dimensional function of this vector. The *Propensity score* is one function:

$$\mathbb{P}(D = 1|X) = P(X) \text{ (Propensity score)} \quad (3)$$

We can get an estimate of ATT in (1) using (2) weighted by (3) on the common support.

The intuition is that we use (3) to build a balanced sample of individuals with which using (2) doesn't cause problem since individuals have similar *key* characteristics. In our case, the goal is to find a balanced group of female and male spouses and children, from which we can compute averages of our variables of interest across non-treated and treated groups. There are three main steps: first, one computes propensity scores using a logistic regression on key observables that affect both treatment and outcome. Then one applies a matching algorithm to match individuals similar with respect to their scores. Finally we compute difference in weighted average across treatment groups to find the *ATT*. For unconfoundedness to be credible, choice variable in first step is key. Ideally we should select all variables that determine simultaneously electricity connection and education and labor outcomes, that

is, all the observable confounders. We provide the results of our logistic regression and variables used, as well as post-matching balance checks, in appendix. Variables selection follows major literature, e.g. Jalan and Ravallion (2003) [?]. We use a nearest-neighbor matching algorithm to match each treated to the individual who is the closest in term of propensity score, to keep a maximum of information. Therefore our parameter of interest will be the following⁴ :

$$\widehat{\tau_{ATT}^{PSM}} = \sum_{i=1}^T \omega_i (y_{i1} - \sum_{j=1}^M W_{ji} y_{ji0}) \quad (4)$$

Where T is the number of treated individuals, M is the number of untreated used for a match. The term in brackets is equal to the change in outcome y for individual i : y_{i1} is his outcome (say, work status), y_{ji0} is the outcome of the j^{th} untreated matched to individual i . The second sum is therefore the matched "counterfactual" for i . ω_i and W_{ji} are sampling weights and matching weights, respectively.

In practice, we will proceed with matching at the *individual* level - note that this is possible even though treatment is at the household level since it will lead to matched pairs where treated and control must be from different families. We use a caliper between 0.04 and 0.1 score points depending on the sample, to enhance the quality of the matching. That is, matches where the score distance between the pair members is higher than this interval are discarded.

5.3 Instrumental Variable

The main drawback of the above-mentioned control methods is that they rely on a conditional Independence assumption to establish causality. In electrification impact-evaluation literature, the endogeneity of the electricity dummy has been widely acknowledged [Salmon & Tanguy, 2016, Dinkelman, 2011]. If we observe all confounders the previous methods are relevant ; otherwise our estimates will be biased. Therefore we use a second approach to push back the conditional independence assumption on another variable : the instrumental variable that requires relevance and exclusion to be verified. Several instruments that rely on cost differential of electricity grid development have been used. Dinkelman (2011) [Dinkelman, 2011] uses land slope gradient to non randomness of the grid. Lipscomb, Mobarak and Barahm [Lipscomb *et al.* , 2013] use an exogenous variation in electricity grid produced by a cost-minimizing model.

According to the latter table, we need two instruments : one at the village level and one at the household level. The former must generate random variation in village-connection costs. The latter must generate random variations in household-level probability of connection.

We derive a new instruments based on the distance from household to main road which has been already used by some authors including Tanguy and Salmon (2016) [?]. For that purpose we compute two estimates. We estimate the area of a village according to the assumption that households in the village are typically centered around the main all-weather road. With this estimation strategy, we estimate 1/a potential to-electrify area 2/a potential overall area. The former is obtained by taking

⁴we build on Jalan and Ravallion for parameter estimation

the difference of the average distance between the two electrified households which are the furthest from the road and the road and the average distance between the two electrified households which are the closest from the road and the road. If our assumption that the village is a circle is correct, then we can use this distance as the radius of a circle to estimate its area with the area equal to π times the square of the radius. The latter is obtained through the same method regardless of whether households are electrified or not. Then we compute a ratio of the potential to-electrify area to the potential overall area of the village. The intuition for the simple area is that, in any case, the wider the village, controlling for population which strengthens exclusion, the more expensive is village connection. This argument works particularly well in the Rwandan case because of the very high degree of land elevation variation. Therefore an area-estimation is also a proxy for land-elevation variation inside of a given village, in the vein of Dinkelman [Dinkelman, 2011]. Therefore this instrument serves to deal with the endogeneity at the village level. The intuition for the ratio is the following: the highest the ratio, the lower the cost to electrify the rest of the households of the village, because there is less grid extension to implement. The lower the ratio, the highest the potential cost because there are more electric cables to pull. This instrument deals, therefore with the household level endogeneity issue. The drawback is that we can use it only between households that are all in electrified villages - the ratio is 0 in non-connected villages.

