Fertility and Rural Electrification in Bangladesh*

Tomoki Fujii

School of Economics, Singapore Management University
90 Stamford Road, Singapore 178903
Phone: +65-6828-0279
Fax: +65-6828-0833
E-mail: tfujii@smu.edu.sg

and

Abu Shonchoy

Institute for Developing Economies, IDE-JETRO
Wakaba 3-2-2, Mihamaku, Chiba, Chiba Prefecture, 261-8545, Japan
Phone: + 81-43-299-9695
Fax: +81-43-299-9548
E-mail: parves.shonchoy@gmail.com

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Abstract

Using a panel data set in Bangladesh, we study the relationship between fertility and rural electrification using infrastructure development and the quality of service delivery as instrumental variables for the adoption of electricity. We find that the adoption of electricity reduces fertility and this impact is more pronounced when the household already has two or more children. This observation can be explained by a simple household model of time use, in which adoption of electricity affects only the optimal number of children but not necessarily the current fertility behavior if the optimal number is not yet reached.

JEL classification codes: O20, J13

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1 Introduction

Access to electricity is an essential element for development. Provision of welfare enhancing utilities like supply of clean water, ameliorated sanitation, and modern healthcare services could be delivered efficiently with electricity. Electricity enables households to enjoy reliable and efficient lighting and heating equipments, improved cooking facilities, robust mechanical power, better transport and telecommunications services, and a modern life-style overall. Unfortunately, nearly 1.3 billion people are still lacking the basic access to electricity in developing countries,[1] who mostly reside in rural areas. Almost half this un-electrified population is in Asia, primarily in South Asia.

While electrification alone may not resolve the energy access problem faced by the developing world (Battacharyya, 2006), it may bring about a number of economic benefits beyond making electricity available to people. Series of studies commissioned by the World Bank under the Energy, Poverty and Gender Project, and

[1] WEO-2103 Electricity Access Database (`http://www.worldenergyoutlook.org/resources/energydevelopment/energyaccessdatabase/#d.en.8609`). Accessed on January 15, 2014.

the Energy Sector Management Assistant Program in various parts of the world reported substantial welfare-improving effects of electrification.

Similar findings have also been made in various other studies. Researchers have found evidence that electrification is associated with income generation and employment creation in Benin (Peters et al., 2011), improved income and educational outcomes in Bangladesh (Khandker et al., 2009a) and in Vietnam (Khandker et al., 2009b), development of manufacturing in India (Rud, 2012) and in Brazil (Lipscomb et al., 2013), and improved female employment in South Africa (Dinkelman, 2011) and in Nicaragua (Grogan and Sadanand, 2013). Other impacts of electrification include reduction in indoor air pollution (World Bank, 2008), air-quality-related health improvement and fire safety (Furukawa, 2013), improved medical services (Bensch et al., 2011), and uptake of modern cooking fuels (Heltberg, 2003, 2004).

Rural electrification may also have a causal link to fertility in developing countries. This is an important link, because high fertility rate is one of the most important factors hindering long-term economic growth (for example see Ashraf et al. (2013)). For example, high fertility rate may result in lack of human capital investment, which in turn leads to low quality of human resource and youth unemployment.

Therefore, we investigate the impact of rural electrification on fertility in this study. There are multiple channels through which electricity may affect fertility. The most direct channel is through the change in consumption pattern and time use. Because the access to electricity allows households to enjoy an array of new goods, it may also induce households to shift resources away from child-related goods to these goods. The access to electricity also alters the opportunity cost of the time for reproductive activities, because the households can use the time, for example, to engage in gainful activity if they have an access to electricity.

Indirect channels of impact include income improvement and employment. As discussed above, electrification has been found to improve income and women employment, which in turn may have an impact on fertility. Moreover, electrification increases the household demand for electricity-related goods, which may compete with expenditures related to maternity and children. Electricity also enables households to have better access to information and telecommunication facilities, which may further change the fertility pattern of households. Despite these interesting and important possibilities, the impact of electrification on fertility has not received much attention in economics.

In fact, earlier academic studies on the impact of rural electrification on fertility in developing countries have been mostly undertaken by demographers. The first academic study on this topic we are aware of is Herrin (1979). He argues that electrification led to demographic changes in the Southern Philippines. Summarizing earlier studies on rural electrification and fertility, Harbison and Robinson (1985) also indicate that there is a link between rural electrification and fertility.

More recently, several studies have tackled this topic using aggregate data in developing countries. For example, Potter et al. (2002) use data at the level of micro-regions in Brazil and find that there is a strong and consistent relationship between the decline in fertility and electrification. Similarly, using a pseudo-panel data at the district level in Indonesia, Grimm et al. (2014) find that electrification contributed to the reduction of fertility. They also find that the two important channels through which electrification affects fertility are exposure to TV and reduced child mortality.

However, to the best of our knowledge, there are only a few studies on rural electrification and fertility that utilize a household-level dataset with a modern econometric method. One such study is Peters and Vance (2011), who use a household-level dataset for Côte d'Ivoire. Using a Poisson regression model, they find a negative association between fertility and the availability of electricity among rural households. Another study based on household-level data is Akpandjar et al. (2014), who find that electrification contributes to the reduction in fertility in rural Ghana.

The current study differs from the above-mentioned studies in two important dimensions. First, none of the published studies we are aware of addresses the endogeneity of adoption of electricity.[2] This casts serious doubt on the validity of estimated impacts of electrification. Second, unlike Peters and Vance (2011), we use a panel dataset. The use of panel dataset has a few distinct advantages. If we use the standard fixed-effects model, we can control for all the time-invariant household-level characteristics, which is not possible with only one period of observation. When we instead use the change in the number of children as a dependent variable, we can clearly show that the magnitude of the fertility-reducing impact of electrification depends on the current number of children.

The latter point is particularly important, because previous studies do not clearly identify the sources of change in fertility. We construct a simple theoretical model of electrification and fertility and argue that the impact of electrification is likely to negatively affect the optimal number of children. Because electrification only affects the optimal number, it does not necessarily affect the fertility behavior when

[2] In an unpublished working paper by Akpandjar et al. (2014), the district-level access to electricity is used as an instrument. However, those households which choose to live in an area with many electrified households may be systematically different from other households and thus there are some concerns about the validity of instruments.

the optimal number is yet to be reached. Hence, our model suggests the existence of the possibility that the impact of electrification on fertility may be small when there is no child in the household but it is more pronounced when the number of children in the household is above a certain threshold. Our empirical results are indeed consistent with this possibility. We find that the impact of electrification is relatively small for households with less than two children. However, the impact tends to be larger for households with two or more children.

Third, we consider various specifications for electrification and fertility. Peters and Vance (2011) use a Poisson regression model because the dependent variable is discrete. However, the Poisson model is highly restrictive about the distribution of the number of children. For example, denoting the probability that a household has k children by p_k, the Poisson model implies that $p_{k+2}/p_{k+1} = (k+2)/(k+1) \cdot p_{k+1}/p_k$, regardless of the characteristics of the household, which appears to be implausible in practice. While it is still possible to justify the use of a Poisson regression in the framework of the pseudo-maximum-likelihood estimation, in which we are essentially fitting the data to the Poisson model,[3] this estimation is sensitive to outliers in the right tail of the distribution. Therefore, we propose to use a bivariate probit-ordered-probit model, which is robust to outliers and allows for the simultaneous determination of the adoption of electricity and fertility with a possible correlation in the unobserved error term.

In addition to the studies discussed above, this study is related to two separate strands of literature. First, this study is related to the macroeconomic literature on baby boom in the developed world, particularly in its relationship with modern household technology including electric appliances. For example, the spread of modern household technology is found to have reduced the cost of having children and resulted in increased fertility (Greenwood et al., 2005a). It also led to an increase in female labor force participation (Greenwood et al., 2005b; Cavalcanti and Tavares, 2008). On the other hand, Baily and Collins (2011) find that levels/changes in country-level appliance ownership and electrification negatively predict levels/changes in fertility rates in the US between 1940 and 1960, though they do not address the endogeneity of the adoption of electricity and appliances as pointed out by Greenwood et al. (2011).

Second, this study is also related to a growing body of literature on the relationship between a specific type of infrastructure and development. There have been studies on dams (Duflo and Pande, 2007), transportation infrastructure (Fer-

[3]This approach is used, for example, in the gravity equation in international trade, where the left-hand-side variable is not a count data. See, for example, Silva and Tenreyro (2006).

nald, 1999; Banerjee et al., 2012), and telecommunications infrastructure (R oller and Waverman, 2001) among others (See also Gramlich (1994) and Straub (2008) for a review of literature). Shedding light on the impact of electrification on fertility that have been largely ignored previously, we underscore the importance of understanding social impact of infrastructure.

Consistent with most of the existing studies reviewed earlier, we find that electricity adoption and fertility are negatively correlated after controlling for some other factors. By using infrastructure development and quality of electricity service delivery as instrumental variables for the adoption of electricity, we find that the impact of electrification on fertility is both economically and statistically significant. We also find that the impact of electrification is larger for those households that already have a few children. On the other hand, we find that the impact tends to be smaller for those households with no or only one child.

This study is organized as follows. In the next section, we briefly discuss some relevant background information on rural electrification in Bangladesh. In Section 3, we present a simple model of electrification and fertility to motivate our estimation models. We then describe the data used in this study and present key summary statistics in Section 4. The estimation results are given in Section 6. Section 7 offers some discussion.

2 Rural Electrification in Bangladesh

In Bangladesh, the Power Division of the Ministry of Power, Energy and Mineral Resources is responsible for formulating electricity policy and supervises, controls, and monitors the development activities in the electricity sector. Two organizations, the office of the Electrical Advisor and Chief Electrical Inspector (EA & CEI) and the Power Cell, are directly under the Power Division. The main responsibility of EA & CEI includes inspection of installations, substations, and lines, whereas the Power Cell basically acts as a technical unit of the Power Division.[4]

Five government entities[5] and some other independent power producers are currently involved in the generation of power in Bangladesh. The power is then transmitted through the national grid by the Power Grid Company of Bangladesh. The power is then distributed to end users by different organizations, which include the Rural Electrification Board (REB), depending on the region and purpose of the use

[4]See, `http://www.powerdivision.gov.bd/`.

[5]Bangladesh Power Development Board (BPDB), Ashuganj Power Station Company Ltd. (APSCL), Electricity Generation Company of Bangladesh Ltd. (EGCB), Rural Power Company Ltd. (RPCL), and North West Power Generation Company Ltd. (NWPGCL).

of power.[6]

REB, which was established in 1977, is a semi-autonomous government organization that has been providing service to rural member consumers and in charge of electrification in rural areas. REB is responsible for planning and developing the distribution network for each phase of the expansion of rural electrification and divested the management responsibility of distribution to end users to the rural electric cooperatives or Palli Biddut Samities (PBS).

The process of rural electrification has been dependent on various factors including (i) the results of pre-phase economic and social impact study, (ii) the development of a PBS, (iii) financially and technically viable electrical distribution system, and (iv) availability of donor funding. Therefore, the variations in the timing of rural electrification are not random, but we treat these variations to be exogenous to fertility.

There are currently 70 operating PBSs, which owns, operates, and manages a rural distribution system within its area of jurisdiction. Since the establishment of REB, rural Bangladesh has become significantly electrified. Today, REB serves over 8.3 million domestic end users in addition to commercial, industrial, irrigation, and other users through PBSs with a total of over 9.7 million connections.[7]

PBS is modelled after the Rural Electric Cooperatives in USA. The members of REB are its consumers, who participate in its policy-making through elected representatives in its governing body. REB provides PBS with technical support and training, negotiates the purchase of power for PBS, approves its tariffs, and supervises other functions. The area coverage of one PBS is usually 5-10 sub-districts (upazilas/thanas) with a geographic expanse of 600-700 square miles.

REB's rural electrification program has been viewed as one of the most successful government programs in Bangladesh (Khandker et al., 2009a). REB has achieved a substantially lower system loss than other major electricity distribution bodies (Alam et al., 2004) and has an almost perfect bill collection record. The success of REB is attributed to its autonomy, minimal bureaucracy, strong culture of integrity, donor support and trust, and strong and independent leadership (Nathan Associates Inc., 2006). The political appeal of REB is that many of the benefits of electrification, such as longer lighted hours and easier access to mass media, are readily visible to the public. However, a recent study by Rahaman et al. (2013)

[6]Other power distributors include Bangladesh Power Development Board (BPDB), Dhaka Electric Supply Company Ltd. (DESCO), Dhaka Power Distribution Company Ltd. (DPDC), West Zone Power Distribution Company Ltd. (WZPDCL), North West Zone Power Distribution Company Ltd. (NWZPDCL), and South Zone Power Distribution Company Ltd. (SZPDCL).

[7]See, `http://www.reb.gov.bd/`.

points out that the performance of REB has been declining since 2006 because of the lack of organizational autonomy, a shortage of funding, unrealistic tariffs, and power supply shortages. They also find that renewable-based, off-grid technologies have been supplementing the on-grid program in remote areas.[8]

3 Model of electrification and fertility

In this section, we propose a simple model of electrification and fertility to motivate our econometric specification in the subsequent analysis. While there exist multiple potential channels through which electricity affects fertility, one of the most obvious and direct channel is reallocation of time use. To fix the ideas, we start with a standard Beckerian-type model (for example, see Becker and Lewis (1973); Becker (1981); Willis (1973)) with a single decision maker, in which each household maximizes a static utility function over the consumption of child goods $n \in \mathbf{R}_+$ and non-child numeraire goods $c \in \mathbf{R}_+$ for given electrification status e. The non-child goods potentially includes the value of leisure time.

Even though the electrification status in our empirical analysis is mostly a binary variable, we treat e as a continuous variable in the reminder of this section for the simplicity of presentation. Therefore, a larger value of e represents better electrified households. For example, e can be interpreted as the proportion of time in which electricity is available.

We also assume that the consumption of child goods is proportionate to the number of children. Hence, we hereafter use the number of children and consumption of child goods interchangeably. The quality of children is assumed away in our model.

For the sake of simplicity, we also assume that the utility function $U(c, n, e)$ is additively separable in (c, e) and n and that the sub-utility from non-child goods depends on e but not on the sub-utility from child goods. Given these assumptions, we can write the household utility as follows:

$$U(c, n, e) = \gamma f(c, e) + (1 - \gamma) g(n), \tag{1}$$

where f and g are the sub-utility functions from non-child and child goods, respectively, and $\gamma (\in (0, 1))$ is a preference parameter representing the weight attached to non-child sub-utility. We assume that f and g are increasing, concave, and twice differentiable.

