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Fertility and Rural Electrification in Bangladesh

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Keywords: time use, infrastructure, fertility, Bangladesh, ordered probit regression, panel data

JEL classification: O20, J13

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Fertility and Rural Electrification in Bangladesh*

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Abstract

We use a panel dataset from Bangladesh to examine the relationship between fertility and the adoption of electricity with the latter instrumented by infrastructure development and the quality of service delivery. 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 current fertility behavior if the optimal number has not yet been reached.

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1 Introduction

Access to electricity is essential for development. Provision of welfare-enhancing utilities such as clean water supplies, improved sanitation, and modern healthcare services can be delivered efficiently with electricity. Electricity enables households to enjoy reliable and efficient lighting and heating equipment, improved cooking facilities, robust mechanical power, better transport and telecommunications services, and an overall modern lifestyle. Unfortunately, approximately 1.3 billion people in developing countries currently lack basic access to electricity,[1] particularly in rural areas. Approximately, half of this unelectrified population lives 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 generate numerous economic benefits beyond simply making electricity accessible to the population. A series of studies commissioned by the World Bank as part of the Energy, Poverty, and Gender Project and the Energy Sector Management Assistance Program conducted

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

in various parts of the world reported substantial welfare-improving effects from electrification.

Similar findings have also been obtained by 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 Vietnam (Khandker et al., 2009b), development of manufacturing sector in India (Rud, 2012) and Brazil (Lipscomb et al., 2013), and improved female employment in South Africa (Dinkelman, 2011) and Nicaragua (Grogan and Sadanand, 2013). Other impacts of electrification include reduced indoor air pollution (World Bank, 2008), air-quality-related health improvements, improved 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 link is important because high fertility rates may result in a lack of human capital investment, which in turn reduces the quality of human resources and youth unemployment. As a result, high fertility is regarded as one of the most important factors hindering long-term economic growth (See, for example, Ashraf et al. (2013)).

However, such a link is not rigorously studied in the literature and in this paper we aim at investigating the impact of rural electrification on fertility. Electricity may affect fertility through multiple channels. The most direct channel is through changes in consumption patterns and time use. Because access to electricity enables households to enjoy an array of new goods, it may also induce households to shift resources away from child-related goods to these new goods. Access to electricity also alters the opportunity cost of time spent in reproductive activities because the households can use that time, for example, to engage in gainful activity if they have access to electricity.

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

In fact, earlier academic studies examining the impact of rural electrification on fertility in developing countries have been mostly undertaken by demographers. The first academic study on this topic of which we are aware is by 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 a link exists between rural electrification and fertility.

More recently, several studies have explored this topic using aggregate data in developing countries. For example, Potter et al. (2002) use microregion-level data on Brazil and find a strong and consistent relationship between declines in fertility and electrification. Similarly, Grimm et al. (2014) use a pseudo-panel data at the district level in Indonesia to find that electrification contributed to reduced fertility. In addition, they find that electrification affects fertility through two important channels: exposure to TV and reduced child mortality.

However, to the best of our knowledge, only a few studies on rural electrification and fertility have utilized a household-level dataset combined with modern econometric methods. One such study is by 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 availability of electricity among rural households. Another study based on household-level data is that by Akpandjar et al. (2014), who find that electrification contributes to reduced fertility in rural Ghana.

This study differs from the aforementioned studies in two important dimensions. First, none of the published studies of which we are aware address the endogeneity of electricity adoption.[2] This questions the validity of the estimated impacts of electrification. Second, unlike Peters and Vance (2011), we use a panel dataset. Using a panel dataset offers several distinct advantages. If we use the standard fixed-effects model, we can control for all time-invariant household-level characteristics, which is not possible with only one observation period. 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 upon the current number of children.

The latter point is particularly important because previous studies do not clearly identify the sources of changes in fertility. We construct a simple theoretical model of electrification and fertility and argue that electrification is likely to negatively af-

[2]In an unpublished working paper by Akpandjar et al. (2014), district-level access to electricity is used as an instrument. However, households choosing to live in an area with many electrified households may systematically differ from other households, and the validity of their instruments is questionable.

fect the optimal number of children. Because electrification only affects the optimal number, it does not necessarily affect fertility behavior before this optimal number is reached. Hence, our model suggests the existence of the possibility that electrifications impact on fertility may be small when no children are in the household but becomes more pronounced when the number of children in the household pass 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 fewer 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 in terms of 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 households characteristics, 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 ties in with the macroeconomic literature on baby booms in the developed world, particularly in their 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, thereby increasing fertility (Greenwood et al., 2005a). Moreover, it increased 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 adoption of electricity and appliances, as suggested 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. Studies have

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

explored the impact of dams (Duflo and Pande, 2007), transportation infrastructure (Fernald, 1999; Banerjee et al., 2012), and telecommunications infrastructure (Röller and Waverman, 2001) among others (See also Gramlich (1994) and Straub (2008) for a review of literature). Emphasizing the impacts of electrification on fertility that have largely been ignored, we underscore the importance of understanding the 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. Using infrastructure development and quality of electricity service delivery as instrumental variables for electricity adoption, we find that the impact of electrification on fertility is both economically and statistically significant. In addition, we find that electrification largely impacts 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. Section 2 briefly discusses some relevant background information on rural electrification in Bangladesh. Section 3 presents a simple model of electrification and fertility to support our estimation models. Section 4 describes the data used in this study and presents key summary statistics. Section 5 discusses the econometric specifications. Section 6 presents the estimation results. 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 the country's electricity policy. It supervises, controls, and monitors development activities in the electricity sector. Moreover, it is directly responsible for two related organizations, the Office of the Electrical Advisor and Chief Electrical Inspector (EA & CEI) and the Power Cell. EA & CEI is mainly responsible for 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] along with several other independent power producers are currently involved in power generation in Bangladesh. This power is transmitted through the national grid by the Power Grid Company of Bangladesh, then distributed to end users by different organizations, including the Rural Electrifica-

[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).

tion Board (REB), depending on the region and purpose of the power usage.[6]

REB was established in 1977 as a semi-autonomous government organization that provides service to rural member consumers and holds responsibility for electrification in rural areas. This remit includes planning and developing the distribution network for each expansion phase of rural electrification.

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 substantially lower system losses than other major electricity distribution bodies (Alam et al., 2004) and has an almost perfect bill collection record. REB's success is attributed to its autonomy, minimal bureaucracy, strong culture of integrity, donor support and trust, and strong and independent leadership (Nathan Associates Inc., 2006). REB's political appeal lies in the fact that many of the benefits of electrification, such as more hours of light and easier access to mass media, are readily visible to the public. In remote areas, however, the on-grid program has been supplemented by renewable-based off-grid technologies (Rahaman et al., 2013).[7] While we focus on the impact of electricity from the national grid, we also briefly consider the effect of access to electricity from solar power.

REB has allocated management responsibility of distribution to end users to rural electric cooperatives or Palli Biddut Samities (PBS). REB provides technical support and training to PBSs, negotiates the purchase of power for PBSs, approves tariffs, and supervises other functions. Today, REB serves over 8.3 million domestic end users in addition to commercial, industrial, irrigation, and other users through PBSs, totaling over 9.7 million connections.[8]

Currently, 70 PBSs are operating, each of whom owns, operates, and manages the rural distribution system within its jurisdiction. PBS members are the electricity consumers, who participate in its policymaking through elected representatives serving on its governing body. One PBS usually covers 5–10 subdistricts (upazilas/thanas) with a geographic expanse of 600–700 square miles.

An important feature of the REB's rural electrification program is the establishment of new PBSs or the extension of existing PBSs to new areas, which are critical for rural households to access electricity from the national grid. This pro-

[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]Rahaman et al. (2013) also reveal that REB's performance has been declining in recent years due to a lack of organizational autonomy, a shortage of funding, unrealistic tariffs, and power supply shortages.