To fix ideas, let us formally present the endogeneity issue in our case. The equations to estimate are the following :

$$E_{jk} = \alpha_0 + \alpha_1 H_{jk} + \alpha_2 V_k + \mu_{jk} + \eta_k + \epsilon_{jk} \quad (5)$$

$$Y_{ijk} = \beta_0 + \beta_1 X_{ijk} + \beta_2 H_{jk} + \beta_3 V_k + \delta E_{jk} + \omega_{ijk} + \mu_{jk} + \eta_k + \sigma_{ijk} \quad (6)$$

Where E_{jk} is the connection status of household j in village k , Y_{ijk} is the outcome of interest for individual i in household j . X_{ijk} is a vector of individual characteristics, H_{jk} is a vector of household characteristics, and V_k is a vector of village characteristics. ω_{ijk} contains individual unobservables, μ_{jk} household unobservables and η_k village unobservables. ϵ_{jk} and σ_{ijk} are normally-distributed error terms.

The problem is the following : if we ignore the unobservables in (6) then E_{jk} is correlated with the error term because of (5) and the classical OLS estimator of δ will be biased. In this case, $\widehat{\tau_{ATT}^{PSM}}$ from 5.1.3 (next) is biased as well since it would mean we omit important confounders in the matching process. Past literature showed this is likely to be the case with household electricity dummy. For example, households may decide to connect because of their labor-leisure-education preferences that are hard to observe. Note that another issue could also be reverse causality : it's because people are employed that they acquire electricity and not the opposite.

A solution to this problem is to take a vector I_{jk} of instruments at the household level that determine connection but are uncorrelated with error term of (6). We take the above mentioned instruments and we estimate the effect through a classical two-stage least squares (2SLS).

6 Main Results

Table 6: Combined electrification effect on time allocated to chores

<i>Combined effect</i>							
Children							
Variables	1 Wood	2 Fodder	3 Cook	4 Water	5 Market	6 Others	7 Total
elec	-1.0822*** (0.022) 0.000	-2.3641*** (0.029) 0.000	-0.3884*** (0.019) 0.000	0.0066 (0.008) 0.432	-0.0776*** (0.007) 0.000	0.2165*** (0.013) 0.000	-1.5565*** (0.013) 0.000
Obs	5,792	5,792	5,792	5,792	5,792	5,792	5,792
Women							
Variables	8 Wood	9 Fodder	10 Cook	11 Water	12 Market	13 Others	14 Total
elec	-1.7182*** (0.024) 0.000	-2.9144*** (0.029) 0.000	-0.4215*** (0.003) 0.000	-0.6311*** (0.014) 0.000	0.4982*** (0.009) 0.000	-0.0554*** (0.009) 0.000	-3.0478*** (0.009) 0.000
Obs	5,394	5,394	5,394	5,394	5,394	5,394	5,394

Table 7: Combined effect of electrification on employment and education

<i>Combined effect</i>												
Children												
Variables	1	2	3	4	5	6	7	8	9	10	11	12
	OLS Ex	PSM Ex	PSM Ex	IV Ex	OLS Rep	PSM Rep	PSM Rep	IV Rep	OLS Drop	PSM Drop	PSM Drop	IV Drop
<i>elec</i>	-0.0097	-0.0234***	-0.0351***	-0.0522	-0.0067	-0.0656***	0.0245***	-0.0178	0.0088	0.0009***	0.0065***	-0.1398
<i>se</i>	(0.010)	(0.000)	(0.000)	(0.136)	(0.018)	(0.000)	(0.000)	(0.170)	(0.007)	(0.000)	(0.000)	(0.087)
<i>p-val</i>	0.349			0.700	0.714			0.917	0.209			0.107
Observations	5,792	1,153	1,062	5,792	6,137	1,282	1,202	6,137	6,137	1,282	1,202	6,137
R-squared	0.216			0.172	0.094			0.064	0.123			0.052
F-stat				34.99				43.43				43.43
Women												
Variables	1	2	3	4	5	6	7	8				
	OLS Ex	PSM Ex	PSM Ex	IV Ex	OLS In	PSM In	PSM In	IV In				
<i>elec</i>	-0.0024	-0.0507***	-0.0344***	0.2557	9.1750***	12.4781***	15.4029***	32.7709**				
<i>se</i>	(0.022)	(0.000)	(0.000)	(0.222)	(1.965)	(0.004)	(0.005)	(15.543)				
<i>p-val</i>	0.913			0.250	0.000			0.035				
Observations	5,394	1,028	973	5,394	1,137	144	126	1,137				
R-squared	0.180			0.043	0.316			-0.053				
F-stat				30.56				5.302				
Trimmed	NO		YES	NO		NO	YES	NO		NO	YES	

We present our main results in Table 6 and 7. In detail, we produced treatment impact estimates mentioned in the first row of Table 5 : treatment group comprises electrified household whose outcome is contrasted to that of a control group of non-electrified households outside grid catchment area. Therefore control households are not contaminated by spillover effects. In Table 6, we present Tobit estimations of the impact of grid connection on time allocated to various household chores to highlight the within household time-reallocation triggered by electrification.

In Table 7, we present the impact on our main final outcome namely education for children, through class repetition and school drop-out and labor outcomes for children and women, through employment probability (extensive margin) and number of hours conditional on being employed (intensive margin) for wage works in-farm or out-of-farm.

Though they have been omitted for the sake of clarity, in all estimation we include as control variables measures of household wealth, education and composition characteristics and a full set of district fixed effects. We relegate to the appending the detailed regression results.