[8] We, however, do not separately take into account the electrification based on off-grid technologies, because the proportion of electrified households in the off-grid villages is very small in our sample.

In our model, each household allocates its effective lighted time (or productive time) to either child-related activities, such as bearing and rearing children, or non-child activities including leisure and work. We denote the *fraction* of the effective lighted time that has to be spent on each child by $\alpha(e)$, which is a function of electrification, and the fraction of effective lighted time spent on non-child activities by l. By definition, l, $\alpha(e)$, and n in our model satisfies the following:

$$l + \alpha(e)n = 1. \tag{2}$$

Note that the physical unit of time may vary across households. That is, some households may have a habit of getting up early and work until it is dark. Compared with other households, they have longer effective lighted time. Eq. (2) only requires that some fraction of effective lighted time has to be spent on each child in the household.

Because households with electricity have more choices to do things for children, the actual number of lighted hours that has to be spent on each child does not increase with electrification. Therefore, even if electricity does not help households save time for child-related activities, the *fraction* of the lighted hours that has to be spent on each child decreases such that the first-derivative of α satisfies $\alpha'(e)(\equiv \mathrm{d}\alpha/\mathrm{d}e) < 0$ thanks to the longer lighted hours that electrified households enjoy.[9] We further assume that non-lighted hours are used only for sleeping or reproductive activities and have no alternative use.

Let us now turn to the budget constraint faced by households. Suppose that $I(e)$ is the maximum potential household income, which the household can earn if all of the household's effective lighted time is spent on work. We assume that $I'(e) > 0$, because longer lighted hours allow households to (potentially) spend more time on gainful activities (See Appendix B and Khandker et al. (2009a,b)).

Assuming that the actual household income earned from work is proportionate to l, we can write the household budget constraint as follows:

$$I(e)l = c + p_n(e)n, \tag{3}$$

where $p_n(e)$ is the "price of having one child", which includes direct costs of child bearing and child rearing, such as food, clothes, and education. Because the opportunities to use electrified appliances would not increase the cost of children, we assume that $p_n'(e) \leq 0$ holds. We ignore the possibility that children potentially

[9] Using the time use data, we find no evidence that this condition is violated. See Appendix B for details.

contribute to the household income once they grow up, because this is a static model.

Households maximize the utility function in eq. (1) subject to the time constraint eq. (2) and the budget constraint eq. (3) over c, n, and l, given their electrification status e. We denote the maximizing arguments with an asterisk and explicitly write the argument e to emphasize their dependence on e (i.e., $c_*(e)$, $n_*(e)$, and $l_*(e)$).

It is straightforward to show that the maximizing arguments satisfy the following condition:

$$\gamma[p_n + I(e)\alpha(e)]f'(c_*(e), e) = (1-\gamma)g'(n_*(e)), \tag{4}$$

where we use f' and g' to denote the first derivatives of f and g with respect to c and n, respectively.

Note that the term $I(e)\alpha(e)$ in the square brackets on the left hand side in eq. (4) can be interpreted as the opportunity cost of having one child, because it corresponds to the amount of income that could be earned using the time spent on raising one child. Therefore, $[p_n + I(e)\alpha(e)]$ represents the total economic cost of having one child. Hence, eq. (4) admits the usual interpretation that the marginal utility per price from child goods is equal to that from non-child goods.

By taking a total differentiation of eqs. (2), (3), and (4) with respect to e and solving for $n'_*(e)$, we obtain the following results:

$$n'_*(e) = \frac{\gamma A(e)}{(1-\gamma)g''(n_*(e)) + \gamma[p_n(e) + I(e)\alpha(e)]^2 f''(c_*(e), e)}, \tag{5}$$

where f'' and g'' are the second derivatives of f and g with respect to c and n, respectively, f'_e is the cross partial derivative of f, and $A(e)$ in the denominator has the following definition:

$$\begin{aligned} A(e) \equiv\ & [p'_n(e) + I'(e)\alpha(e) + I(e)\alpha'(e)]f'(c_*(e), e) + [p_n(e) + I(e)\alpha(e)] \cdot \\ & [f''(c_*(e), e)(I'(e) - (p'_n(e) + \alpha'(e)I(e) + \alpha(e)I'(e))n_*(e)) + f'_e(c_*(e), e)] \\ =\ & [f' - (p_n + I\alpha)n_* f'']p'_n + [If' - (p_n + I\alpha)In_* f'']\alpha' + \\ & [\alpha f' + (p_n + I\alpha)l_* f'']I' + [p_n + I\alpha]f'_e, \end{aligned} \tag{6}$$

where we have used $I' - \alpha I' n_* = l_* I' (> 0)$ and dropped the arguments for the simplicity of presentation.

As can be seen from the last line of eq. (6), $A(e)$ can be divided into four terms, each involving p'_n, α', I', and f'_e. Roughly speaking, the first and second terms are driven by the price effects induced by electrification through the changes in, respectively, the direct and opportunity costs of children. It is straightforward to verify that the first term is non-positive and the second term is negative. Because the denominator of eq. (5) is unambiguously negative from the concavity assumption about f and g, we can see that the price effects of electrification on fertility is positive.

The third term involving I' represents the effect due to the change in potential household income. This effect is ambiguous because $\alpha f' > 0$ and $(p_n + I\alpha)l_* f'' < 0$. The fourth term involving f_e' represents the effects due to complementarity between electricity and non-child goods. This complementarity effect affects fertility negatively when $f_e' > 0$. While we do not assume $f_e' > 0$, it is likely to hold. This is because access to electricity allows households to enjoy a wide range of additional goods, including electric lights, cooking appliances, refrigerators, fans, and televisions. Therefore, given the consumption level of non-child goods, the marginal sub-utility of non-child goods for electrified households would be no smaller than that for non-electrified households.

The following proposition directly follows from eqs. (2), (3), and (5):

Proposition 1 *The necessary and sufficient condition for the optimal number of children $n_*(e)$ to be decreasing with electrification (i.e., $n_*'(e) < 0$) is:*

$$A(e) > 0. \tag{7}$$

Further, when this condition is satisfied, we have:

$$\begin{cases} c_*'(e) &= l_* I' - (p_n + \alpha I)n_*' - (p_n' + \alpha' I)n_* > 0. \\ l_*'(e) &= -(\alpha' n_* + \alpha n_*') > 0. \end{cases}$$

From this proposition and the preceding discussion, it can be seen that the optimal number of children tends to decrease as the household is electrified when at least some of the following conditions are satisfied: (i) the marginal utility from non-child goods is relatively large and declining only slowly (i.e., f' is large and f'' is small in absolute value), (ii) the complementarity between electricity and non-child goods is strong (i.e., f_e' is positive and large), and (iii) the direct and opportunity costs of children do not decline much with electrification (i.e., p_n' and α' are small in absolute value).

Proposition 1 describes the relationship between n_*', c_*', and l_*'. When we observe a negative relationship between electrification and fertility, the consumption of non-child goods and the fraction of the lighted hours spent on non-child activities should be both positively related with fertility. Therefore, even though our primary interest is in the relationship between electrification and fertility, we can also carry out a test to check the consistency of data with our theoretical model, provided that we have relevant data. Because we do not have detailed consumption data to differentiate the consumption of child goods from that of non-child goods, we cannot test the sign of c_*. However, because we have time use data (of limited quality), we can test the sign of l'_*. In Appendix B, we show that there is no evidence to suggest that $l'_* > 0$ is violated.

Since our model is static, n_* can be interpreted as the optimal number of children in the long run or the number of children the household plans to have. If this interpretation is adopted, little difference between electrified and non-electrified households is expected in fertility behavior when the current number of children is well below their respective optimal number of children. This is because both types of households wish to increase the number of children and because the speed at which they can increase the number of children is largely governed by the biological limit.

Suppose now that eq. (7) is satisfied and consider electrified and non-electrified households with $n_*(1)(< n_*(0))$ children, which is the optimal number for electrified households but is less than the optimal number for non-electrified households. In this case, the former would not wish to increase the number of children any further, whereas the latter continues to try to increase. Therefore, it is likely that the fertility-reducing impact of electrification can be relatively easily identified.

So far, we have ignored the heterogeneity across households. However, even given the electrification status, the optimal number of children is likely to vary across households because, for example, households have or face different values of γ, I, and p_n. Therefore, it is quite likely that $n_*(1)$ for some households is greater than $n_*(0)$ for other households. Even in this case, the discussion above remains applicable and the negative relationship between electrification and fertility is likely to be most apparent when the households already have some children (grater than $n_*(1)$ for most households) but not too many (fewer than $n_*(0)$ for most households) unless important household characteristics are controlled for.

Similarly, when there are many children already in the household, the differences in the subsequent fertility behavior between electrified and non-electrified households may not be very clear especially when important household characteristics are not adequately controlled for. This is because the number of children is likely to be already at or close to the optimal number regardless of the electrification status of household.

One important limitation of the model presented in this section is that the adoption of electricity is given exogenously. This is potentially problematic because the number of children household plans to have in the long run changes when it chooses to adopt electricity. Therefore, we use variations in electricity adoption exogenous to fertility decisions to address this issue.

4 Data and Summary Statistics

The main data source for our study is the household survey data collected under the *Socio-economic Monitoring and Impact Evaluation (SEM & IE) of Rural Electrification and Renewable Energy Programme in Bangladesh*. The SEM & IE study was conducted in order to (i) document benefits and impacts of rural electrification; (ii) develop valuable, replicable "good practices" for application in future rural-electrification (RE) projects; and (iii) institutionalize and apply "good practices" concerning measuring benefits and impacts of RE for future RE projects in Bangladesh.

The survey took place in two rounds. The first round was conducted in 2005 and collected by the consortium consisting of Bangladesh Engineering and Technological Services Ltd. (BETS) and Bangladesh Unnayan Parishad (BUP). The second round was conducted in 2010 by e.Gen Consultants Ltd. Some of the households in the data appear in both rounds. Therefore, these data are partial panel data.

Both rounds cover 45 PBS out of the 70 PBSs operating in Bangladesh, covering all six divisional regions of Bangladesh. In Round 1, a stratified random sample was drawn according to the electrification status such that roughly one half of the villages are with electricity and the other half are without electricity. The domestic, commercial, industrial, and irrigation samples were selected based on the actual distribution within rural Bangladesh, but we only use the domestic data because our main interest is fertility, which is predominantly a household decision.[10]

In the second round of the survey, a subsample of households were followed up. Both electronic and printed lists of identified household and non-household units were obtained to match those surveyed in 2005. These lists contain household identification information, their location information (village, sub-district, PBS, etc.), their location status (electrified village, project non-electrified village, and non-project non-electrified village), and their electrification status. This information was used as the basis for the sampling design for the Round 2 survey (e.Gen Consultants Ltd., 2006).

The selection of villages was based on the attrition rate found in the retracing

[10] For additional information on Round 1, see Bangladesh Engineering and Technological Services Ltd. and Bangladesh Unnayan Parishad (2006) and Khandker et al. (2009a).

survey and villages were selected from all three types of villages in 2005, including (i) those villages that were already electrified, (ii) those villages that were to be electrified in future within the duration of the project (i.e., electrified between the two rounds of the survey), and (iii) those villages that were not to be electrified under the life of the project (i.e., not electrified by the time of Round 2). Those villages which had no more than 10 households in Round 1 were excluded from the sample in Round 2. Further, no more than 25 households were selected from each village. The number of villages was kept to a minimum in Round 2 while the required number of households were sampled for each PBS.

We have also collected the age and the system loss from the grid for each PBS from the Bangladesh Rural Electrification Board Management Information System.[11] We take the former as an indicator of infrastructure development and the latter as an indicator of the efficiency of service delivery, both of which are likely to be related to the adoption of electricity. That is, when the age of PBS is higher, electricity is likely to have been available to the household for a longer period of time. Because the establishment of PBS is largely dependent on the choice of areas for rural electrification projects by policy-makers in the government and donors, there is little concern for the endogeneity of the household's choice of the location of residence.

The second instrument, system loss variable of PBS, is also important because the management of PBS is likely to be poor when system loss is larger, which in turn would negatively affect the adoption of electricity. System loss variable also has no obvious link to fertility. Therefore, the age and the system loss variables of PBS can be interpreted, respectively, as supply- and demand-side instrumental variables for the adoption of electricity for households. We merge these PBS-level variables into household-level variables.

To minimize the complications arising from the differences in the household structure, we only use the data for households whose household head is male[12] and married to a woman aged between 15 and 49, an age group for which fertility decision is relevant. We also eliminate about one percent of households in each round that had multiple wives. After further eliminating a small fraction of households whose demographic, education, or income variable is missing, we have 16,369 households in Round 1 and 4,180 households in Round 2 in the data.

Because the raw dataset did not contain a unique individual-level identifier, a panel dataset was produced by matching the names of the husband and wife

[11]Source: Document number: FMTF 075-001 (Version 1) Date: 11-07-2013.

[12]In Bangladesh, an overwhelming majority of households are headed by male.

between the two rounds for each household manually.[13] We exclude from our panel-data analysis those households which cannot be matched between the two rounds, those with missing observations in some key variables as well as a small fraction of households in which the number of surviving children has changed by more than four between the two rounds of survey. As a result, we have a balanced panel data set with 5,094 observations with two observations for each of 2,547 households. Table 1 provides summary statistics of some key household variables by the status of electrification in Round 1, HHELEC^1, where HHELEC$=^1 = 0$ [HHELEC$^1 = 1$] means that the household does not have access to electricity from the national grid.[14]

Four cautions are in order here. First, because we do not have household weights for the version of Round 2 data we received, we apply the same household weights to the Round 2 data as those included in the Round 1 data. Based on these weights, about 52.8 percent of households live in an electrified village and 31.6 percent of households had electricity at home in Round 1. The corresponding figures for Round 2 are 71.9 percent and 54.5 percent, respectively. We only report un-weighted regression results in Section 6 but the results are generally similar even when the weights are applied.

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[13]The matching of names between the two rounds is not always exact because of the variations in the English spelling of names. However, only those households that were matched with high confidence were retained in the dataset used in this study.

[14]We also provide a table of summary statistics for the panel households in Table 12 in Appendix C. Because of the sample restriction described above, the panel households are on average younger. The distributions of other characteristics do not differ much between the panel and whole samples.

Table 1: Key summary statistics for Rounds 1 and 2 by the electrification status of households.

