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# Rural Electrification and Household Labor Supply: Evidence from Nigeria

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## Abstract

Using recent household survey data, this paper investigates how electrification affects female and male labor supply decisions within rural households in Nigeria. Focusing on matched husband-wife data, we propose to consider dependence in spouses' labor supply decisions and to address adequately zero hours of work using a copula-based bivariate hurdle model. In parallel, we opt for an instrumental variable strategy to identify the causal effect of electrification. Our findings show that such dependence is strongly at work and critical to consider when assessing the impact of electrification on spouses' labor supply outcomes. Electrification is found to increase the working time of both spouses in a separate examination of their labor supply, while the joint analysis emphasizes only a positive effect of electrification on husbands' working time. However, whatever the econometric specification, we find no significant effect of electricity on spouses' employment probability.

**Keywords:** rural electrification, labor supply, developing countries, joint decision-making, bivariate hurdle model, copulas

**JEL Classification:** C3, C31, C35, D1, J22, O13

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# 1 Introduction

In developing countries, electrification is an important challenge for future economic and social development, especially in Africa where electrification rate is the lowest in the world. Less than 20% of the population in Africa is estimated to have a direct access to electricity. The situation is even worse in rural areas: less than 10% of sub-Saharan rural households are electrified (Haanyika 2006). While macroeconomic interactions between electrification, growth and development have been well documented (Ozturk 2010), the microeconomic effects of a grid connection at the household level have been less studied. Following an emerging literature devoted to the impact of electrification on labor supply in developing countries, we propose in this paper an empirical contribution on this relationship in Nigeria, a large African country where rural electrification remains a burning issue.

Until then, only a few empirical studies have been devoted to the consequences of electrification in the labor market, but all emphasize that electrification encourages women to move away from domestic work to participate in the labor market. In South Africa, Dinkelman (2011) shows that rural electrification significantly increases female employment, without thereby affecting male employment. Grogan and Sadanand (2009, 2013) and Grogan (2012) outline a similar increase in female employment following household electrification in Nicaragua, Guatemala and Columbia, respectively. In Bangladesh, Chowdhury (2010) also shows that electrification increases the employment probability of women and underlines that, at the same time, it decreases the total time that women spend on unpaid work.

This positive effect of electrification on people labor supply, and primarily on female labor supply, can be analyzed through different theoretical channels. The main one assumes that electrification enables people to save domestic time and/or provides them additional time each day. As a major use of electricity in rural households (Kohlin et al. 2011), lighting is a potential channel through which electrification may affect people labor supply by enabling households to extend artificially the day, and thereby the potential working day. Electrification may also enable households to save domestic time by increasing the efficiency of domestic chores (cooking, water and fuelwood collection, laundry, childcare) through the use of some electrical appliances (e.g. cooker, sewing machine, water pump, refrigerator). This release of domestic time then provides people the opportunity to increase the time devoted to the labor market or even to start working. As domestic chores are mainly carried out by women, their labor supply is supposed to be more impacted by electrification than men. But this relationship is not so trivial because first it relies on actual use of electrical appliances, and therefore household investment in such appliances. Bernard (2010) shows that electricity is more often a complement than a substitute to traditional fuels in sub-Saharan Africa. For instance, many rural electrified households continue to use fuelwood to prepare meals in this region. Then, if electrification enables households to save time, their members may also decide to devote this extra time to leisure. Thus, such effect of electrification on people labor supply is not definitely settled.

Beyond this main theoretical channel, electrification may increase female labor supply through two other channels. First, electricity is known to have positive externalities on health and safety. Once electrified, households can decrease their consumption of candles or kerosene lamps and thereby reduce indoor air pollution, accident and fire risks. For instance, Röllin et al. (2004) show that rural electrified households in South Africa have significantly less indoor air pollution than their non-electrified counterparts. In South Africa again, Spalding-Fecher and Matibe (2003) emphasize strong positive health externalities from electrification, due to a substantial decrease in the use of "dirty" fuels like coals, firewood and paraffin. Second, through better access to television and Information and Communication Technologies (ICT hereafter), electrification may

contribute to the “empowerment of women” (Duflo 2012). Indeed, better access to media is likely to improve knowledge broadcasting on issues like health, education and women rights. Dahal (2013) shows, in Nepal, that the development of a community radio has a significant role in the socialization process of women, which is the first step in empowerment. More generally speaking, the development of ICT in households enhances the position of women in society, as discussed more thoroughly in Shirazi (2012) or in Bullough et al. (2012).

In Nigeria, rural electrification is a critical issue, due to the low household electrification rate and to the poor quality of the grid. In 2011, only 32.3% of rural households were electrified, against 86.7% of urban households<sup>1</sup>. The different states are unequally endowed: in 2008, about 88.8% of households in the Taraba State did not have electricity access against only 0.3% in Lagos. Oseni (2012) shows, in addition, that the electrification rate has decreased over the last decade, due to a higher growth in the Nigerian population than in electricity supply. As a result, electricity consumption per capita is comparatively low in Nigeria i.e. approximately 125 kWh, while it is 4500 kWh in South Africa and 1934 kWh in Brazil (Oseni 2012). The poor quality of the electrical grid can also be illustrated with some facts. In 2011, 53% of rural households and 48% of urban households experienced blackouts every day. Then, the same year, most rural electrified households had only a few hours of electricity per day and very few had a permanent access. In September 2013, the Power Holding Company of Nigeria (PHCN)<sup>2</sup>, i.e. the public monopoly in electricity provision, was privatized due to unreliable electricity provision. This led to the creation of 18 successor firms: 11 for electricity distribution, 6 for power generation, and one for transmission.

In this paper, we propose to assess for the first time the impact of rural electrification on male and female labor supply in this specific Nigerian context. Apart from the data originality, we contribute to the literature by addressing two empirical shortcomings in previous studies on this issue: first, these studies rely on the implicit assumption that people labor supply decisions are made independently within the household, which is a highly questionable assumption; second, some authors handle the identification of the causal effect of electrification on employment probability but fail to identify the effect on working time. For this purpose, we rely on matched husband-wife data from the 2010-2011 General Household Survey (GHS) and analyze simultaneously spouses’ labor supply outcomes – i.e. participation and time allocation in the labor market – using the bivariate hurdle model proposed by Deb et al. (2013). We identify the causal effect of electrification on both labor supply outcomes using an instrumental variable strategy.

The rest of the paper proceeds as follows: Section 2 describes the Nigerian household survey data, and discusses data processing and summary statistics. Section 3 outlines the different econometric specifications. Section 4 examines the effects of household electrification on husbands’ and wives’ labor supply first separately and then jointly. Section 5 concludes.

## 2 Data and variables

### 2.1 General Household Survey (GHS) data

We mainly rely in this paper on the General Household Survey (GHS) conducted by the Nigerian government. In Nigeria, the GHS is the analogous to the Living Standards Measurement Survey (LSMS) of the World Bank in terms of variable coverage. In its standard form, this survey is conducted yearly and data are collected from randomly selected households all over the country

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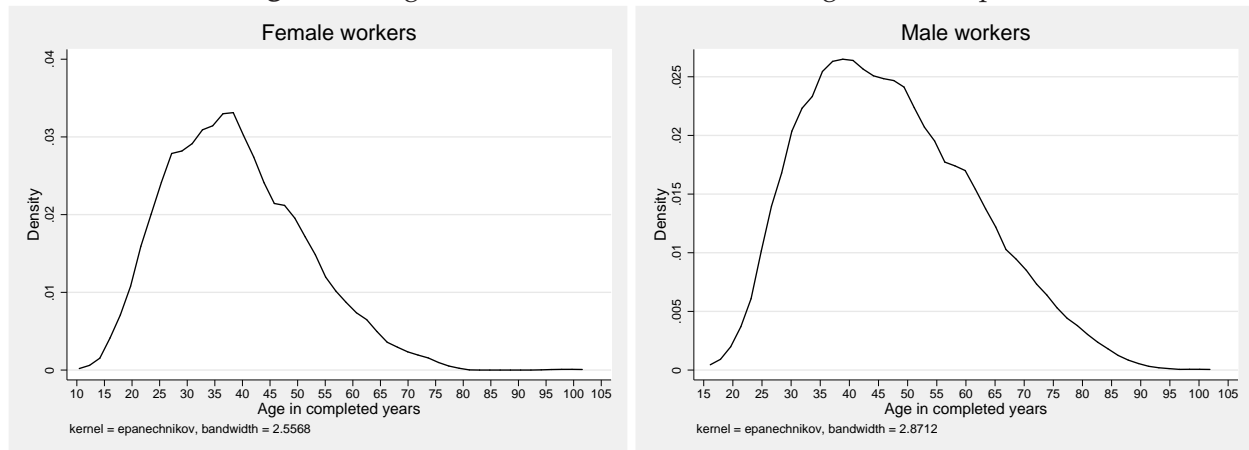
1. Authors’ own calculus using the GHS household sample.

2. Formerly National Electric Power Authority (NEPA).

during the four quarters of the year. One drawback of this survey is that different households are surveyed in each survey year. The survey period used in this paper is 2010-2011, yielding data for an initial sample of 28 075 people from 4 878 households. This edition of the survey is the first of the GHS-Panel, i.e. households surveyed in this edition are expected to be also surveyed in subsequent editions. Unlike the standard annual GHS, the GHS-Panel is carried out every two years. The 2010-2011 edition was carried out in two visits: post-planting visit in August-October 2010 and post-harvest visit in February-April 2011. We specifically use data from the post-harvest visit, since only this visit includes data on energy issues.

This paper focuses on the effect of electrification on labor supply in rural households, representing approximately 70% of the initial sample, i.e. 3 326 rural households and 20 155 individuals. For the purpose of testing dependence between spouses' labor supply decisions within the household, we focus our analysis on husband-wife pairs. After removing from the sample husband-wife observations for which one or both spouses report a missing value for at least one of our variables of interest, we get a sample of 2 720 husband-wife pairs or 5 440 individuals. Unlike previous studies in the literature (e.g. Abdulai and Delgado 1999), we only consider monogamous households in our empirical analysis, thereby reducing the sample to 2 033 husband-wife pairs. Among these last households, some are composed of multiple monogamous pairs, i.e. also include pairs formed by parents or children in addition to the main pair of the household. To limit any potential bias, we initially focus on households composed of only one monogamous pair, restricting then the sample to 1 996 households. Finally, we decide to limit our analysis to adults of working age and thus keep in the sample husbands and wives aged from 20 to 75. This age restriction is quite consistent with previous literature (e.g. Grogan and Sadanand 2013) and may be easily justified on the basis of workers' age structure in the sample (see Figure 1). Under this restriction, we finally get a sample of 1 819 husband-wife pairs.