Results confirm the expected impacts of electrification on household chores. Households spend less time doing chores, which is consistent with the conceptual framework, especially for wood forage - we notice a decrease by almost 3 hours - and consistent with farm activity substitution - fodder search decreases by almost 10 hours. Consistently, also, with the absence of time-saving appliances acquisition, the time spent cooking just only slightly decreases by half an hour though the summary statistics show it is initially a big part of household chores. Note that the time spent going to market increases, indicating either a higher preference for leisure or just the fact that, with higher revenues as a consequence of more extensive and intensive work households go to market to spend this extra revenue.

Considering the combined effect of electricity on household, that is the direct effect and the spillover effect, we find a strong positive impact on women employment that work essentially at the intensive margin: already working women supply more hours of work. The effect on the extensive margin though large is not statistically significant in IV estimations, while other method of estimations suggest rather a negative and small impact. Looking at children outcome results suggest rather a negative effect on employment, though they are not consistently estimated across estimation methods, we do not find any statistically significant impact neither on any educational outcome. The fact that impacts on women are in order of magnitude higher than that on children is consistent with the fact that women are also more impacted with respect to time allocated to household chores. Combining both results suggest a clear substitution from domestic to wage-labor activities. However the strike differences in coefficients magnitude between Table 6 and Table 7, also suggest that access to energy allow greater efficiency to time use, indeed more hours are supplied in the labor market than hours saved on household chores. This observation is all in line with our theoretical mechanism that posit that access to electricity can be considered as a positive shock to time endowment, at least for women already working.

At this stage we can make 2 remarks. First, the results for women are those expected from electrification in the rural context. Women tend to work more in proportion for a wage, and more intensively. This shows the empowering ability of electrification for women in rural African areas since wage jobs can provide more independence than other kind of activities.

7 Spillover or Household Effects?

In Table 8 we consider similar outcomes to that in Table 7 but our treated group corresponds to non-electrified households in electrified villages, control households are still households in non-electrified villages. That is, we discarded those households in electrified villages that are electrified. Non-electrified households within the grid catchment area may experience a change in their outcome as the result of spillover effects that work through general equilibrium effect within local labor market for instance.

Here again our results do not show any significant impact on children outcome. In almost all estimation methods the effects size are small and non statistically different from zero. Results for women are somehow different than previous ones; First spillover effect exert a positive impact on women labor market outcome, though the effect seems to work essentially at the extensive margin, that is new employment opportunities seem to have pushed more women out-off domestic employment into the wage labor market. Considering the IV estimation, the employment rate of women increases by 17%. In contrast we didn't found any meaning full effect on hours worked. This is interesting as this result suggests that it is probably women with relatively lower wage potential that benefited the most from electricity access at the extensive margin. Indeed, our results suggest that changes in outside local labor market conditions, instead of changes within the household, that pushes their wage potential above their reservation wage.

Finally in Table 9, we provide results allowing to assess the importance of the household level connection to the grid, that is we perform the treatment-control group comparison suggested in the third row of Table 5. We restrict our analysis to households within grid catchment area in order to control for spillover effect. Within the grid catchment area, electrified households will experience different outcomes than non electrified ones mostly due to their direct access to electricity, everything else equal. Results of Table 9 that these direct effects are particularly important for children, indeed after controlling for unobserved heterogeneity we find that employment rate of children of electrified household, relatively to children from households non-connected to the grid, is 9 pp higher! At the same they time they are, 17 pp less likely to repeat a grade. This two results are rather surprising given the usual trade-off between working and studying. However it can be understood in light of our model that view access to electricity as a positive shock on household time endowments. Indeed, the benefit of artificial light allows households to relax their day-light time endowment and a better management of their domestic tasks across the journey allowing children to effectively work more without any detrimental impact on schooling. The fact that these effects are found only at the household level treatment effect and not at the village effect comfort the idea that this is a supply effect which is driving households out of domestic work into wage labor rather than a demand effect working through changes in local labor market conditions.

Results for women at the household level treatment effect parallel those of Table 7. The direct effect for electrified household is half that of the total effect which combine direct and spillover impact