Description	Round 1			Round 2		
	Non-electrified ($HHELEC^1$=0)	Electrified ($HHELEC^1$=1)	All	Non-electrified ($HHELEC^2$=0)	Electrified ($HHELEC^2$=1)	All
Head's age	40.9	42.4	41.4	43.0	44.8	43.8
Spouse's age	32.8	34.0	33.2	34.9	35.9	35.4
# surviving children spouse has given birth to	2.68	2.66	2.67	2.78	2.75	2.77
Ratio of boys among children under 15 (%)†	52.2	52.7	52.3	51.5	51.4	51.5
Head has some primary education (%)	60.5	78.9	66.4	69.2	77.2	73.0
Head has some lower secondary education (%)	37.5	55.2	43.1	38.6	48.1	43.1
Head has some matric education (%)	18.4	31.0	22.4	20.1	25.9	22.9
Spouse has some primary education (%)	54.1	71.0	59.5	67.4	76.0	71.5
Spouse has some lower secondary education (%)	29.3	42.6	33.5	32.6	40.2	36.2
Spouse has some matric education (%)	8.4	13.5	10.0	10.3	13.2	11.6
Household expenditure per capita (Tk.)	29.1	33.6	30.5	60.6	172.0	113.6
Average hours of TV watching time by spouse	0.24	1.00	0.48	0.38	1.37	0.85
Landless (0.00-0.04 acres)	5.0	3.9	4.7	10.0	10.5	10.3
Marginal land owner(0.05-0.49 acres)	50.0	51.9	50.6	37.0	40.5	38.7
Small land owner (0.50-2.49 acres)	30.7	32.8	31.3	33.7	36.2	34.9
Medium land owner (2.50-7.49 acres)	11.9	10.1	11.3	16.8	11.2	14.2
Large land owner(7.50+ acres)	2.5	1.3	2.1	2.5	1.6	2.0
Number of observations	8926	7443	16369	1723	2457	4180

†: The average was taken over those households with at least one child under the age of 15. Therefore, the number of observations used for this calculation is about 10-15 percent lower than other rows in each round and each electrification status.

Second, the educational attainment is taken as an ordered variable to make it easier to understand the marginal impact of education. For example, if the head in a given household has at least some matric education, then he automatically has some primary and lower secondary education. Therefore, the proportion of households with some primary education but no secondary education in Round 1 is $23.3(= 66.4 - 43.1)$ percent.

Third, the sex ratio of children born to the wife is likely to matter for the subsequent fertility decisions as it is common in Bangladesh to prefer boys to girls. However, we observe only the number of surviving children born to the wife, NCHILD, but not the number of boys and girls separately. Therefore, we use the ratio of boys among children under the age of 15 in the household, which may include those children whose mother is not the spouse of the male household head. For those households with no children under 15, we assign the value of half in the regression analysis, but the average reported in Table 1 excludes those households.

Finally, we are primarily interested in the electricity from the national grid because our identification uses the age and system loss from the grid for each PBS. Thus, the non-electrified households may actually be able to use electricity from non-grid sources such as the solar power. While we ignore it for most of our analysis, we shall briefly discuss the impact of electricity from the solar power in Section 6.

We use NCHILD as an observable measure of fertility because we do not observe the complete history of pregnancy and birth for each woman in the data. Therefore, NCHILD is affected not only by the number of children the wife has given birth to but also by the number of children who have died before the time of interview.

As shown in Table 1, electrified households tend to be slightly older than non-electrified households. The average of NCHILD is similar for both types of households but electrified households tend to have a smaller number of children. One of the major differences between non-electrified and electrified households in Table 1 is the educational attainment of their heads. At each level of educational attainment, the proportion of educated households for electrified households is higher than that for non-electrified households. For example, nearly 80 percent of household heads in electrified households had at least some primary education in Round 1. However, the corresponding ratio is only around 60 percent for non-electrified households. Similarly, the educational attainment of spouse is also higher in electrified households.

Electrified households and non-electrified households are also economically and statistically different in terms of expenditure per capita. As expected, electrified households are on average wealthier than non-electrified households. Furthermore, the increase in average consumption between the two rounds is higher than that for non-electrified households. On the other hand, while the proportion of landless households for the electrified households is significantly smaller than that for non-electrified households, the land distributions for electrified and non-electrified households are similar overall. Table 1 also shows that the daily average hours of watching TV is small but positive for non-electrified households. This is because one can watch TV in a neighbor's house, for example.

For the panel households, we can use the change in the number of surviving children between the two rounds, ΔNCHILD, as an observable measure of fertility. On average, electrified households (based on Round 1 electrification status) increases 0.346 surviving children and non-electrified households 0.456 surviving children between the two rounds (See Table 4 discussed in the next section). The difference in average ΔNCHILD between non-electrified and electrified households is statistically significant.

As with NCHILD, ΔNCHILD reflects both births and deaths of children that have taken place between the two rounds of survey. However, for the most part of our analysis, we ignore the deaths of children and drop the qualifier "surviving" to keep the presentation simple, because the probability of deaths, especially between the two rounds of surveys, is limited.[15] We do, however, retain the households for which ΔNCHILD is negative in our panel analysis. This is because if we only retain the households for which ΔNCHILD is non-negative, we essentially retain high fertility households that tend to have additional children in the event of deaths of children, which leads to a sample selection bias in our estimation.

5 Econometric specifications

The discussion in Section 3 suggests that the availability of electricity may affect fertility decisions. Let us now bring this idea to the data. To highlight some econometric issues, let us begin with the simplest cross-sectional specification in a linear form.

$$\text{NCHILD}_i^t = \alpha \text{HHELEC}_i^t + \gamma X_i^t + u_i^t, , \tag{8}$$

[15]The child mortality rate under five per 1,000 live births in Bangladesh is 68 in 2005 and 47 in 2010 according to the World Development Indicators. This number is certainly not negligible but still relatively small. Further, children are most vulnerable to death in their first five years of life and older children are more likely to survive between the two rounds of survey. In our sample, less than 9 percent of panel households experienced a net decrease in the number of surviving children between the two rounds. As shown later, we also find that controlling for the infant mortality rate does not alter our regression results much.

where the superscript $t \in \{1,2\}$ represents the round of the survey and X_i^t is a vector of covariates, which includes a constant term. When the error is conditionally uncorrelated with the regressors and follows an iid process, the model parameters such as α and γ can be consistently estimated by ordinary least-squares (OLS) regression. However, one obvious problem here is the endogeneity of HHELEC. That is, because those who have access to grid electricity may be systematically different from those who do not, the (mean-zero) error term u_i^t may be conditionally correlated with HHELEC_i^t and thus OLS estimates may be biased.

With some additional assumptions, this problem can be resolved. Suppose that ϵ_i^t can be decomposed into the time-specific effect η_t, household-specific effect δ_i and idiosyncratic effect ϵ_i^t such that eq (9) reduces to:

$$\text{NCHILD}_i^t = \alpha\text{HHELEC}_i^t + \gamma X_i^t + \eta_t + \Delta_i + \epsilon_i^t. \tag{9}$$

When ϵ_i^t is uncorrelated with X_i^t, η_t, and δ_i. In this case, even when η_t or δ_i is correlated with HHELEC_i^t, we can obtain a consistent estimate. In this case, we can use fixed-effects OLS (FE-OLS) regression using a panel data set.

However, this specification implies that the expected number of children that are born between the two rounds is completely determined by HHELEC and X, regardless of the number of surviving children in Round 1. This seems to be unrealistic because those households that already have a long-run optimal number of children would not increase the number of children. Further, the way the number of children increases may also depend on a time-invariant characteristic, a situation that is not allowed in fixed-effects OLS. Therefore, we also consider the following change-on-level specification:

$$\Delta NCHILD_i = \alpha\text{HHELEC}_i^1 + \beta\text{NCHILD}_i^1 + \gamma X_i^1 + e_i^t, , \tag{10}$$

As discussed in Section 3, it is possible that the effect of the electrification depends on whether the existing number of children (NCHILD_i^1) has reached a certain threshold. To allow for this possibility, we also consider the following variant of equation:

$$\begin{aligned} \Delta NCHILD_i \;&=\; \alpha\text{HHELEC}_i^1 \cdot \nVdash(\text{NCHILD}_i^1 \geq M) + \beta_1 \cdot \nVdash(\text{NCHILD}_i^1 \geq M) \\ &\quad +\beta_2\text{NCHILD}_i^1 + \gamma X_i^1 + e_i^t, , \end{aligned} \tag{11}$$

where the threshold value M is varied from 1 to 4. This can be estimated consistently by OLS when e_i^t is conditionally uncorrelated with $\text{HHELEC}_i^1 \cdot \nVdash(\text{NCHILD}_i^1 \geq M)$.

In the specifications above, we cannot completely exclude the possibility that HHELEC_i^1 is endogenous in each of the four specifications. Further, it is not possible to predict in advance in which direction the OLS estimate is biased in the presence of endogeneity, because both positive selection and negative selection are possible.

On one hand, it is possible to argue that those households that value electric appliances more tend to have adopted electricity early and they also tend to have a lower optimal number of children because, say, they have a higher value of γ. In this case, the negative selection occurs and the estimated coefficient on household electrification status is biased downwards. On the other hand, if those households which have a better prospect of future income adopt electricity early and tend to have more children subsequently, the selection is positive and coefficient tends to be biased upwards.

To deal with this issue, we instrument it with the adoption of electricity by the age and the system loss from grid for the PBS that covers the location of household i. While we have only discussed linear specifications above, we also consider some non-linear specifications that take into account the discreteness of the left-hand-side variables.

6 Results

We now consider the impact of rural electrification on fertility based on the econometric specifications considered in Section 5.

Cross-sectional analysis

We start with simple cross-sectional specification given in eq. (8). While this specification suffers from the issues discussed earlier, it has a practical advantage that we are able to take advantage of all the observations.

Table 2: Cross-sectional regression results for Rounds 1 and 2.

Dependent Variable: NCHILD	Round 1				Round 2			
	OLS		GMM-IV		OLS		GMM-IV	
	Mean	(S.E.)	Mean	(S.E.)	Mean	(S.E.)	Mean	(S.E.)
HHELEC	-0.002	(0.022)	-5.001 ***	(0.883)	-0.037	(0.042)	-2.921 ***	(0.845)
Ratio of boys among children	-0.072 ***	(0.027)	-0.059	(0.060)	-0.222 ***	(0.053)	-0.266 ***	(0.081)
Head's age	0.086 ***	(0.014)	0.164 ***	(0.031)	0.056 ***	(0.019)	0.109 ***	(0.031)
Head's age squared†	-0.046 ***	(0.016)	-0.119 ***	(0.032)	-0.037 *	(0.021)	-0.073 **	(0.031)
Spouse's age	0.160 ***	(0.016)	0.139 ***	(0.034)	0.196 ***	(0.027)	0.121 **	(0.048)
Spouse's age squared†	-0.148 ***	(0.025)	-0.089 *	(0.049)	-0.185 ***	(0.040)	-0.086	(0.066)
Head has some primary education	0.117 ***	(0.033)	0.616 ***	(0.109)	-0.071	(0.063)	0.002	(0.093)
Head has some lower secondary education	-0.029	(0.032)	0.039	(0.068)	-0.015	(0.059)	0.046	(0.088)
Head has some matric education	0.015	(0.033)	0.111	(0.073)	-0.053	(0.065)	-0.105	(0.097)
Spouse has some primary education	-0.099 ***	(0.032)	0.337 ***	(0.100)	-0.148 **	(0.064)	0.071	(0.108)
Spouse has some lower secondary education	-0.129 ***	(0.029)	-0.036	(0.066)	-0.133 **	(0.054)	0.008	(0.093)
Spouse has some matric education	-0.152 ***	(0.033)	-0.089	(0.082)	-0.202 ***	(0.065)	-0.149	(0.106)
log (HH expenditure per capita)	-0.582 ***	(0.032)	0.012	(0.121)	-0.318 ***	(0.050)	-0.078	(0.092)
R^2	0.323				0.261			
1st Stage F			21.10 ***				12.23 ***	
Test of endogeneity			122.57 ***				22.51 ***	
OIR Test			0.04				2.61	
CLR Test			122.78 ***				25.74 ***	
N	16369		16369		4180		4180	

Note: † denotes that the regressor is divided by 100. A constant term is included in each model (not reported). Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. In GMM-IV estimation, HH Electrified variables has been instrumented with age and the system loss from the grid for each PBS and R^2 provides the coefficient of determination for the first-stage regression.

We run regressions for each of the two rounds separately. The regression results are provided in Table 2. For each round, we report both the OLS and Generalized Method of Moment Instrumental Variables (GMM-IV) regression results, where HHELEC is instrumented by the age and system loss from the grid for each PBS.

The main variable of interest is HHELEC. As can be seen from Table 2, the coefficient is close to zero when the OLS specification is used. On the other hand, it is highly negative when HHELEC is instrumented. Therefore, this indicates the presence of positive selection.

For GMM-IV regressions, we report the first stage Robust F statistics, the difference-in-Sargan C statistic for the test of endogeneity and the Hansen's J-statistic for the overidentification restriction (OIR) test. Because the first stage F-statistics are not always as large as those reported in Table 2, we also report the conditional likelihood ratio (CLR) test statistic based on the Lagrange multiplier.[16] This statistic allows us to test $\alpha = 0$ even when the instrument is weak.

In addition to HHELEC, we add several control variables. As demographic controls, we include the ratio of boys among children to allow for the possibility that the sex of the existing children may affect the subsequent behavior. For example, if people have a strong preference for a boy, they may continue to try to increase the number of children until they have a boy. The point estimate is negative in all the regressions and significant except for GMM-IV for Round 1.

We also include the age and age squared (rescaled by dividing by 100) for both the head and his spouse. These terms are included because older households tend to have more children but this effect is likely to decline when the number of children has reached the optimal. In all cases, their estimated coefficients have the expected sign and they are mostly statistically significant.

We also include education variables for both the head of household and his spouse. We do not have a consistent pattern of signs for the head's education variables. On the other hand, all the education variables for the spouse are negative in the OLS model, suggesting that households with a better educated mother tend to have fewer children, a finding that is consistent with many existing studies. However, this observation does not hold for GMM-IV regressions. In addition, we also control for the logarithmic expenditure per capita to control for the household's standards of living, which may affect both electrification and fertility.

[16]The CLR test statistic was calculated using the STATA implementation by Finlay et al. (2013), which uses the fast and accurate algorithm by Mikusheva and Poi (2006).

Table 3: Results for fixed-effects OLS regressions.