**Figure 1 – Age structure of workers in monogamous couples**

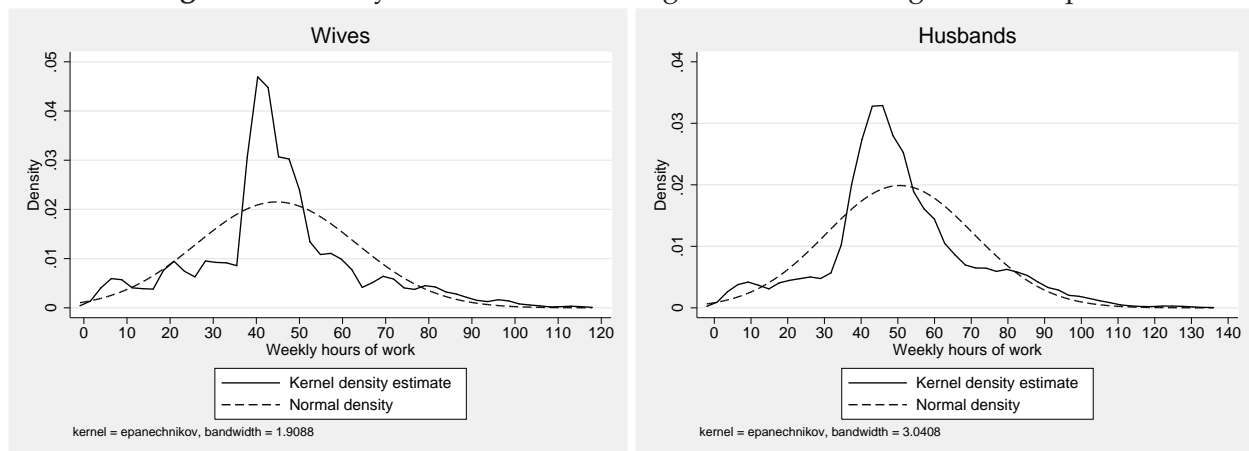


## 2.2 Variables of interest

The variables of interest are defined in accordance with the purpose of the paper, i.e. to assess the impact of household electrification on spouses' labor supply. Following previous studies on this issue (e.g. Grogan and Sadanand 2013) and remarks made above, we assess household electrification using a dummy variable, which is equal to 1 if the household is connected to the grid and reports use of electricity over the week preceding the survey, equal to 0 otherwise. In Table 1, we can see that 33.7% of households in our sample are connected to the electricity grid.

The labor supply analysis is based in this paper on weekly hours of work, recorded for each spouse over the week preceding the survey. The distribution of positive hours of work is reported in Figure 2 for both husbands and wives from the restricted sample of monogamous pairs. As shown in Table 1, a large proportion of husbands and wives report zero hours of work during the previous week – more than 10% of husbands and approximately 30% of wives.

**Figure 2 – Weekly hours of work among workers in monogamous couples**



### 2.3 Control variables

To our knowledge, the relationship between electrification and household labor supply in Nigeria has not been studied yet. A few studies have been devoted to the determinants of household labor supply in Nigeria (Aminu 2010; Anugwom 2009; Fadayomi and Ogunrinola 2013). We rely on this short literature and on the rising literature devoted to the impact of electrification on household labor supply to select the appropriate control variables.

We first introduce as control variables some standard individual and household characteristics controlled when analyzing labor supply outcomes in rural households, including age, education, religion, number of children and adults (see, e.g., Abdulai and Delgado 1999; Huffman and Lange 1989; Tokle and Huffman 1991). Age is a proxy of general experience, that increases the marginal value of time in each activity (Abdulai and Delgado 1999), while age squared enables to control for the nonlinear life cycle. Education is a proxy of productivity potential. Any increase in an individual's education level may increase her probability to participate in the labor market and time devoted to work, if it increases her opportunity costs for staying at home (Abdulai and Delgado 1999). The number of children in the household indicates the number of dependents and is particularly likely to determine wives' participation in the labor market. However, some empirical results in other developing countries demonstrate that child-rearing and off-farm work are not necessarily competing activities and so the number of children is likely to have no significant effect on spouses' time spent at work (e.g. Skoufias 1994). The number of adults in the household increases the household's capacity for diversifying its income-generating activities and, therefore, is likely to increase both participation in the labor market and time devoted to work (Matshe and Young 2004).

Then, to control for the strength of the local labor market, we also include the unemployment rate among rural people in the state, which is derived from the 2006 Census, the latest in Nigeria. In a cross-section study, this variable exhibits relatively little variation and is likely to pick up



**Table 1** – Variable definitions and descriptive statistics

Variable name	Definition	Mean	Std. Dev.	Min	Max
<i>Individual / household characteristics</i>					
age <sub>h</sub>	Husband's age, in years	47.343	12.926	21	75
age <sub>w</sub>	Wife's age, in years	36.821	10.931	20	71
educ <sub>h</sub>	Husband's years of education	5.383	5.364	0	17
educ <sub>w</sub>	Wife's years of education	4.169	4.842	0	16
christian	Christian religion	0.553	—	0	1
muslim	Muslim religion	0.424	—	0	1
kids06	Number of children under age 6	1.450	1.405	0	10
kids612	Number of children aged 6-12	1.153	1.073	0	5
kids1218	Number of children aged 12-18	0.816	0.995	0	5
adults	Number of adults (age ≥ 18)	2.811	1.233	2	11
assets / head	Value of assets per household head, in Naira. Assets include all household assets (e.g. bed, computer, bicycle) and agricultural assets.	14 047.12	54 555.54	0	1 546 025
electricity	Electricity is working in the dwelling	0.337	—	0	1
<i>Regional characteristics</i>					
rural unempl.	Unemployment rate in rural areas at the state level (2006 Census)	0.138	0.092	0.0001	0.461
% urban	Fraction of the LGA population living in urban areas in 2011.	0.036	0.140	0	0.848
<i>Dependent variables</i>					
d <sub>h</sub>	= 1 if husband participates in work	0.894	—	0	1
d <sub>w</sub>	= 1 if wife participates in work	0.714	—	0	1
y <sub>h</sub>	Total husband hours allocated to work	45.222	24.523	0	133
y <sub>w</sub>	Total wife hours allocated to work	31.898	25.571		
<i>Instrumental variables</i>					
pop. density	Population density in the Local Government Area (LGA), measured as the ratio population / surface, using the 2006 Census	323.345	471.771	0.048	4 063.502
km to road	Household distance to nearest major road, in kilometers	18.014	19.296	0	115.2
Observations		1 819			

Notes: The data source is the Nigeria 2010-2011 General Household Survey (GHS) - Panel. Only individuals from monogamous households, aged between 20 and 75, are considered.

partly the location effect. There are more recent data on states' aggregate unemployment, provided by the National Bureau of Statistics (NBS), but only census data provide information on unemployment among rural people. Indeed, the average unemployment rate of a given state may not reflect the labor market context in its rural areas, given generally strong differences between urban and rural areas about employment. To control for the household wealth and socioeconomic status, which are likely to determine both participation and time allocation decisions in the labor market, we also include among control variables the per capita value of household assets. In

previous literature, household wealth is proxied using the value of household productive assets (e.g. Matshe and Young 2004), but also household possession of a water pipe and/or a dirt floor (e.g. Grogan and Sadanand 2013). Variables definition and descriptive statistics are reported in Table 1.

Finally, we also control in all regressions for location effects. Nigeria is decomposed into 36 states and Abuja, the federal capital territory (FCT)<sup>3</sup>. These states are then divided into 774 Local Government Areas (LGA). The inclusion of LGA fixed effects in the econometric regressions would be valuable since they refer to small geographic areas where local economic conditions are likely to be similar. However, introducing here LGA fixed effects may be inefficient, given the small size of our sample. State fixed effects are thus preferred in our case.

### 3 Econometric specifications

As outlined above, household labor supply is analyzed, in this paper, using time use data, i.e. hours of work over the last week. Linear regression models are generally inappropriate in analyzing such data, due to violation of the normality assumption resulting from exact zeros and a right-skewed distribution of data<sup>4</sup>. Although linear regression models may be robust to violations of the normality assumption, the very right-skewed distribution of such data is likely to result in biased parameter estimates<sup>5</sup>.

The Tobit model is often justified with time-use data in adjusting for the zeros, as for instance in Grogan and Sadanand (2013). Despite its frequent use in such cases, the Tobit model is deficient in interpreting the zero observations. Indeed, in this model, a zero value corresponds to a corner solution in the utility maximization program, i.e. refers to an individual supposed to participate in the labor market – or a potential worker – but who chooses not to work at the current level of exogenous variables – e.g. economic incentives, wages. However, zero observations on working time may arise for other reasons. First, some individuals may prefer not to participate in the labor market, due to personal preferences, inadequate qualifications or other disabilities. This is abstention rather than a corner solution. Second, work may be undertaken on an infrequent basis only, due to other household commitments, and the survey was conducted at a time when no work was sought. Thus, some zero observations may be sampling zeros – resulting from the fact that the reference period of the data is shorter than the period over which decisions are made – rather than corner solutions.

In coherence with its interpretation of zeros, the Tobit estimator is restrictive in assuming that the process that generates variation in the censoring process is proportional to the process that generates variation in the distribution of the dependent variable, conditional on it is being observed. When analyzing labor supply, the process determining the decision to participate in the labor market would be assumed to be the same as the one that determines time allocated to work – and so determined by the same variables. However, the factors that explain the participation decision in the labor market need not have the same effect on the time allocation decision in this activity. When these decisions turn out to be two very different processes, one is likely to have an endogenous participation problem. One way to deal with this problem is to model two separate

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3. See Appendix B.