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

cess depends on feasibility assessment which is based on a census taken on projected beneficiary household as well as irrigation, and commercial electricity loads of the next potential expansion areas. This census is utilized for prioritizing the approval system for any extension phase (Murphy et al. (2002)) which are based on various factors including (i) the results of pre-phase economic and social impact based studies, [9] (ii) the development of a PBS, [10] (iii) presence of a financially and technically viable electrical distribution system, [11] and (iv) availability of donor funding.

Although the distribution network of electricity in the rural areas are based on Area Coverage Rural Electrification (ACRE), which does not only target areas of economic growth poles rather target based on equity and fair distribution of electricity for all the households in the PBS areas, one can reasonably assume that the variations in the timing of rural electrification may not be random. However, these factors can be considered as exogenous to the household fertility decisions. Therefore, we use the characteristics of PBSs, namely, infrastructure development and efficiency of service delivery, as instrumental variables to identify the effects of electrification upon fertility.

3 Model of electrification and fertility

This section proposes a simple model of electrification and fertility to underlie our econometric specification in the subsequent analysis. While electricity affects fertility through multiple potential channels, reallocation of time use is one of the most obvious and direct channel. To delineate this idea, we begin 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 the given electrification status $e \in [0, 1]$. These non-child goods potentially include the value of leisure time.

Even though electrification status in our empirical analysis is mostly a binary variable, we treat e as a continuous variable in the remainder of this section for simplicity of presentation. Therefore, a larger value of e represents households receiving better electricity service with $e = 0$ and $e = 1$ representing no and full electricity

[9]This comprehensive field survey then becomes the primary source of demand data that REB uses to analyze the proposed PBS's ability to meet certain revenue criteria.

[10]This is based on existing road infrastructure, number of households, state of industrial and commercial development, existing social and community institutions, number of pumps, rice mills and tube wells for irrigation and percentage of the area prone to flooding

[11]Accessibility to the Bangladesh Power Development Boards's 33kV line and adequate capacity at the grid sub-station

access, respectively. It is possible to interpret e as the proportion of time in which electricity is available.

In addition, we 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 simplicity, we also assume that the utility function $U(c, n, e)$ is additively separable in (c, e) and n. We further assume that the sub-utility from non-child goods depends on e but the sub-utility from child goods does not. 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.

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 required 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 satisfy 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 working until dark. Compared with these households, other households may have a shorter effective lighted time. Eq. (2) only requires that a fixed proportion of the effective lighted time has to be spent on each child in the household, given its electrification status.

Because households with electricity have more ways to handle child-related matters, the actual number of lighted hours that has to be spent on each child would not increase with electrification. Therefore, even if the access to electricity does not help households spend less time on child-related activities, the *fraction* of lighted hours that must be spent on each child decreases such that the first derivative of α satisfies the following inequality due to the longer lighted hours generated by electricity:

$$\alpha'(e)(\equiv \mathrm{d}\alpha/\mathrm{d}e) < 0. \tag{3}$$

Eq.(3) has some empirical support based on the time use data (See Appendix B for details). We also 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 it spends all of its effective lighted time on work. Because longer lighted hours enable households to (potentially) spend more time on gainful activities (See Appendix B and Khandker et al. (2009a,b)), we assume the following inequality:

$$I'(e) > 0. \tag{4}$$

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

$$I(e)l = c + p_n(e)n, \tag{5}$$

where $p_n(e)$ is the "price of having one child," which includes direct costs of child bearing and rearing, such as food, clothes, and education. Because the opportunity 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 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. (5) 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:

$$\gamma[p_n + I(e)\alpha(e)]f'(c_*(e), e) = (1-\gamma)g'(n_*(e)), \tag{6}$$

where f' and g' 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. (6) 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 raising one child. Therefore, $[p_n + I(e)\alpha(e)]$ represents the total economic cost of having one child and eq. (6) allows the usual interpretation that the marginal utility per price from child goods equals that from non-child goods.

Taking a total differentiation of eqs. (2), (5), and (6) with respect to e and solving for $n'_*(e)$, we obtain the following results:

$$n'_*(e) = \frac{\gamma A(e)}{(1-\gamma)g''(n_*(e)) + \gamma[p_n(e) + I(e)\alpha(e)]^2 f''(c_*(e), e)}, \tag{7}$$

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 numerator has the following definition:

$$\begin{aligned} A(e) \equiv\ & [p'_n(e) + I'(e)\alpha(e) + I(e)\alpha'(e)]f'(c_*(e), e) + [p_n(e) + I(e)\alpha(e)] \cdot \\ & [f''(c_*(e), e)(I'(e) - (p'_n(e) + \alpha'(e)I(e) + \alpha(e)I'(e))n_*(e)) + f'_e(c_*(e), e)] \\ =\ & [f' - (p_n + I\alpha)n_* f'']p'_n + [If' - (p_n + I\alpha)In_* f'']\alpha' + \\ & [\alpha f' + (p_n + I\alpha)l_* f'']I' + [p_n + I\alpha]f'_e, \end{aligned} \tag{8}$$

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

As can be seen from the last line of eq. (8), $A(e)$ can be divided into four terms, each involving p'_n, α', I', and f'_e. The first and second terms are driven by the price effects induced by electrification through changes in the direct and opportunity costs of children, respectively. It is straightforward to verify that the first term is non-positive and the second term is negative. Because the denominator of eq. (7) is unambiguously negative from the concavity assumption about f and g, we can see that the price effects are positive.

The third term involving I' represents the effect due to changes 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 complementarity effects between electricity and non-child goods. This negatively affects fertility when $f'_e > 0$. While we do not assume $f'_e > 0$, it is likely to hold because access to electricity enables 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), (5), and (7):

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*

$$A(e) > 0. \tag{9}$$

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 a household becomes electrified when at least some of the following conditions are satisfied: (i) the marginal utility from non-child goods is relatively large and declines 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 values).

Proposition 1 describes the relationship between n'_*, c'_*, and l'_*. When we observe a negative relationship between electrification and fertility, both the consumption of non-child goods and the fraction of lighted hours spent on non-child activities should be positively related with fertility. Therefore, even though we primarily focus on the relationship between electrification and fertility, we can also check the consistency of the data with our theoretical model. Indeed, based on the time use data, we have some empirical support for $l'_* > 0$ as detailed in Appendix B.

Testing the sign of c'_* is more challenging because we cannot distinguish between child goods and non-child goods consumption. However, when we use the household consumption expenditure per capita exclusive of food, education and health as a proxy for non-child goods consumption, we find $c'_* > 0$ holds (See Appendix B for further details).

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 the short-run fertility behavior when the current number of children is well below their respective optimal number of children. This is because the speed at which households can increase the number of children is largely governed by the biological limit.

Suppose now that eq. (9) is satisfied and consider electrified and non-electrified households with $n_*(1)(< n_*(0))$ children, which is the optimal number for electrified households but less than the optimal number for non-electrified households. In this case, the former would not wish to further increase its number of children, whereas the latter continues to try to have additional children. Therefore, it is likely that the fertility-reducing impact of electrification can be identified relatively easily.

Thus far, we have ignored 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, $n_*(1)$ for some households is quite likely to be 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 households already have some children (greater than $n_*(1)$ for most households).

Similarly, when the household already has many children, 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 have already reached or be close to the optimal number regardless of household electrification status.

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 that a 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 based on the household survey data collected under the *Socioeconomic Monitoring and Impact Evaluation (SEM & IE) of Rural Electrification and Renewable Energy Programme in Bangladesh*. The SEM & IE study was conducted 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 was conducted over two rounds. The first round was conducted in 2005, with data collected by a consortium comprising 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 households in the data appear in both rounds. Therefore, these data are partial panel data.

Both rounds cover 45 of the 70 PBSs operating in Bangladesh, covering all six of Bangladesh's divisional regions. In Round 1, a stratified random sample was drawn according to electrification status such that approximately one half of the villages had electricity and the other half were without electricity. The domestic, commercial, industrial, and irrigation samples were selected based on their actual distributions within rural Bangladesh, but only the domestic data are used in this study because we mainly focus on fertility, which is predominantly a household decision.[12]

Round 2 of the survey followed up with a sub-sample of households. 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, location information (village, subdistrict, PBS, etc.), location status (electrified village, project non-electrified village, and non-project non-electrified village), and electrification status. This information was used as the basis for the sampling design for the Round 2 survey (e.Gen Consultants Ltd., 2006).

Village selection was based on the attrition rate found in the retracing survey, and villages were selected from all three types of villages in 2005, namely (i) villages that were already electrified, (ii) villages scheduled to be electrified within the duration of the project (i.e., electrified between the two rounds of the survey), and (iii) villages not scheduled to be electrified during the life of the project (i.e., not electrified by the time of Round 2). Villages having 10 or fewer households in Round 1 were excluded from the sample in Round 2. Furthermore, no more than 25 households were selected from any one village. The number of villages was kept to a minimum in Round 2 while the required number of households were sampled for each PBS.

The Bangladesh Rural Electrification Board Management Information System provided information on the age and system loss from the grid for each PBS.[13] 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 electricity adoption. That is, when a PBS is older, electricity is likely to have been available to the household for a longer period of time. Because the establishment of a PBS largely depends on the areas chosen by policymakers in the government and donors to receive rural electrification projects, there is little concern for the endogeneity of household choice of residential location.

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

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

The second instrument, the system loss from the grid, is also important because a PBS's management is likely to be poor when system losses are larger, which in turn would negatively affect the adoption of electricity. The system loss variable also has no obvious direct 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 household's adoption of electricity. We merge these PBS-level variables into household-level variables.

To minimize complications arising from differences in household structure, we only use data for households whose household head is male[14] and married to a woman aged between 15 and 49, an age group for whom fertility decisions are relevant. We also eliminate households where the head had multiple wives, which totaled approximately one percent of households in each round. After further eliminating a small fraction of households with a missing demographic, education, or income variable, we were left with a dataset comprising 16,369 households in Round 1 and 4,180 households in Round 2.

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

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

Description	Round 1			Round 2		
	Non-electrified ($\text{HHELEC}^1=0$)	Electrified ($\text{HHELEC}^1=1$)	All	Non-electrified ($\text{HHELEC}^2=0$)	Electrified ($\text{HHELEC}^2=1$)	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
Hours of TV watched 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, depending on the survey round and electrification status.

Table 1 provides some summary statistics of key household variables by electrification status in Round 1, HHELEC^1, where HHELEC^1 = 1 [HHELEC^1 = 0] means that the household has [does not have] access to electricity from the national grid. As shown in Table 1, electrified households tend to be slightly older than non-electrified households. The number of surviving children born to the spouse (wife), NCHILD, is on average similar between the electrified and non-electrified households, but it is slightly smaller for the former. Note here that NCHILD is used as an observable measure of fertility in this study because the complete history of pregnancy and birth is unavailable in the data. Therefore, NCHILD is affected not only by the number of children that the wife has given birth to but also by the number of children who died before the time of interview.

One of the major differences between non-electrified and electrified households in Table 1 is the educational attainment of their respective heads. At each level of educational attainment, the proportion of educated households for electrified households is higher than that of non-electrified households. For example, approximately 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, spouses also had higher educational attainment in electrified households.

Electrified and non-electrified households also economically and statistically differ 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 among electrified households is significantly smaller than that among non-electrified households, the land distributions for electrified and non-electrified households are otherwise similar overall. Note that the daily average for hours spent watching TV is small but positive for non-electrified households. This may reflect watching TV in a neighbor's house.

Four cautions are in order. 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 utilized in the Round 1 data in Table 1. Based on these weights, approximately 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 regression results are generally similar even when the weights are applied and could be available upon request.

Second, educational attainment is considered as an ordered variable to enable easier understanding of the marginal impact of education. For example, if a given household's head has at least some matric education, 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 is likely to influence subsequent fertility decisions as it is not uncommon in Bangladesh to prefer boys to girls. However, we observe only the number of surviving children born to the wife (i.e., NCHILD) but not separate numbers of boys and girls. Therefore, we use the household ratio of boys out of all children under the age of 15, which may include children whose mother is not the spouse of the male household head. For households with no children under 15, we assign a value of half in the regression analysis, but the average reported in Table 1 excludes those households.

Finally, we primarily focus on electricity provided by the national grid because our identification uses each PBS's age and system loss from the grid. Thus, non-electrified households may in fact be able to use electricity from non-grid sources such as solar power. While not considered in most of our analysis, we shall briefly discuss the impact of electricity from solar power in Section 6.

Because the raw dataset we acquired did not contain a unique individual-level identification code, a panel dataset was constructed by manually matching the names of the husband and wife between the two rounds for each household.[15] We exclude from our panel-data analysis those households that could be matched between the two rounds as well as those with missing observations in some key variables, plus the small fraction of households in which the number of surviving children 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.[16]

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) had an increase of 0.348 surviving children and non-electrified households had an increase

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

[16]A table of summary statistics for the panel households is provided in Table 12 in Appendix C. Because of the sample restrictions described above, the panel households are on average younger. Otherwise, the distributions of other characteristics are generally similar between the panel and whole samples.

of 0.455 surviving children between the two rounds (See Table 4 discussed in Section 6). The difference in average ΔNCHILD between non-electrified and electrified households is statistically significant.

As with NCHILD, ΔNCHILD reflects both child births and deaths that occurred between the survey's two rounds. However, as most of our analysis ignores the child deaths and drops the qualifier "surviving" to keep the presentation simple because the probability of death, especially between the two rounds of the survey, is limited.[17] We , however, retain in our panel analysis approximately nine percent of the households for which ΔNCHILD is negative. This is because if we only retain the households for which ΔNCHILD is non-negative, we essentially retain only high fertility households that tend to have additional children in the event of child death, which leads to a sample selection bias in our estimation.

5 Econometric specifications

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

$$\text{NCHILD}_i^t = \alpha \text{HHELEC}_i^t + \gamma X_i^t + u_i^t, \tag{10}$$

where the superscript $t \in \{1, 2\}$ represents the relevant survey round and X_i^t is a vector of covariates, which includes a constant term. When the error is conditionally uncorrelated with the regressors and independently and identically distributed, model parameters such as α and γ can be consistently estimated by an ordinary least squares (OLS) regression. However, this raises the issue of endogeneity of HHELEC because those who have access to grid electricity may differ systematically from those who do not and thus the error term u_i^t may be conditionally correlated with HHELEC_i^t and the OLS estimates may be biased as a result.

This problem can be resolved when some additional assumptions are made. Suppose that ϵ_i^t can be decomposed into a time-specific effect η_t, a household-specific effect δ_i, and an idiosyncratic effect ϵ_i^t such that eq. (10) reduces to

[17] The child mortality rate under five per 1,000 live births in Bangladesh was 68 in 2005 and 47 in 2010 according to the World Development Indicators. This number is certainly not negligible but still relatively small. Furthermore, 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 greatly alter our regression results.

$$\text{NCHILD}_i^t = \alpha \text{HHELEC}_i^t + \gamma X_i^t + \eta_t + \delta_i + \epsilon_i^t, \tag{11}$$

where 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. We are therefore able to use a fixed-effects OLS (FE-OLS) regression using a panel data set.

However, this specification implies that the expected number of children born between the two survey 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 reached their long-run fertility decision would not have additional children regardless of the electrification status. Furthermore, the manner in which the number of children increases may also depend on a time-invariant characteristic, a situation that FE-OLS regression cannot cope with. Therefore, we also consider the following change-on-level specification:

$$\Delta \text{NCHILD}_i = \alpha \text{HHELEC}_i^1 + \beta \text{NCHILD}_i^1 + \gamma X_i^1 + \epsilon_i^t, \tag{12}$$

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

$$\begin{aligned} \Delta \text{NCHILD}_i \;&=\; \alpha \text{HHELEC}_i^1 \cdot \mathbf{1}(\text{NCHILD}_i^1 \geq M) + \beta_1 \cdot \mathbf{1}(\text{NCHILD}_i^1 \geq M) \\ &\quad + \beta_2 \text{NCHILD}_i^1 + \gamma X_i^1 + \epsilon_i^t, \end{aligned} \tag{13}$$

where $\mathbf{1}(\cdot)$ is an indicator function that takes the value of one if the argument is true and zero otherwise. The threshold value M varies from 1 to 4 in our regressions. Eq. (13) can be estimated consistently by OLS when ϵ_i^t is conditionally uncorrelated with $\text{HHELEC}_i^1 \cdot \mathbf{1}(\text{NCHILD}_i^1 \geq M)$.

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

For example, it is possible to argue that households that highly value electric appliances tend to adopt electricity earlier and tend to have a lower optimal number of children because they have a higher value of γ. In this case, negative selection occurs and the estimated coefficient on household electrification status is biased downwards. On the other hand, if households that have a better prospect of future income adopt electricity early and subsequently tend to have more children, the selection is positive and the coefficient tends to be biased upwards. To deal with this issue, we instrument the adoption of electricity by the age and system loss from the grid for the PBS that covers the household's location i.

We also consider some non-linear specifications that address the discreteness of NCHILD and ΔNCHILD, which linear models cannot appropriately take account of. Instead of the highly restrictive Poisson regression model used in Peters and Vance (2011), we propose a bivariate probit-ordered probit (BPOP) model with HHELEC and ΔNCHILD as dependent variables because the BPOP model has several advantages relevant to our application over the Poisson model as elaborated in the next section.

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 the simple cross-sectional specification given in eq. (10). While this specification suffers from the issues discussed earlier, it has a practical advantage wherein we can use all the observations in each round instead of just the panel households.

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 the GMM-IV estimation, HHELEC is instrumented by the age and system loss from the grid for each PBS.

Cross-sectional regressions are run for each of the two rounds individually and the results are presented in Table 2. For each round, we report both the OLS and generalized method of moments instrumental variables (GMM-IV) regression results. In the latter, HHELEC is instrumented by the age and system loss from the grid for each PBS.

The main variable of interest is HHELEC. As shown in Table 2, the coefficient is close to zero when the OLS specification is used. However, it is highly negative when HHELEC is instrumented. Therefore, this indicates the presence of positive selection.

For the GMM-IV regressions, we report the first stage robust F-statistic, the difference-in-Sargan C-statistic for the test of endogeneity, and Hansen's J-statistic for the overidentification restriction (OIR) test. Because the first stage F-statistics for other regressions 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 in this and subsequent tables.[18] This statistic enables us to test $\alpha = 0$ even with weak instruments.

In addition to HHELEC, we have added several control variables. As demographic controls, we include the ratio of boys out of all children to allow for the possibility that the gender of a household's current children may affect subsequent fertility behavior. For example, a strong preference for a boy may motivate people to attempt to have additional children until they have a boy. The point estimate is negative in all regressions and significant for all but the GMM-IV for Round 1, suggesting that the ratio of boys influences fertility decisions.

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

We also include education variables for both the head of household and spouse. A consistent pattern of signs does not emerge for the head's education variables. On the other hand, all 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 consistent with those of 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

[18] 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 $\times$ $\mathbf{1}(\text{NCHILD}^1 \geq 1)$		-1.308 ***			
		(0.182)			
HHELEC $\times$ $\mathbf{1}(\text{NCHILD}^1 \geq 2)$			-0.716 ***		
			(0.100)		
HHELEC $\times$ $\mathbf{1}(\text{NCHILD}^1 \geq 3)$				-0.540 ***	
				(0.093)	
HHELEC $\times$ $\mathbf{1}(\text{NCHILD}^1 \geq 4)$					-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 in the brackets. Household-specific and round-specific fixed-effects terms are included in each model. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively.

for a household's standard of living, which may affect both electrification and fertility. This variable has a negative and significant coefficient for the OLS regressions in both rounds but not in the GMM-IV regressions.

Fixed-effects Specifications

Let us now consider eq. (11) using the panel households. Because the majority of demographic and education characteristics are time invariant after controlling for the time-specific fixed effect, we only retain logarithmic household expenditure per capita in the set of regressors. Table 3 reports FE-OLS estimates with household-specific and time-specific fixed effects.

As shown in column (a), the coefficient on household electrification status is weakly negative and statistically insignificant. This is not surprising for two reasons. First, there may be positive selection, as discussed in relation to Table 2. Second, we are identifying the impact of electrification only via households whose electrification status has changed without considering a household's current number of children in Round 1.

In columns (b)–(e), we add the interaction between electrification status and indicator variable for the number of children exceeding a specific threshold between one and four. Therefore, these coefficients pick up the impact of electrification on fertility when a household already has one–four children, respectively. The results reported in Table 3 indicate that the negative impact of electrification on fertility

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.

tends to increase when the household initially has a larger number of children.

Note here that we are controlling for, among other factors, all the time-invariant household characteristics in the FE-OLS models. As a result, the estimated 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 changes in the number of children upon the initial number of children and household heterogeneity, we consider change-on-level specifications such as eqs (12) and (13).

Change-on-level Specifications

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 examine the impact of electrification conditional on the number of children being greater than $n_*(1)$ but less than $n_*(0)$ for most households.

To further underscore the importance of subsequent fertility's dependence on current fertility, we consider Table 4, which presents the mean of ΔNCHILD and its standard error by electrification status and the number of children in Round 1. For example, non-electrified households on average have 0.455 more children in Round 2 than they had 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 their number of children if they have three or fewer children already.

For electrified households, the number of children tends to increase when NCHILD^1 is two or less. For electrified households with at least three children, the number of children remains unchanged significantly over time in our data. Given these findings, it would be reasonable to argue that the optimal number of children for electrified and non-electrified households are on average approximately three and two, respectively (i.e., $n^*(0) \simeq 3$ and $n^*(1) \simeq 2$).

Table 5: Results for parsimonious specifications.

Dependent Variable: ΔNCHILD	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
$\mathbf{1}(\text{NCHILD}^1 \geq 1)$					-0.990 ***			
					(0.082)			
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 1)$					-0.100 ***			
					(0.037)			
$\mathbf{1}(\text{NCHILD}^1 \geq 2)$				-0.307 ***		-0.343 ***		
				(0.073)		(0.063)		
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 2)$				-0.216 *		-0.130 ***		
				(0.122)		(0.042)		
$\mathbf{1}(\text{NCHILD}^1 \geq 3)$							0.375 ***	
							(0.072)	
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 3)$							-0.150 **	
							(0.065)	
$\mathbf{1}(\text{NCHILD}^1 \geq 4)$								0.627 ***
								(0.088)
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 4)$								-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: OLS estimation for all columns. 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.

We will now bring the discussion above into the regression context. We start with most parsimonious specifications that are consistent with the above discussion. We report the regression results under various specifications based on the panel households in Table 5.

Column (a) shows that for households electrified in Round 1, the difference in the number of children between the two rounds is on average smaller than that observed for non-electrified households by 0.107 children. In column (b), we control for NCHILD as well, but the size of the coefficient on the electrification status in Round 1 does not vary greatly. In column (c), we also include their interaction term ($\text{HHELEC}^1 \times \text{NCHILD}^1$). While both household electrification status and the interaction term are insignificant, the marginal impact of electrification significantly differs from zero when a household has one (P-value = 0.066), two (P-value = 0.006), or three (P-value = 0.025) children, but this is not the case when there are four or more children.[19]

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 electrification's impact is most pronounced in the absence of household-level control variables. We check the robustness of our results with respect to this choice of threshold value.

In column (d), we include the indicator variable for two or more children (i.e., $\mathbf{1}(\text{NCHILD}^1 \geq 2)$) as well as its interaction with household electrification status (i.e., $\text{HHELEC} \times \mathbf{1}(\text{NCHILD}^1 \geq 2)$). As the table shows, both the indicator variable and interaction term are significant. On the other hand, coefficients on HHELEC^1 and its interaction with NCHILD^1 are insignificant.

In columns (e)–(h), we vary the threshold value M from one to four without HHELEC^1 and $\text{HHELEC}^1 \times \text{NCHILD}^1$. As column (h) shows, the impact of household electrification status is insignificant when a household already has four or more children. On the other hand, the impact of electrification tends to be higher for a higher threshold value when $M \leq 3$.

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 dataset we received, the village code information is unfortunately unreliable. For example, the village code is missing for some households in Round 2 and appears inconsistent between the two rounds for some panel households. Furthermore, the village data collected along with the

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

household data cannot be merged for a sizable fraction of households using the village code.

However, even if the village code is wrong, as long as the error terms are independently (and not necessarily identically) distributed, the use of clustered standard errors would nevertheless asymptotically lead to correct inferences because of the nature of the sandwich estimators. However, in a finite sample, the use of clustered standard errors may produce estimates that are either too conservative or too optimistic. In particular, when the effects of clustering is weak, clustered standard errors may not perform better than heteroskedasticity-robust standard errors. These shortcomings, notwithstanding, we ran an OLS regression with the errors clustered at the village level and found that the magnitudes of standard errors do not greatly change.[20]

An alternative to clustering would be to include village fixed-effects terms. However, given the issues with the village code mentioned above, we instead choose to include subdistrict fixed-effects terms in the regression. The inclusion of subdistrict fixed-effects terms does not alter the statistical significance of $HHELEC^1$ and both the coefficient and standard errors remain similar.[21] This indicates that local conditions such as geographic location, labor market conditions, and existence of family planning campaigns may not matter in the estimation of electrification's impact.

There are, however, two issues with the use of this subdistrict fixed-effects model. First, the subdistrict fixed-effects terms are highly collinear with our instrumental variables because the boundaries of PBS and subdistricts are closely related. Second, and more importantly, they cannot be used in the probit-ordered probit model because of the incidental parameter problem. Therefore, we choose to report the robust standard errors.

Controlling for Heterogeneity across Households

The specifications in Table 5 suffer from the obvious problem of not controlling for heterogeneity across households in terms of observable characteristics. Therefore, we report the change-on-level regression results based on eqs. (12) and (13) with the basic set of control variables in Table 6.

[20] Detailed results are reported in Table 13 in Appendix C.
[21] Detailed results are reported in Table 14 in Appendix C.

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 $\times$ $\mathbf{1}$(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)
$\mathbf{1}$(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 in brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. In GMM-IV estimation, HHELEC or HHELEC $\times$ $\mathbf{1}$(NCHILD$^1 \geq M$) is treated as an endogenous variable and instrumented by 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.

Column (a) reports 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. After controlling for various demographic and education characteristics and a 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 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 further find no evidence of misspecification. While the F-statistic is slightly small, the CLR test indicates that the statistical significance of the coefficient on HHELEC^1 still holds. Therefore, when we consider the endogeneity of electricity adoption, the coefficient on HHELEC^1 becomes even more statistically and economically significant.

Let us now consider the possibility that the impact of electrification is not linearly dependent on a household's current number of children. Similar to columns (e) to (g) in Table 5, we replace household electrification status by its interaction with an indicator variable that NCHILD^1 exceeds a certain threshold M (i.e., $\mathbf{1}(\text{NCHILD}^1 \geq M)$) 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 Table 5, the negative impact of electrification tends to be larger when a household already contains a higher number of children, and the coefficients in the GMM-IV regressions are more highly negative and significant than the corresponding coefficients in the OLS regressions. Furthermore, as with column (a), the interaction variable is found to be endogenous and the OIR test has passed at conventional levels of statistical significance for all the GMM-IV regressions.

Table 6 also shows that the coefficients on demographic and education characteristics are mostly insignificant, with two notable exceptions. First, the spouse's primary education is positive and significant for all 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 fertility behavior prior to Round 1. Therefore, the positive coefficient on spouse's primary education likely reflects the fact that the women who have at least some primary school education tend to have higher child-bearing ages.

The coefficient on the ratio of boys among children is negative and significant in all OLS regressions reported in Table 6. This suggests the existence of preference for boys in rural Bangladesh. However, the statistical significance diminishes once we use the GMM-IV regression, because the standard error associated with the coefficient increases. Nevertheless, the difference between the OLS and GMM-IV estimates are well within two times the standard error 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, their statistical significance does not hold once HHELEC^1 is instrumented because of the larger standard errors.

Additional Covariates

Thus far, we have only included a fixed set of covariates. However, a few concerns arise concerning the possibility of omitted-variable bias in the specifications used in Table 6. First, it could be argued that mortality is related to electrification, presumably because some incidents of child deaths could be prevented by using electrically operated medical (or other) appliances. If this is indeed the case, the coefficient on household electrification status may be confounded with reduced mortality. To address this issue, we add the infant mortality rate at the subdistrict 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 insignificant and the coefficient on HHELEC^1 does not change significantly.

In column (b), we control for the average number of hours the spouse spends watching TV per day to see if the findings of Grimm et al. (2014) are relevant in Bangladesh. As shown in the table, the coefficient on the number of hours watching TV 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, in a specification (not reported) in which both HHELEC^1 and the hours spent watching TV are taken as endogenous variables, the point estimate on HHELEC^1 remains significant at a 10 percent level, whereas the coefficient on the hours of TV watched is insignificant. More importantly, the test of endogeneity suggests that HHELEC^1 is endogenous but the hours spent watching TV is not. Therefore, we conclude that watching TV 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 levels. Their inclusion allows for

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 watched 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 by the age and system loss from the grid for each PBS.

the possibility that changes in the number of children may depend not only on a household's current standard of living but also on its overall wealth level. We find that households owning more land tend to have lower fertility but the coefficient is statistically insignificant except for medium landowners. Furthermore, the inclusion of the landholding categories does not significantly change the coefficient on HHELEC^1.

Finally, in column (d), we simultaneously include the infant mortality rate, hours of TV watched, and landholding 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 the interaction term is statistically insignificant. In addition, the coefficient on the hours of TV watched 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 number of children exceeding two (i.e., $\mathbf{1}(\text{NCHILD}^1 \geq 2)$ and its interaction with HHELEC^1 (i.e., $\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 2)$).[22]

Origins 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 a household's fertility. However, it is plausible that people's behavior is influenced by their neighbors' actions. For example, information that someone in an electrified household obtains from TV may be transmitted to people living in non-electrified households in the same village, which in turn change the latter's behaviors. It is also possible that the non-electrified households may be affected by the adoption of electricity by others in the village, because, for example, it leads to a better environment for child bearing and rearing.

Therefore, we take the status of village electrification into account. To this end, we create an indicator variable, VGELEC^t, denoting that the village is connected to the national grid in Round $t \in \{1, 2\}$.[23] To test the impact of this variable, we separately analyze the following two subsamples: (S1) households that reside in a village that was electrified in Round 1 (i.e., $\text{VGELEC}^1 = 1$) and (S2) households that reside in a village electrified between the two rounds (i.e., $\text{VGELEC}^1 = 0$ and $\text{VGELEC}^2 = 1$). Because the households in subsample (S2) lack access to electricity from the grid in Round 1, we use electrification status in Round 2 (HHELEC^2)

[22] The details of the regression results in this specification are reported in Table 15 in Appendix C.

[23] VGELEC is included in the household-level dataset. Therefore, the analysis is unaffected even if the village codes are incorrect.

instead of Round 1 ($HHELEC^1$) to compare the impact of electrification for the two subsamples.

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: † denotes that the regressor is rescaled by dividing by 100. GMM-IV estimation is used for all models. A constant term is included in each regression (not reported). Robust standard errors in the 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 by the age and system loss from the grid for each PBS.

To determine the consequences of using HHELEC^2 instead of HHELEC^1, we first run the same GMM-IV regression as reported in column (b) of Table 6, but 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 impacts stemming from electrification that occurred just prior to the 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 provision of electrification.

In column (b), we run the same regression as reported in column (a) but only for subsample (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 net of the village-level effect of electrification.

In column (c), we report the results of the same regression, this time for subsample (S2). Because these villages were electrified between the two rounds, the village-level impact of the adoption of electricity would be, if any, much smaller than that in subsample (S1). This specification unfortunately suffers from the weak instrumental variable problem. This is not surprising because the instruments cannot predict whether the adoption of electrification would occur within the relatively short time window between the two survey rounds. Given this issue together with 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 draw a strong conclusion about the village-level effect of adopting electricity.

To investigate further the village-level effect, we also run regressions by taking village electrification status 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 with only HHELEC^1 treated as an endogenous regressor, 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).

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 is endogenous whereas VGELEC^1 is not. Hence, we have no apparent evidence of misspecification for the model results reported in column (e).

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

Alternative Variables for Electrification

To examine the robustness of our results, a few alternative choices of electrification variables are considered. First, we take the outage of electricity into consideration. This is potentially important because electrification is unlikely to have a large impact if electricity is generally unavailable due to outages. To account for this possibility, we use OUTAGE^2, i.e., the proportion of time in which electricity was unavailable in the village in Round 2. However, the previously mentioned problems with the village codes required us to aggregate the outage variable to the subdistrict level for approximately 60 percent of villages. For a very small fraction of households, we needed to aggregate to a PBS level to merge the outage variable.

Table 9: Alternative choices 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: † denotes that the regressor is rescaled by dividing by 100. GMM-IV estimation is used for all models. A constant term is included in each regression (not reported). Robust standard errors 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 by the age and system loss from the grid for each PBS.

The specification in column (a) of Table 9 is the same as that in column (a) of Table 8 except that HHELEC^2 is replaced with $\text{HHELEC}^2 \times (1 - \text{OUTAGE}^2)$, where the latter can be interpreted as the fraction of time during which the household can use electricity. This variable has an advantage in that it is closer to the definition of e in Section 3 than HHELEC. 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 that was found to be endogenous in an unreported regression where both are treated as endogenous. While the coefficient on OUTAGE^2 is only marginally significant, this result shows that prolonged outages tend to offset the fertility-reducing effect of electrification.

In column (c), we replace HHELEC^1 with YRELEC^1, or the number of years for which the household has received electricity, which is observed only in Round 1. As the table shows, the results are consistent with the previous discussion. Households with a longer history of access to electricity show a higher negative impact on fertility. 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 a 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 access to electricity from the grid. We treat SOLAR^1 as an exogenous variable. This specification, given 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 are treated as endogenous variables.

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

Discrete Specifications

The linear models 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 number of expected children can be negative. In this light, Peters and Vance (2011) propose the use of 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.[24]

In this study, we propose a 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. This formulation offers three advantages. 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 change 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, which helps yield more accurate estimation results. 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 considered in this study 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. Furthermore, the coefficients on demographic and education covariates included in the model are qualitatively similar to those found in Table 2.

The table also shows that households that are richer or where the spouse has more education 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 the age of PBS is insignificant for Round 2.

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 thresholds essentially tells us how difficult it is to move to the next category (in terms of the number of children).The table also reveals that the largest difference between two contiguous thresholds occurs at the $[\kappa_2, \kappa_3]$ interval in both rounds. Beyond κ_3, the difference between two contiguous thresholds tends to shrink. Therefore, our model implies that the fertility-reducing effect of electrification is greatest when the household has high potential fertility as computed from the observable indicators (i.e., a high value of $X_{2h}\beta_2$).

[24]Since Peters and Vance (2011) only use cross-sectional data, they only consider the number of children as a dependent variable. When we use Poisson models, the results are qualitatively similar to those reported in Tables 16 and 17 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)
κ_1	2.980		(0.178)	2.676		(0.378)	-4.121		(0.718)
κ_2	3.649		(0.180)	3.424		(0.387)	-3.616		(0.702)
κ_3	4.471		(0.183)	4.417		(0.398)	-3.154		(0.697)
κ_4	5.152		(0.186)	5.151		(0.405)	-2.600		(0.691)
κ_5	5.692		(0.188)	5.704		(0.410)	-0.888		(0.670)
κ_6	6.138		(0.191)	6.186		(0.414)	0.088		(0.660)
κ_7	6.548		(0.193)	6.647		(0.418)	0.726		(0.654)
κ_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.

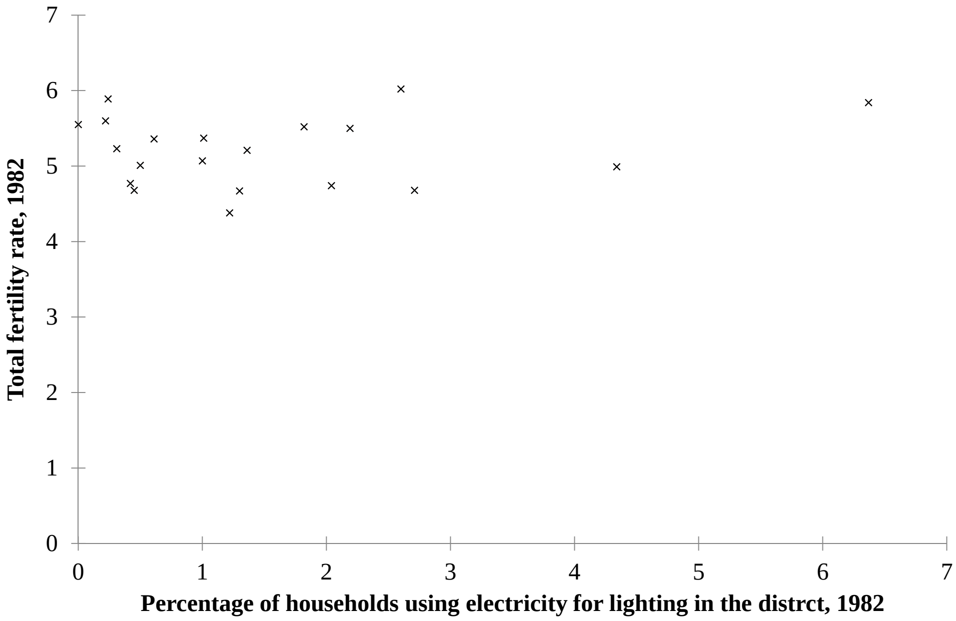

Figure 1: Percentage of households using electricity for lighting and total fertility rate at the district level in rural Bangladesh in 1982. Source:Bangladesh Bureau of Statistics (1988a,b).

The second row from the bottom reports the correlation ρ in the idiosyncratic terms for the two underlying latent dependent variables. A high positive correlation is found, revealing the presence of positive selection. It also indicates that we can gain efficiency by simultaneously estimating the two models, because the error term contained in the household electrification status model is informative of the error term in the NCHILD model.

In column (c), 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 negative and significant. We also find that those households where the head has primary or higher education 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 implications qualitatively similar to those of the linear models. As with the linear case discussed earlier, the regression results change only slightly when the error terms are clustered at the subdistrict level for all columns, as reported in Table 10.

As Table 10 shows, we consistently observe positive selection. This may be because of the differences in the initial condition across villages. While we have limited data on the initial condition, there is a modest positive correlation (0.165) between the percentage of households using electricity for lighting and total fertility rate at the district level in 1982 when the rural electrification was still at an early stage as shown in Figure 6. Because it is inappropriate to include a large number of dummies, we also ran the BPOP regression with fixed-effects terms at the level of six divisions. When these fixed-effects terms are included, ρ tends to become smaller but other results are quantitatively similar (See Table 18 in Appendix C for details).

The non-linearity of the BPOP regressions means that we must be cautious when quantitatively comparing the results in Table 10 with the GMM-IV regression results in Table 2 and column (b) of Table 6. To make quantitative comparisons, we therefore 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 household characteristics including the adoption of electricity (see Appendix A for the formal definition of Δ_h). We then take an average across all households to arrive at the average marginal impact of electrification upon the number of children, which is -1.51 for Round 1 and -1.33 for Round 2 based on columns (a) and (b), respectively. The average marginal impact on ΔNCHILD based on column (c) is -0.89 children. As expected, this number is smaller than the two figures mentioned above because the latter refers only to fertility changes over a five-year period.

It is possible to disaggregate the average impact by household characteristics. Therefore, to check the 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 impact for those households with NCHILD≥ 2 is substantially larger in absolute value than that for households with NCHILD≤ 1.