Dependent Variable: NCHILD	(a)	(b)	(c)	(d)	(e)
HHELEC	-0.001	1.165 ***	0.492 ***	0.210 ***	0.108 **
	(0.048)	(0.179)	(0.087)	(0.059)	(0.049)
HHELEC $\times \mathbb{1}(\text{NCHILD}^1 \geq 1)$		-1.308 ***			
		(0.182)			
HHELEC $\times \mathbb{1}(\text{NCHILD}^1 \geq 2)$			-0.716 ***		
			(0.100)		
HHELEC $\times \mathbb{1}(\text{NCHILD}^1 \geq 3)$				-0.540 ***	
				(0.093)	
HHELEC $\times \mathbb{1}(\text{NCHILD}^1 \geq 4)$					-0.683 ***
					(0.143)
log (HH expenditure per capita)	-0.258 ***	-0.240 ***	-0.243 ***	-0.247 ***	-0.253 ***
	(0.041)	(0.040)	(0.040)	(0.040)	(0.040)
R^2	0.862	0.867	0.865	0.864	0.864
N	5094	5094	5094	5094	5094

Note: Robust standard errors are in the brackets. Household-specific and round-specific fixed-effects are controlled for in each model. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively.

Fixed-effects Specification

Let us now consider eq. (9) using the panel households. Because most demographic and education characteristics are mostly time invariant after controlling for the time-specific fixed effect, we choose to keep only the logarithmic household expenditure per capita in the set of regressors. In Table 3, we report FE-OLS estimates with household-specific and time-specific fixed effects.

As shown in column (a), the coefficient on household electrification status is only weakly negative and statistically insignificant. This is not surprising for two reasons. First, there may be positive selection as with Table 2. Second, we are identifying the impact of electrification only through those households in which the electrification status has changed without taking into account how many children there already are in Round 1.

In columns (b)-(e), we replace household electrification status with the interaction between electrification status and indicator variable for number of children (using different thresholds). Therefore, these coefficients pick up the impact of electrification on fertility when the household already has one to four children, respectively. The results reported in Table 3 indicate that the negative impact of electrification on fertility tends to increase when the household has a larger number of children to begin with.

It should be noted here that we are controlling for, among others, all the time-invariant household characteristics in the FE-OLS models. As a result, the estimated

Table 4: The average of the changes in the number of surviving children between the two rounds (ΔNCHILD) by the number of surviving children in Round 1 (NCHILD^1).

NCHILD^1	Non-electrified (HHELEC^1=0)				Electrified (HHELEC^1=1)			
	Mean		(S.E.)	N	Mean		(S.E.)	N
0	1.858	***	(0.092)	148	1.778	***	(0.100)	99
1	0.684	***	(0.043)	288	0.700	***	(0.059)	203
2	0.340	***	(0.034)	453	0.234	***	(0.040)	334
3	0.202	***	(0.045)	342	0.000		(0.058)	247
4+	-0.079		(0.064)	253	-0.144		(0.089)	180
Total	0.455	***	(0.026)	1484	0.348	***	(0.032)	1063

Note: Statistical significance of a one-sided t-test of inequality for the population mean μ of ΔNCHILD with $H_0 : \mu = 0$ and $H_a : \mu > 0$ at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively.

coefficients in columns (b)-(e) capture not only the effect of electrification but also the effect of lower subsequent fertility given the number of surviving children in Round 1. To simultaneously address the dependence of the change in the number of children on the initial number of children and the heterogeneity of households, we consider change-on-level specification such as eqs (10) and (11).

Change-on-level Specification

In Section 3, we have argued that, in the absence of appropriate control variables at the household level, the fertility-reducing impact of electrification is likely to be most apparent when we look at the impact of electrification conditional on the number of children being greater than $n_*(0)$ but less than $n_*(1)$ for most households. Therefore, to further underscore the importance of the dependence of subsequent fertility on current fertility , we start with Table 4.

This table presents the mean of ΔNCHILD and its standard error by the electrification status and the number of children in Round 1. For example, non-electrified households on average have 1.858 more children in Round 2 than in Round 1. Based on a one-sided t-test, this figure is significantly positive. Hence, the table shows that non-electrified households tend to increase the number of children if there are three children or fewer in the households.

On the other hand, the statistical significance disappears for households with four children or more already. For electrified households, the number of children tend to increase when NCHILD in Round 1 is two or fewer. For those electrified households with at least three children, the number of children do not change significantly over time in our data. Given these, it would be reasonable to say that the optimal number of children for electrified and non-electrified households are on average roughly around three and two, respectively.

Table 5: Results for basic-specification OLS regressions.

Dependent Variable: ΔNCHILD	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
$\nVdash(\text{NCHILD}^1 \geq 1)$					-0.990 ***			
					(0.082)			
$\text{HHELEC}^1 \times \nVdash(\text{NCHILD}^1 \geq 1)$					-0.100 ***			
					(0.037)			
$\nVdash(\text{NCHILD}^1 \geq 2)$				-0.307 ***		-0.343 ***		
				(0.073)		(0.063)		
$\text{HHELEC}^1 \nVdash \times (\text{NCHILD}^1 \geq 2)$				-0.216 *		-0.130 ***		
				(0.122)		(0.042)		
$\nVdash(\text{NCHILD}^1 \geq 3)$							0.375 ***	
							(0.072)	
$\text{HHELEC}^1 \times \nVdash(\text{NCHILD}^1 \geq 3)$							-0.150 **	
							(0.065)	
$\nVdash(\text{NCHILD}^1 \geq 4)$								0.627 ***
								(0.088)
$\text{HHELEC}^1 \times (\text{NCHILD}^1 \geq 4)$								-0.078
								(0.112)
NCHILD^1		-0.329 ***	-0.328 ***	-0.255 ***	-0.213 ***	-0.234 ***	-0.418 ***	-0.447 ***
		(0.016)	(0.020)	(0.027)	(0.017)	(0.023)	(0.028)	(0.022)
HHELEC^1	-0.107 **	-0.103 ***	-0.099	-0.060				
	(0.042)	(0.037)	(0.083)	(0.083)				
$\text{HHELEC}^1 \times \text{NCHILD}^1$			-0.002	0.050				
			(0.034)	(0.048)				
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R^2	0.010	0.204	0.204	0.219	0.267	0.218	0.211	0.224
N	2547	2547	2547	2547	2547	2547	2547	2547

Note: A constant term is included in each model (not reported). Robust standard errors are in the brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively.

Now, we bring the discussion above into the regression context. We start with a stripped-down specification that is consistent with the discussion above. We report the regression results under various specifications based on the panel households in Table 5.

Column (a) shows that the difference in the number of children between the two rounds for electrified household (in Round 1) is on average smaller than Non-electrified households by 0.109 children. In column (b), we control for NCHILD as well, but the size of coefficient on electrification status (in Round 1) does not change much. In column (c), we also include their interaction term (HH Electrified$\times$NCHILD). While both household electrification status and the interaction term are insignificant, the marginal impact of electrification is significantly different from zero when there is one (P-value=0.066), two (P-value=0.006), or three (P-value=0.025) children but it is not the case when there are four or more children.[17]

Given the results in Table 4 and the fact that the P-value is smallest when NCHILD=2, we hereafter take two as the main threshold value above which the impact of electrification is most pronounced in the absence of household-level control variables. We also check the robustness of our result with respect to the choice of the threshold value.

In column (d), we include the indicator variable which takes the value one if NCHILD$\geq$ 2 in Round 1 but zero otherwise, as well as its interaction with HH electrification status (i.e., HHELEC$\times$(NCHILD$^1 \geq 2$)). As the table shows, both the indicator variable and interaction term are significant. In columns (e)-(h), we vary the threshold value from one to four. As column (h) shows, the impact of household electrification status tends to diminish when there is already a large number of children (greater than or equal to 4). However, the impact of electrification tends to go up as we have more children ranging between one and three.

The statistical inferences so far have been based on heteroskedasticity-robust standard errors. This is potentially problematic because the errors may be correlated in the same location. In this case, a popular approach is to cluster the error terms, for example, at the village level. However, in the data set we received, the village code unfortunately appears to be somewhat problematic. For example, the village code is missing for some households in Round 2 and appears inconsistent between the two rounds for some panel households. Further, the village data that was collected together with the household data cannot be merged for a sizable fraction of households by the village code.

Of course, even if the village code is completely wrong, so long as the error

[17]The marginal impact is calculated as $\alpha + \text{NCHILD}^1 \cdot \beta_{\text{HHELEC}^1 \times \text{NCHILD}^1}$.

terms are independently (and not necessarily identically) distributed, the use of clustered standard errors would asymptotically lead to correct inferences because of the nature of the sandwich estimators. However, in a finite sample, the use of clustered standard errors can lead to both too conservative or too optimistic estimates. In particular, when the effects of clustering is weak, clustered standard errors may perform better than heteroskedasticity-robust standard errors. These shortcomings notwithstanding, we have run OLS regression with the errors clustered at the village level and found that the magnitudes of standard errors do not change much.[18]

An alternative to clustering would be to include fixed-effects terms. Because of the issues with the village code mentioned above, we instead included the sub-district fixed-effects terms in the regression. The inclusion of sub-district fixed-effects terms does not alter the statistical significance of HHELEC^1. In fact, both the coefficient and standard errors remain similar.[19] This indicates that the local conditions such as geographic location, labor market condition, and existence of family planning campaigns may not matter for the estimation of the impact of electrification.

There are, however, two issues with the use of the sub-district fixed-effects model. First, they are highly collinear with our instrumental variables because the boundaries of PBS and sub-districts are closely related. Second, and more importantly, they cannot be used in the probit-ordered-probit model due to the incidental parameter problem. For these reasons, we choose to report the robust standard errors.

Controlling for heterogeneity across households

One obvious problem with the specifications in Table 4 is that it does not controlling for heterogeneity across households in observable characteristics. Therefore, we report the change-on-level regression results based on eqs. (10) and (11) with the basic set of control variables in Table 6.

[18]Detailed results are reported in Table 17 in the Appendix.

[19]Detailed results are reported in Table 16 in the Appendix.

Table 6: Results for regressions with household-level control variables.

Dependent Variable: ΔNCHILD	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
M			$M=1$	$M=1$	$M=2$	$M=2$	$M=3$	$M=3$
HHELEC[1]	-0.065 *	-2.024 **						
	(0.039)	(0.812)						
HHELEC[1] $\times \mathbb{1}(\text{NCHILD}^1 \geq M)$			-0.062	-1.787 **	-0.092 **	-2.622 **	-0.116 *	-3.315 **
			(0.038)	(0.812)	(0.044)	(1.136)	(0.066)	(1.449)
$\mathbb{1}(\text{NCHILD}^1 \geq M)$			-1.021 ***	-0.311	-0.440 ***	0.683	0.356 ***	1.698 ***
			(0.083)	(0.347)	(0.070)	(0.510)	(0.072)	(0.613)
NCHILD[1]	-0.358 ***	-0.358 ***	-0.235 ***	-0.234 ***	-0.261 ***	-0.272 ***	-0.442 ***	-0.442 ***
	(0.022)	(0.028)	(0.022)	(0.029)	(0.025)	(0.038)	(0.032)	(0.047)
Ratio of boys among children	-0.142 ***	-0.074	-0.114 **	-0.048	-0.155 ***	-0.115	-0.137 ***	-0.066
	(0.049)	(0.075)	(0.046)	(0.070)	(0.049)	(0.072)	(0.048)	(0.074)
Head's age	0.006	0.036	-0.017	0.006	0.021	0.056	-0.001	0.029
	(0.033)	(0.043)	(0.031)	(0.039)	(0.035)	(0.045)	(0.033)	(0.040)
Head's age squared†	0.001	-0.034	0.023	-0.005	-0.020	-0.060	0.010	-0.022
	(0.043)	(0.054)	(0.039)	(0.049)	(0.044)	(0.058)	(0.042)	(0.051)
Spouse's age	-0.007	0.005	0.107 **	0.094 *	0.065	-0.049	0.008	-0.076
	(0.043)	(0.060)	(0.043)	(0.054)	(0.045)	(0.076)	(0.044)	(0.069)
Spouse's age squared†	0.005	0.007	-0.181 **	-0.142	-0.107	0.102	-0.021	0.126
	(0.071)	(0.098)	(0.071)	(0.090)	(0.074)	(0.134)	(0.072)	(0.118)
Head has some primary education	0.025	0.305 **	0.018	0.237 *	0.013	0.254 *	0.018	0.158
	(0.052)	(0.138)	(0.049)	(0.124)	(0.051)	(0.133)	(0.051)	(0.100)
Head has some secondary education	-0.091	-0.079	-0.065	-0.045	-0.093 *	-0.076	-0.096 *	-0.117
	(0.056)	(0.080)	(0.054)	(0.073)	(0.055)	(0.082)	(0.056)	(0.080)
Head has some matric education	-0.001	0.069	0.007	0.059	0.017	0.050	0.006	0.061
	(0.059)	(0.094)	(0.057)	(0.083)	(0.059)	(0.094)	(0.059)	(0.094)
Spouse has some primary education	0.085 *	0.286 ***	0.094 *	0.261 ***	0.097 *	0.324 **	0.091 *	0.286 **
	(0.051)	(0.109)	(0.048)	(0.100)	(0.050)	(0.127)	(0.051)	(0.117)
Spouse has some lower secondary education	-0.049	-0.110	-0.057	-0.115	-0.055	-0.072	-0.052	-0.081
	(0.052)	(0.078)	(0.050)	(0.072)	(0.052)	(0.077)	(0.052)	(0.076)
Spouse has some matric education	-0.100	-0.037	-0.091	-0.056	-0.121 **	-0.145	-0.096	-0.098
	(0.061)	(0.102)	(0.059)	(0.088)	(0.061)	(0.101)	(0.061)	(0.091)
log (HH expenditure per capita)	-0.243 ***	-0.010	-0.224 ***	-0.019	-0.254 ***	-0.034	-0.243 ***	-0.115
	(0.054)	(0.123)	(0.052)	(0.117)	(0.053)	(0.124)	(0.053)	(0.096)
Estimation	OLS	GMM-IV	OLS	GMM-IV	OLS	GMM-IV	OLS	GMM-IV
R^2	0.2211		0.283		0.2396		0.2289	
1st Stage Robust F		6.25 ***		5.64 ***		4.74 ***		4.63 ***
Test of endogeneity		11.70 ***		8.17 ***		11.33 ***		11.16 ***
OIR test		0.11		0.12		0.03		0.48
CLR test		12.54 ***		8.86 ***		12.18 ***		12.72 ***
N	2547	2547	2547	2547	2547	2547	2547	2547

Note: † denotes that the regressor is divided by 100. A constant term is included in each regression (not reported). Robust standard errors are in brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. In GMM-IV estimation, HHELEC or HHELEC $\times$ (NCHILD[1] $\geq M$) is treated as an endogenous variable and instrumented with the age and system loss from the grid for each PBS. The null hypothesis for the CLR test is that the coefficient on the endogenous variable is zero.