4. The exact zeros represent a problem for standard regression models because no transformation can produce a normal distribution of the data: the zeros are just transformed to another value.

5. A linear regression model may well approximate the fitted values, especially those near the mean values of the independent variables, but may result in negative fitted values and negative predictions for the dependent variable when more extreme values of the independent variables are considered (Wooldridge 2012).

decisions: (i) whether or not to participate in the labor market, and (ii) the amount of time the participant allocates to work.

### 3.1 Distinction in the labor supply decisions: participation and time allocation

The double-hurdle model (Blundell et al. 1987; Cragg 1971) – or two-part model – offers a general approach to model participation in the labor market and time allocation to work as two separate decisions. It is a parametric generalization of the Tobit model, where the decision to participate in the labor market and the level of participation are determined by two separate stochastic processes. The Heckman’s sample selection model (1979) is also a candidate in such a context but it remains still restrictive, assuming that none of the zero observations may be due to a corner solution<sup>6</sup>. In the double-hurdle model, a two-stage process must have been completed so that we observe positive hours of work: (i) the individual has decided to participate in the labor market, and (ii) this individual has allocated some amount of time to work. Thus, we may observe no working time due to one of these two processes. Very popular in labor supply analysis (e.g. Blundell et al. 1987; Matshe and Young 2004), the double-hurdle model is here specified by two latent variables,  $d_{ji}^*$  and  $y_{ji}^*$ , that refer to the labor market participation and time allocation decisions respectively, for spouse  $j$  in household  $i$ :

$$\begin{aligned} d_{ji}^* &= \mathbf{Z}_i' \gamma + \varepsilon_i, & \varepsilon_i &\sim \mathcal{N}(0, 1), & j &= h, w \\ y_{ji}^* &= \mathbf{X}_i' \beta + u_i, & u_i &\sim \mathcal{N}(0, \sigma^2), & j &= h, w \end{aligned}$$

where  $u_i$  and  $\varepsilon_i$  are independently distributed.

The original double-hurdle model assumes that residuals are normally distributed in the positive part, so that the positive values are modeled with a standard linear model, i.e. OLS. However, the maximum likelihood (ML) estimator of this model may be inconsistent when this normality assumption is violated (Arabmazar and Schmidt 1982). We test this normality assumption in residuals in several ways, using residual estimates from a truncated regression model. First, the Shapiro-Wilk  $W$  test gives, for both husbands and wives, a very small p-value (0.000), indicating that we can reject that residuals are normally distributed. Then, some graphs may also give indications of non-normality in residuals for both husbands and wives: Kernel density plot (see Figure 3), normal probability plot (see Figure 4) and normal quantile plot (see Figure 5).

To allow a more flexible modelling of positive values, we use a generalized linear model (GLM) specification, in which we can adopt a non-normal distribution<sup>7</sup>. The GLM specification requires to define the link function  $g(\cdot)$ , that characterizes how the conditional mean is related to the set of covariates:

$$g(\mu_i) = \mathbf{X}_i' \beta \quad \Rightarrow \quad g^{-1}(\mathbf{X}_i' \beta) = \mu_i$$

The two most commonly used link functions are the identity link and the log link. With an identity link, the covariates act additively on the mean and the coefficients are interpreted in

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6. In the Heckman’s sample selection model (1979), if a variable affects the number of work hours, it cannot sequentially lead to reduced and then zero work hours, although it may have that effect if it appears in the participation equation.

7. Another way to relax this normality assumption is to use a transformation to normality for the dependent variable, such as the Box-Cox transformation (Jones and Yen 2000; Yen 1993). The GLM specification remains more convenient since predictions are provided (or made) on the real scale and do not need a retransformation. To be consistent with the specification used in the subsequent bivariate analysis, we confine ourselves here to the use of a non-normal distribution in the GLM framework.

the same way as OLS, whatever the distribution chosen. In contrast, a log link<sup>8</sup> supposes that covariates act multiplicatively on the mean, that changes the interpretation of coefficients:

$$\ln [E(y_i|\mathbf{X}_i)] = \mathbf{X}'_i \beta \quad \Rightarrow \quad E(y_i|\mathbf{X}_i) = \exp(\mathbf{X}'_i \beta)$$

There is no single test to identify the appropriate link. While some authors (e.g. Hardin and Hilbe 2012) have recommended use of the information statistics (log-likelihood, AIC, BIC) to select the appropriate link, these statistics are not stable when the distributional family changes. So we prefer to employ the following different tests of fit: the Pregibon (1980) link test, the modified Hosmer and Lemeshow (2000) goodness-of-fit test and the Pearson's correlation test. A particular link function will be selected if all three tests yield to non-significant p-values. Conversely, if one or more of these tests give(s) a significant p-value, the concerned link will be rejected.

The conditional distribution of the positive values should reflect the relationship between the variance and the mean, such that:

$$\text{Var}(y_i|\mathbf{X}_i) = \phi E(y_i|\mathbf{X}_i)^\nu$$

where  $\phi$  is the dispersion parameter and  $\nu$  determines the appropriate distributional family. If  $\nu = 0$ , this implies that the variance is proportional to the mean, so the Gaussian (or normal) family is suitable. If  $\nu = 1$ , the variance is proportional to the mean, that corresponds to the Poisson family. If  $\nu = 2$ , the variance is proportional to the square of the mean and so the Gamma family will be appropriate. And, if  $\nu = 3$ , the variance is proportional to the cube of the mean, which characterizes the Inverse Gaussian or Wald family. In order to determine the appropriate family distribution, we apply a modified Park test (Manning and Mullahy 2001), which is based on  $\nu$  parameter<sup>9</sup>.

### 3.2 Identification of the causal effect of electrification

Exogeneity of the electricity dummy is questionable, given the empirical evidence on this issue in recent literature. Grogan and Sadanand (2013), for instance, show that electricity access is endogenous with regard to employment probability, due to the effect of some unobserved factors – such as household wealth or individual taste for work and leisure – both on electricity access and on employment probability.

To address this potential bias, we implement the two-stage residual inclusion (2SRI) estimator advocated by Terza et al. (2008). The 2SRI estimator is a nonlinear extension of the conventional instrumental variable (IV) method. Instead of replacing the endogenous variable by the first-stage predictor in the second stage – i.e. the conventional IV method –, the 2SRI method consists of including first-stage residuals as additional regressors in the second stage. First proposed by Hausman (1978) in the linear context, this method proves to be consistent in the class of nonlinear models, where the two-stage predictor substitution is inconsistent (see Terza et al. 2008).

The first-stage equation specifies household electricity access as a function of exogenous variables, including those introduced in the labor supply equations ( $\mathbf{X}$ ) and others that just affect electricity access ( $E$ ). The first stage consists of a probit model and is specified by a latent variable,  $E_{ji}^*$ , that corresponds to the electricity status (0, 1) of household  $i$ .

$$E_i^* = \mathbf{X}'_i \delta_1 + \mathbf{Z}'_i \delta_2 + v_i, \quad v_i \sim \mathcal{N}(0, 1)$$

8. This differs from log-OLS, which assumes that  $E[\ln(y_i)|\mathbf{X}_i] = \mathbf{X}'_i \beta$ . And  $E[\ln(y)|\mathbf{X}] \neq \ln[E(y_i|\mathbf{X}_i)]$ .

9. This test consists of regressing  $\ln[(y_i - \hat{y}_i)^2]$  on  $\ln(\hat{y}_i)$  plus a constant. Then, the estimated coefficient provides an evaluation of the  $\nu$  parameter.

where  $\mathbf{Z}$  is a vector of instrumental variables that is correlated with electricity access ( $E$ ) but uncorrelated with the residuals  $\varepsilon_i$  and  $u_i$ , and is thus excluded from  $d_{ji}^*$  and  $y_{ji}^*$  equations. Both properties of  $\mathbf{Z}$  must be satisfied to ensure that IV estimates are more consistent. A nonzero correlation between the instruments and the residuals  $\varepsilon_i$  and  $u_i$ , as well as a weak correlation between the instruments and electricity, can induce inconsistency in the IV estimates, that may exceed the inconsistency of naive estimates. We rely on the existing literature to select appropriate instruments. The cost differential between local governments to extend the electric grid from urban to rural areas may represent an exogenous variation in household electrification. As suggested by Grogan and Sadanand (2013), such a variation can be proxied by the historic population density within the geographical area of interest. Thus, we use the population density in the LGA, derived from the 2006 Census data<sup>10</sup>.

The second-stage equations are then specified as:

$$\begin{aligned} d_{ji}^* &= \mathbf{X}'_i \gamma_1 + \gamma_2 v_i + \varepsilon_i, & \varepsilon_i &\sim \mathcal{N}(0, 1), & j &= h, w \\ y_{ji}^* &= \mathbf{X}'_i \beta_1 + \beta_2 v_i + u_i, & u_i &\sim \mathcal{N}(0, \sigma^2), & j &= h, w \end{aligned}$$

where the vector  $\mathbf{X}_i$  includes the observed electricity access ( $E$ ) of household  $i$  and  $v$  is the residual from the first-stage equation. Implementing a significance test on the  $\gamma_2$  et  $\beta_2$  coefficients provides a simple and direct way to test the assumption that electricity ( $E$ ) is exogenous in participation and time allocation equations, respectively. If  $v$  has a significant effect in one or both equations, we can reject the exogeneity assumption of the electricity variable in the corresponding equations.

### 3.3 Consideration of the dependence between spouses' labor supply decisions

Several authors argue that the labor supply decisions of husbands and wives are jointly determined within households (e.g. Huffman and Lange 1989). If this is the case, estimating labor supply decisions with ordinary univariate procedures would misrepresent the processes that going on at the household level. New insights can be gained by considering labor supply decisions in a two-worker – or husband-wife – model (e.g. Huffman and Lange 1989). A joint estimation procedure, using a simultaneous equation estimator, would increase the statistical efficiency of the parameter estimates, considering that the husband's and wife's labor supply decisions are affected by the same economic shocks and may be made jointly (Mishra and Goodwin 1997; Togle and Huffman 1991).