7 Discussion

Numerous studies have examined the economic impacts of rural electrification. However, relatively few studies investigate the impact of rural electrification on fertility in developing countries. While the idea that a relationship may exist between the availability of electricity and fertility is not new in itself, there remains a dearth of rigorous econometric analyses based on household surveys.

Our main finding is that rural electrification negatively affects fertility, particularly when the positive selection of adoption of electricity is considered. This finding is robust with respect to (1) the choice of estimation method, (2) the choice of set of regressors, (3) the choice of a measure of access to electricity, and (4) the assumed structure of the 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 for electrification to affect fertility is through increased standards of living. As shown in Table 1, the increase in the average household expenditure per capita is higher for electrified households.[25] Because the coefficient on the logarithmic household expenditure per capita is generally negative though not always significant, we can conclude that electrification can indeed affect fertility negatively through this channel. However, the persistence of the negative and significant coefficient on the measures of adoption of electricity, especially after controlling for the endogeneity issue, suggests that other channels are likely to exist.

Our empirical findings are consistent with a simple theoretical model in which the optimal number of children changes according to the household's electrification status, where the optimal number is driven by, among other factors, the changes in direct and opportunity costs of children. The model predicts that the proportion of lighted time not spent on children increases once the household becomes electrified. This prediction has empirical support in the analysis of time use in Appendix B. However, unlike Grimm et al. (2014), we find no evidence that the fertility-reducing effect of electrification comes from longer hours spent watching TV or lower infant mortality in Bangladesh.

This study makes several contributions to the literature. First, to the best of our knowledge, this is the first panel study based on a household-level dataset. Using this dataset enables us to estimate a model of fertility conditional on the household's existing number of children. If we adopt the fixed-effects specification, we can also control for all 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 electricity adoption. 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 considered.

Third, we propose an alternative strategy to estimate the simultaneous determi-

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

nation of the adoption of electricity and fertility by using the BPOP model, which has a few distinct advantages discussed in the previous section. We find a strong correlation in the unobserved error terms even after controlling for various demographic and education characteristics. While we are unable to fully identify the source of the revealed positive selection, our results indicate that it is partly due to the differences in the initial condition. The BPOP model exploits the correlational structure to efficiently estimate the model coefficients and serves as an alternative specification to the linear or Poisson regression models.

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

This study's findings contain 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 those typically considered in impact assessment studies. Second, this study shows that policymakers cannot simply expect lower fertility rates to result simply by electrifying villages. If they want to incorporate the potential impact of electrification on fertility into an electrification project's design, it is essential to also consider the affected households' current demographic characteristics, especially current number of children, in the 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 a household's access to electricity $h \in \{1, \cdots, H\}$ be y_{1h}^*. We assume 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 $y_{1h} = \mathbf{1}(y_{1h}^* > 0)$.

As noted in Section 4, we only consider the fertility of the spouses of male-headed households wherein the household head has one and only one spouse. Because of this choice, we can use index h for spousal fertility. 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 this does not include a constant term. The index of latent fertility is related to the number of children[26] 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 $\kappa_{K+1} \equiv +\infty$.[27]

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

[27]We take $K = 8$ in our empirical analysis, where k corresponds to the number of children except that $k = 8$ corresponds to eight or more children. Given that we had very few observations with NCHILD≥ 9, we do not distinguish between those having eight or more children.

Because some omitted covariates may exist 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 parameters 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 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 expected fertility rates with and without electrification conditional on current electrification status. To this end, we use X_{2h}^0 to denote all 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 status, the probability that the number of children equals 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 $\hat{\rho}$, we obtain the estimates of A_{hk} [B_{hk}].

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

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

We can similarly define $\hat{A}_{hk}^0$ and $\hat{A}_{hk}^1$ for electrified households. Using 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 obtain the average marginal impact.

Appendix B: Testing the signs of α', I', l', and c'

The Round 1 survey contains data on the wife's use of time. However, 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 for one's body, (13) shopping, (14) resting (excluding sleeping), (15) socializing, (16) performing 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 performed during lighted hours. However, other activities may exist that are not appropriately covered in this list. For example, if one has to commute to a workplace, time spent travelling may not be captured in this list. Furthermore, activities such as listening to the radio can be done without light or engaged in simultaneously with other activities. However, data limitations lead us to ignore these possibilities and assume that (1) the listed activities are performed only during lighted hours, (2) they are the only activities performed during lighted hours, and (3) they are performed separately. When we have a missing value of τ_j for some j, we treat the missing value as zero. To avoid including those households for which the time-use records are incomplete or seemingly problematic, we dropped approximately 1.8 percent of observations for which $12 \leq T \leq 22$ was not satisfied.

As is clear from the definition of α, this quantity can be calculated only from those households with at least one child. Even after excluding childless households, close to ninety percent of households report no time spent on taking care of children. This, of course, may be because their children are old enough to care for themselves. However, the very high rate of zero response appears to indicate that taking care of children may be done in conjunction with other activities. Therefore, we use a subsample of households with non-zero α for our main analysis.

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

Finding the empirical counterparts of I and c is a challenge. For I, we should only include income from work in principle. However, the data does not allow us to clearly distinguish between non-work and work incomes. Therefore, we use the logarithmic household income per capita. For c, we need a measure of non-child consumption. Because we are unable to distinguish between consumption expenditure for children and adults, we use the logarithmic total consumption expenditure exclusive of food, education, and health care as a proxy for the consumption of non-child goods.

Table 11: OLS regression of α, I, l, and c for Round 1 data.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Dep var	α	α	I	I	l	l	c	c
Covariates†	N	Y	N	Y	N	Y	N	Y
HHELEC[1]	-0.0034	-0.0019	0.1702 ***	0.0734 **	0.0096 ***	0.0088 ***	0.3701 ***	0.2533 ***
	(0.0022)	(0.0020)	(0.0314)	(0.0304)	(0.0027)	(0.0028)	(0.0450)	(0.0441)
N	1047	1047	1047	1047	1047	1047	1047	1047
R^2	0.0023	0.2097	0.0273	0.1692	0.0122	0.0191	0.0607	0.1787

	(k)	(l)	(m)	(n)	(i)	(j)	(o)	(p)
HHELEC[1]	-0.0003	-0.0001	0.1489 ***	0.0670 ***	0.0008 *	0.0006	0.3749 ***	0.2884 ***
	(0.0002)	(0.0003)	(0.0083)	(0.0079)	(0.0005)	(0.0005)	(0.0122)	(0.0119)
N	14628	14628	14627	14627	14628	14628	14628	14628
R^2	0.0001	0.0067	0.0216	0.1673	0.0002	0.0008	0.0610	0.1543

†: The standard covariates 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), and the spouse's education (primary/secondary/matric).

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. Columns (a)–(h) use a subsample of observations with $\alpha > 0$. columns (i)–(p) use a subsample of observations with NCHILD[1] > 0.

To test the signs of l', α', I', and c', we run OLS regressions of l, α, I, and c on HHELEC^1. We report the regression results for a subsample of households with non-zero α in columns (a)–(h) and subsample of households with at least one child in columns (i)–(p) in Table 11.

Columns (a) and (b) show that the coefficient on HHELEC^1 for α is negative but insignificant whether or not a set of covariates is included. Therefore, we do not have evidence that contradicts eq. (3). As columns (c) and (d) show, the coefficient for I is positive and significant. Therefore, eq. (4) holds empirically.

Columns (e) and (f) show that $l' > 0$ is empirically satisfied whereas columns (g) and (h) show that $c' > 0$ is empirically satisfied. Because the results presented in Section 6 indicate that $n' < 0$ holds empirically, the predictions about the signs of l' and c' in Proposition 1 are satisfied, whether or not we control for a set of covariates.

Columns (a)–(h) only report OLS results because the null hypothesis that HHELEC^1 is exogenous cannot be rejected at the conventional levels of significance in the GMM-IV regressions (unreported) with a set of covariates for all dependent variables except for c, where HHELEC^1 is instrumented by the age and system loss from the grid for each PBS. The OIR test shows that the instrumental variable is not valid for c, even though the coefficient on HHELEC^1 remains positive and significant. This may be because the instrumental variables may be conditionally correlated with electricity-related expenditures.

As the comparison between Columns (a)–(h) and columns (i)–(p) indicate, the results generally do not change qualitatively even when we include the households with $\alpha = 0$. Therefore, the results in Table 11 provide empirical support for eqs. (3) and (4) as well as Proposition 1

Appendix C: Additional Tables

Table 12 provides the same set of summary statistics as those reported in Table 1 but only for panel households. Table 13 and 14 are the same as Table 5 except that the error is clustered at the village level in Table 13 and the subdistrict-specific fixed-effects terms are included in Table 14. Tables 16 and 17 are the Poisson analogues of Tables 2 and 3, respectively. Table 18 is the same as Table 10 except that the former includes the fixed-effects terms at the divisional level.

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
Hours of TV watched 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, depending on the survey round and electrification status.

Table 13: Results for parsimonious specifications with clustered errors at the village-level.

Dependent Variable: ΔNCHILD	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
$\mathbf{1}(\text{NCHILD}^1 \geq 1)$					-0.990 ***			
					(0.084)			
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 1)$					-0.100 **			
					(0.042)			
$\mathbf{1}(\text{NCHILD}^1 \geq 2)$				-0.307 ***		-0.343 ***		
				(0.072)		(0.065)		
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 2)$				-0.216 *		-0.130 ***		
				(0.115)		(0.048)		
$\mathbf{1}(\text{NCHILD}^1 \geq 3)$							0.375 ***	
							(0.077)	
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 3)$							-0.150 **	
							(0.072)	
$\mathbf{1}(\text{NCHILD}^1 \geq 4)$								0.627 ***
								(0.088)
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 4)$								-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: OLS estimation for all columns. 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.

Table 14: Results for parsimonious specifications with sub-district-level fixed-effects.

Dependent Variable: ΔNCHILD	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
$\mathbf{1}(\text{NCHILD}^1 \geq 1)$					-0.790 ***			
					(0.084)			
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 1)$					-0.088 **			
					(0.041)			
$\mathbf{1}(\text{NCHILD}^1 \geq 2)$				-0.196 **		-0.235 ***		
				(0.076)		(0.065)		
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 2)$				-0.205 *		-0.112 **		
				(0.123)		(0.047)		
$\mathbf{1}(\text{NCHILD}^1 \geq 3)$							0.287 ***	
							(0.070)	
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 3)$							-0.123 *	
							(0.067)	
$\mathbf{1}(\text{NCHILD}^1 \geq 4)$								0.427 ***
								(0.090)
$\text{HHELEC}^1 \times \mathbf{1}(\text{NCHILD}^1 \geq 4)$								-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: OLS estimation for all columns. The fixed-effects terms for each of the 173 sub-districts are included in each model. Robust standard errors in the brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively.

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

Dependent Variable: ΔNCHILD	(a)		(b)		(c)		(d)		(e)	
HHELEC^1 × $\mathbf{1}$(NCHILD^1 ≥ 2)	-2.874	**	-2.952	*	-2.379	**	-2.809	**	-0.040	
	(1.216)		(1.605)		(0.965)		(1.359)		(0.046)	
$\mathbf{1}$(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 watched 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: † denotes that the regressor is rescaled by dividing by 100. A constant term is included in each regression (not reported). Robust standard errors in the brackets. Statistical significance at 10, 5, and 1 percent levels are denoted by *, **, and ***, respectively. HHELEC^1 and its interaction terms are instrumented by the age and system loss from the grid for each PBS.

Table 16: 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 the brackets. 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 the age and system loss from the grid for each 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 17: 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 $\times$ $\mathbf{1}(\text{NCHILD}^1 \geq 1)$			-2.470	***						
			(0.489)							
HHELEC $\times$ $\mathbf{1}(\text{NCHILD}^1 \geq 2)$					-0.699	***				
					(0.085)					
HHELEC $\times$ $\mathbf{1}(\text{NCHILD}^1 \geq 3)$							-0.320	***		
							(0.042)			
HHELEC $\times$ $\mathbf{1}(\text{NCHILD}^1 \geq 4)$									-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 included 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 18: Bivariate probit-ordered-probit regression results with fixed effects at the divisional level.

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	0.009		(0.028)	-0.034		(0.056)	0.107		(0.071)
Head's age	0.042	***	(0.014)	0.046	**	(0.019)	0.056		(0.046)
Head's age squared†	-0.040	***	(0.015)	-0.030		(0.019)	-0.064		(0.058)
Spouse's age	-0.004		(0.016)	-0.057	*	(0.030)	0.025		(0.063)
Spouse's age squared†	0.020		(0.023)	0.077	*	(0.041)	-0.017		(0.103)
Head has some primary education	0.284	***	(0.030)	0.120	**	(0.059)	0.439	***	(0.076)
Head has some lower secondary education	0.054	*	(0.030)	0.071		(0.059)	0.035		(0.077)
Head has some matric education	0.049		(0.032)	-0.018		(0.068)	0.065		(0.088)
Spouse has some primary education	0.251	***	(0.029)	0.261	***	(0.058)	0.322	***	(0.074)
Spouse has some lower secondary education	0.077	***	(0.029)	0.110	*	(0.057)	-0.059		(0.073)
Spouse has some matric education	0.046		(0.037)	0.076		(0.078)	0.107		(0.101)
log (HH expenditure per capita)	0.311	***	(0.031)	0.233	***	(0.048)	0.304	***	(0.077)
Age of PBS	0.015	***	(0.002)	0.016	***	(0.006)	0.020	**	(0.008)
System loss of PBS	0.003		(0.004)	-0.004		(0.009)	0.023	*	(0.012)
Dep var for ordered-probit model	NCHILD			NCHILD			ΔNCHILD		
HHELEC	-1.005	***	(0.055)	-0.859	***	(0.162)	-0.264		(0.249)
NCHILD							-0.488	***	(0.027)
Ratio of boys among children	-0.035	*	(0.021)	-0.193	***	(0.043)	-0.161	***	(0.059)
Head's age	0.062	***	(0.011)	0.054	***	(0.016)	-0.037		(0.039)
Head's age squared†	-0.041	***	(0.012)	-0.042	***	(0.016)	0.050		(0.051)
Spouse's age	0.187	***	(0.014)	0.221	***	(0.027)	0.053		(0.051)
Spouse's age squared†	-0.194	***	(0.020)	-0.229	***	(0.037)	-0.086		(0.084)
Head has some primary education	0.153	***	(0.026)	0.008		(0.048)	0.004		(0.074)
Head has some lower secondary education	0.040		(0.025)	0.025		(0.047)	-0.078		(0.067)
Head has some matric education	0.040		(0.026)	-0.032		(0.053)	0.009		(0.072)
Spouse has some primary education	0.043	*	(0.025)	0.029		(0.051)	0.128	*	(0.067)
Spouse has some lower secondary education	-0.030		(0.023)	-0.087	*	(0.046)	-0.022		(0.062)
Spouse has some matric education	-0.073	***	(0.028)	-0.141	**	(0.058)	-0.079		(0.079)
log (HH expenditure per capita)	-0.423	***	(0.031)	-0.205	***	(0.046)	-0.407	***	(0.071)
κ_1	2.341		(0.182)	2.689		(0.392)	-6.272		(0.701)
κ_1	3.020		(0.184)	3.460		(0.405)	-5.726		(0.689)
κ_1	3.877		(0.186)	4.511		(0.422)	-5.218		(0.687)
κ_1	4.600		(0.189)	5.305		(0.434)	-4.603		(0.687)
κ_1	5.177		(0.192)	5.908		(0.443)	-2.673		(0.680)
κ_1	5.649		(0.195)	6.429		(0.451)	-1.544		(0.676)
κ_1	6.078		(0.198)	6.919		(0.458)	-0.798		(0.673)
κ_1	6.457		(0.201)	7.267		(0.462)	-0.157		(0.675)
ρ	0.624		(0.037)	0.491		(0.103)	0.104		(0.150)
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.