In column (a), the OLS regression of ΔNCHILD on the household electrification status in Round 1 (HHELEC^1), the number of surviving children in Round 1 (NCHILD^1), and other covariates is reported. After controlling for various demographic and education characteristics and household's standards of living, the coefficient on HHELEC^1 remains negative and significant, albeit at a 10 percent level.

The GMM-IV counterpart of column (a) is reported in column (b), where HHELEC^1 is instrumented by the age and system loss from the grid at the PBS level. As with Table 2, we report some diagnostic statistics for GMM-IV, such as the first stage robust F-statistic as well as the test statistics for the test of endogeneity, OIR test, and CLR test at the bottom of the table. We again find that HHELEC^1 is endogenous and that there is no evidence of misspecification. While the F-statistic is somewhat small, the CLR test indicates that the statistical significance of the coefficient on HHELEC^1 holds when its instruments are weak. Therefore, when the endogeneity of the adoption of electricity is taken into account, the coefficient on HHELEC^1 is even more statistically and economically significant.

Let us now consider the possibility that the impact of electrification depends non-linearly on the current number of children. Similar to columns (e) to (g) in Table 5, we replace the household electrification status by its interaction with an indicator variable that NCHILD^1 exceeds a certain threshold M (i.e. $\mathbb{1}(\text{NCHILD}^1 \geq M)$) for $M \in \{1, 2, 3\}$. The OLS regression estimates for these cases are given in columns (c), (e), and (g), respectively, for $M = 1$, $M = 2$, and $M = 3$. Their GMM-IV counterparts are respectively reported in columns (d), (f), and (h).

As with the case of Table 5, the negative impact of electrification tends to be larger when there are already more children, and the coefficients in the GMM-IV regressions are more negative and significant than the corresponding coefficients in the OLS regressions. This conclusion holds even when we use the CLR test. Further, as with column (a), the interaction variable (i.e., $\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq M)$) is found to be endogenous and the OIR test has passed at conventional levels of statistical significance for all of the GMM-IV regressions.

Table 6 also shows that the coefficients on demographic and education characteristics are mostly insignificant with two notable exceptions. One exception is the ratio of boys among children. First, the spouse's primary education is positive and significant for all the models in the table. This may appear surprising given the results in Table 2 and the importance of mother's education to lower fertility found in the literature. However, it should be reiterated that the dependent variable is ΔNCHILD and the regressor NCHILD captures all the fertility behavior up to Round 1 and the standards of living is controlled for by the logarithmic household expenditure per capita. Therefore, the positive coefficient on spouse's primary education likely reflects the fact that the child-bearing age tends to be higher for those women who have at least some primary school education

Another notable exception is the ratio of boys among children. The coefficients are all negative and significant in all the OLS regressions reported in Table 6. This suggests the existence of preference for boys in rural Bangladesh. However, the statistical significance goes away once we use the GMM-IV regression, because the standard error associated with the coefficient goes up. Yet, the difference between the OLS and GMM-IV estimates are well within the two times the standard errors for the latter.

The coefficient on the logarithmic expenditure per capita exhibits a similar pattern. The coefficients are all negative and significant in the OLS regressions. However, the statistical significance do not hold once HHELEC^1 is instrumented because of the larger standard errors.

Additional Covariates

So far, we have only included a fixed set of covariates. However, there are potentially a few concerns for omitted-variable bias in the specifications used in Table 6. First, it could be argued that the mortality is related to electrification, presumably because a few incidents of child death could be prevented by using electricity-operated appliances. If this is indeed the case, the coefficient on household electrification status may be confounded with the reduced mortality. To address this issue, we add the infant mortality rate at the sub-district level in 2005 to the specification used in column (b) of Table 6. As shown in column (a) of Table 7, the coefficient on the infant mortality rate is not significant and the coefficient on HHELEC^1 do not change much.

In column (b), we control for the average number of hours that the wife watches TV in a day to see if what Grimm et al. (2014) found is relevant in Bangladesh. As shown in the table, the coefficient on TV watching hours is insignificant and the coefficient of the interaction term remains unaffected. While we choose to treat this variable as an exogenous variable, the qualitative implication does not change even when TV is treated as an endogenous variable.

That is, we have also considered a specification (not reported) in which both HHELEC^1 and the hours of TV watching are taken as endogenous variables. In this specification, the point estimate on HHELEC^1 remains significant at a 10 percent level whereas the coefficient on TV watching is insignificant. More importantly, the test of endogeneity suggests that $\mathrm{HHELEC}C^1$ is endogenous but hours of TV

Table 7: Results for regressions with additional household-level control variables.

Dependent Variable: ΔNCHILD	(a)		(b)		(c)		(d)		(e)	
HHELEC[1]	-2.033	***	-2.124	**	-1.837	***	-1.969	**	-0.004	
	(0.735)		(1.063)		(0.696)		(0.814)		(0.042)	
NCHILD[1]	-0.358	***	-0.362	***	-0.354	***	-0.357	***	-0.358	***
	(0.028)		(0.028)		(0.027)		(0.027)		(0.022)	
Ratio of boys among children	-0.074		-0.092		-0.074		-0.089		-0.140	***
	(0.074)		(0.074)		(0.072)		(0.071)		(0.049)	
Head's age	0.036		0.027		0.033		0.025		0.008	
	(0.043)		(0.044)		(0.041)		(0.043)		(0.032)	
Head's age squared†	-0.035		-0.026		-0.030		-0.022		-0.001	
	(0.054)		(0.056)		(0.052)		(0.054)		(0.041)	
Spouse's age	0.005		0.021		0.003		0.017		-0.010	
	(0.061)		(0.063)		(0.057)		(0.060)		(0.043)	
Spouse's age squared†	0.007		-0.017		0.012		-0.010		0.010	
	(0.099)		(0.101)		(0.093)		(0.096)		(0.070)	
Head has some primary education	0.306	**	0.274	*	0.278	**	0.256	**	0.032	
	(0.129)		(0.143)		(0.121)		(0.117)		(0.051)	
Head has some lower secondary education	-0.079		-0.086		-0.065		-0.071		-0.089	
	(0.080)		(0.080)		(0.077)		(0.077)		(0.056)	
Head has some matric education	0.069		0.056		0.076		0.065		0.001	
	(0.093)		(0.094)		(0.088)		(0.089)		(0.059)	
Spouse has some primary education	0.287	***	0.277	**	0.278	***	0.275	***	0.087	*
	(0.102)		(0.120)		(0.101)		(0.104)		(0.051)	
Spouse has some lower secondary education	-0.111		-0.133		-0.086		-0.106		-0.044	
	(0.077)		(0.087)		(0.071)		(0.076)		(0.052)	
Spouse has some matric education	-0.037		-0.082		-0.039		-0.079		-0.086	
	(0.102)		(0.099)		(0.095)		(0.093)		(0.062)	
log (HH expenditure per capita)	-0.009		-0.144	*	0.013		-0.101		-0.214	***
	(0.116)		(0.086)		(0.126)		(0.090)		(0.055)	
IMR 2005 at sub-district level	0.000						0.000		-0.001	
	(0.002)						(0.002)		(0.001)	
Hours of TV watching time by spouse			0.338				0.302	*	-0.094	***
			(0.218)				(0.165)		(0.024)	
Marginal land owner (0.05-0.49 acres)					-0.097		-0.071		-0.013	
					(0.124)		(0.124)		(0.088)	
Small land owner (0.50-2.49 acres)					-0.144		-0.109		-0.042	
					(0.131)		(0.130)		(0.092)	
Medium land owner (2.50-7.49 acres)					-0.454	*	-0.434	*	-0.005	
					(0.232)		(0.237)		(0.106)	
Large land owner (7.50+ acres)					-0.507		-0.479		0.093	
					(0.332)		(0.344)		(0.156)	
Estimation	GMM-IV		GMM-IV		GMM-IV		GMM-IV		OLS	
R^2									0.2267	
1st Stage F	7.76	***	4.04	**	7.78	***	6.53	***		
Test of endogeneity	14.09	***	8.27	***	11.67	***	10.63	***		
OIR Test	0.11		1.36		0.24		1.58			
CLR Test	15.01	***	9.73	***	12.63	***	11.91	***		
N	2547		2547		2547		2547		2547	

Note: GMM-IV estimation is used for all models. † regressor is rescaled by dividing by 100. A constant term is included in each regression (not reported). Robust standard errors are in brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. HHELEC[1] is instrumented with the age and system loss from the grid for each PBS.

watching is not. Therefore, we conclude that TV-watching is not an important channel through which electrification negatively affects fertility in rural Bangladesh.

In column (c), we include several indicator variables for various land-holding categories as proxy variables for overall wealth level. The purpose of including them is to allow for the possibility that the change in the number of children depends may depend not only the current standards of living but also on the overall wealth level. We find that larger land owners tend to have a lower fertility but the coefficient is statistically significant only for the medium landowners. Further, the inclusion of the land-holding categories does not change much the coefficient on the household electrification status in Round 1.

Finally, in column (d), we simultaneously include the infant mortality rate, hours of TV watching, and land-holding categories. This again does not change the coefficient on HHELEC^1. However, the endogeneity of the interaction term is very important for our purpose. If we use OLS regression instead of GMM-IV regression, the coefficient on interaction term is statistically insignificant and the coefficient on hours of TV watching becomes negative and significant as shown in column (e). The results reported in this table are qualitatively the same when we replace HHELEC^1 with the indicator function of children exceeding two (i.e., $\mathbb{1}(\text{NCHILD}^1 \geq 2)$ and its interaction with HHELEC^1 (i.e., $\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq 2)$).[20]

Source of the Impact of Rural Electrification

In the discussion so far, we have only considered the possibility that the household-level adoption of electricity affects the household's fertility. However, it is plausible that the way people behave is influenced by what their neighbors do, For example, information that someone in an electrified household obtains from TV may be transmitted to others in non-electrified households in the same village, which in turn change their behaviors. Iit is also possible that the non-electrified households may be affected by the adoption of electricity at the village, because, for example, it leads to a better environment for child bearing and child rearing,

Therefore, we take the status of village electrification into account. To this end, we denote the indicator variable that the village is electrified in Round $t \in \{1, 2\}$ by VGELEC^t.[21] To see if there is any evidence that VGELEC matters, we separately analyze the following two sub-samples: (S1) those households that reside in a village that was electrified village in Round 1 (i.e., VGELEC$^1 = 1$) and

[20]The details of regression results in this specification is reported in Table 13 in the Appendix.

[21]VGELEC is observed in the household-level data set. Therefore, the analysis is unaffected even when the village codes are wrong.

(S2) those households that reside in village electrified between the two rounds (i.e., $\text{VGELEC}^1 = 0$ and $\text{VGELEC}^2 = 1$). Because the households in sub-sample (S2) do not have access to electricity from the grid in Round 1, we use the electrification status in Round 2 (HHELEC^2) instead of Round 1 (HHELEC^1) in order to compare the impact of electrification for the two sub-samples.

To see if there is any consequence of using HHELEC^2 instead of HHELEC^1, we first run the same GMM-IV regression as column (b) of Table 6 with HHELEC^1 replaced by HHELEC^2 As reported in column (a) of Table 8, the results are generally similar except that the point estimate is smaller in absolute value, even though the difference is not significant. This result is not surprising because the impact of electrification that occurred just before Round 2 survey would not show up in ΔNCHILD. This result also indicates that the expectation of future electrification is unlikely to be as important as the actual realization of electrification.

In column (b), we run the same regression as column (a) but only for sub-sample (S1). Because households in electrified villages are likely to have been affected by the village-level effect of electrification, the estimated coefficient can be interpreted as the impact of electrification after net the village-level effect of electrification.

In column (c), we run the same regression for sub-sample (S2). Because the village was electrified between the two rounds, the impact of the adoption of electricity in the village would be, if any, much smaller than that in sub-sample (S1). This specification unfortunately suffers from the weak instrumental variable problem. This is not surprising because the instruments cannot predict the adoption of electrification that occur within a relatively short time window between the two rounds. As a result of this and the small sample size, the estimated coefficient is insignificant. Hence, even though the point estimate of the coefficient on HHELEC^2 is substantially larger in absolute value than that reported in column (b), we cannot make a strong inference about the effect of village-level adoption of electricity.

To investigate further the village-level effect, we also run regressions by taking the status of village electrification in Round 1 (VGELEC^1) instead of HHELEC^1 as an endogenous regressor. As reported in column (d), the impact of electrification is found to be negative and significant. However, when we include both HHELEC^1 and VGELEC^1 in the model, the former is found to have a negative and significant impact on fertility whereas the latter is found to have a positive and significant impact as reported in column (e).

In column (e), we treat only HHELEC^1 as an endogenous regressor. We also run a regression in which both HHELEC^1 and VGELEC^1 are treated as endogenous regressors (not reported). The test of endogeneity indicates that HHELEC^1

Table 8: Sub-sample regressions and regressions with village-level electrification status.