We rely on the bivariate hurdle model proposed by Deb et al. (2013), to address the potential dependence between spouses' labor supply within households. This model is particularly attractive since, to our knowledge, the joint estimation of hurdle models has been little explored in the literature. This model considers four configurations of outcomes and each configuration corresponds to a specific distribution, which is derived from the product of a bivariate hurdle probability and a density for the positive outcomes<sup>11</sup>:

$$\begin{aligned} y_h = 0, y_w = 0 &: F(y_h = 0, y_w = 0) \\ y_h > 0, y_w = 0 &: F(y_h > 0, y_w = 0) \cdot f_h(y_h | y_h > 0, y_w = 0) \\ y_h = 0, y_w > 0 &: F(y_h = 0, y_w > 0) \cdot f_w(y_w | y_h = 0, y_w > 0) \\ y_h > 0, y_w > 0 &: F(y_h > 0, y_w > 0) \cdot f_{hw}(y_h, y_w | y_h > 0, y_w > 0) \end{aligned}$$

10. The 2006 Census is the last census in Nigeria. Before 2006, census data dated back to 1991. These older can not be used to compute LGAs' historic population density, given changes in states and LGAs since 1991.

11. We voluntarily omit the household subscript  $i$  to simplify the notation.

where  $F$  is a bivariate distribution defined over binary labor participation outcomes,  $f_h$  and  $f_w$  are univariate densities defined over positive hours of work, and  $f_{hw}$  is a bivariate density defined over a pair of positive hours of work from both spouses. Deb et al. (2013) initially propose this model to analyze health expenditures and choose to specify positive values according to the gamma density. Thus, the univariate densities for positive hours of work ( $f_h, f_w$ ) would be defined as:

$$f_j(y_j | y_j > 0, y_{-j} = 0) = \frac{\exp(-\frac{y_j}{\mu_j}) y_j^{\eta_j - 1}}{\mu_j^{\eta_j} \Gamma(\eta_j)}, \quad j = h, w; \quad \mu_j > 0; \quad \eta_j > 0$$

with  $y_{-j}$  refers to the outcome of the other spouse,  $\mu_j = \exp(\mathbf{X}' \beta_j)$  is the scale parameter and  $\eta_j$  is the shape parameter of the gamma distribution.

The desired joint (or bivariate) distributions are generated using a copula-based approach, pioneered by Sklar (1973). A copula is a function that links a multivariate distribution to its one-dimensional marginal distributions. Here, it implies that for the two dependent variables  $y_h$  and  $y_w$ , with respective marginal distributions  $F_h$  and  $F_w$ , there exists a copula  $C$  such that:

$$C [F_h(y_h), F_w(y_w); \theta] = F(y_h, y_w)$$

where  $\theta$  is a dependence parameter and  $F$  is the joint distribution function of  $(y_h, y_w)$ . Thus, the copula representation  $C(F(y_h), F(y_w); \theta)$  can be used in place of the unknown cumulative distribution function (cdf)  $F(y_h, y_w)$ . Several copulas have been proposed in the literature, and each of these imposes a different dependence structure on the data (see, e.g., Trivedi and Zimmer 2005). The appropriate copula for a particular application is the one that best captures the dependence features of the data. We rely here on the specific class of Archimedean copulas (see Genest and Rivest 1993). These copulas are popular in the empirical literature, since they can be stated easily and allow to capture wide ranges of dependence. Since we have no *ex ante* knowledge about the dependence structure for our data, we use different copulas: (i) the Frank copula, (ii) the Clayton copula, (iii) the survival Clayton (SCLayton) copula (see Table 2). The Frank copula is popular because it permits both negative and positive dependence between marginals, while the two others restrict the dependence parameter to be positive. But this copula allows only weak tail dependence and exhibits the strongest dependence in the middle of the distribution. In contrast, both Clayton and SCLayton copulas allow asymmetric and strong tail dependence. The Clayton copula exhibits strong lower tail dependence and relatively weak upper tail dependence. Thus, it is most appropriate for outcomes which are strongly related at low values but less correlated at high values. Conversely, the SCLayton copula will be more suitable for modeling strong upper tail dependence. To examine which of these copulas best fits the data, we rely on the Akaike and Schwarz Bayesian Information Criteria (AIC, BIC), as usually done for choosing between non-nested parametric models estimated by maximum likelihood.

In the hurdle parts of the model, the marginal distributions are derived using the probit formulation, so that:

$$\Pr(y_j > 0) = \Phi_j(\mathbf{X}' \beta_{0j}), \quad j = h, w$$

where  $\mathbf{X}$  is a vector of explanatory variables introduced in each hurdle model and  $\beta_{0j}$  is the corresponding vector of coefficients to be estimated. The joint probability distribution of positive husband and wife work hours is derived as:

$$F(y_h > 0, y_w > 0) = C (\Phi_h(\cdot), \Phi_w(\cdot); \theta^0)$$

**Table 2** – Some Archimedean Copula functions

Copula	(1) Copula function: $C(u_1, u_2)$ (2) Copula density: $c(u_1, u_2)$	$\theta$ interval
<b>Frank</b>	(1) $-\theta^{-1} \log \left[ 1 + \frac{(e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}{e^{-\theta} - 1} \right]$ (2) $\frac{\theta (1 - e^{-\theta}) e^{-\theta(u_1+u_2)}}{[(1 - e^{-\theta}) - (1 - e^{-\theta u_1})(1 - e^{-\theta u_2})]^2}$	$] - \infty, \infty[$
<b>Clayton</b>	(1) $(u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}$ (2) $(1 + \theta) u_1^{-1-\theta} u_2^{-1-\theta} (-1 + u_1^{-\theta} + u_2^{-\theta})^{-2-\frac{1}{\theta}}$	$[0, \infty[$
<b>SClayton</b>	(1) $((1 - u_1)^{-\theta} + (1 - u_2)^{-\theta} - 1)^{-1/\theta} + u_1 + u_2 - 1$ (2) $(1 + \theta)(1 - u_1)^{-1-\theta}(1 - u_2)^{-1-\theta} [-1 + (1 - u_1)^{-\theta} + (1 - u_2)^{-\theta}]^{-2-\frac{1}{\theta}}$	$[0, \infty[$

where  $C$  is the selected copula function and  $\theta^0$  is a dependence parameter, that captures dependence between the probabilities of any positive outcome. The related probabilities are derived as:

$$\begin{aligned} F(y_h = 0, y_w = 0) &= 1 - \Phi_h(\cdot) - \Phi_w(\cdot) + C(\Phi_h(\cdot), \Phi_w(\cdot); \theta^0); \\ F(y_h > 0, y_w = 0) &= \Phi_h(\cdot) - C(\Phi_h(\cdot), \Phi_w(\cdot); \theta^0); \\ F(y_h = 0, y_w > 0) &= \Phi_w(\cdot) - C(\Phi_h(\cdot), \Phi_w(\cdot); \theta^0). \end{aligned}$$

The copula-based joint distribution of positive hours of work is given by:

$$f_{hw}(y_h, y_w | y_h > 0, y_w > 0) = c(F_h^+(\cdot), F_w^+(\cdot); \theta^+) \times f_h^+(\cdot) \times f_w^+(\cdot)$$

where  $f_h^+$  and  $f_w^+$  are the marginal distributions of positive hours of work when both spouses work, which are defined as:

$$f_j^+(y_j | y_h > 0, y_w > 0) = \frac{\exp\left(-\frac{y_j}{\mu_j}\right) y_j^{\eta_j^+ - 1}}{\mu_j^{\eta_j^+} \Gamma(\eta_j^+)} \quad \text{for } j = h, w; \mu_j > 0; \eta_j^+ > 0$$

$c(\cdot)$  is the corresponding copula density, and  $F^+$  is the cumulative distribution function (cdf) version of  $f^+$ . For simplification,  $\mu$  is specified to be the same between  $f$  and  $f^+$ , but  $\eta^+$  is likely to differ from  $\eta$  – we will test this difference in the next section. Indeed, the distributional shape of each outcome may differ depending on whether the other outcome equals zero. Also, the dependence parameter  $\theta^+$  between positive outcomes is allowed to differ from the dependence parameter  $\theta^0$ .

The joint likelihood is formed using the probability expression for each situation. Using the marginal and joint expressions previously defined, the log likelihood function for the bivariate hurdle model is given by:

$$\begin{aligned} \ln L = & \sum_{0,0} [\ln(F(y_h = 0, y_w = 0), \mathbf{X}; \theta^0)] \\ & + \sum_{+,0} [\ln(F(y_h > 0, y_w = 0), \mathbf{X}; \theta^0) + \ln(f_h(\cdot | \mathbf{X}))] \\ & + \sum_{0,+} [\ln(F(y_h = 0, y_w > 0), \mathbf{X}; \theta^0) + \ln(f_w(\cdot | \mathbf{X}))] \\ & + \sum_{+,+} [\ln(F(y_h > 0, y_w > 0), \mathbf{X}; \theta^0) + \ln(f_{hw}(y_h, y_w | y_h > 0, y_w > 0, \mathbf{X}; \theta^+))] \end{aligned}$$

where “0” indicates summation over the zero observations in the sample, and “+” refers to summation over strictly positive observations. The log-likelihood  $\ln L$  is maximized using a Newton-Raphson algorithm with numerical derivatives, implemented using Stata `m1` command (`lf` method).

## 4 Results

We present our empirical results in two broad steps. First, we focus on the independent estimates from the labor-supply regressions for wives and husbands, successively. Then, we will analyze the estimates from the bivariate hurdle model and discuss the changes induced by this simultaneous-equation approach in comparison to the independent estimates.