Table 8: Village-level effect of electrification on education and employment

<i>Village effect</i>												
Children												
Variables	1	2	3	4	5	6	7	8	9	10	11	12
	OLS Ex	PSM Ex	PSM Ex	IV Ex	OLS Rep	PSM Rep	PSM Rep	IV Rep	OLS Drop	PSM Drop	PSM Drop	IV Drop
elec	0.0022	0.0081***	-0.0094***	-0.0143	0.0199	0.0394***	0.0038***	0.0178	0.0029	-0.0006***	0.0012***	-0.0492
se	(0.008)	(0.000)	(0.000)	(0.063)	(0.013)	(0.000)	(0.000)	(0.073)	(0.005)	(0.000)	(0.000)	(0.038)
p-val	0.794			0.821	0.121			0.806	0.560			0.190
Observations	6,652	2,761	2,613	6,652	7,000	2,902	2,826	7,000	7,000	2,902	2,826	7,000
R-squared	0.216			0.176	0.093			0.066	0.130			0.107
F-stat				116.5				142.3				142.3
Women												
Variables	1	2	3	4	5	6	7	8				
	OLS Ex	PSM Ex	PSM Ex	IV Ex	OLS In	PSM In	PSM In	IV In				
elec	0.0507***	0.0484***	0.0432***	0.1738**	2.2275***	2.5688***	1.8473***	2.5163				
se	(0.015)	(0.000)	(0.000)	(0.083)	(0.820)	(0.002)	(0.002)	(3.978)				
p-val	0.001			0.036	0.007			0.527				
Observations	6,198	2,511	2,499	6,198	1,391	626	613	1,391				
R-squared	0.183			0.064	0.081			0.033				
F-stat				135.3				37.60				
Trimmed		NO	YES			NO	YES			NO	YES	

Table 9: Household-level effect of electrification on education and employment

<i>Household Effect</i>													
Children													
Variables	1	2	3	4	5	6	7	8	9	10	11	12	
	OLS Ex	PSM Ex	PSM Ex	IV Ex	OLS Rep	PSM Rep	PSM Rep	IV Rep	OLS Drop	PSM Drop	PSM Drop	IV Drop	
elec	-0.0203	-0.0458***	-0.0113***	0.0902*	-0.0434**	-0.0055***	-0.0142***	-0.1709**	0.0043	0.0072***	0.0044***	-0.0128	
se	(0.014)	(0.000)	(0.000)	(0.055)	(0.022)	(0.000)	(0.000)	(0.080)	(0.008)	(0.000)	(0.000)	(0.035)	
p-val	0.155			0.099	0.047			0.033	0.607			0.711	
Observations	2'216	1'050	1'012	2'216	2'395	1'165	1'125	2'395	2'395	1'165	1'125	2'395	
R-squared	0.216			0.143	0.094			0.033	0.111			0.095	
F-stat				48.71				51.79				51.79	
Women													
Variables	1	2	3	4	5	6	7	8					
	OLS Ex	PSM Ex	PSM Ex	IV Ex	OLS In	PSM In	PSM In	IV In					
elec	-0.0795***	-0.0677***	-0.0796***	0.1313	6.0621***	10.4639***	8.0629***	15.1049**					
se	(0.027)	(0.000)	(0.000)	(0.122)	(2.152)	(0.005)	(0.006)	(6.889)					
p-val	0.003			0.282	0.005			0.028					
Observations	2,010	927	902	2,010	448	118	103	448					
R-squared	0.213			0.052	0.395			0.095					
F-stat				28.77				9.460					
Trimmed		NO	YES			NO	YES		NO		YES		

of electricity. As a result of access to electricity women in connected households raises their hours of wage work by 15 hours. Changes in labor supply is concentrated as previously on the intensive margin, that among women with relatively already good wage potential.

8 Conclusion

We analyzed the causal relationship between connection to the electric grid at the household level and household aggregate outcomes and household individual members labor and education outcomes, in particular for women spouses and children. We are in a context where households are too poor to buy time-saving appliances and with a theoretical reasoning according to which they might extend their active daytime with electric light to either education, work, home production or leisure. Using various control approaches, included OLS, matching, regression-based IPW methods and 2SLS instrumental variable approach we show that electrification leads to a decrease in time allocated to chores, and to an increase in time allocated to wage activities. We show that household level analysis and village level analysis allows identifying different treatment effects. Contrasting these two level of treatment allows us to separate the household level direct effect of electricity on labor and human capital outcome, from indirect effect that spillover to all households within the grid catchment area. Mixing both treatments show strong and positive effects at both intensive and extensive margin for women, extensive margin for children, and negative at the intensive margin for children. Distinguishing household level treatment pulls down all the coefficients, which highlights the presence of spillover effects at the village level : non-electrified households are impacted by the effect of village connection. More interestingly our results comfort our theoretical premises that access to electricity allow household to relax their light-time endowment and to better manage their domestic tasks across the journey. As a consequence, despite greater incidence of child labor among connected households we found a strong and positive effect on human capital accumulation.

References

- [Alby *et al.* , 2013] Alby, Philippe, Dethier, Jean-Jacques, & Straub, Stephane. 2013. Firms Operating under Electricity Constraints in Developing Countries. *World Bank Economic Review*, **27**(1), 109 – 132.
- [Apps & Rees, 2015] Apps, Patricia, & Rees, Ray. 2015. Household models : a historical perspective. *CESifo Working Papers Series*.
- [Atkin, 2016] Atkin, David. 2016. Endogenous Skill Acquisition and Export Manufacturing in Mexico. *American Economic Review*, August.
- [Bernard, 2012] Bernard, Tanguy. 2012. Impact Analysis of Rural Electrification Projects in Sub-Saharan Africa. *World Bank Research Observer*, February.
- [Cabraal *et al.* , 2005] Cabraal, R. Anil, Barnes, Douglas F., & Agarwal, Sachin G. 2005. Productive uses of Energy for rural development. *Annual Review of Environment and Resources*.
- [Dinkelman, 2011] Dinkelman, Taryn. 2011. The Effects of Rural Electrification on Employment: New Evidence from South Africa. *American Economic Review*, December.
- [Fuchs *et al.* , 2016] Fuchs, Alan, Gertler, Paul, Shelef, Orie, & Wolfram, Catherine. 2016. The Demand for energy using assets among the world’s rising middle classes. *American Economic Review*.
- [Grogan & Sadanand, 2009] Grogan, Louise, & Sadanand, Asha. 2009 (April). *Electrification and the Household*.
- [Grogan & Sadanand, 2012] Grogan, Louise, & Sadanand, Asha. 2012. Rural Electrification and employment in Poor countries : evidence from Nicaragua.
- [Gronau, 1977] Gronau, Reuben. 1977. Leisure, Home Production, and Work-The Theory of the Allocation of Time Revisited. *Journal of Political Economy*.
- [Jimenez, 2017] Jimenez, Raul. 2017 (January). *Development Effects of Rural Electrification*. Policy Brief. InterAmerican Development Bank.
- [Kirubi *et al.* , 2009] Kirubi, Charles, Jacobson, Arne, Kammen, Daniel M., & Mills, Andrew. 2009. Community-Based Electric Micro-Grids Can Contribute to Rural Development: Evidence from Kenya. *World Development*, **37**(7), 1208–1221.
- [Kohlin *et al.* , 2011] Kohlin, Gunnar, Sills, Erin O., Pattanayak, Subhrendu K., & Wilfong, Christopher. 2011 (Sept.). *Energy, gender and development: what are the linkages ? where is the evidence ?* Policy Research Working Paper Series 5800. The World Bank.
- [Lee *et al.* , 2017] Lee, Kenneth, Miguel, Edward, & Wolfram, Catherine. 2017. Electrification and Economic Development : A Microeconomic Perspective. *Oxford Policy Management*, May.
- [Lee *et al.* , 2018] Lee, Kenneth, Miguel, Edward, & Wolfram, Catherine. 2018. Experimental Evidence on the Demand for and Costs of Rural Electrification. *NBER Working Papers*, May.

- [Lipscomb *et al.* , 2013] Lipscomb, Molly, Mobarak, A. Mushfiq, & Barham, Tania. 2013. Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil. *American Economic Journal: Applied Economics*, April.
- [Rud, 2012] Rud, Juan Pablo. 2012. Electricity Provision and Industrial Development : Evidence from India. *Journal of Development Economics*.
- [Salmon & Tanguy, 2016] Salmon, Claire, & Tanguy, Jeremy. 2016. Rural Electrification and Household Labor Supply: Evidence from Nigeria. *World Development*.
- [Squires, 2015] Squires, Tim. 2015. The Impact of Access to Electricity on Education: Evidence from Honduras. *job market paper*, March, 36.
- [Wolfram *et al.* , 2012] Wolfram, Catherine, Shelef, Orie, & Gertler, Paul. 2012. How Will Energy Demand Develop in the Developing World? *Journal of Economic Perspectives*, Winter.
- [World-Bank, 2004] World-Bank. 2004 (January). *The Impact of Energy on women lives in India*. Tech. rept. World Bank.

A Gronau model extended to education

The household maximizes the amount of commodity $Z = Z(x, e)$, a combination of goods x and education time consumption e . The function Z thus contains household's preferences nature for material goods and education goods. x can either be purchased in the market (x_m) or produced at home (x_h) through a production function $f(h)$ with household production time h as a unique input and positive decreasing marginal productivity $f'(h) > 0, f''(h) < 0$. The household is endowed with T units of time. Therefore it solves the following :

$$\begin{aligned} \max_{x,e} Z &= Z(x, e) \\ x &= x_h + x_m \text{ with } x_h = f(h) \\ T &= e + h + l \\ x_m &= wl + R \end{aligned}$$

With l the time allocated to market labor supply and w the wage rate. The problem amounts to :

$$\begin{aligned} \max_{h,e,n,x_m} Z(x_m + f(h), e) \\ \text{u.c of time and budget} \end{aligned}$$

This yields the usual condition from the F.O.Cs, that the MRS between education and time should be equal to marginal productivity and wage rate, i.e

$$MRS_{e-x} = f' = w$$

. That is, the relative value of education consumption with respect to material good consumption should be equal to the gain of sacrificing a unit of time from education to either home production or labor market.

We investigate the effect of dT on the the allocation of time, i.e on e , h , and n . It is straightforward from the above condition that it depends on both the production function and consumption function shapes which determine the initial situation of the household. This intuition is shown in the graph of section 3.

B Matching quality tests

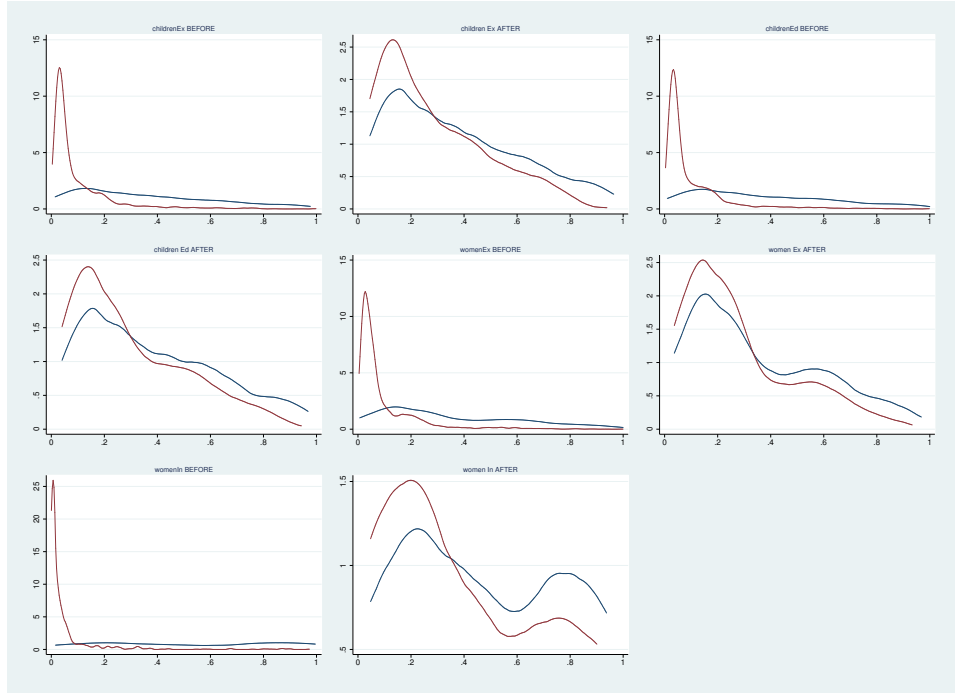


Figure 5: Combined effect sample. Propensity score distribution plots.

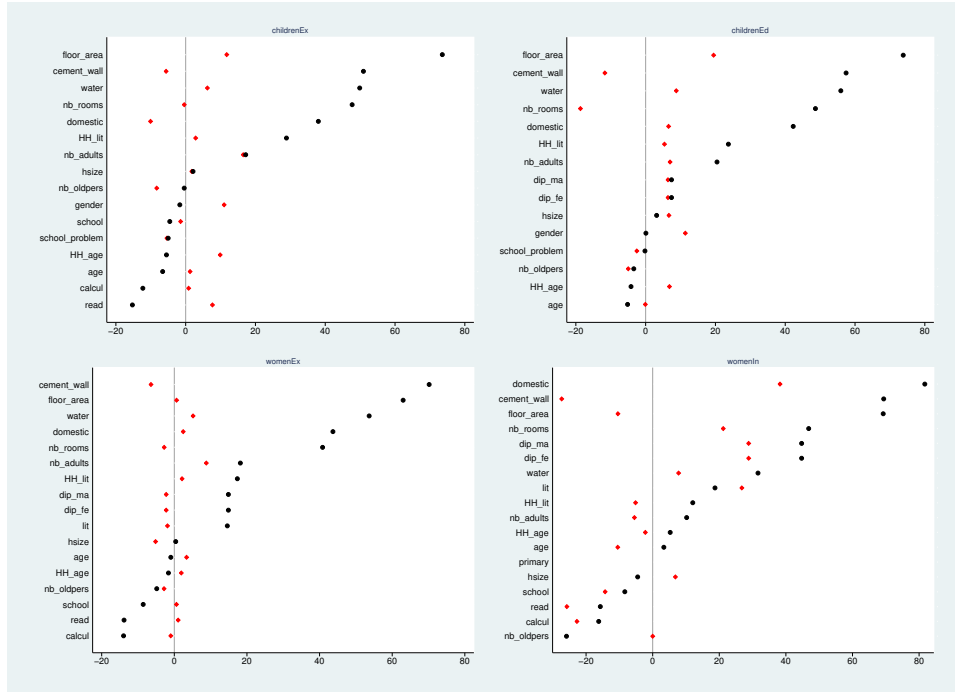


Figure 6: Combined effect. Standardized percentage bias plot.

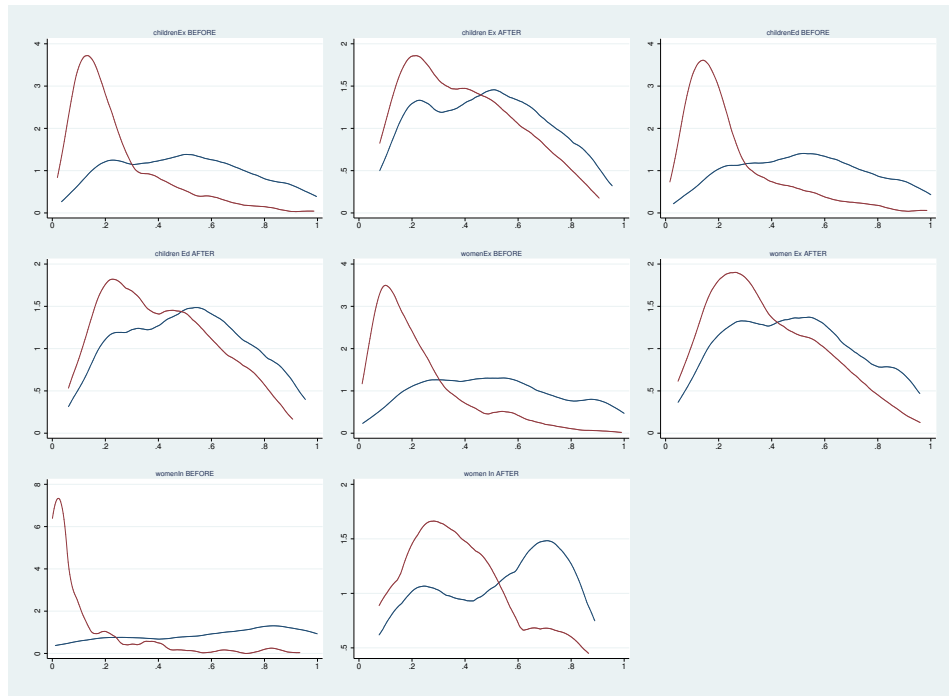


Figure 7: Combined effect sample. Propensity score distribution plots.

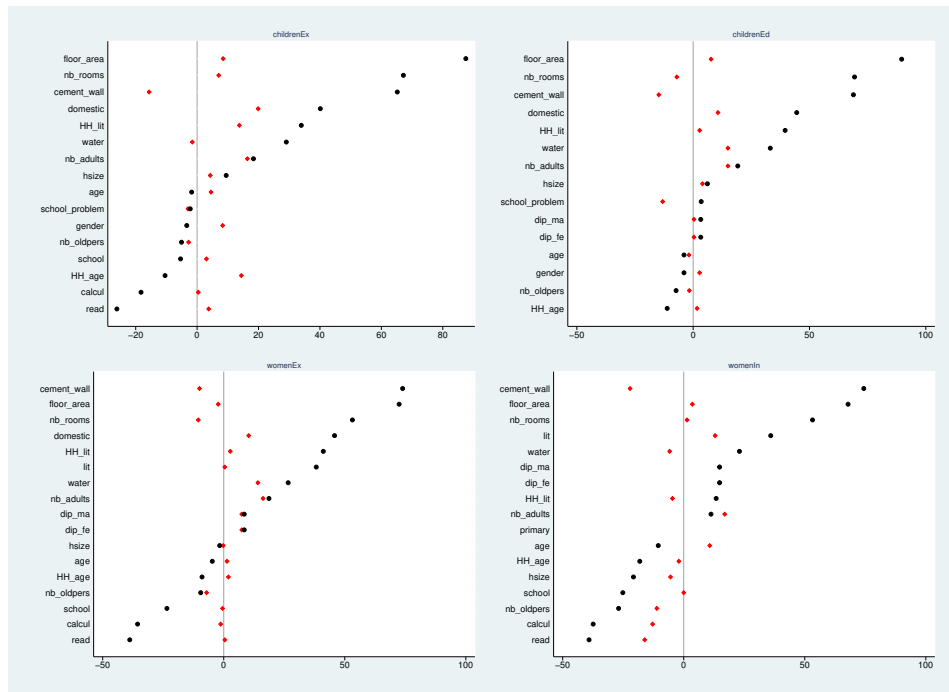


Figure 8: Combined effect. Standardized percentage bias plot.

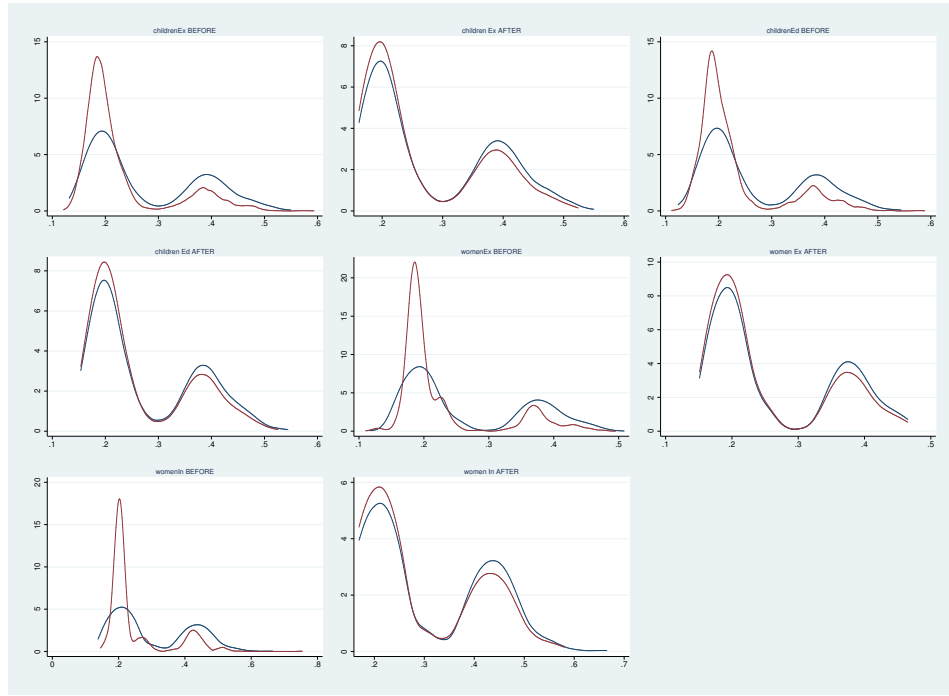


Figure 9: Combined effect sample. Propensity score distribution plots.

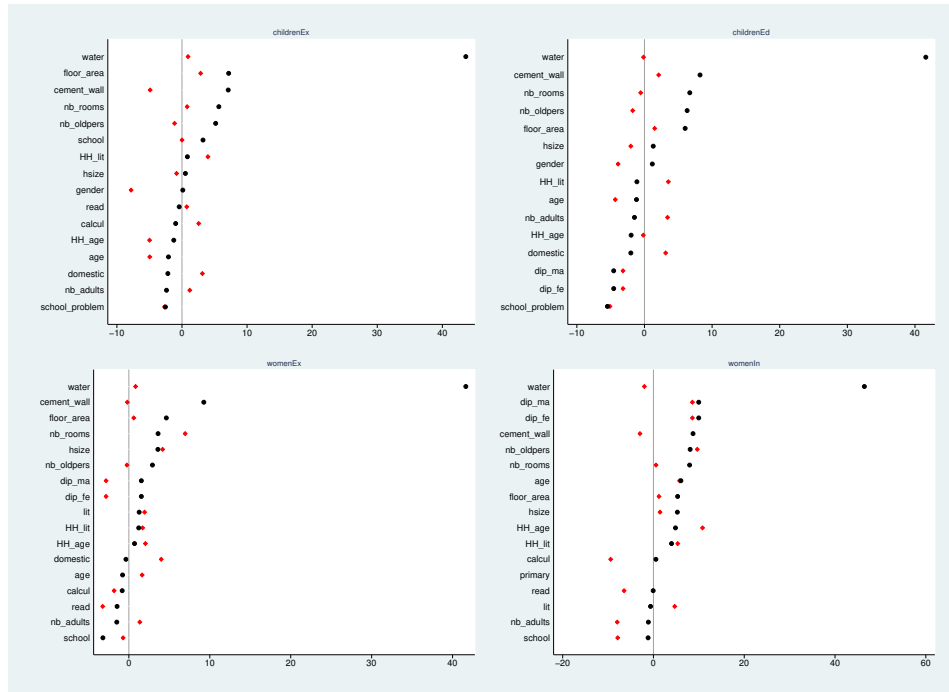


Figure 10: Combined effect. Standardized percentage bias plot.

C Robustness check

D Additional econometric results

D.1 Household and village-level effect on chores

Table 10: Household-level effect of electrification on time allocated to chores

<i>Household Effect</i>							
Children							
Variables	1 Wood	2 Fodder	3 Cook	4 Water	5 Market	6 Others	7 Total
elec	-1.0120*** (0.027) 0.000	-1.2273*** (0.029) 0.000	-1.1777*** (0.023) 0.000	-0.2310*** (0.010) 0.000	-0.2449*** (0.008) 0.000	0.0333*** (0.013) 0.010	-1.7599*** (0.013) 0.000
Obs	2,216	2,216	2,216	2,216	2,216	2,216	2,216
Women							
Variables	8 Wood	9 Fodder	10 Cook	11 Water	12 Market	13 Others	14 Total
elec	-1.2611*** (0.028) 0.000	-0.6568*** (0.031) 0.000	0.2142*** (0.004) 0.000	-0.5369*** (0.016) 0.000	0.1603*** (0.008) 0.000	-0.6460*** (0.012) 0.000	-2.0929*** (0.011) 0.000
Obs	2,010	2,010	2,010	2,010	2,010	2,010	2,010

Table 11: Village level effect of electrification on time allocated to chores

<i>Village effect</i>							
Children							
Variables	1 Wood	2 Fodder	3 Cook	4 Water	5 Market	6 Others	7 Total
elec	0.0409*** (0.010) 0.000	-1.0645*** (0.015) 0.000	0.4427*** (0.011) 0.000	0.1928*** (0.004) 0.000	0.1287*** (0.005) 0.000	0.2364*** (0.009) 0.000	-0.1976*** (0.007) 0.000
Obs	6,652	6,652	6,652	6,652	6,652	6,652	6,652
Women							
Variables	8 Wood	9 Fodder	10 Cook	11 Water	12 Market	13 Others	14 Total
elec	-0.1369*** (0.008) 0.000	-1.5094*** (0.017) 0.000	-0.5995*** (0.002) 0.000	-0.2684*** (0.007) 0.000	0.1880*** (0.006) 0.000	0.1214*** (0.006) 0.000	-1.2381*** (0.006) 0.000
Obs	6,198	6,198	6,198	6,198	6,198	6,198	6,198

D.2 Propensity scores estimation