	(a)		(b)		(c)		(d)		(e)	
$HHELEC^2$	-1.552 ***	(0.559)	-2.253 *	(1.228)	-3.835	(4.798)				
$HHELEC^1$									-4.265 *	(2.250)
$VGELEC^1$							-2.253 **	(1.012)	2.925 *	(1.579)
NCHILD	-0.365 ***	(0.025)	-0.333 ***	(0.039)	-0.444 ***	(0.112)	-0.359 ***	(0.030)	-0.357 ***	(0.034)
Ratio of boys among children	-0.088	(0.066)	-0.064	(0.093)	-0.227	(0.264)	-0.019	(0.095)	-0.160 *	(0.088)
Head's age	0.033	(0.040)	0.104	(0.074)	-0.065	(0.167)	0.047	(0.049)	0.016	(0.052)
Head's age squared†	-0.032	(0.050)	-0.112	(0.092)	0.099	(0.215)	-0.048	(0.060)	-0.010	(0.064)
Spouse's age	-0.024	(0.055)	-0.003	(0.084)	-0.097	(0.203)	-0.030	(0.067)	0.047	(0.083)
Spouse's age squared†	0.053	(0.090)	-0.002	(0.136)	0.192	(0.336)	0.060	(0.110)	-0.060	(0.131)
Head has some primary education	0.168 *	(0.086)	0.262	(0.173)	-0.088	(0.397)	0.262 *	(0.137)	0.305 *	(0.180)
Head has some lower secondary education	-0.052	(0.073)	-0.036	(0.114)	0.198	(0.499)	-0.128	(0.084)	-0.019	(0.112)
Head has some matric education	-0.028	(0.076)	0.062	(0.096)	-0.383	(0.449)	0.001	(0.094)	0.144	(0.124)
Spouse has some primary education	0.271 ***	(0.094)	0.176	(0.122)	0.933	(0.830)	0.249 **	(0.107)	0.294 **	(0.146)
Spouse has some lower secondary education	-0.079	(0.066)	0.063	(0.094)	-0.247	(0.282)	-0.204 *	(0.104)	0.023	(0.103)
Spouse has some matric education	-0.089	(0.084)	-0.119	(0.106)	0.078	(0.445)	-0.063	(0.105)	-0.015	(0.120)
log (HH expenditure per capita)	-0.133 *	(0.080)	-0.042	(0.175)	-0.209	(0.246)	-0.112	(0.104)	0.075	(0.196)
First Stage F	9.580 ***		4.365 **		0.354		4.312 **		2.790 *	
Test of endogeneity	10.609 ***		5.093 **		3.182 *		10.365 ***		11.341 ***	
OIR Test	0.770		0.013		0.255		0.888		0.181	
CLR Test	12.000 ***		5.490 **		4.300		11.730 ***		11.960 ***	
N	2547		1475		569		2547		2547	

Note: GMM-IV estimation is used for all models. † regressor is rescaled by dividing by 100. A constant term is included in each regression (not reported). Robust standard errors are in brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. $HHELEC^2$ in columns (a), (b), and (c), $VGELEC^1$ in column (d), and $HHELEC^1$ in column (e) are instrumented with the age and system loss from the grid for each PBS.

is endogenous whereas VGELEC1 is not. Hence, we have no apparent evidence of mis-specification for the model in column (e).

The balance of evidence from Table 8 appears to indicate that there is a negative effect of electrification on fertility at the household level but the effect is positive at the village level.

Alternative variables for electrification

To see the robustness of our results, let us now consider a few alternative choices of electrification variables. First, we take into account the outage of electricity. This is potentially important because the impact of electrification is unlikely to be large if electricity is unavailable most of time due to outage. To take into account, we use OUTAGE^2, or the proportion of time in which electricity was unavailable in the village. However, because of the problems with the village code, the outage variable was aggregated to the upazila level for about 60 percent of villages. For a very small fraction of households, we needed to aggregate to a PBS level to merge the outage variable.

In column (a) of Table 9, we replace HHELEC^2 with $\text{HHELEC}^2 \times (1 - \text{OUTAGE}^2)$ in column (a) of Table 8, where the latter can be interpreted as the fraction of time in which the household can use electricity. The results are similar except that the point estimate becomes slightly larger in absolute value.

In column (b), we include HHELEC^2 and OUTAGE^2 separately, where only the former is taken as the endogenous regressor, because only the former was found to be endogenous in an unreported regression where both are treated as endogenous. While the coefficient on OUTAGE is only marginally significant, this result show that prolonged outage tends to offset the fertility-reducing effect of electrification.

In column (c), we replace HHELEC^1 with YRELEC^1, or the number of years in which the household has electricity, which is observed only in Round 1. As the table shows, the results are consistent with the previous discussion. In households with a longer history of access to electricity, the negative impact on fertility is larger. When we include both HHELEC^1 with YRELEC^1 as endogenous regressors, both were individually insignificant due to high collinearity but they were jointly significant in weak-instrument-robust Anderson-Rubin test.

Finally, in column (d), we include the access to solar electricity in Round 1 (SOLAR^1) in addition to the access to electricity from grid. We treat SOLAR^1 as an exogenous variable. This specification in column (d) appears reasonable because only the latter is found to be an endogenous variable in the test of endogeneity for an unreported GMM-IV regression of ΔNCHILD in which both SOLAR and HHELEC

Table 9: Alternative choice of electrification variables.

	(a)			(b)			(c)			(d)		
HHELEC^2×(1-OUTAGE)	-2.573	**	(1.060)									
HHELEC^2				-2.671	**	(1.252)						
OUTAGE				1.701	*	(0.908)						
YRELEC							-0.159	***	(0.061)			
HHELEC^1										-1.831	**	(0.815)
SOLAR^1										-1.221	**	(0.510)
NCHILD	-0.351	***	(0.028)	-0.333	***	(0.035)	-0.353	***	(0.026)	-0.357	***	(0.027)
Ratio of boys among children	-0.094		(0.075)	-0.079		(0.086)	-0.059		(0.074)	-0.109		(0.067)
Head's age	0.038		(0.046)	0.035		(0.050)	0.000		(0.043)	0.014		(0.042)
Head's age squared†	-0.034		(0.056)	-0.029		(0.061)	0.014		(0.056)	-0.003		(0.053)
Spouse's age	-0.005		(0.062)	0.025		(0.071)	0.066		(0.065)	0.022		(0.058)
Spouse's age squared†	0.019		(0.101)	-0.031		(0.115)	-0.099		(0.103)	-0.022		(0.094)
Head has some primary education	0.225	*	(0.115)	0.400	**	(0.200)	0.211	**	(0.100)	0.280	**	(0.137)
Head has some lower secondary education	-0.052		(0.084)	-0.089		(0.093)	-0.039		(0.080)	-0.067		(0.076)
Head has some matric education	-0.028		(0.088)	0.101		(0.115)	0.129		(0.103)	0.137		(0.101)
Spouse has some primary education	0.369	***	(0.141)	0.388	**	(0.168)	0.206	**	(0.081)	0.265	**	(0.106)
Spouse has some lower secondary education	-0.099		(0.078)	-0.133		(0.095)	-0.020		(0.074)	-0.070		(0.070)
Spouse has some matric education	-0.104		(0.099)	-0.034		(0.120)	-0.139		(0.102)	-0.060		(0.090)
log (HH expenditure per capita)	-0.071		(0.107)	0.107		(0.191)	-0.014		(0.115)	0.057		(0.151)
First Stage F	5.310	***		3.748	**		7.510	***		5.924	***	
Test of endogeneity	10.854	***		11.425	***		12.043	***		8.547	***	
OIR Test	0.660			0.000			0.090			2.158		
CLR Test	12.060	***		11.890	***		12.510	***		11.270	***	
N	2547			2547			2547			2547		

Note: GMM-IV estimation is used for all models. † regressor is rescaled by dividing by 100. A constant term is included in each regression (not reported). Robust standard errors are in brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. HHELEC^2×(1-OUTAGE) in column (a), HHELEC^2 in column (b), YRELEC in column (c), and HHELEC^1 in column (d) are instrumented with the age and system loss from the grid for each PBS.

treated as endogenous variables.

As column (d) shows, both SOLAR^1 and HHELEC^1 are found to have a significant and negative coefficient. Further, their coefficients are close in magnitude. This provides a partial support for our theoretical because the source of electricity should not matter in our model provided that the same lighted hours are made available.

Discrete specifications

The linear models we used so far ignore the fact that both NCHILD and ΔNCHILD are discrete variables. This is unsatisfactory, especially in the cross sectional regressions, because the implied expected number of children can be negative. In this light, Peters and Vance (2011) propose to use Poisson regressions. However, as discussed in Section 1, the underlying assumptions for the Poisson model is highly restrictive and thus it is unclear whether the Poisson model is necessarily better than linear models. Furthermore, the Poisson model is not applicable to ΔNCHILD as they can take a negative value.[22]

In this study, we propose a bivariate probit-ordered-probit (BPOP) regression model to address this issue, where household electrification status is modeled with a probit model and NCHILD or ΔNCHILD is modeled with an ordered probit model, the details of which are given in Appendix A. There are three advantages in this formulation. First, the ordered probit model is flexible with respect to the relationship between the linear index ($X_{2h}\beta_2$ using the notations in Appendix A) and the outcome (NCHILD or ΔNCHILD) because the threshold values can adjust in the estimation. In comparison, the Poisson model imposes a rigid relationship between the linear index and the outcome. Second, the BPOP model exploits the correlation in the error terms and this helps us to obtain more accurate estimation results than the estimation that doesn't exploit the correlation. Finally, the ordered probit models are more robust to outliers once the top (or bottom) categories are merged. On the other hand, the linear and Poisson models we have considered are sensitive to outliers.

Table 10 reports the BPOP regression results. In columns (a) and (b), we run a BPOP regression of NCHILD and household electrification status for Rounds 1 and 2, respectively. As with previous models, the coefficient on household electrification status is significant and negative. Further, the coefficients on demographic and education covariates included in the model are qualitatively similar to those found

[22]Since Peters and Vance (2011) only use a cross-sectional data, they only consider the number of children as a dependent variable. When we use Poisson models, the results are qualitatively similar as reported in Tables 14 and 15 in Appendix C.

Table 10: Bivariate probit-ordered-probit regression results.

Column	(a)			(b)			(c)		
Data	Round 1 only			Round 2 only			Panel		
Dep var for probit model	HHELEC			HHELEC			HHELEC		
Ratio of boys among children	0.010		(0.028)	-0.034		(0.055)	0.098		(0.070)
Head's age	0.039	***	(0.013)	0.047	**	(0.018)	0.044		(0.044)
Head's age squared†	-0.037	**	(0.015)	-0.029		(0.019)	-0.051		(0.055)
Spouse's age	-0.008		(0.016)	-0.069	**	(0.029)	0.029		(0.061)
Spouse's age squared†	0.027		(0.023)	0.090	**	(0.040)	-0.021		(0.100)
Head has some primary education	0.273	***	(0.030)	0.061		(0.058)	0.403	***	(0.075)
Head has some lower secondary education	0.037		(0.030)	0.050		(0.058)	-0.007		(0.076)
Head has some matric education	0.048		(0.032)	-0.033		(0.067)	0.095		(0.087)
Spouse has some primary education	0.243	***	(0.029)	0.217	***	(0.057)	0.313	***	(0.073)
Spouse has some lower secondary education	0.058	**	(0.029)	0.127	**	(0.056)	-0.093		(0.072)
Spouse has some matric education	0.034		(0.037)	0.041		(0.076)	0.092		(0.098)
log (HH expenditure per capita)	0.309	***	(0.029)	0.243	***	(0.046)	0.321	***	(0.076)
Age of PBS	0.022	***	(0.002)	0.020	***	(0.005)	0.014	**	(0.007)
System loss of PBS	-0.007	**	(0.003)	-0.027	***	(0.007)	-0.031	***	(0.009)
Dep var for ordered-probit model	NCHILD			NCHILD			ΔNCHILD		
HHELEC	-1.050	***	(0.041)	-0.951	***	(0.096)	-0.947	***	(0.165)
NCHILD							-0.377	***	(0.027)
Ratio of boys among children	-0.042	*	(0.021)	-0.182	***	(0.043)	-0.130	**	(0.060)
Head's age	0.085	***	(0.010)	0.060	***	(0.015)	0.006		(0.037)
Head's age squared†	-0.060	***	(0.011)	-0.044	***	(0.016)	0.000		(0.047)
Spouse's age	0.156	***	(0.013)	0.184	***	(0.025)	0.022		(0.050)
Spouse's age squared†	-0.163	***	(0.019)	-0.191	***	(0.035)	-0.043		(0.082)
Head has some primary education	0.182	***	(0.025)	-0.040		(0.048)	0.151	**	(0.066)
Head has some lower secondary education	0.006		(0.025)	0.004		(0.046)	-0.107		(0.066)
Head has some matric education	0.036		(0.026)	-0.050		(0.052)	0.047		(0.072)
Spouse has some primary education	0.027		(0.024)	-0.001		(0.048)	0.187	***	(0.062)
Spouse has some lower secondary education	-0.060	***	(0.023)	-0.051		(0.045)	-0.062		(0.061)
Spouse has some matric education	-0.098	***	(0.028)	-0.153	***	(0.057)	-0.096		(0.079)
log (HH expenditure per capita)	-0.281	***	(0.026)	-0.156	***	(0.040)	-0.156	**	(0.068)
c_1	2.980		(0.178)	2.676		(0.378)	-4.121		(0.718)
c_2	3.649		(0.180)	3.424		(0.387)	-3.616		(0.702)
c_3	4.471		(0.183)	4.417		(0.398)	-3.154		(0.697)
c_4	5.152		(0.186)	5.151		(0.405)	-2.600		(0.691)
c_5	5.692		(0.188)	5.704		(0.410)	-0.888		(0.670)
c_6	6.138		(0.191)	6.186		(0.414)	0.088		(0.660)
c_7	6.548		(0.193)	6.647		(0.418)	0.726		(0.654)
c_8	6.913		(0.196)	6.975		(0.422)	1.277		(0.652)
ρ	0.651		(0.027)	0.574		(0.061)	0.538		(0.102)
N	16369			4180			2547		

Note: † denotes that the regressor is divided by 100. Robust standard errors in the bracket. Estimation is carried out by maximum likelihood estimation. A constant term is included in each probit model. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. For columns (a) and (b), the base category is NCHILD=0 and κ_1 to κ_8 respectively correspond to the thresholds for one child to eight children (and over). For column (c), the base category is ΔNCHILD=-4 and κ_1 to κ_8 respectively correspond the thresholds for -3 to +4.

in Table 2.

The table also shows that households that are richer and have a better educated wife are more likely to adopt electricity in both rounds. As expected, the age of PBS has a positive coefficient whereas system loss has a negative coefficient, though age of PBS for Round 2 is insignificant.

At the bottom of the table, we also report the threshold values (κ's) for the ordered probit model. For example, κ_k for $k \in \{1, \cdots, 8\}$ is the threshold value of the latent variable for fertility (y^*_{2h} in Appendix A) above which the number of children is equal to k or more. Therefore, the difference between the two contiguous threshold essentially tells us how difficult it is to move to the next category (in terms of the number of children). It can be seen from the table that the largest difference between two contiguous thresholds occur for at the $[\kappa_2, \kappa_3]$ interval in both rounds. Beyond κ_3, the difference between two contiguous thresholds tend to decline. Therefore, our model implies that the fertility-reducing effect of electrification is greatest when the household has a high potential fertility computed from the observable indicators (i.e., a high value of $X_{2h}\beta_2$).

The second row from the bottom reports the correlation ρ in the idiosyncratic terms for the two underlying latent dependent variables. There is a high correlation, which means that we can gain efficiency by simultaneously estimating the two models. Thus, even if we are not intrinsically interested in the household electrification status model, simultaneous estimation is still useful because the error term contained in the household electrification status model is informative of the error term in the NCHILD model. This can also be taken as evidence of positive selection.