Previously, we report in Table 3 the specification tests for spouses’ positive hours of work. According to the modified Park test, the Poisson family proves to be the most appropriate distributional family to model wives’ positive hours of work. Both identity and log links may be used to relate the conditional mean of wives’ hours of work to the set of covariates; but p-values from Pregibon and modified Hosmer and Lemeshow test are higher when the log link is employed. The result of the likelihood-ratio (LR) test of  $\alpha = 0$  strongly suggests that the negative binomial model is more appropriate than the Poisson model, so we only report the other test statistics when using the Negative Binomial distribution and ignore those obtained from the Poisson distribution. Then, we observe that the test statistics are very similar between the log-link Negative Binomial distribution and the log-link Gamma distribution. For husbands’ positive hours of work, we first see that the original double-hurdle model is not adequate to model such data. Indeed, two tests for the link function report significant p-values when the normal (or Gaussian) distribution is employed with an identity link. Keeping the same distribution but now using a log link is not a fully satisfactory solution: the Pregibon link test still reports a significant p-value. Yet, the modified Park test first recommends use of the Gaussian distribution. Note that the  $\chi^2$  test reports a weak significant p-value for  $\nu = 1$ , supporting use of the Poisson distribution. As for wives, the LR test of  $\alpha = 0$  supports the use of the Negative Binomial distribution rather than the Poisson distribution. When this last distribution is employed with a log link, all tests on the link function report non-significant p-values, suggesting a better fit. For husbands’ data, test statistics are again very close between the log-link Negative Binomial distribution and the log-link Gamma distribution.

### 4.1 Independent estimates of spouses’ labor supply

In Table 4, we report the labor-supply regression parameters for wives. In the first columns, the electricity dummy is assumed to be exogenous in labor supply equations. Under this assump-



**Table 3 – GLM specification tests: link and distribution**

Link: Family:	Wives				Husbands			
	Identity Gaussian	Log Gaussian	Log NegBin	Log Gamma	Identity Gaussian	Log Gaussian	Log NegBin	Log Gamma
<i>Modified Park test: <math>\chi^2</math> (p-value)</i>								
$\nu$ coefficient	1.073	1.052	1.119	1.119	0.345	0.310	0.377	0.377
$\nu = 0$ : Gaussian	15.458 (0.000)	15.110 (0.000)	16.523 (0.000)	16.531 (0.000)	0.997 (0.318)	0.847 (0.357)	1.137 (0.286)	1.139 (0.286)
$\nu = 1$ : Poisson	0.071 (0.790)	0.037 (0.849)	0.187 (0.665)	0.188 (0.665)	3.605 (0.058)	4.199 (0.041)	3.110 (0.078)	3.104 (0.078)
$\nu = 2$ : Gamma	11.560 (0.001)	12.286 (0.001)	10.237 (0.001)	10.232 (0.001)	22.999 (0.000)	25.187 (0.000)	21.100 (0.000)	21.074 (0.000)
$\nu = 3$ : Inverse Gaussian	49.925 (0.000)	51.859 (0.000)	46.674 (0.000)	46.662 (0.000)	59.179 (0.000)	63.812 (0.000)	55.106 (0.000)	55.051 (0.000)
<i>Tests for link function</i>								
Pearson correlation test	1.000	0.907	0.922	0.923	1.000	0.890	0.863	0.863
Pregibon link test	0.265	0.273	0.874	0.882	0.072	0.082	0.348	0.353
Hosmer-Lemishow test	0.742	0.403	0.849	0.853	0.063	0.108	0.451	0.406
LR test of $\alpha = 0$ : $\bar{\chi}^2$ (p-value)			4986.14 (0.000)				7365.55 (0.000)	

NOTES: NegBin stands for Negative Binomial.

tion, electricity has no significant effect on wives' labor supply, both in terms of participation and time allocation in the labor market. Despite its frequent use in previous studies, the standard Tobit model is strongly rejected against the double-hurdle model, according to the likelihood-ratio (LR) test reported at the bottom of the table<sup>12</sup>. Thus, there is evidence suggesting the existence of two separate decision-making stages in which wives make independent decisions regarding participation and time allocation in the labor market. From the tests previously carried out, the negative binomial distribution with a log link is the most suitable specification to model wives' positive hours of work. Using this alternative specification does not change the significance of the parameter estimates. Moreover, the log-link Gamma distribution provides quasi-identical parameter estimates as those obtained with the log-link negative binomial distribution. Thus, whatever the distribution and the link function employed for positive hours of work, electricity has no significant effect on the amount of time that wives allocate to work.

On the right side of Table 4, we then test the exogeneity of household electrification with regard to wives' labor supply decisions. For this, we implement the two-stage residual inclusion (2SRI) estimator described in the previous section. Table 5 contains the parameter estimates from the first-stage Probit models on the probability of having electricity. The first-stage regression includes all control variables previously defined plus an instrument. It is worth noting that the first stage for wives differs from that used for husbands. In fact, the instrument used for wives, i.e. the LGA population density, proves to be not a valid instrument for husbands: it is

12. Since the standard Tobit model is nested within the double-hurdle model, the LR test is suitable to choose between these specifications.

**Table 4 – Electricity and wives’ labor supply: independent estimates**

	<i>Exogenous electricity</i>					<i>Endogenous electricity</i>			
	Tobit	Two-Part Models				Two-Part Models			
		1st part	2nd part: $y_w$			1st part	2nd part: $y_w$		
			$y_w^*$	Normal	Log NegBin		Log Gamma	$1(y_w > 0)$	Normal
electricity	-1.875 (1.918)	-0.093 (0.093)	-0.088 (1.363)	-0.003 (0.029)	-0.003 (0.029)	-0.838 (0.690)	15.605 (11.753)	0.428* (0.246)	0.430* (0.246)
1st-stage residual	—	—	—	—	—	0.310 (0.283)	-6.528 (4.860)	-0.179* (0.101)	-0.180* (0.101)
age <sub>w</sub>	2.275*** (0.504)	0.089*** (0.023)	0.875** (0.365)	0.019** (0.008)	0.019** (0.008)	0.085*** (0.023)	0.945** (0.369)	0.021** (0.008)	0.021** (0.008)
age <sub>w</sub> <sup>2</sup> /100	-2.582*** (0.613)	-0.097*** (0.028)	-1.123** (0.450)	-0.024** (0.010)	-0.024** (0.010)	-0.092*** (0.028)	-1.221*** (0.457)	-0.027*** (0.010)	-0.027*** (0.010)
educ <sub>w</sub>	0.480** (0.192)	0.010 (0.010)	0.339** (0.136)	0.007** (0.003)	0.007** (0.003)	0.023 (0.015)	0.092 (0.238)	0.000 (0.005)	0.000 (0.005)
muslim	-6.638** (2.661)	-0.416*** (0.124)	0.492 (1.788)	0.002 (0.039)	0.002 (0.039)	-0.373*** (0.131)	-0.367 (1.940)	-0.020 (0.041)	-0.020 (0.041)
kids06	-0.392 (0.571)	-0.015 (0.028)	-0.147 (0.402)	-0.003 (0.009)	-0.003 (0.009)	-0.014 (0.028)	-0.174 (0.401)	-0.004 (0.009)	-0.004 (0.009)
kids612	0.999 (0.761)	0.054 (0.037)	-0.047 (0.549)	-0.004 (0.012)	-0.004 (0.012)	0.053 (0.038)	0.007 (0.550)	-0.003 (0.012)	-0.003 (0.012)
kids1218	1.681** (0.806)	0.054 (0.041)	1.032* (0.602)	0.023* (0.012)	0.023* (0.012)	0.072 (0.044)	0.694 (0.641)	0.013 (0.013)	0.013 (0.013)
adults	-0.030 (0.608)	0.023 (0.033)	-0.363 (0.472)	-0.010 (0.010)	-0.010 (0.010)	0.037 (0.035)	-0.636 (0.540)	-0.017 (0.011)	-0.017 (0.011)
assets/head	1.487** (0.606)	0.060** (0.028)	0.691 (0.442)	0.011 (0.010)	0.011 (0.010)	0.097** (0.044)	-0.096 (0.745)	-0.010 (0.016)	-0.010 (0.016)
rural unempl.	-43.664*** (14.829)	-1.356* (0.785)	-38.802*** (8.757)	-0.854*** (0.196)	-0.852*** (0.196)	-1.409* (0.787)	-37.810*** (8.795)	-0.830*** (0.195)	-0.829*** (0.195)
% urban	-3.897 (6.400)	-0.382 (0.273)	1.138 (4.361)	0.033 (0.091)	0.033 (0.091)	-0.428 (0.276)	1.914 (4.401)	0.054 (0.092)	0.054 (0.092)
constant	-16.563 (11.119)	-0.830 (0.515)	25.334*** (8.222)	3.437*** (0.180)	3.438*** (0.180)	-1.067* (0.570)	30.781*** (9.220)	3.575*** (0.197)	3.577*** (0.197)
Instrument exclusion: Wald test p-value						0.801	0.818	0.625	0.621
LR test		610.689				613.753			
ln L	-6 663.232	-839.060	-5 521.080	-6 226.438	-6 211.591	-838.517	-5 520.068	-6 226.192	-6 211.336
		(0.000)				(0.000)			
Observations	1819	1819	1298	1298	1298	1819	1298	1298	1298

NOTES: The data source is the Nigeria 2010-2011 General Household Survey (GHS) - Panel. Only wives from monogamous households and aged between 20 and 75 are considered. State fixed effects are included in all specifications. Robust standard errors are reported in parentheses. \*, \*\*, \*\*\* indicate significance at 10%, 5% and 1%, respectively.

significantly correlated with the husbands’ labor outcomes. Conversely, the instrument included in the husbands’ first stage – i.e. km to road – is significantly correlated with the residuals in the wives’ labor supply equations. In contrast, each instrument is found to have a significant effect on the household probability to be electrified. The residuals from this first-stage regressions are

**Table 5** – First-stage probit estimates

	Dependent variable: electricity			
	Wives		Husbands	
	Coef.	(Std. Error)	Coef.	(Std. Error)
age <sub>w</sub>	-0.022	(0.024)	—	—
age <sub>w</sub> <sup>2</sup> /100	0.031	(0.030)	—	—
educ <sub>w</sub>	0.070***	(0.010)	—	—
age <sub>h</sub>	—	—	0.017	(0.024)
age <sub>h</sub> <sup>2</sup> /100	—	—	-0.014	(0.024)
educ <sub>h</sub>	—	—	0.063***	(0.008)
muslim	0.354***	(0.131)	0.250*	(0.136)
kids06	0.008	(0.029)	0.017	(0.029)
kids612	-0.012	(0.038)	-0.032	(0.038)
kids1218	0.108**	(0.043)	0.089**	(0.042)
adults	0.089***	(0.035)	0.090***	(0.034)
assets/head	0.253***	(0.034)	0.234***	(0.034)
rural unempl.	-0.865	(1.756)	-0.598	(1.950)
% urban	-0.555*	(0.319)	-0.523*	(0.316)
constant	-4.637***	(0.650)	-4.624***	(0.732)
<b>Instruments:</b>				
pop. density	0.125***	(0.032)	—	—
km to road	—	—	-0.011***	(0.003)
ln L	-758.658		-753.432	
Observations	1 819		1 819	

NOTES: The data source is the Nigeria 2010-2011 General Household Survey (GHS) - Panel. Only husbands and wives from monogamous households, aged between 20 and 75, are considered. State fixed effects are included in all specifications. Robust standard errors are reported in parentheses. \*, \*\*, \*\*\* indicate significance at 10%, 5% and 1%, respectively.

then included as additional regressors in the second-stage equations (1st-stage residual) and thus allow to test directly the exogeneity of the electricity dummy in these equations.

In the first-hurdle equation (Table 4), the coefficient on the first-stage residual is not significant at conventional levels, so we cannot reject the null that electricity is exogenous with respect to wives' employment probability. Thus, there is no evidence there are uncontrolled factors that significantly affect for wives both their likelihood of having electricity at home and their employment probability. In contrast, this coefficient is significant (and negative) in the hours of work equation, when employing the log-link negative binomial distribution. So we can reject that electricity is exogenous with respect to wives' working time and the left side estimates of Table 4 are downward biased. The negative sign of the coefficient on the first-stage residual here implies that there are unobserved factors that affect both wives' likelihood of having electricity and working time, but in opposite directions. Such factors could include, for instance, the individual taste for leisure: it is likely to increase the probability of having electricity and conversely to decrease the amount of time devoted to work. Note that the coefficient on the first-stage residual is non-significant in the hours of work equation when the standard normal distribution is used for positive hours in combination with a canonical link function, i.e. as in the standard double-hurdle model. This

demonstrates again the importance of the econometric specification in assessing the effect of electrification on individual labor supply. When accounting for the endogeneity of the electricity dummy, we find that wives from electrified households have the same probability to work than their counterparts from non-electrified households. But when they work, wives from electrified households devote significantly more time in the labor market than wives from non-electrified households *ceteris paribus*. The significance of this effect is rather weak but its magnitude is quite large. Since we use a log link, we can say that having electricity increases the log mean working time of wives by 0.430. The exponentiated coefficient is the factor by which the mean outcome on the original scale is multiplied. This implies that in electrified households the working time of wives is  $\exp(0.430) = 1.537$  times higher than that prevailing in non-electrified households, *ceteris paribus*.

The independent estimates for husbands' labor supply, reported in Table 6, provide the same pattern of results with regard to the electricity coefficient. The electricity dummy has no effect on husbands' labor supply outcomes when it is considered as exogenous in the corresponding equations. The LR test of the double-hurdle model against the Tobit model strongly rejects the latter specification (see Table 6), but both specifications result in a non-significant effect of electricity on husbands' labor supply. Using more adequate distributions and link function for positive hours of work – i.e. Log NegBin or Log Gamma – does not change the significance of the parameters in this part of the model. Using the 2SRI estimator induces more changes in the parameter estimates in the second-hurdle equation. In the first-hurdle equation, the first-stage residual has no significant coefficient and its inclusion does not alter the significance of the electricity coefficient. This may suggest that we reasonably control for factors that affect both the electrification probability and the employment probability. In the second-hurdle equation, the coefficient on the first-stage residual is significant at conventional levels and this regardless of the specification used for positive values. The inclusion of this residual thus induces important changes in parameter estimates and specifically in the electricity coefficient, which is now positive and significant at the 5% significance level. As for wives, the results for husbands imply that we fail to control for all factors affecting the electrification probability and the working time of husbands simultaneously. The negative sign of the coefficient on the first-stage residual suggests there are unobserved factors exerting opposite effects on these two outcomes, as discussed previously for wives' estimates. The estimates in the left side of Table 6 are thus downward biased. Taking into account the endogeneity of the electrification status allows to identify a large positive effect of electrification on the time devoted by working husbands in the labor market. For otherwise comparable characteristics, employed husbands spend in average more hours at work per week when coming from an electrified household. This extra working time is quite high in our estimates. In fact, employed husbands from electrified households have a working time around 50% higher than their counterparts from non-electrified households<sup>13</sup>.

These independent estimates are quite consistent with existing empirical evidence, in the sense that electrification tends to impact positively people activity in the labor market. But, at this stage of the empirical analysis, our results diverge from previous ones by identifying a positive effect of electrification on the time allocation decision rather than on the participation decision in the labor market. The singularity of these preliminary results also lies in the more pronounced effect of electrification on male labor supply than on female labor supply, while previous studies emphasize a significant effect primarily on female labor supply. This discrepancy should be interpreted with caution, given the substantial sample selection performed in this paper. What

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13. In fact, the working time of husbands in electrified households is  $\exp(0.397) = 1.486$  times higher than that in non-electrified households.

**Table 6** – Electricity and husbands' labor supply: independent estimates

	<i>Exogenous electricity</i>					<i>Endogenous electricity</i>				
	Tobit	Two-Part Models				Two-Part Models				
		$y_h^*$	1( $y_h > 0$ )	2nd part: $y_h$			1( $y_h > 0$ )	2nd part: $y_h$		
				Normal	Log NegBin	Log Gamma		Normal	Log NegBin	Log Gamma
electricity	0.940 (1.603)	0.021 (0.111)	0.761 (1.334)	0.013 (0.026)	0.013 (0.026)	0.607 (0.819)	20.454** (9.285)	0.395** (0.186)	0.396** (0.187)	
1st-stage residual	—	—	—	—	—	-0.244 (0.334)	-8.193** (3.832)	-0.159** (0.077)	-0.159** (0.078)	
age <sub>h</sub>	1.168*** (0.394)	0.074*** (0.026)	0.363 (0.319)	0.006 (0.006)	0.006 (0.006)	0.071*** (0.027)	0.282 (0.321)	0.005 (0.006)	0.005 (0.006)	
age <sub>h</sub> <sup>2</sup> /100	-1.526*** (0.403)	-0.091*** (0.026)	-0.573* (0.325)	-0.010 (0.006)	-0.010 (0.006)	-0.088*** (0.026)	-0.509 (0.326)	-0.009 (0.006)	-0.009 (0.006)	
educ <sub>h</sub>	0.122 (0.140)	-0.008 (0.010)	0.253** (0.116)	0.005** (0.002)	0.005** (0.002)	-0.017 (0.015)	-0.037 (0.179)	-0.000 (0.003)	-0.000 (0.003)	
muslim	7.619*** (2.244)	0.323* (0.168)	5.145*** (1.858)	0.104*** (0.037)	0.104*** (0.037)	0.282 (0.177)	4.122** (1.857)	0.084** (0.037)	0.084** (0.037)	
kids06	0.879* (0.478)	0.049 (0.035)	0.489 (0.407)	0.008 (0.008)	0.008 (0.008)	0.046 (0.035)	0.414 (0.407)	0.007 (0.008)	0.007 (0.008)	
kids612	0.214 (0.599)	0.109** (0.047)	-0.696 (0.510)	-0.013 (0.010)	-0.013 (0.010)	0.113** (0.048)	-0.538 (0.516)	-0.010 (0.010)	-0.010 (0.010)	
kids1218	0.487 (0.688)	0.005 (0.049)	0.405 (0.564)	0.009 (0.011)	0.009 (0.011)	-0.004 (0.050)	0.099 (0.580)	0.002 (0.011)	0.002 (0.011)	
adults	-0.362 (0.586)	-0.064* (0.035)	0.522 (0.454)	0.007 (0.009)	0.007 (0.009)	-0.075** (0.037)	0.167 (0.483)	-0.000 (0.009)	-0.000 (0.009)	
assets/head	0.941* (0.502)	0.034 (0.032)	0.561 (0.424)	0.009 (0.008)	0.009 (0.008)	0.006 (0.049)	-0.367 (0.610)	-0.009 (0.012)	-0.009 (0.012)	
rural unempl.	-36.359*** (11.188)	0.227 (1.472)	-32.233*** (10.119)	-0.616*** (0.191)	-0.615*** (0.190)	0.048 (1.493)	-31.515*** (10.152)	-0.599*** (0.192)	-0.599*** (0.192)	
% urban	11.738** (4.672)	0.991** (0.498)	1.980 (4.101)	0.048 (0.078)	0.048 (0.078)	1.021** (0.503)	3.392 (4.129)	0.073 (0.078)	0.073 (0.078)	
constant	20.968** (10.541)	0.193 (0.713)	40.900*** (8.505)	3.764*** (0.165)	3.765*** (0.165)	0.511 (0.854)	51.279*** (9.587)	3.962*** (0.185)	3.962*** (0.185)	
<i>Instrument exclusion: Wald test p-value</i>						0.644	0.780	0.874	0.875	
LR test	350.805 (0.000)					350.863 (0.000)				
ln L	-7785.094	-506.708	-7113.645	-8015.181	-7998.985	-506.480	-7111.672	-8014.896	-7998.693	
Observations	1819	1819	1627	1627	1627	1819	1627	1627	1627	

NOTES: The data source is the Nigeria 2010-2011 General Household Survey (GHS) - Panel. Only husbands from monogamous households and aged between 20 and 75 are considered. State fixed effects are included in all specifications. Robust standard errors are reported in parentheses. \*, \*\*, \*\*\* indicate significance at 10%, 5% and 1%, respectively.

we observe for monogamous men and their wife is not necessarily true for all men and women. We decide not to interpret these preliminary results more deeply, since they are based on the questionable assumption that labor supply decisions are independent within the household. We keep further analysis of the results for the next section, in which we actually test this assumption.

## 4.2 Joint estimates of spouses' labor supply

As outlined in section 3.3, our empirical strategy to test independence in labor supply decisions within households is to use a joint estimation procedure for spouses' labor supply outcomes. The simultaneous estimation of hurdle models has been little explored in the past and we rely on the copula-based bivariate hurdle model proposed by Deb et al. (2013). We report in Table 7 the main parameter estimates derived from the bivariate hurdle model, using the three selected copulas.

We focus first on the dependence parameters  $\theta^0$  and  $\theta^+$ , which measure dependence of participation and time allocation outcomes respectively, once controlling for the effect of all explanatory variables. The significance of each of these dependence parameters, whatever the copula used, provides evidence that spouses' labor supply outcomes are jointly determined. Thus, this simultaneous equation model should be preferred over the previous independent models. According to these parameters, the dependence is positive in both parts of the model, meaning that both the employment probability and the working time are positively correlated between spouses. For instance, a wife is more likely to work when her husband is working. In addition, when both spouses work, the working time of a spouse is positively correlated to working time of the other: more the wife works, the more the husband works and *vice versa*.

On the basis of the information criteria (AIC, BIC), we observe that the Clayton copula better fits the data than the Frank copula, which in turn is more appropriate than the SClayton copula. The better fit of the Clayton copula provides evidence of a strong lower tail dependence and a relatively weak upper tail dependence between labor supply outcomes. Thus, spouses' labor supply outcomes are relatively more strongly related at low values but less correlated at high values. For positive values, for instance, this means that the working time of a woman tends to increase with the working time of her husband, essentially for lower values of working time in the sample. It is worth noting that the copula ranking provided by the information criteria is rather consistent, since the Frank copula and the SClayton copula better fit data that exhibit weak tail dependence and upper tail dependence, respectively.

Focusing then on the parameter estimates from the Clayton copula (see Table 7), we find that the magnitude of the dependence is larger in the first part ( $\theta^0 = 1.311$ ) than in the second part ( $\theta^+ = 0.708$ ) of the bivariate hurdle model, with similar levels of significance. This implies that between spouses, the employment probabilities are more closely related than working times. One can also wonders whether the working time of a spouse depends on the employment status of the other spouse. We rely on the shape parameters,  $\eta_j^+$  and  $\eta_j$ , derived from the Gamma distributions in the respective cases where the other spouse works and does not work. We test the null hypothesis that  $\eta_j = \eta_j^+$  using a chi-square test. For  $j = w$ , we actually test that the distribution of wives' positive hours of work has the same shape depending on whether or not the husband works. Alternatively, for  $j = h$ , we test whether the distribution of husbands' positive hours of work is the same depending on whether or not the wife works. We reject the null hypothesis in all specifications, implying that for both husbands and wives the distribution of positive hours of work varies significantly depending on the other spouse works or not.

Previous comments apply to both sides of Table 7, i.e. with or without taking into account endogeneity of the electrification status. But other parameter estimates vary significantly between the two situations, since the electrification status proves to be endogenous with respect to husbands' labor supply. All joint estimation parameters using the Clayton copula are reported in Table 8. When considering first the left side of the table, with assumed exogenous electricity status, we find that taking into account the dependence between spouses' labor supply decisions induces significant changes in parameter estimates for the electricity dummy and also for the

**Table 7** – Electrification and spouses' labor supply: bivariate estimates

	<i>Exogenous electricity</i>				<i>Endogenous electricity</i>			
	Hurdle part		Positive part		Hurdle part		Positive part	
	$1(y_w > 0)$	$1(y_h > 0)$	$y_w$	$y_h$	$1(y_w > 0)$	$1(y_h > 0)$	$y_w$	$y_h$
<b>Frank copula</b>								
electricity	-0.533 (0.714)	-0.585* (0.330)	0.011 (0.033)	0.043 (0.034)	-3.285 (4.659)	-0.552 (2.559)	0.135 (0.233)	0.413** (0.196)
1st-stage residual	—	—	—	—	1.189 (1.977)	-0.008 (1.040)	-0.052 (0.096)	-0.154* (0.081)
$\chi^2$ test for $\eta_j = \eta_j^+$	—	—	147.81*** (0.000)	130.78*** (0.000)	—	—	148.35*** (0.000)	131.12*** (0.000)
$\theta^0; \theta^+$	2.462*** (0.370)		5.872*** (0.433)		2.462*** (0.370)		5.876*** (0.434)	
ln L		-14 203.242				-14 200.686		
AIC		28 806.263				28 811.036		
BIC		29 757.571				29 782.483		
<b>Clayton copula</b>								
electricity	-0.668 (0.879)	-0.679* (0.367)	0.009 (0.030)	0.044 (0.027)	-5.975 (5.799)	-0.703 (3.013)	0.231 (0.238)	0.397* (0.207)
1st-stage residual	—	—	—	—	2.274 (2.454)	0.017 (1.221)	-0.092 (0.098)	-0.147* (0.086)
$\chi^2$ test for $\eta_j = \eta_j^+$	—	—	257.56*** (0.000)	213.86*** (0.000)	—	—	258.43*** (0.000)	212.78*** (0.000)
$\theta^0; \theta^+$	1.311*** (0.241)		0.708*** (0.099)		1.311*** (0.241)		0.706*** (0.099)	
ln L		-14 170.066				-14 167.501		
AIC		28 739.913				28 744.667		
BIC		29 691.220				29 716.114		
<b>SClayton copula</b>								
electricity	-0.520 (0.670)	-0.565* (0.305)	0.022 (0.037)	0.043 (0.034)	-3.622 (4.249)	-0.246 (2.328)	0.240 (0.240)	0.356* (0.207)
1st-stage residual	—	—	—	—	1.328 (1.799)	-0.126 (0.938)	-0.091 (0.099)	-0.130 (0.085)
$\chi^2$ test for $\eta_j = \eta_j^+$	—	—	112.71*** (0.000)	94.06*** (0.000)	—	—	112.57*** (0.000)	94.04*** (0.000)
$\theta^0; \theta^+$	0.336*** (0.058)		1.479*** (0.197)		0.336*** (0.058)		1.478*** (0.198)	
ln L		-14 286.477				-14 284.416		
AIC		28 972.734				28 978.497		
BIC		29 924.041				29 949.944		

NOTES: The data source is the Nigeria 2010-2011 General Household Survey (GHS) - Panel. Only husbands and wives from monogamous households, aged between 20 and 75, are considered. State fixed effects are included in all specifications. Robust standard errors are reported in parentheses. \*, \*\*, \*\*\* indicate significance at 10%, 5% and 1%, respectively.

control variables. Focusing on our variable of interest, the bivariate hurdle model reports a weak significant negative effect of electricity on the employment probability of husbands whereas no significant effect is identified in independent models. In addition, we note a decrease in the significance of the coefficients on some control variables, e.g. age. Including the previously defined first-stage residual in each equation of the bivariate hurdle model suggests that parameter estimates in the left side are biased. The coefficient on the residual is significant and negative in  $y_h$

**Table 8 – Bivariate hurdle model with Clayton copula**

	<i>Exogenous electricity</i>				<i>Endogenous electricity</i>			
	Hurdle part		Positive part		Hurdle part		Positive part	
	$1(y_w > 0)$	$1(y_h > 0)$	$y_w$	$y_h$	$1(y_w > 0)$	$1(y_h > 0)$	$y_w$	$y_h$
electricity	-0.668 (0.879)	-0.679* (0.367)	0.009 (0.030)	0.044 (0.027)	-5.975 (5.799)	-0.703 (3.013)	0.231 (0.238)	0.397* (0.207)
1st-stage residual	—	—	—	—	2.274 (2.454)	0.017 (1.221)	-0.092 (0.098)	-0.147* (0.086)
age <sub>w</sub>	0.268* (0.143)	—	0.011 (0.007)	—	0.238 (0.153)	—	0.012 (0.008)	—
age <sub>w</sub> <sup>2</sup> /100	-0.277 (0.171)	—	-0.015 (0.009)	—	-0.235 (0.185)	—	-0.016* (0.009)	—
educ <sub>w</sub>	0.084 (0.072)	—	0.004* (0.003)	—	0.180 (0.114)	—	0.001 (0.005)	—
age <sub>h</sub>	—	0.076 (0.093)	—	0.003 (0.006)	—	0.076 (0.093)	—	0.001 (0.006)
age <sub>h</sub> <sup>2</sup> /100	—	-0.053 (0.096)	—	-0.007 (0.006)	—	-0.054 (0.096)	—	-0.006 (0.006)
educ <sub>h</sub>	—	0.008 (0.035)	—	0.004** (0.002)	—	0.006 (0.052)	—	-0.001 (0.004)
muslim	0.708 (1.534)	0.156 (0.548)	-0.042 (0.036)	0.072* (0.040)	0.919 (1.515)	0.180 (0.490)	-0.054 (0.038)	0.052 (0.040)
kids06	0.034 (0.202)	0.096 (0.134)	-0.003 (0.009)	0.005 (0.008)	0.066 (0.199)	0.094 (0.135)	-0.004 (0.009)	0.004 (0.008)
kids612	-0.269 (0.263)	0.223 (0.178)	-0.009 (0.011)	-0.022** (0.011)	-0.251 (0.262)	0.220 (0.179)	-0.008 (0.011)	-0.019* (0.011)
kids1218	0.125 (0.378)	-0.475* (0.251)	0.024** (0.012)	0.022** (0.011)	0.264 (0.418)	-0.480* (0.255)	0.019 (0.013)	0.016 (0.012)
adults	-0.282* (0.163)	0.090 (0.190)	-0.009 (0.010)	0.003 (0.009)	-0.178 (0.207)	0.085 (0.198)	-0.013 (0.011)	-0.003 (0.010)
assets/head	0.179 (0.325)	0.181 (0.118)	0.012 (0.009)	0.003 (0.009)	0.462 (0.456)	0.181 (0.206)	0.001 (0.014)	-0.014 (0.013)
rural unempl.	3.519 (3.819)	-3.646* (1.997)	-0.800*** (0.180)	-0.403** (0.188)	5.179 (3.434)	-3.604 (2.208)	-0.802*** (0.180)	-0.391** (0.189)
% urban	1.368 (.)	-0.428 (1.337)	-0.023 (0.103)	0.078 (0.090)	1.557 (.)	-0.363 (1.280)	-0.013 (0.103)	0.099 (0.090)
constant	-2.915 (3.553)	1.543 (2.225)	1.896*** (0.174)	2.141*** (0.173)	-5.135 (3.986)	1.532 (2.792)	1.964*** (0.184)	2.323*** (0.199)
Observations	1 819	1 819	1 298	1 627	1 819	1 819	1 298	1 627

NOTES: The data source is the Nigeria 2010-2011 General Household Survey (GHS) - Panel. Only husbands and wives from monogamous households, aged between 20 and 75, are considered. State fixed effects are included in all specifications. Robust standard errors are reported in parentheses. \*, \*\*, \*\*\* indicate significance at 10%, 5% and 1%, respectively.

equation but non significant in other equations. As a consequence, the coefficient on the electricity dummy is significant and positive, implying that husbands work more when their dwelling is electrified *ceteris paribus*. The significance of this positive effect is smaller than that of the effect estimated previously with the independent model. The bivariate hurdle model induces a greater change in the coefficient on the electricity variable for wives' hours of work. While the independent estimates suggest that electrification significantly increases the time devoted by wives in the



labor market – conditional on working –, this positive effect no longer appears when controlling dependence between spouses.

These last results differ from the existing evidence on this issue in the literature. Indeed, recent studies in developing countries suggest a positive effect of rural electrification primarily on female employment (e.g. Dinkelman 2011; Grogan and Sadanand 2013). Considering the labor supply of monogamous men and their wives, we finally show that rural electrification in Nigeria rather impacts, significantly and positively, male working time – conditional on working. The population studied in this paper is more restrictive than in previous studies and calls for great caution in any inference of the results. Although these findings are valid only for married and monogamous people, they emphasize the need to control the interdependence of decisions within the household to properly assess the effect of electrification on individual labor supply. In consideration of the significant changes occurred in the electricity coefficient when taking into account this dependence, one may qualify the empirical findings that ignore it.

Despite these demographic restrictions, the last findings can be interpreted quite easily in view of the specific characteristics of electricity supply in Nigeria, particularly in rural areas. Reminder, the electricity supply in Nigeria is characterized by a very poor quality of the grid, that can be illustrated with the everyday experience of blackouts in more than half of rural households. In rural Nigeria, most households report only few hours of electricity per day and virtually no household has a permanent access to the grid. In this context, it is difficult to conceive electricity as a substitute for traditional fuels (firewood, kerosene...). Electricity is more likely to be a complementary form of energy in rural electrified households, still dependent on traditional forms of energy. For households substitute electricity to these more expensive fuels, both in time and money, it would require they reach a sufficient utilization rate of electrical appliances. But the current quality of the grid does not allow that. This therefore disqualifies some of the positive effects of electrification on labor supply discussed in the introduction of the paper. In particular, electrification is unlikely to induce a significant reduction in the burden of domestic chores and therefore in the time devoted by women to these chores in rural households. Likewise, the positive externalities of electricity in terms of health and safety may be scarce if it coexists with dirty fuels. In fact, rural electrification would essentially enable households to extend the day using artificial light, in favor only of male labor supply according to our findings.

## 5 Conclusion

Using the 2010-2011 General Household Survey (GHS), we investigated in this paper the effect of rural electrification on household labor supply in Nigeria. This relationship has been explored recently by a few studies in other developing countries, but not to our knowledge in Nigeria. Existing studies conclude to a positive effect of electrification on individual employment, primarily on female employment, and mainly link this effect to an alleviation of time constraints: time saving in domestic chores – use of electrical appliances, reduced time in collecting other fuels – and extension of the day using artificial lighting. But these studies have some limitations and we propose to deal with two of them in this paper: first, previous authors only identify a causal effect on the employment probability and tend to ignore the working time dimension; second, they rely on the strong and questionable assumption that labor supply decisions are independent within the household. To test this assumption, we analyze in this paper the labor supply of monogamous married men and of their wife, so as to jointly assess changes in their labor supply with electrification. Our econometric strategy lies in the class of hurdle models – also called two-part models – to properly handle the large number of zero values in weekly hours of work,

our dependent variable. The identification of the causal effect is achieved using instrumental variables in line with existing literature: the historic population density in the local area and the distance from the household to the nearest major road. A joint estimation of spouses' labor supply outcomes is carried out using the bivariate hurdle model proposed by Deb et al. (2013).

Our empirical analysis shows that electrification affects positively the time spouses devote to work, once the endogeneity of the electrification status is handled, and that this effect varies significantly depending on whether the dependence of spouses' labor supply decisions is controlled or not. Electrification is found to have no significant effect on spouses' employment probability but to increase working time of both spouses – conditional on working – when their labor supply outcomes are analyzed as independent. The joint analysis highlights that spouses' labor supply decisions are significantly dependent and controlling for this dependence induces a remaining positive effect of electrification only on husbands' working time. Our findings thus differ from previous empirical evidence but are quite understandable in the specific Nigerian context. In fact, the very poor quality of the electricity grid in Nigeria would not enable rural electrified households to alleviate the burden of domestic chores, essentially borne by women in this region. Although rural electrification is unlikely to enable women to save domestic time, it provides a means to extend artificially the day and that way it would enable men to increase their working time. In addition, our results suggest that assessing the impact of electrification on the labor supply of individuals supposedly devoid of any interaction with other household members could lead to misleading conclusions.

This paper provides a first evaluation of the effect of rural electrification on within-household labor supply decisions in Nigeria and suggests some extensions for future research. First, our results show the importance of taking into account the dependence of the labor supply decisions between two spouses when assessing the impact of electrification on these outcomes. Beyond this husband-wife configuration, it would be useful to explore alternative ways to control such a dependence among a larger set of individuals. In the Nigerian context, studying only the monogamous pairs leads to ignore a large part of the population, including polygamous households and extended families. By managing to control this dependence between more than two people, then it would be possible to consider these family configurations in which three or more adults are likely to work. It would also provide the opportunity to extend the analysis to child labor, which is rather prevalent in this world region. Second, in countries like Nigeria, the mere connection to the electricity grid proves to be a rather poor measure of the actual use of electricity within the household. Using information on the electrical appliances owned by the household and the utilization rate of these equipments seems to be a more relevant empirical strategy for future research. Third, we discussed the recent privatization of the public firm PHCN (ex NEPA), the sole electricity supplier until 2013, leading to the rise of several private suppliers. It could be interesting to investigate whether this privatization has actually improved the quality of the grid and to assess how it has impacted household labor supply decisions.

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# Appendices

## A Testing the normality assumption of residuals

Figure 3 – Kernel and normal density estimates of residuals

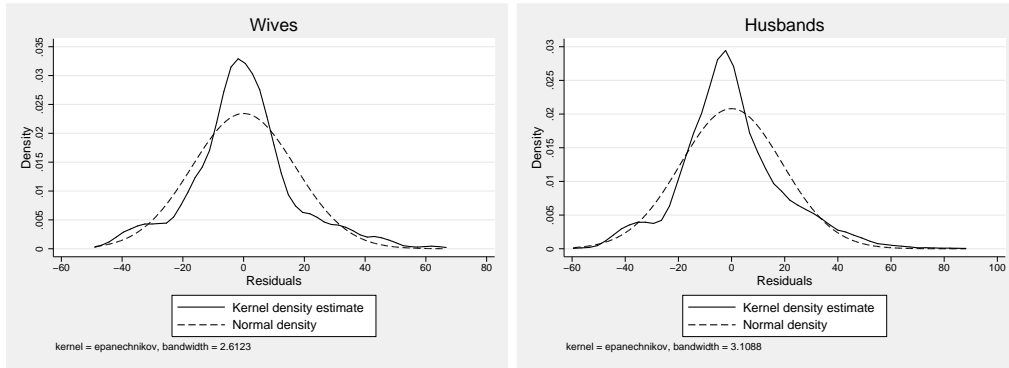


Figure 4 – Normal probability plots of residuals

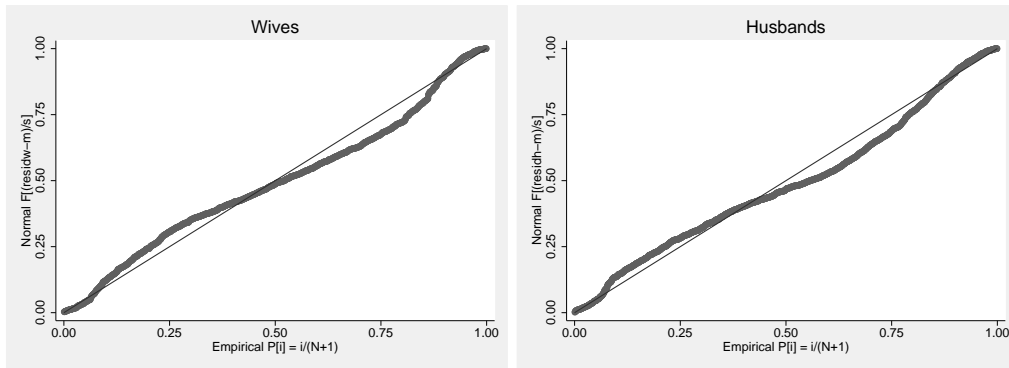
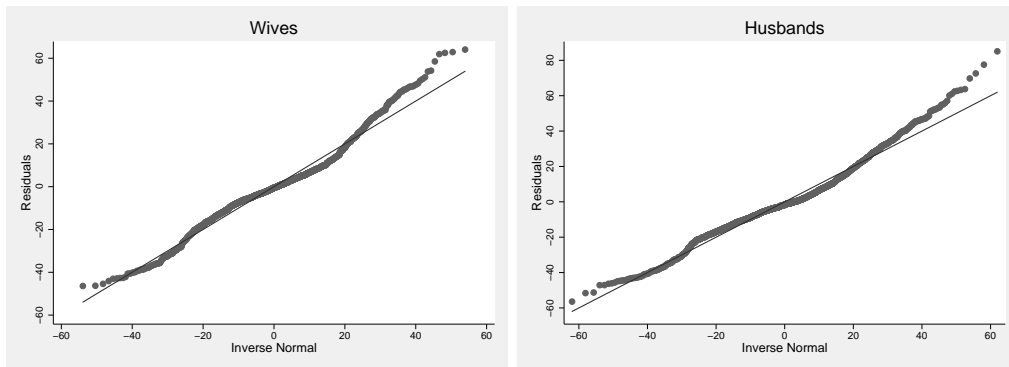


Figure 5 – Normal quantile plots of residuals



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