In column (c) of Table 10, we report the BPOP regression for ΔNCHILD, which can be thought of as a discrete analogue of column (b) in Table 6. In this model, too, household electrification status remains significant. We also find that those households who have primary education or more tend to have more children after controlling for, among others, the expenditure per capita in logarithm. Overall, we find from Table 10 that the level-on-level (columns (a) and (b)) and change-on-level regressions (column (c)) provide similar implications because the coefficients have the same signs wherever they are significant. Further, we also find that the discreteness of the dependent variable does not alter the qualitative nature of our results presented earlier. As with the linear case discussed earlier, the regression results change only slightly when the error terms are clustered at the upazila level for all columns in Table 10.

Because of the non-linearity of the BPOP regressions, it requires a caution to quantitatively compare the results in Table 10 with GMM-IV regression results in

Table 2 and column (b) of Table 6. To make quantitative comparisons, we calculate the marginal impact of electrification by taking the difference Δ_h in NCHILD or ΔNCHILD for each household h in the expected number of children with and without the adoption of electricity, given its household characteristics including the adoption of electricity (See Appendix A for the formal definition of Δ_h). We then take an average over all the households to arrive at the average marginal impact of electrification on the number of children, which is -1.51 for Round 1 and -1.33 for Round 2 based on columns (a) and (b), respectively. We have also computed the average marginal impact on ΔNCHILD based on column (c), which is -0.89 children. As expected, this number is smaller than the two figures mentioned above because the latter refers only to the change in fertility over a five-year period.

It is possible to disaggregate the average impact by household characteristics. Therefore, to check our argument made in Section 3 in a cross-sectional context, we disaggregated the average marginal impact by the number of children. For both rounds, the size of impact for those households with NCHILD$\geq$ 2 is the substantially larger than that for those households with NCHILD$\leq$ 1.

7 Discussion

There have been a number of studies on the economic impacts of rural electrification. However, a relatively small number of studies investigate the impact of rural electrification on fertility in developing countries. While the idea that there may be some relationship between the availability of electricity and fertility is not new in itself, there remain a dearth of rigorous econometric analysis based on household surveys.

Our main findings is that rural electrification negatively affects fertility, particularly when the positive selection of the adoption of electricity is taken into account. This finding is robust with respect to the choice of estimation method, the choice of set of regressors, the choice of a measure of access to electricity, and the assumed structure of error terms. This finding also has external validity. When we run regressions similar to those reported in Table 2 using the Bangladesh Demographic and Health Survey for 2004, we also obtain qualitatively similar results.

One obvious channel through which electrification affects fertility is through the increase in the standards of living. As Table 1 shows, the increase in the average household expenditure per capita is higher for the households that are electrified.[23]

[23] If we use the panel households only, the difference between electrified and non-electrified households is not as dramatic, but this point still holds.

Because the coefficient of logarithm of per capita household expenditure is generally negative though not always significant, electrification can indeed affect fertility negatively through this channel. However, the persistence of the negative and significant coefficient on the measures of the adoption of electricity, especially after controlling for the endogeneity issue, suggests that there are likely to be other channels.

Our empirical findings are consistent with a simple theoretical model in which the optimal number of children changes according to the status of electrification, where the optimal number is driven by the changes in direct and opportunity costs of children as well as the shape of utility function. The model predicts that the proportion of the lighted time not spent on children increases as the household is electrified. This prediction has empirical support in the analysis of time use in Appendix B. However, unlike the existing studies done elsewhere, we find no evidence that the fertility-reducing effect of electrification comes from longer TV-watching or lower infant mortality in Bangladesh.

This study makes a few contributions to the literature. First, to the best of our knowledge, this is the first panel study based on a household-level data-set. Because of our data-set, we can estimate a model of fertility conditional on the existing number of children. If we adopt the fixed-effects specification, we can also control for all the time-invariant household-level characteristics, though this specification has some drawbacks.

Second, unlike previous studies, we treat the endogeneity of the adoption of electricity seriously. We exploit the infrastructure development and service delivery of electricity as a source of exogenous variations in the adoption of electricity. Our results show that the adoption of electricity is indeed endogenous and the negative impact of electrification is even more pronounced once the endogeneity issue is taken into account.

Third, we propose an alternative strategy to estimate the simultaneous determination of the adoption of electricity and fertility by the BPOP model, which has a few distinct advantages as discussed in the previous section. We find that there is indeed a moderately strong correlation in the unobserved error terms even after controlling for various demographic and education characteristics. We argue that the BPOP model can be used as an alternative specification to the linear or Poisson regression models.

Finally, previous studies have ignored the dependence of the impact of electrification on the current number of children. However, our theoretical argument underscores this possibility. In various specifications we have considered, the negative impact of electrification on fertility tends to be small when there is no or only one child but it tends to become larger when there are two or more children.

The findings of this study entail at least two policy implications. First, our study highlights the possibility that some infrastructure investments, such as rural electrification, may have significant social impacts that go well beyond the types of impacts typically considered in impact assessment studies. Second, this study also shows that policy-makers cannot simply hope for lower fertility just by electrifying villages. If they want to take into consideration the potential impact of electrification on fertility in the design of an electrification project, it is essential to take into account the current demographic characteristics of households, especially the current number of children, in the potential project locations.

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Appendix A: Bivariate Probit-Ordered-Probit Model

Formally, the BPOP model can be written in the following manner: Let the latent variable for the electricity access for household $h \in \{1, \cdots, H\}$ be y_{1h}^*. We assume that it is related to a vector of covariates X_{1h} by $y_{1h}^* \equiv X_{1h}\beta_1 + \varepsilon_{1h}$, where ε_{1h} is the idiosyncratic error term standardized to have a zero mean and a unit variance. We assume that the latent variable is related to the indicator variable y_{1h} for the adoption of electricity by $y_{1h} = \mathbf{1}(y_{1h}^* > 0)$, where $\mathbf{1}(\cdot)$ is an indicator function that takes one if the argument is true and zero otherwise.

As noted in Section 4, we only consider the fertility of the spouses of male-headed households in which the household head has one and only one spouse. Because of this choice, we can use index h for the fertility of the spouse (i.e., wife). We assume that the latent fertility by y_{2h}^* is related to a vector X_{2h} of covariates by $y_{2h}^* = X_{2h}\beta_2 + \varepsilon_{2h}$, where ε_{2h} is the idiosyncratic error term for the ordered probit model with a zero mean and a unit variance. We allow X_{2h} to include y_{1h} but it does not include a constant term. The index of latent fertility is related to the number of children[24] in the household by $y_{2h} = \Sigma_{k=0}^{K} I(\kappa_k \leq y_{2h}^* < \kappa_{k+1}) \cdot k$, where K is the maximum number of children in the household, κ_k for $k \in \{1, \cdots, K\}$ is the cutoff to be estimated, $\kappa_0 \equiv -\infty$, and $\kappa_{K+1} \equiv +\infty$.[25]

Because there may be some omitted covariates that affect both fertility and electricity access, it is important to allow for the possibility of correlation between the idiosyncratic error terms for the two latent dependent variables. Therefore, we assume that the error terms $(\varepsilon_{1h}, \varepsilon_{2h})$ jointly follow a standard bivariate normal distribution with correlation ρ. Therefore, the set of parameter to be estimated is $\Theta \equiv \{\beta_1, \beta_2, \rho, \kappa_1, \ldots, \kappa_K\}$.

We denote the cumulative distribution functions for the univariate and bivariate standard normal distributions by Φ_1 and Φ_2, respectively, where we use the following for the simplicity of presentation: $\Phi_1(-\infty) = \Phi_2(a, -\infty, \rho) = 0$, $\Phi_1(\infty) = 1$, and $\Phi_2(a, \infty, \rho) = \Phi_1(a)$. We estimate the BPOP model by the maximum likelihood estimator $\hat{\Theta}_{MLE}$, which solves the following problem:

$$\hat{\Theta}_{MLE} = \arg\max \prod_h \sum_k \left[A_{hk} I(y_{1h} = 1) + B_{hk} I(y_{1h} = 0)\right] I(y_{2h} = k),$$

where A_{hk} and B_{hk} are defined as follows:

$$\begin{cases} A_{hk} \equiv \Phi_1(\kappa_{k+1} - X_{2h}\beta_2) - \Phi_1(\kappa_k - X_{2h}\beta_2) - B_{hk} \\ B_{hk} \equiv \Phi_2(-X_{1h}\beta_1, \kappa_{k+1} - X_{2h}\beta_2, \rho) - \Phi_2(-X_{1h}\beta_1, \kappa_k - X_{2h}\beta_2, \rho), \end{cases}$$

To find the marginal impact of electrification on fertility, we consider the expected fertility with and without electrification conditional on the current status of electrification. To this end, We denote by X_{2h}^0 all the covariates for NCHILD other than household electrification status and its coefficients by β_2^0. The coefficient on household electrification status is denoted by β_2^1.

Now, let us consider a household that is currently electrified [not electrified]. Conditional on that, the probability that the number of children is equal to k is given by $A_{hk}/\Phi_1(X_{1h}\beta_1)$ [$B_{hk}/\Phi_1(-X_{1h}\beta_1)$]. Therefore, by replacing β_1, β_2^0, β_2^1, κ_k, and ρ with the corresponding maximum-likelihood estimates $\hat{\beta}_1$, $\hat{\beta}_2^0$, $\hat{\beta}_2^1$, $\hat{\kappa}_k$, and $\hat{\rho}$,

[24] We only consider the case where y_{2h} is NHCILD. However, the discussion is essentially the same even when y_{2h} is DNCHILD.

[25] We take $K = 8$ in our empirical analysis, where k corresponds to the number of children except that $k = 8$ corresponds to eight children or more. However, because there are very few observations with NCHILD≥ 9, we do not distinguish between eight and above.

we obtain the estimates of A_{hk} $[B_{hk}]$.

Now, we can consider the probability that the household has k children conditional on the household's observable characteristics. For example, we can define $\hat{B}^0_{hk}$ and $\hat{B}^1_{hk}$ for non-electrified households in the following manner:

$$\begin{aligned}
\hat{B}^0_{hk} &\equiv \Phi_2(-X_{1h}\hat{\beta}_1, \hat{c}_{k+1} - X^0_{2h}\hat{\beta}^0_2, \hat{\rho}) - \Phi_2(-X_{1h}\hat{\beta}_1, \hat{c}_k - X^0_{2h}\hat{\beta}^0_2, \hat{\rho}) \\
\hat{B}^1_{hk} &\equiv \Phi_2(-X_{1h}\hat{\beta}_1, \hat{c}_{k+1} - X_{2h}\hat{\beta}^0_2 - \hat{\beta}^1_2, \hat{\rho}) - \Phi_2(-X_{1h}\hat{\beta}_1, \hat{c}_k - X^0_{2h}\hat{\beta}^0_2 - \hat{\beta}^1_2, \hat{\rho}).
\end{aligned}$$

We can similarly define $\hat{A}^0_{hk}$ and $\hat{A}^1_{hk}$ for electrified households. With these, we define Δ_h in the following manner:

$$\Delta_h \equiv \sum_{k=0}^{K} \left[\frac{(\hat{B}^1_{hk} - \hat{B}^0_{hk})\mathbf{1}(y_{1h} = 0)}{\Phi_1(-X_{1h}\hat{\beta}_1)} + \frac{(\hat{A}^1_{hk} - \hat{A}^0_{hk})\mathbf{1}(y_{1h} = 1)}{\Phi_1(X_{1h}\hat{\beta}_1)} \right] \cdot k.$$

By taking the average of Δ_h over h, we have the average marginal impact.

Appendix B: Testing the signs of α' and l'

In Round 1 survey, we have data on the wife's time use. The dataset is not completely ideal because we only know how many hours a day on average each person spends time on each of the following 18 activities: (1) listening to the radio, (2) watching TV, (3) processing food, (4) collecting fuel, (5) working as an agricultural worker, (6) working as a non-agricultural worker, (7) engaging in other income-generating activities, (8) fetching water, (9) washing clothes and cleaning, (10) cooking and serving, (11) eating, (12) bathing or caring body, (13) shopping, (14) resting (excluding sleeping), (15) socializing, (16) doing religious practices, (17) reading and studying, and (18) taking care of children. We denote the number of hours spent on the j-th activity ($1 \leq j \leq 18$) by τ_j and the total number of hours spent on these activities by $T \equiv \sum_{1 \leq j \leq 18} \tau_j$.

This list presumably covers most of the important activities that are carried out during the lighted hours. However, there may be some other activities not appropriately covered in this list. For example, if one has to commute to the work place, it may not be captured in this list. Further, some of these activities such as listening to the radio can be done without light or simultaneously with other activities. However, because of the data limitations, we ignore these possibilities and assume that the listed activities are the only activities performed during the lighted hours and that they are carried out separately. Further, when we have a missing value of τ_j for some j, we treat the missingness as zero. To avoid including those households for which these treatments are problematic, we drop about 1.8 percent of observations for which $12 \leq T \leq 22$ is not satisfied.

Since l is the proportion of the lighted hours not spent on taking care of children, we calculate l by $l = 1 - \tau_{18}/T$. Similarly, we calculate α by $\alpha = \tau_{18}/T/n$, because it corresponds to the proportion of the lighted hours spent on taking care of each child on average.

As is clear from the definition of α, this quantity can only be calculated only from those households with at least one child. Even after excluding the households without children, close to ninety percent of households report no time spent on taking care of children. This, of course, may be because children are old enough to take care of themselves. However the very high fraction of zero response appears to indicate that taking care of children is most likely to be done in conjunction with other activities.

Therefore, to test the signs of l' and α', we run regression of l and α on HHELEC^1 for households with non-zero α. For our main analysis, we use the sub-sample of observations in which observed α is non-zero. As shown in Table 11, the coefficient on HHELEC^1 is positive and significant for the regression of l, suggesting that $l' \leq 0$ indeed holds. On the other hand, it is negative and insignificant for the regression of α. Hence, we have evidence to support $l' < 0$ and no evidence to suggest that α' is positive or highly negative such that eq. (7) fails to hold.

Appendix C: Additional Tables

Table 12 provides the same set of summary statistics as those reported in Table 1 but only for panel households. Tables 14 and 15 are the Poisson analogues of Tables 3 and 2, respectively.

Table 11: OLS Regression of l and α for Round 1 data.

	(a)		(b)		(c)		(d)
Dep var: l							
HHELEC[1]	0.0096	***	0.0088	***	0.0007	*	0.0005
	(0.0027)		(0.0028)		(0.0004)		(0.0004)
Covariates	N		Y		N		Y
N	1047		1047		16076		16076
R^2	0.0122		0.018		0.0002		0.0017
Dep var: α							
HHELEC[1]	-0.0034		-0.0023		-0.0003		-0.0001
	(0.0022)		(0.0020)		(0.0002)		(0.0003)
Covariates	N		Y		N		Y
N	1047		1047		14628		14628
R^2	0.0023		0.2144		0.0001		0.0066

Note: OLS estimation is used for all models. Regressions for l and α were run separately. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. The standard covariates used in column (b) and (d) are as follows: the ratio of boys among children, the head's age and its squared term, the spouse's age and its squared term, the head's education (primary/secondary/matric), the spouse's education (primary/secondary/matric), and the logarithmic household expenditure per capita.

Table 12: Key summary statistics for Rounds 1 and 2 by the electrification status of households, panel households only.

Description	Round 1			Round 2		
	Non-electrified (HHELEC^1=0)	Electrified (HHELEC^1=1)	All	Non-electrified (HHELEC^2=0)	Electrified (HHELEC^2=1)	All
Head's age	36.8	38.2	37.2	41.3	42.9	42.0
Spouse's age	29.1	30.3	29.5	33.7	34.5	34.1
# surviving children spouse has given birth to	2.26	2.25	2.26	2.69	2.61	2.66
Ratio of boys among children under 15 (%)†	50.3	53.5	51.2	51.7	52.3	52.0
Head has some primary education (%)	59.7	80.0	65.6	68.6	76.8	72.3
Head has some lower secondary education (%)	17.1	27.5	20.1	37.4	45.5	41.0
Head has some matric education (%)	8.6	14.5	10.3	19.5	24.1	21.5
Spouse has some primary education (%)	60.5	76.3	65.1	68.6	77.7	72.6
Spouse has some lower secondary education (%)	34.3	45.0	37.4	32.0	41.2	36.1
Spouse has some matric education (%)	10.2	16.4	12.0	10.5	13.0	11.6
Household expenditure per capita (Tk.)	28.5	32.0	29.5	60.4	68.9	64.2
Average hours of TV watching time by spouse	0.22	0.87	0.41	0.38	1.40	0.83
Landless (0.00-0.04 acres)	5.0	4.6	4.9	11.6	11.9	11.7
Marginal land owner(0.05-0.49 acres)	49.9	53.5	51.0	39.0	43.6	41.1
Small land owner (0.50-2.49 acres)	29.4	33.2	30.5	32.9	34.1	33.4
Medium land owner (2.50-7.49 acres)	13.6	7.6	11.8	14.0	9.0	11.8
Large land owner(7.50+ acres)	2.1	1.2	1.8	2.6	1.4	2.1
Number of observations	1484	1063	2547	1131	1416	2547

†: The average was taken over those households with at least one child under the age of 15. Therefore, the number of observations used for this calculation is about 10-15 percent lower than other rows in each round and each electrification status.

Table 13: Results for regressions with additional household-level control variables.

Dependent Variable: ΔNCHILD	(a)	(b)	(c)	(d)	(e)
HHELEC[1] $\times \mathbb{1}$(NCHILD[1] ≥ 2)	-2.874 **	-2.952 *	-2.379 **	-2.809 **	-0.040
	(1.216)	(1.605)	(0.965)	(1.359)	(0.046)
$\mathbb{1}$(NCHILD[1] ≥ 2)	0.799	0.781	0.581	0.731	-0.449 ***
	(0.547)	(0.683)	(0.437)	(0.584)	(0.071)
HHELEC[1]	-0.273 ***	-0.267 ***	-0.268 ***	-0.264 ***	-0.264 ***
	(0.040)	(0.040)	(0.036)	(0.039)	(0.025)
Ratio of boys among children	-0.112	-0.131 *	-0.112	-0.124 *	-0.152 ***
	(0.076)	(0.075)	(0.069)	(0.073)	(0.049)
Head's age	0.058	0.051	0.053	0.048	0.023
	(0.047)	(0.048)	(0.043)	(0.046)	(0.034)
Head's age squared†	-0.062	-0.056	-0.056	-0.052	-0.021
	(0.060)	(0.062)	(0.055)	(0.059)	(0.043)
Spouse's age	-0.058	-0.040	-0.039	-0.035	0.062
	(0.080)	(0.082)	(0.070)	(0.076)	(0.045)
Spouse's age squared†	0.119	0.092	0.088	0.086	-0.103
	(0.141)	(0.147)	(0.122)	(0.135)	(0.074)
Head has some primary education	0.277 *	0.235	0.232 **	0.226 *	0.021
	(0.142)	(0.144)	(0.117)	(0.127)	(0.051)
Head has some lower secondary education	-0.074	-0.082	-0.060	-0.065	-0.092 *
	(0.087)	(0.086)	(0.079)	(0.085)	(0.055)
Head has some matric education	0.053	0.040	0.060	0.055	0.020
	(0.100)	(0.100)	(0.089)	(0.096)	(0.059)
Spouse has some primary education	0.349 **	0.332 **	0.316 ***	0.339 **	0.099 **
	(0.136)	(0.153)	(0.117)	(0.142)	(0.050)
Spouse has some lower secondary education	-0.072	-0.095	-0.050	-0.068	-0.051
	(0.082)	(0.084)	(0.073)	(0.079)	(0.052)
Spouse has some matric education	-0.147	-0.206 *	-0.137	-0.193 *	-0.106 *
	(0.107)	(0.119)	(0.093)	(0.109)	(0.062)
log (HH expenditure per capita)	-0.010	-0.163 *	-0.010	-0.110	-0.227 ***
	(0.133)	(0.091)	(0.127)	(0.100)	(0.054)
IMR 2005 at sub-district level	-0.001			-0.001	-0.001
	(0.002)			(0.002)	(0.001)
Hours of TV watching time by spouse		0.363		0.335	-0.081 ***
		(0.247)		(0.207)	(0.023)
Marginal land owner (0.05-0.49 acres)			-0.184	-0.182	0.002
			(0.145)	(0.161)	(0.088)
Small land owner (0.50-2.49 acres)			-0.235	-0.225	-0.025
			(0.156)	(0.172)	(0.092)
Medium land owner (2.50-7.49 acres)			-0.564 *	-0.611 *	0.011
			(0.288)	(0.352)	(0.107)
Large land owner (7.50+ acres)			-0.530	-0.566	0.073
			(0.351)	(0.412)	(0.157)
Estimation	GMM-IV	GMM-IV	GMM-IV	GMM-IV	OLS
R^2					0.2437
1st Stage F	4.65 ***	2.87 *	5.95 ***	3.83 **	
Test of endogeneity	13.00 ***	8.43 ***	11.31 ***	9.45 ***	
OIR Test	0.03	0.82	0.12	1.20	
CLR Test	13.83 ***	9.85 ***	12.28 ***	11.16 ***	
N	2547	2547	2547	2547	2547

Note: GMM-IV estimation is used for all models. † regressor is rescaled by dividing by 100. A constant term is included in each regression (not reported). Robust standard errors are in brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. HHELEC[1] and its interaction terms are instrumented with the age and system loss from the grid for each PBS.

Table 14: Fixed-effects Poisson regression results.

Dependent Variable: NCHILD	(a)	(b)	(c)	(d)	(e)
HHELEC	0.001	2.405 ***	0.601 ***	0.190 ***	0.079 ***
	(0.021)	(0.490)	(0.083)	(0.037)	(0.025)
HHELEC $\times \mathbb{1}(\text{NCHILD}^1 \geq 1)$		-2.470 ***			
		(0.489)			
HHELEC $\times \mathbb{1}(\text{NCHILD}^1 \geq 2)$			-0.699 ***		
			(0.085)		
HHELEC $\times \mathbb{1}(\text{NCHILD}^1 \geq 3)$				-0.320 ***	
				(0.042)	
HHELEC $\times \mathbb{1}(\text{NCHILD}^1 \geq 4)$					-0.265 ***
					(0.040)
log (HH expenditure per capita)	-0.124 ***	-0.118 ***	-0.116 ***	-0.118 ***	-0.121 ***
	(0.018)	(0.017)	(0.017)	(0.017)	(0.018)
Wald χ^2	404.7	455.2	468.8	453.5	449.4
N	5050	5050	5050	5050	5050

Note: Robust standard errors in the brackets. Household-specific and round-specific fixed-effects terms are controlled for in each model. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. There are 22 households (44 observations) for which NCHILD=0 for both rounds and these households are excluded from the analysis.

Table 15: Results for Poisson regressions with household-level control variables.

Dependent Variable: NCHILD	Round 1						Round 2					
	Poisson			IV-Poisson			Poisson			IV-Poisson		
	Mean		(S.E.)	Mean		(S.E.)	Mean		(S.E.)	Mean		(S.E.)
HHELEC	0.000		(0.008)	-1.864	***	(0.329)	-0.014		(0.015)	-1.094	***	(0.304)
Ratio of boys among children	-0.028	***	(0.011)	-0.019		(0.023)	-0.080	***	(0.020)	-0.104	***	(0.031)
Head's age	0.054	***	(0.005)	0.086	***	(0.012)	0.026	***	(0.008)	0.042	***	(0.012)
Head's age squared†	-0.040	***	(0.006)	-0.069	***	(0.013)	-0.019	**	(0.008)	-0.029	**	(0.012)
Spouse's age	0.131	***	(0.007)	0.155	***	(0.014)	0.132	***	(0.013)	0.137	***	(0.021)
Spouse's age squared†	-0.154	***	(0.010)	-0.177	***	(0.020)	-0.149	***	(0.017)	-0.156	***	(0.029)
Head has some primary education	0.042	***	(0.012)	0.233	***	(0.041)	-0.024		(0.021)	-0.004		(0.033)
Head has some lower secondary education	-0.012		(0.013)	0.021		(0.026)	-0.008		(0.022)	0.002		(0.033)
Head has some matric education	0.010		(0.013)	0.050	*	(0.028)	-0.011		(0.025)	-0.023		(0.038)
Spouse has some primary education	-0.033	***	(0.012)	0.123	***	(0.037)	-0.040	*	(0.021)	0.046		(0.038)
Spouse has some lower secondary education	-0.052	***	(0.012)	-0.021		(0.025)	-0.051	**	(0.021)	0.003		(0.035)
Spouse has some matric education	-0.076	***	(0.015)	-0.055	*	(0.032)	-0.103	***	(0.029)	-0.088	*	(0.046)
log (HH expenditure per capita)	-0.224	***	(0.012)	-0.056		(0.045)	-0.123	***	(0.018)	-0.020		(0.034)
N	16369			16369			4180			4180		

Note: † denotes the regressor is divided by 100. A constant term is included in each model (not reported). Robust standard errors in bracket. Poisson regression is estimated by maximum likelihood estimation and IV-Poisson regression is estimated by the cost-function method with HHELEC taken as an endogenous variable and age and system loss of PBS as well as all the other regressors taken as exogenous variables. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively.

Table 16: Results for basic-specification fixed-effects OLS regressions.

Dependent Variable: ΔNCHILD	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
$\mathbb{1}(\text{NCHILD}^1 \geq 1)$					-0.790 ***			
					(0.084)			
$\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq 1)$					-0.088 **			
					(0.041)			
$\mathbb{1}(\text{NCHILD}^1 \geq 2)$				-0.196 **		-0.235 ***		
				(0.076)		(0.065)		
$\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq 2)$				-0.205 *		-0.112 **		
				(0.123)		(0.047)		
$\mathbb{1}(\text{NCHILD}^1 \geq 3)$							0.287 ***	
							(0.070)	
$\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq 3)$							-0.123 *	
							(0.067)	
$\mathbb{1}(\text{NCHILD}^1 \geq 4)$								0.427 ***
								(0.090)
$\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq 4)$								-0.023
								(0.117)
NCHILD^1		-0.384 ***	-0.384 ***	-0.335 ***	-0.282 ***	-0.315 ***	-0.450 ***	-0.463 ***
		(0.016)	(0.020)	(0.029)	(0.018)	(0.024)	(0.027)	(0.022)
HHELEC^1	-0.086 *	-0.091 **	-0.089	-0.050				
	(0.047)	(0.041)	(0.085)	(0.085)				
$\text{HHELEC}^1 \times \text{NCHILD}^1$			-0.001	0.048				
			(0.035)	(0.049)				
R^2	0.066	0.334	0.334	0.341	0.370	0.341	0.338	0.342
N	2547	2547	2547	2547	2547	2547	2547	2547

Note: There are 173 sub-districts in the panel sample and fixed-effects terms for each sub-district is controlled for in each model. Robust standard errors are in the brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively.

Table 17: Results for basic-specification OLS regressions with village-level clustering.

Dependent Variable: ΔNCHILD	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
$\mathbb{1}(\text{NCHILD}^1 \geq 1)$					-0.990 ***			
					(0.084)			
$\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq 1)$					-0.100 **			
					(0.042)			
$\mathbb{1}(\text{NCHILD}^1 \geq 2)$				-0.307 ***		-0.343 ***		
				(0.072)		(0.065)		
$\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq 2)$				-0.216 *		-0.130 ***		
				(0.115)		(0.048)		
$\mathbb{1}(\text{NCHILD}^1 \geq 3)$							0.375 ***	
							(0.077)	
$\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq 3)$							-0.150 **	
							(0.072)	
$\mathbb{1}(\text{NCHILD}^1 \geq 4)$								0.627 ***
								(0.088)
$\text{HHELEC}^1 \times \mathbb{1}(\text{NCHILD}^1 \geq 4)$								-0.078
								(0.114)
NCHILD^1		-0.329 ***	-0.328 ***	-0.255 ***	-0.213 ***	-0.234 ***	-0.418 ***	-0.447 ***
		(0.018)	(0.021)	(0.026)	(0.018)	(0.023)	(0.030)	(0.024)
HHELEC^1	-0.107 **	-0.103 **	-0.099	-0.060				
	(0.043)	(0.043)	(0.088)	(0.091)				
$\text{HHELEC}^1 \times \text{NCHILD}^1$			-0.002	0.050				
			(0.036)	(0.046)				
R^2	0.013	0.204	0.204	0.219	0.267	0.218	0.211	0.224
N	2547	2547	2547	2547	2547	2547	2547	2547

Note: A constant term is included in each model (not reported). Standard errors in brackets are clustered at the level of 432 villages based on the village code in Round 1. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively.