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(Citation)
GSICS Working Paper Series,36:1-32

(Issue Date)
2020-01

(Resource Type)
technical report

(Version)
Version of Record

(URL)
https://hdl.handle.net/20.500.14094/81011975

GSICS Working Paper Series

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No. 36

January 2020

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Cooperation Studies
Kobe University

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Abstract

We analyze the effect of electrification on changes in employment structure in Cambodia, which is still in early stage of electrification and structural change. In our analysis, we aim to examine the movement out of agriculture by looking into different categories of nonagricultural employment: nonagricultural self-employment, nonagricultural wage employment and nonagricultural unpaid workers. In order to mitigate the problem of non-random placement of electricity, we use the inverse probability of treatment weighting regression adjustment (IPWRA) method to conduct two different estimations, one with individual-level repeated cross-section data and another with district-level panel data, taking advantage of large and representative sample from the Cambodia General Population Census in 1998 and 2008. We found that the movement out of agriculture is dominated by non-farm self-employment activities. Access to electricity increases nonagricultural self-employment of both men and women by 10-12 percentage points. We also confirm a lack of external effects of electrification in rural Cambodia possibly due to low electrification rates among rural households.

Key words – electrification, self-employment, wage employment, doubly robust, difference-in-difference, rural Cambodia

Declarations of interest: none

1. Introduction

Electricity is considered one of the basic necessities for most people in the developed world, whereas in developing countries, millions of people still lack access to electricity. The U.S. Energy Information Administration (2013) estimated that approximately 1.3 billion people (i.e., 19% of the world's population) did not have access to electricity in 2010. Recent studies on various developing countries provide evidence of positive effects of electricity on household income and education of children (Chakravorty, Pelli, & Marchand, 2014; Khandker, Barnes, & Samad, 2012, 2013; Khandker, Samad, Ali, & Barnes, 2014; Lipscomb, Mobarak, & Barham, 2013; Litzow, Pattanayak, & Thinley, 2019; Saing, 2018; van de Walle, Ravallion, Mendiratta, & Koolwal, 2017). But these studies provide no direct evidence on how electrification improves income and education.

One important pathway leading to higher income and more education is changes in occupation to jobs with higher earnings and diversification of income sources. However, previous literature regarding the effects of electrification on employment structure in developing countries is still inconclusive (Dinkelman 2011; Grogan and Sadanand 2012; Akpandjar and Kitchens 2017; van de Walle et al. 2017; Rathi and Vermaak 2018).

In this study, we analyze the effect of electrification on changes in employment structure in Cambodia, which is still in early stage of electrification and structural change. Cambodia ranks lowest in terms of per-capita income among the countries analyzed in the previous literature on electrification and employment. Hence the demand for non-food items is still limited. Cambodia also experienced three decades of the civil war (from 1968 to 1998), and needs to start electrification from the very low level of electricity access (with 5.4% in rural area in 1998). Investigation of initial progress of electricity expansion in Cambodia would provide important clue to understand how electricity begins to benefit welfare of people in other low-income countries.

In our analysis, we aim to examine the movement out of agriculture by looking into three types of nonagricultural employment: nonagricultural self-employment, nonagricultural wage employment and nonagricultural unpaid workers. Understanding such structural changes in the labor market is important because non-farm employment plays a vital role in lifting people out of poverty. Recent research, including Lanjouw and Shariff (2004), Olugbire et al. (2011), and Seng (2015), has shown that participation in the rural non-farm sector substantially increases incomes and reduces vulnerability of farm households in rural areas in developing countries including Cambodia. In addition, by looking further into nonagricultural self-employment and unpaid employment, we aim to provide evidence on the important contributions of informal sector in the rural economy.

Estimating the effects of electrification can be challenging as it is clear that access to electricity is not randomly placed but chosen by households. In order to mitigate the problem of non-random placement of electricity, we use the inverse probability of treatment weighting regression adjustment (IPWRA) method to conducts two different estimations, one with individual-level repeated cross-section data and another with district-level panel data. By comparing the results of individual-level and district-level analyses, we can also capture the extent of the external effects of rural electrification.

Our estimation results show that the movement out of agriculture is dominated by non-farm self-employment activities. Access to electricity increases nonagricultural self-employment of both men and women by 10-12 percentage points. We also confirm a lack of external effects of electrification in rural Cambodia possibly due to low electrification rates among rural households.

In the next section, we give a brief background of electricity development in Cambodia, which is followed by review of literature in Section 3. Section 4 outlines empirical strategies. Explanation of the data is presented in Section 5. Section 6 discusses empirical results, and Section 7 concludes.

2. Background of Electricity Development in Cambodia

After suffering from 3 decades of civil war (1968-1998), Cambodia's infrastructure including electricity was in disarray. During the Khmer Rouge regime (1975-1979), all kinds of electricity facilities, including generation, transmission and distribution systems, were destroyed. After peace and stability were restored in 1998, the Electricity Law of the Kingdom of Cambodia was promulgated in 2001 with the objective of establishing a framework for all operations involving electric power supply and services throughout Cambodia (EAC, 2004). One of the most important features of the law was "the principles for the promotion of private ownership of the facilities for providing electric power services", aiming to attract private investors to participate in Cambodia's ongoing power sector development (EAC, 2004, p. 6).

Nowadays, electricity generation and distribution in Cambodia are run by both state-owned and private enterprises. A government-owned company named Electricité du Cambodge (EDC) and private independent power producers (IPPs) supply power in the city and provincial towns, while private Rural Electricity Enterprises (REEs or licensees) supply power in rural areas.[1]

According to the Electricity Authority of Cambodia (2009), in 2008 Cambodia imported approximately 20% of its total electricity supply from Vietnam and Thailand. The main sources of electricity generation in Cambodia in 2008 were diesel/heavy fuel oil (HFO) (95%), hydropower (3.12%), coal (1.57%), and wood/biomass (0.31%). As a result of low capacity, high fuel price and imports, electricity costs in Cambodia are quite high, especially in rural areas. The electricity tariff charged by private electricity providers are generally higher than the tariffs charged by the EDC. In 2008, the electricity tariff of the EDC ranged between 0.16 and 0.31 USD per kWh, while the electricity tariff of private electricity providers ranged from 0.38 to 0.90 USD per kWh (EAC, 2009). In response to fluctuation in diesel and HFO prices, the EAC has introduced a Fuel Cost Adjustment (FCA) mechanism in which the tariff to be used by licensees is determined and fixed after the process of public consultation (EAC, 2009, p. 32).

The current policies which support the involvement of the private sector and import of electricity from neighboring countries may be deemed appropriate for the current situation of Cambodia whose power sector still has limited capacity; however, these policies accompany significant disadvantages including high tariff rates and less-populated areas being left out without electricity. As stated by the International Energy Agency (2017), “one of the key elements that hamper the extension of electricity access is the issue of affordability” (p.105). Therefore, in order to promote the expansion of electricity, especially in rural areas, the electricity tariff should be affordable. Furthermore, affordability can also determine whether and how much electricity is consumed among low-income households. Similarly, for enterprises, high electricity prices would increase production cost, resulting in loss of competitiveness of the business. Therefore, the government has been increasing power generation capacity through hydropower and coal-fired plant projects in order to improve self-sufficiency and efficiency of the power supply (EDC, 2016).

Although the electricity sector in Cambodia has been making progress in terms of area coverage, the proportion of electrified households is still very low compared to other countries in the region. As shown in Table 1, the average electrification rates in Cambodia were the lowest among the ten ASEAN countries in 1998 and 2008. Table 2 shows the differences in the share of electrified households in urban and rural areas in 1998 and 2008. Approximately, 13.10% of rural households had access to electricity in 2008, up from 5.42% in 1998. The average electrification rates are much higher in urban areas, where the rates were 62.83% and 87.04% in 1998 and 2008, respectively (NIS, 2009).

Table 1. *Electrification rate among ASEAN countries (% of population).*

Countries	**1998**	**2008**
Brunei	100.0	100.0
Cambodia	18.7	26.4
Indonesia	80.9	92.7
Lao PDR	37.4	66.0
Malaysia	N.A.	99.3 *[1]
Myanmar	47.0*[2]	50.5
Philippines	71.3	83.3
Singapore	100.0	100.0
Thailand	82.1*[3]	95.5
Vietnam	83.9	95.2

Notes: Data for Malaysia in 1998 is not available.

*[1] Data in 2009.

*[2] Data in 2002.

*[3] Data in 2000.

Source: World Development Indicators (2019).

Table 2. *Share of electrified households by region in 1998 and 2008.*

	Year	**Number of Households**	**Electrified Households (%)**
Rural	1998	1,797,505	5.42
	2008	2,311,058	13.10
Urban	1998	364,581	62.83
	2008	506,579	87.04
Total	1998	2,162,086	15.11
	2008	2,817,637	26.39

Note: Electricity category includes city power, generator and both.

Source: NIS (2009).

3. Literature Review

There are many previous studies which investigate the effects of electricity expansion in developing countries. Most studies examine effects on poverty and/or children's education (Chakravorty, Pelli, & Marchand, 2014; Khandker, Barnes, & Samad, 2012, 2013; Khandker, Samad, Ali, & Barnes, 2014; Lipscomb, Mobarak, & Barham, 2013; Litzow, Pattanayak, & Thinley, 2019; Saing, 2018; van de Walle, Ravallion, Mendiratta, & Koolwal, 2017), and find positive effects. However, results on employment structure have been mixed (Akpandjar & Kitchens, 2017; Dinkelman, 2011; Grogan & Sadanand, 2012; Rathi & Vermaak, 2018; van de Walle et al., 2017).

Both Dinkelman (2011) and Grogan and Sadanand (2012) find positive significant effects of rural electrification on female employment, but not on male employment, in South Africa and Nicaragua, respectively. Dinkelman (2011) provides evidence that electrified areas have shown increase in the use of electric lighting and electric appliances for cooking along with the reduction in the use of wood-fueled cooking. With the use of electricity for home production, South African women are able to work outside the home or run their own micro enterprises. Grogan and Sadanand (2012) find that electrified households in rural Nicaragua spend less time in firewood collection as households are able to work longer hours with the availability of electricity. The authors suggest that extra income generated from longer working hours enable households to buy firewood instead of collecting it. Compared to South Africa, the use of household electric appliances is not as prevalent among rural Nicaraguan households.

Contrary to the findings above, van de Walle et al. (2017) report that electrification enables men to shift from casual wage work to regular wage work, while such change is not found for women in India. While electrification may enable the use of electric stoves and other time-saving appliances in South Africa, rural Indian households continue to use bio-fuels and firewood for cooking, and continue to rely on kerosene for lighting along with electricity (Mathur & Mathur, 2005; Rehman et al., 2005, as cited in van de Walle et al., 2017). In addition, the social norms in India which prevent women from working outside the home may also explain the results found by van de Walle et al. (2017).

The study in India by van de Walle et al. (2017) also finds no significant effects of electrification on agricultural and nonagricultural self-employment of both men and women. On the other hand, Akpandjar and Kitchens (2017) find that access to electricity can lead to increases in small businesses, wage-earning occupation, skill composition, and decreases in agricultural employment for both men and women in Ghana.

The findings of a recent cross-country analysis by Rathi and Vermaak (2018) reveal some major differences from previous studies which focused on the same country. The authors find that access to electricity in India increases paid employment for women, while it decreases paid employment for men. The authors explain that access to modern technology via electricity frees up women's time from household chores to income generating activities. On the other hand, men may drop out of the labor force as a result of extra earning from female members. The authors also stated that male farmers might withdraw from their secondary jobs as a result of improved agricultural productivity when electric pump sets are used.

These findings by Rathi and Vermaak (2018) seem to be contradictory to those of van de Walle et al. (2017) who find that electrification in India releases male labor supply from leisure and casual wage work to regular wage work, while such effect is not found for women. In South Africa, Rathi and Vermaak (2018) find that access to electricity increases the probability of being employed for both men and women; however, the effect is not statistically significant at conventional levels. The authors explained that even if electrification may enable people to have more time for income generating activities as suggested by Dinkelman (2011), the employment does not increase due to South Africa's lack of labor absorptive capacity. Nonetheless, it should be noted that the findings of Rathi and Vermaak (2018) focus primarily on paid employment. Although rural electrification might not translate into wage employment, the time saving effects of electrification can result in self-employment activities in the form of home-based microenterprises as suggested by previous studies.

Although the countries examined in the previous studies are all developing countries, they are located in different continents with different levels of income. The mixed findings shown in previous studies hint that the pathways between rural electrification and employment structure are specific to each country's context. From the review, we hypothesize three possible mechanisms of how electricity access changes employment structure. First, electricity access changes the pattern of time use, due to less time required to collect firewood, use of time-saving electrical appliances for household chores, or use of agricultural machineries. Another mechanism can work through access to information by watching TV or access to Internet. This mechanism was not investigated in previous studies, probably because it is more relevant for migrant work and participation in market transaction. Use of electricity may also provide an incentive to local or foreign entrepreneurs for setting up new mechanized factories in rural areas, which provide new employment opportunity. Which of the three mechanisms dominates the process of structural change depends on the extent of electricity access and its quality, income level and demand structure, economic and institutional environment and policies of the country.

In Cambodia, income level is still low and electrification is still limited in rural areas. With problems of high cost and low quality of electricity, expansion of wage employment opportunity cannot be expected to happen in rural Cambodia. Thus the main channels of changes in employment structure in rural areas must be flexible use of work time and better access to information. Under such circumstances, we hypothesize that family-based small-scale business such as grocery stores or tea shops provides main sources of new work opportunity brought about by electricity access in rural areas. We expect that non-farm self-employment and unpaid family worker are the categories of employment to expand through rural electrification, which we empirically examine below.

4. Empirical Strategies

First, we estimate the effect of electrification on employment in different categories by using pooled cross-section data at the individual level. The estimation equation is

$$Y_{idt} = \boldsymbol{X}'_{idt}\boldsymbol{\beta} + \gamma Z_{idt} + \theta_{dt} + \varepsilon_{idt} \qquad (1)$$

where Y_{idt} is a dummy variable for different category of employment for individual i in district d in year t, $\boldsymbol{X}_{idt}$ is a vector of individual and household characteristics, Z_{idt} is a dummy for electricity connection, θ_{dt} is a district-year fixed effect, ε_{idt} is an error term, and $\boldsymbol{\beta}$ and γ are parameters to be estimated. The household characteristics include dummy variables of house ownership, living in a house with three rooms or more, having toilet and having access to piped water. The individual characteristics include age, age squared, years of education, and years of education squared, a female dummy, dummy variables of marital status (married, divorced, and widowed), dummy variables of religion (buddhist, muslim, and Christian) and a vector of birth-cohort fixed effects.[4] A vector of birth cohort fixed effects can control for common events or shocks experienced by people in the same age groups. For instance, political turmoil, natural disasters and economic shocks can halt or slow down the process of electrification in Cambodia. These kinds of events have a different effect on different age cohorts, for instance, between those still in school and those who just reached working age.

The effect of electrification on employment is estimated by the coefficient γ by OLS if electrification Z_{idt} is exogenous to other factors affecting employment choice. Obviously such exogeneity assumption cannot be supported. Even with the availability of an electricity grid within a village, households make their own decision whether to acquire connection to electricity or not. Furthermore, as stated by Saing (2018), one of the primary objectives of electricity development in Cambodia is to extend the existing grid (and off-grid) supply network of the EDC and REEs. Therefore, communities located close to those already electrified are more likely to become connected. Moreover, the government has encouraged the private sector to invest in providing electricity services in rural areas since 2001 (EAC, 2004). Naturally, private investors choose to invest in areas with relatively high income levels and potential for future economic development. Therefore, electricity grids are more likely to become available for relatively more developed rural communities, indicating the absence of random electricity placement.

In order to deal with the endogeneity problem, some of previous studies used an instrumental variable (IV) approach. The instrumental variables which were employed in previous studies include land gradient (Dinkelman, 2011; Duflo & Pande, 2007; Grogan & Sadanand, 2012), distance to electricity line (Khandker et al., 2012), and proportion of electrified households in the area (Khandker at al., 2014). However, it is questionable whether these instrumental variables can be valid instrumental variables to apply in the case of Cambodia. First, land gradient can be associated with agricultural productivity and agricultural employment growth in Cambodia as the majority of rural Cambodians (84.9%) are involved in agriculture, fishing and forestry. Second, the placement of electricity lines can be endogenous since they are more likely to be placed through economically active areas where there are relatively higher income households. This is especially applicable to the case of rural Cambodia, where electricity is run by private enterprises with the aim of maximizing profits. Similarly, the high proportion of electrified households in the community would create spillover effects of electrification to the whole community through greater employment opportunities or general equilibrium price effects, which might violate the exogeneity assumption for a valid IV, as observed in the paper of van de Walle et al. (2017).

As any of the IVs is not appropriate in the case of Cambodia, we implement two estimation strategies to assess the effects of rural electrification on employment structure in Cambodia. The first method is the inverse probability of treatment weighting regression adjustment (IPWRA) to estimate equation (1) with pooled cross-section individual-level data. The second estimation takes advantage of representative nature of our samples, and constructs a district-level panel data with average characteristics in each district. Then, we estimate the modified version of equation (1) by method combining difference-in-differences and inverse probability of treatment weighting regression adjustment (DID-IPWRA). We will explain details of each estimation strategy in turn.

4.1 Individual-level analysis

The inverse probability of treatment weighting (IPW) method uses weights based on the propensity score to create a synthetic sample in which the distribution of observed covariates is independent of electricity access (Austin, 2011). Weights are given by $w_i = \frac{Z_i}{p_i} + \frac{1-Z_i}{1-p_i}$, where p_i is the propensity score of individual i and z_i is an indicator of individual i belonging to the treatment group. In our estimation, the treatment group is defined to be those with access to electricity. Thus, individuals in electrified households are given the weight of $w_i = \frac{1}{p_i}$, while individuals in non-electrified households are given the weight of $w_i = \frac{1}{1-p_i}$.

First, we need to estimate the propensity score, p_{idt}, of individual i in district d in time t, which can be written as:

$$p_{idt} = Pr\,(Z_{idt} = 1 \mid \boldsymbol{V}_{idt}\,, \theta_{dt}), \qquad 0 < p_{idt} < 1. \qquad (2).$$

In our specification, $\boldsymbol{V}_{idt}$ represents individual and household characteristics including birth cohort fixed effects. θ_{dt} is a vector of district-year fixed effects to capture shocks common to individuals living in a particular district in a particular year. District-specific time trends can partially control for the possibility of simultaneous changes in other factors, such as changes in other types of infrastructure, affecting electricity access over the decade.

Table 3 reports the results of the logit estimation of the propensity score, while table A1 in the appendix presents summary statistics of variables used in our individual-level estimations. Validity of the propensity score method depends on the conditional independence assumption (CIA), requiring that outcomes are independent of treatment assignment conditional on the propensity scores (Rosenbaum and Rubin, 1983). In order to check whether the CIA is valid in our specification, we provide balancing tests before and after implementing the propensity score weighting later in table 5.

Hirano and Imbens (2002) have explored the method of combining weighting based on the propensity score with regression adjustment to allow for a flexible specification of both the propensity score and the regression function. Subsequent research called the combination method "doubly robust estimator" by proving that only one of the two models need to be correctly specified in order to obtain a consistent estimator (Funk et al., 2011; Vansteelandt & Daniel, 2014; Waernbaum, 2012). Therefore, our study utilizes the doubly robust estimator or the inverse probability of treatment weighting regression adjustment (IPWRA) to further reduce the possibility of model misspecification.

The functional form for the conditional expectations is assumed to be linear and was shown above in equation (1), which we reproduce here:

$$Y_{idt} = \boldsymbol{X}'_{idt}\boldsymbol{\beta} + Z_{idt}\gamma + \theta_{dt} + \varepsilon_{idt} \qquad (1).$$

It should be noted that $\boldsymbol{X}_{idt}$ in equation (1) is different from $\boldsymbol{V}_{idt}$ in equation (2). While the $\boldsymbol{V}_{idt}$ in equation (2) aims to capture the treatment assignment, the $\boldsymbol{X}_{idt}$ in equation (1) aims to control for factors influencing the outcomes. Specifically, the vector $\boldsymbol{X}_{idt}$ additionally includes the number of children aged less than 5 years old.

Table 3. *Logit regression to estimate propensity score (treatment = electrified households).*

Variables	**Coefficient**	**Standard Error**
Household Characteristics		
Toilet	1.7690***	0.0085
Piped water	1.8887***	0.0146
House with 3 rooms or more	0.7390***	0.0150
Own the house	-1.1858***	0.0177
Household size	0.0384***	0.0018
Individual Characteristics		
Years of schooling	0.0871***	0.0035
Years of schooling squared	0.0024***	0.0003
Age	0.0536***	0.0078
Age squared	-0.0005***	0.0001
Female gender	0.0552***	0.0085
Married	-0.1905***	0.0134
Divorced	-0.1896***	0.0304
Widowed	-0.2297***	0.0260
Buddhist	0.1837***	0.0568
Muslim	0.8422***	0.0623
Christian	1.0634***	0.0806
Birth-cohort fixed effects	Y	
District-specific time trends	Y	
Treatment	84,974	
Controls	720,526	
Number of observations	805,500	
Pseudo R-squared	0.2155	
Log likelihood	-212959.42	

Note: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.2 District-level analysis

The second estimation uses district-level panel data, constructed from individual observations by calculating average characteristics in each district. Analyzing the effect of electrification on employment structure at the district level enables us to capture the external effects of electrification. As explained by van de Walle et al. (2017), external effects of household electrification include shared lighting, safer streets, changing social norms, and general equilibrium effects on wages and employment opportunities. By examining both individual and district-level estimates, Akpandjar and Kitchens (2017) find that the effects of electrification at the district-level are larger than individual-level estimate because of external effects of electrification.

With the constructed panel data at the district level, we can also improve upon our individual-level analysis by incorporating DID to the IPWRA method in order to account for potential time-invariant unobservable factors such as social norms of female outside employment. Following Akpandjar and Kitchens (2017), after aggregating the individual-level data to the district level, we define treatment and control districts as those whose relative increase in the share of households with electricity between 1998 and 2008 was in the top and bottom quartile, respectively.

Let p_d be the propensity score of district d, and we estimate the propensity score by the following equation:

$$p_d = Pr\,(Z_d = 1 \mid \boldsymbol{V}_d), \qquad 0 < p_d < 1 \qquad (4)$$

where Z_d is a dummy variable for the treatment district. In our propensity score specification, $\boldsymbol{V}_d$ consists of the variables measured in the base year (1998): average share of households (within the district) with a toilet, with piped water, with 3 rooms or more, average share of households that own the house, average household size, average years of education, average years of education squared, sex ratio, natural log of district population, natural log of distance to nearest provincial town, a dummy indicating districts located along the border, a dummy indicating districts located in mountainous or plateau areas, and the share of electrified households in the base year. We include the share of electrified households in the base year because it can be negatively correlated with the variable indicating the relative increase in electrification. Districts with a low level of electrification in the base year—which are likely to be under-developed—tend to show a higher increase in the percentage share of electrified households.

Our outcome specification (regression adjustment model) follows the DID framework. Since we have only two time periods, we estimate the following first-differenced equation:

$$\Delta Y_d = \Delta \boldsymbol{X}'_d \boldsymbol{\beta} + Z_d \gamma + \Delta \varepsilon_d \qquad (5),$$

where ΔY_d is the change in the share of different categories of employment in district d between 1998 and 2008, Z_d is the dummy variable for treatment districts [5], $\Delta \boldsymbol{X}_d$ is the vector of changes in several district characteristics between 1998 and 2008, which include average share of households with a toilet, average share of households with piped water, average share of households with 3 rooms or more, average share of households that own the house, average household size, average years of formal schooling, average years of formal schooling squared, sex ratio, natural log of district population, average age of adults, average age of adults squared, average share of elderly aged 60 years old or older, average share of individuals with infants aged less than 5 years old, and the variables capturing shares of bdifferent types of marital status and religions. It should be noted again that $\boldsymbol{X}_d$ in equation (5) is different from $\boldsymbol{V}_d$ in equation (4). While the $\boldsymbol{V}_d$ in equation (4) aims to capture the treatment assignment, the $\boldsymbol{X}_d$ in equation (5) aims to control for factors influencing the outcomes. From the weighted regression results separately estimated for treatment and control groups, we predict $\hat{Y}_{1d}$ and $\hat{Y}_{0d}$ by the predicted values of the corresponding estimated model, and the average differences give an estimate of the average effect of electrification.

5. Data

This study employs the 10% representative sample of the Cambodian General Population Census conducted in 1998 and 2008, obtained from IPUMS-International.[6] Cambodia has conducted three population censuses since the first democratic election in 1993; however, the results of the census in 2019 have not yet been published. The number of observations in each census is 223,518 households (or 1,141,254 individuals) in 1998 and 289,562 households (or 1,340,121 individuals) in 2008, respectively.

The smallest administrative area identified in these data is district. There are 161 districts contained in the 1998 census data, while 168 districts are included in the 2008 census data.[7] The increase in the number of districts is a result of the Royal Sub-decree on Administrative Area change issued in January 2008, wherein 7 districts were created and the borders of certain districts were changed.[8] As a result of the Royal Sub-decree on Administrative Area changes, Koh Kong province (3 districts), Preah Sihanouk province (3 districts), and 18 other rural districts have to be excluded from the analysis.[9]

Besides analyzing repeated cross-section of individual-level data, we also constructed a panel dataset of district aggregate variables using the censuses. Additional data from another source was added: distance to the provincial town measured by using Distance Calculator.[10]

The two censuses employed different definitions of urban areas. In the 1998 census, urban areas included provincial town (whole district) of each province, four districts of Phnom Penh Municipality, and the entire town of Sihanoukville, Kep and Pailin. In the 2008 census, urban areas were identified using commune-level data: "(a) Population density exceeding 200 per km^2 (b) Percentage of male employment in agriculture below 50 percent (c) Total population of the commune should exceed 2,000" (NIS, 2009). As our analysis focuses on rural areas, we have to either convert the 1998 census or the 2008 census to use the same definition of urban areas for comparison purposes. As this study employs both individual and district-level analysis, the definition classifying the whole district into urban or rural area is more preferable for our purposes. Therefore, we decided to use the 1998 census's definition of urban areas. Besides, the commune-level data is not available to enable us to employ the definition of the 2008 census. We also decided to exclude the 3 districts in Phnom Penh Municipality which the 1998 census classified as rural without using any specific rules.[11] After considering these factors, a total of 34 districts and 23 provincial towns were excluded from the sample, leaving 111 rural districts for the sample of our analysis.

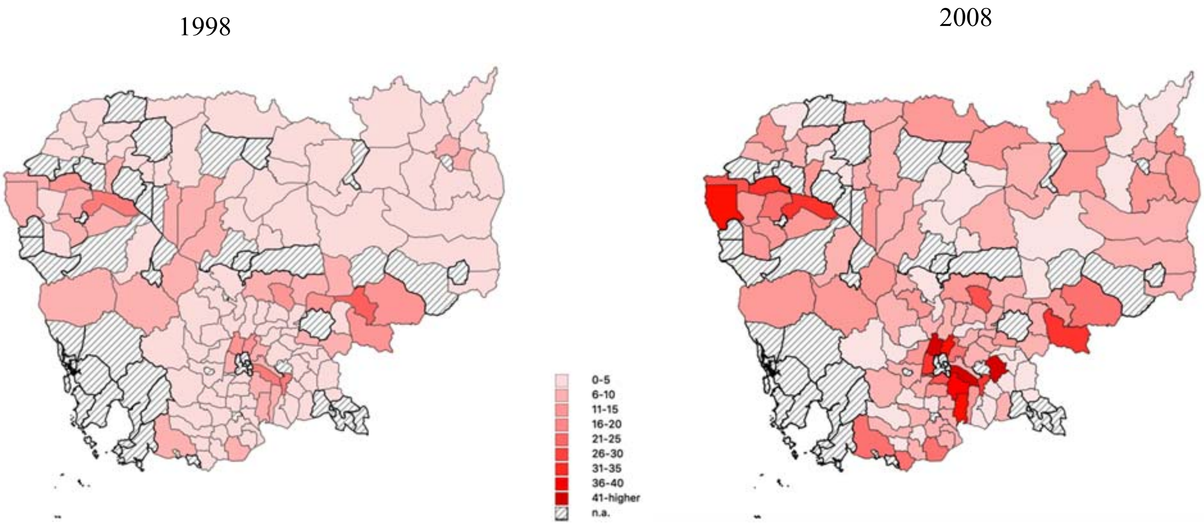

Figure 1. *District-level electrification rates in rural Cambodia in 1998 and 2008*

Notes: The numbers represent the proportion (%) of electrified households in each district. The areas without a line pattern are in the analysis. The areas with the line pattern represent urban districts and the districts whose areas were changed as a result of the Royal Sub-decree on Administrative Area changes in 2008, which are excluded from the analysis.

Source: Authors' calculations based on 10% representative samples of Cambodian general population census in 1998 and 2008.

The data available in both censuses include individual characteristics such as age, sex, marital status, religion, education, economic activity, employment sector and migration status. Additionally, the data include information about housing and facilities such as main source of lighting, main source of cooking fuel, main source of drinking water, number of rooms, and toilet. The electricity status is inferred from having electricity as the source of lighting. It should be noted that the number of hours in a day that electricity is available can be different from place to place. In some rural areas, electricity is available 24 hours a day, while in other areas, it is only available from 5PM to 10PM, for instance. However, the information on the duration of the availability of electricity is not available in the census.

We limit the sample to individuals aged 15 years or older as age of 15 is the minimum age for employment in Cambodia in the Labour Law. The retirement age is 60, however, we do not limit the sample to people aged under 60 because older persons can still engage in self-employment and unpaid employment activities. In addition, we restrict the sample to only individuals who are in the labor force which also includes those who are currently unemployed. As our study aims to capture the effects of electrification on employment structure, the main analysis uses individual-level data; however, we also include analysis with limited sample of household heads in the robustness checks section. The main sample of the pooled cross section data of individual-level analysis includes 805,500 individuals, while the main sample of district-level panel data includes 111 districts. In the DID-IPWRA specification, there are 28 districts in the treatment group and another 28 districts in the control group.

6. Empirical Results

6.1 Descriptive statistics

Table 4 compares the characteristics of electrified and non-electrified individuals. The summary statistics in the table show some remarkable differences between electrified and non-electrified households, which are confirmed by simple statistical tests of differences in means. There are significant differences between electrified and non-electrified households in the use of toilet, piped water, years of formal education, and gender. On average, approximately 56% of electrified households have a toilet, while roughly 13% of non-electrified households have a toilet. Similarly, about 18% of electrified households use piped water, while 2% of non-electrified households use piped water. Individuals living in electrified households completed, on average, a 5.6 years of formal education, while those in non-electrified households completed, on average, a 3.5 years of formal education. This result shows that better educated people are more likely to be connected to electricity. In addition, on average, approximately 49% of people with access to electricity are female, while 54% of people without access to electricity are female, reflecting that women are less likely to have connection to electricity than men.

Regarding outcome variables, remarkable differences between people with and without access to electricity are apparent. On average, approximately 89% of people without access to electricity are employed in the agricultural sector, while 52% of people with access to electricity are employed in the agricultural sector. On the other hand, roughly 45% of people with access to electricity are employed in the nonagricultural sector, comparing to 9% of people without access to electricity. In addition, about 20%, 19%, and 6% of people with access to electricity are employed in nonagricultural self-employment, wage employment and unpaid employment, respectively, while roughly 3%, 5%, and 1% of people without access to electricity are employed in these three employment categories, respectively. These results show that people with electricity are more likely to engage in nonagricultural income-generating activities.

Table 4. *Characteristics of electrified and non-electrified households.*

Variables	**1998**	**2008**	**Δ**	**Non-electrified**	**Electrified**	**Δ**
<u>Outcome Variables</u>						
Nonagri total emp	0.103	0.146	0.043***	0.090	0.450	0.360***
Nonagri self-emp	0.047	0.052	0.005***	0.033	0.195	0.162***
Nonagri wage emp	0.045	0.077	0.032***	0.049	0.191	0.142***
Nonagri unpaid emp	0.009	0.017	0.007***	0.008	0.063	0.055***
Agricultural total emp	0.856	0.843	-0.012***	0.887	0.520	-0.367***
<u>Household Characteristics</u>						
Toilet	0.064	0.250	0.186***	0.125	0.561	0.436***
Piped water	0.017	0.049	0.032***	0.018	0.177	0.159***
House with 3 rooms or more	0.031	0.047	0.016***	0.031	0.121	0.090***
Own the house	0.978	0.965	-0.013***	0.976	0.921	-0.055***
Household size	5.601	5.199	-0.402***	5.350	5.528	0.178***
Number of children aged less than 5	0.515	0.355	-0.160***	0.435	0.318	-0.117***
<u>Individual Characteristics</u>						
Years of schooling	3.187	4.107	0.920***	3.498	5.580	2.082***
Age	35.409	36.787	1.378***	36.188	36.340	0.152***
Female gender	0.540	0.525	-0.015***	0.536	0.492	-0.044***
Married	0.711	0.720	0.009***	0.717	0.708	-0.009***
Divorced	0.029	0.022	-0.007***	0.026	0.021	-0.005***
Widowed	0.055	0.043	-0.012***	0.050	0.035	-0.015***
Buddhist	0.969	0.969	0.000	0.970	0.963	-0.007***
Muslim	0.016	0.017	0.001***	0.016	0.027	0.011***
Christian	0.003	0.003	0.000***	0.003	0.006	0.003***

Variables	1998	2008	Δ	Non-electrified	Electrified	Δ
Observations	340,313	465,187		720,526	84,974	
	340,283	465,180		720,500	84,963	

Notes: The lower row in observations represents number of observations for variables: nonagricultural self-employment, nonagricultural wage employment, and nonagricultural unpaid workers. The upper row in observations represents number of observations for the remaining variables.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level

6.2 Econometric analysis

6.2.1 Results of individual-level estimation

As discussed earlier, in order to address the issue of non-random placement of electricity in our sample, the IPWRA method is employed to balance the covariates. Table 5 reports covariate balance summary before and after implementing the propensity score weighting, which includes standardized differences and variance ratio of measured covariates. Different from the simple statistical tests of differences in means in table 4, the standardized difference compares the difference in means in units of the pooled standard deviation and is not influenced by sample size (Austin, 2011).[12]

The standardized differences and variance ratios of measured covariates before weighting are mostly greater than those after weighting, and the propensity score weighting made the standardized differences closer to 0 and variance ratios closer to 1. These results imply that the distributions of all covariates of the two groups—people with and without access to electricity—are similar after weighing.

Table 6 reports the results of individual-level estimation by IPWRA. Each row corresponds to a different outcome variable of employment categories, while each column reports the results of estimation with different sub-samples of interests. Column 1 reports our main analysis which includes all working age individuals to capture the effects of electricity connection on employment among those in the labor force. We examine the results when restricting the sample to only household heads in column 2, different sub-samples of interest such as female and male in columns 3 and 4, respectively. We also test for the potential of selective migration by restricting the sample to only nonmigrants in column 5. Robust standard errors adjusted for clustering at the district level are presented in parentheses.

Table 5. *Covariate balance summary before and after propensity score weighting.*

Covariates	**Standardized difference**		**Variance ratio**	
	Raw	**Weighted**	**Raw**	**Weighted**
Household Characteristics				
Toilet	1.0344	0.0091	2.2438	1.0156
Piped water	0.5553	-0.0031	8.0550	0.9846
House with 3 rooms or more	0.3427	-0.0098	3.5099	0.9553
Own the house	-0.2525	-0.0113	3.1382	1.0630
Household size	0.0788	0.0040	1.1072	1.0182
Individual Characteristics				
Years of schooling	0.6047	-0.0141	1.2794	1.0187
Years of schooling squared	0.5824	-0.0043	2.0317	1.0025
Age	0.0106	0.0142	0.9141	1.0371
Age squared	-0.0061	0.0186	0.8889	1.0552
Female gender	-0.0877	-0.0067	1.0050	1.0007
Married	-0.0206	0.0006	1.0196	0.9993
Divorced	-0.0299	0.0059	0.8281	1.0360
Widowed	-0.0769	-0.0043	0.7022	0.9815
Buddhist	-0.0386	-0.0256	1.2232	1.1425
Muslim	0.0736	0.0222	1.6455	1.1698
Christian	0.0507	-0.0027	2.2156	0.9527

The results in column 1 indicate that electrification had statistically significant and economically large effects on employment structure of the labor market in rural Cambodia. To start with, people with electricity access are 19.75 percentage points less likely to work in agriculture. Relative to the mean of 0.849, access to electricity is associated with a 23% relative decrease in agricultural employment. On the other hand, individuals with electricity access are 18.56 percentage points more likely to work in nonagricultural jobs. Relative to the mean of 0.128 access to electricity is associated with a 145% relative increase in nonagricultural employment.

To explain the movement out of agriculture, we look at different employment categories within the nonagricultural jobs. We find that individuals with electricity access are 11.08 percentage points more likely to engage in nonagricultural self-employment activities. Relative to the mean of 0.05, this suggests that there is a 221% relative increase in nonagricultural self-employment. In addition, it is found that access to electricity increases nonagricultural wage employment by 4.02 percentage points, which is a 63% relative increase. Similarly, we also find that access to electricity increases nonagricultural unpaid employment by 3.41 percentage points, which is a 243% relative increase. By comparing the magnitudes of each estimated coefficient within the category of nonagricultural employment, we confirm that a large portion of the movement out of agriculture is toward self-employment activities, which suggests the importance of growth in nonfarm self-employment in early stage of poverty reduction.

Table 6. *Results of individual-level analysis (IPWRA).*

Outcome Variables	Baseline	All Heads	Females	Males	Nonmigrants
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Agricultural employment	-0.1975***	-0.1928***	-0.1953***	-0.1981***	-0.1799***
	(0.0083)	(0.0079)	(0.0086)	(0.0088)	(0.0084)
Nonagricultural employment	0.1856***	0.1902***	0.1825***	0.1877***	0.1703***
	(0.0077)	(0.0078)	(0.0078)	(0.0084)	(0.0079)
Nonagricultural self-employment	0.1108***	0.1448***	0.1053***	0.1162***	0.1035***
	(0.0051)	(0.0064)	(0.0054)	(0.0057)	(0.0051)
Nonagricultural wage employment	0.0402***	0.0447***	0.0241***	0.0580***	0.0344***
	(0.0033)	(0.0032)	(0.0030)	(0.0044)	(0.0031)
Nonagricultural unpaid workers	0.0341***	0.0005**	0.0526***	0.0131***	0.0321***
	(0.0021)	(0.0002)	(0.0033)	(0.0011)	(0.0021)
Observations (individual)	805,500	327,776	428,105	377,395	740,979
	805,463	327,766	428,093	377,370	740,951

Notes: Robust standard errors clustered at district level are presented in parentheses. The upper row in of observations represents number of observations in regression of agricultural employment and nonagricultural employment, while the lower row represents number of observations in regression of nonagricultural self-employment, nonagricultural wage employment, and nonagricultural unpaid workers.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Columns 2, 3, and 4 present the results when we restrict the sample to only household heads, female adults, and male adults, respectively. Although the overall results are quite similar, it can be seen that the electrification effects on certain employment categories are more concentrated within certain sub-samples. For example, in column 2 where we restrict the sample to only the heads of household, it is found that the magnitude of the coefficient for non-agricultural self-employment is bigger than the baseline, and the magnitude for non-agricultural unpaid workers is smaller than the baseline. Possibly because household heads are likely to be the main income earner, household heads are more likely to be self-employed and unlikely to be employed as unpaid workers. In columns 3 and 4, we find that men are more likely to engage in nonagricultural wage employment than women, while women are more likely to work as nonagricultural unpaid workers than men. On the other hand, the results indicate that the effect of electrification on nonagricultural self-employment are similar between male and female sub-samples in the case of rural Cambodia.

Last but not least, as people can migrate to areas where there are potentials for better employment opportunity, our estimation results may include the effect of the changes in composition of workforce due to migration. In order to address this issue, in column 5, we restrict the sample to only individuals who have been residing in the current locality for more than 5 years. As a result, there are 64,521 people who were dropped from the sample. The results in column 5 are in line with our baseline results, albeit smaller in magnitudes. Nevertheless, the results are qualitatively similar to the baseline specification, indicating that the effect of selective migration is minor and thus is not a threat to our estimating results.

6.2.2 Results of district-level estimation

Table 7 reports the results of district-level analysis, for which we provide estimation results for fixed-effect panel estimation and DID-IPWRA. In the fixed effects specifications, the full panel sample of 111 districts in 2 time periods are used to derive within estimators. The treatment variable in the fixed-effect estimation is the change in the electrification rate of each district over the 2 time periods. In DID-IPWRA specifications, only 56 districts either in the top or bottom quartile are chosen to be in the treated and control groups. Column 1 reports the results of fixed-effect estimation without district-level controls, while in column 2, we include the control variables. Columns 1 and 2 present robust standard errors clustered at district level. Time fixed effects are included in both specifications. Column 3 reports our main findings of the DID-IPWRA method.

Table 7. *Results of district-level analysis (Fixed effects and DID-IPWRA).*

Outcome Variables	**Fixed Effects**		**DID-IPWRA**
	(1)	**(2)**	**(3)**
Agricultural employment	-0.5461*** (0.1548)	-0.1870** (0.0941)	-0.2403*** (0.0029)
Nonagricultural employment	0.5400*** (0.1334)	0.1805** (0.0772)	0.1979*** (0.0020)
Nonagricultural self-employment	0.1391*** (0.0548)	0.0955*** (0.0201)	0.1294*** (0.0072)
Nonagricultural wage employment	0.3735*** (0.0803)	0.0619 (0.0740)	0.0277*** (0.0015)
Nonagricultural unpaid worker	0.0285*** (0.0096)	0.0251*** (0.0091)	0.0248*** (0.0002)
District characteristics	N	Y	Y
Time fixed effects	Y	Y	Y
Observations (district)	222	222	56

Notes: Unit of observation is district-year. The total number of observations in each time period is 111. All regressions are weighted with district population in 1998; standard errors (presented in parentheses) are robust, clustered at district level except in column 3. In the DID-IPWRA model, treatment and control districts are determined as those whose relative increase in share of households with electricity between 1998 and 2008 was in the 75th-100th percentile and 0-25th percentile, respectively. It should be noted that not all households in the treatment districts are electrified, and a small portion of households in the control districts also have electricity access. The mean of the change in the proportion of electrified households in treatment districts is 19.377%, while the mean of the change in the proportion of electrified households in control districts is 0.459%. Thus, the DID-IPWRA results presented in column 3 are adjusted for the change in electrification by 18.918%.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Comparing the coefficients of the fixed effects regressions to the DID-IPWRA, we can see that the direction and magnitude are very similar after adjusting the DID-IPWRA coefficients to the difference in average changes in electrification rates between the treatment and control districts. Column (3) shows that nonagricultural self-employment increases by 12.9 percentage points, nonagricultural wage employment increases 2.8 percentage points, and nonagricultural unpaid worker rises 2.5 percentage points. It should be noted that the coefficient of nonagricultural wage employment in the fixed effects specification in column (2) is much larger in magnitude, but it is not statistically significant at conventional levels.

Moving on to the comparison between individual-level and district-level analyses in Tables 6 and 7, we find that both direction and magnitudes are very similar, which is different from previous studies that indicate greater effects of regional-level analysis as in Akpandjar and Kitchens (2017). As previously mentioned in section 5.2, the stronger effects of electrification in regional-level analysis arise from the external effects of electrification. Our results from both individual and district-level analyses indicate the absence of the external effects of electrification in rural Cambodia. It is understandable as the average proportion of electrified households in the rural districts was only 12.3% in 2008. This level is very low compared to the average of 46.78% in Ghana in the study by Akpandjar and Kitchens (2017).

7. Conclusion

This study uses the Cambodia General Population Census in 1998 and 2008 to investigate the effects of electrification on changes in employment structure in rural Cambodia by using two different estimation strategies: one with individual-level pooled cross-section data and another with district-level panel data. Both estimation methods rely on the inverse probability of treatment weighting regression adjustment (IPWRA) to deal with the problem of endogenous electricity placement. The estimates of all our specifications show consistent results on directions and magnitudes of the effects of rural electrification on employment structure in Cambodia.

One of our main contributions of the study is by looking into the main channel through which electrification affects people's welfare, which is through their employment categories. Specifically, we try to fill the gap in the literature by examining the effects of electrification on employment structure—the outcomes which previous studies show inconclusive findings. Besides categorizing employment structure into agricultural and nonagricultural sectors, we examine the movement out of agriculture by further looking into three types of nonagricultural employment: nonagricultural self-employment, nonagricultural wage employment and nonagricultural unpaid workers. It is important to understand such structural changes in the labor market because non-farm employment plays a vital role in lifting people out of poverty (Lanjouw & Shariff, 2004; Olugbire et al., 2011; Seng, 2015). Additionally, we aim to provide evidence on the important contributions of informal sector, such as self-employment and unpaid employment, in the rural economy during early transition to non-agricultural activities.

We find evidence that rural electrification pulls people out of agricultural employment toward nonagricultural employment by 18-19 percentage points. We also find that the movement out of agriculture is dominated by self-employment activities. Access to electricity increases nonagricultural self-employment of both men and women by 10-12 percentage points, while it increases nonagricultural wage employment and unpaid worker only by 3-4 and 2-3 percentage points, respectively. Thus, in early stage of electrification in rural Cambodia, we confirm that structural changes start from the movement of workforce out of agriculture to non-farm self-employment activities, and such movement is facilitated by rural electrification. We also find no external effects of electrification, which may be the result of low electrification rate in rural Cambodia.

The main policy implication that can be drawn from our findings is the importance of the expansion of electricity in rural Cambodia. Compared to other developing countries, access to electricity in Cambodia is still limited. Therefore, the expansion of electrification access is crucial for long-term rural development as well as poverty eradication in Cambodia. At the same time, the government of Cambodia need to tackle the issues of relatively high cost of electricity, low levels of capacity and unreliability of electricity that can hinder the potential effects of electricity in enabling more income-generating activities. Investigation of how these factors interact to limit rural development and poverty alleviation is a topic for future research.

Notes

1. All the IPPs have their own electricity generation facilities, while some of the REEs purchase electricity from other sources and redistribute it (EAC, 2004).
2. Authors' calculation using a 10% representative sample of census data between 1998 and 2008.
3. Authors' calculation using Cambodian 2011 Economic Census.
4. We group individuals according to their birth year with an interval of 5 years in each birth cohort.
5. The districts in the second and third quartiles are dropped in this method.
6. https://international.ipums.org/international/
7. The number 161 represents the number of districts in the dataset. In several cases, more than one district are combined into one single district.
8. "Many administrative changes were introduced such as re-naming certain provinces and districts, shifting of communes from one district to another within a province, formation of new districts and cities within a province by regrouping communes, shifting of a few communes (wholly and partly) from Koh Kong province to Preah Sihanouk province, and converting province headquarter districts into Krongs" (NIS, 2009).
9. The 18 rural districts include 1 rural district in Phnom Penh city.
10. https://distancecalculator.globefeed.com/Cambodia_Distance_Calculator.asp
11. As a capital city, Phnom Penh has developed quite fast in a way that is exceptional to other provinces. With close proximity to developed infrastructure, goods and services, the three districts would show exceptional results, and thus should be excluded from the analysis.
12. For the formula of standardized differences, see (Austin, 2011, p. 412).

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Appendices

Table A1. *Summary statistics of variables used in individual-level analysis.*

Variables	**Obs.**	**Mean**	**S.D.**	**Min.**	**Max.**
<u>Outcome Variables</u>					
Agricultural total employment	805,500	0.849	0.358	0	1
Nonagricultural total employment	805,500	0.128	0.334	0	1
Nonagricultural self-employment	805,463	0.050	0.218	0	1
Nonagricultural wage employment	805,463	0.064	0.244	0	1
Nonagricultural unpaid employment	805,463	0.014	0.117	0	1
<u>Variable of Interest</u>					
Electrified households	805,500	0.105	0.307	0	1
<u>Household Characteristics</u>					
Toilet	805,500	0.171	0.376	0	1
Piped water	805,500	0.035	0.184	0	1
House with 3 rooms or more	805,500	0.041	0.197	0	1
Own the house	805,500	0.970	0.169	0	1
Household size	805,500	5.368	2.216	1	27
Number of children aged less than 5	805,500	0.422	0.671	0	8
<u>Individual Characteristics</u>					
Years of schooling	805,500	3.717	3.333	0	13
Age	805,500	36.204	14.560	15	98
Female gender	805,500	0.531	0.499	0	1
Married	805,500	0.716	0.450	0	1
Divorced	805,500	0.025	0.157	0	1
Widowed	805,500	0.048	0.214	0	1
Buddhist	805,500	0.969	0.172	0	1
Muslim	805,500	0.017	0.129	0	1
Christian	805,500	0.003	0.055	0	1

Table A2. *Summary statistics of variables used in district-level analysis.*

Variables	**Obs.**	**Mean**	**S.D.**	**Min.**	**Max.**	**Mean (1998)**	**Mean (2008)**	**Δ**
Outcome Variables (%)								
Agri. total emp.	222	84.391	9.989	39.210	95.354	83.686	85.096	1.410
Nonagri. total emp.	222	13.426	9.107	2.830	59.344	12.584	14.268	1.684*
Nonagri. self-emp.	222	4.928	3.619	0.157	19.556	4.555	5.301	0.746*
Nonagri. wage emp.	222	7.093	6.350	2.034	43.794	6.876	7.310	0.434
Nonagri. unpaid emp.	222	1.255	1.067	0	6.916	0.889	1.621	0.732***
Variable of Interest (%)								
Electrified households	222	8.668	9.579	0	69.722	5.035	12.300	7.265***
District Characteristics (%)								
Toilet	222	13.773	12.473	0	62.671	5.680	21.867	16.187***
Piped water	222	3.114	4.401	0	27.718	1.587	4.641	3.053***
Households with 3 rooms or more	222	3.661	3.113	0	16.135	2.965	4.358	1.392***
Own the house	222	95.238	3.213	79.255	99.488	95.097	95.379	0.282
Household size	222	5.347	0.432	3.938	6.874	5.521	5.173	-0.347***
Individual with children aged less than 5	222	33.656	6.150	21.191	52.995	38.048	29.265	-8.782***
Elderly aged > 59	222	7.654	2.248	0.808	15.067	6.965	8.343	1.378***
Average years of schooling	222	3.445	1.029	0.523	6.578	2.960	3.930	0.969***
Average age	222	35.794	1.788	31.876	41.962	35.024	36.563	1.538***
Sex ratio (female/male)*100	222	110.35	15.122	51.077	143.559	111.649	109.051	-2.598
Married	222	71.544	3.776	62.028	79.763	71.075	72.014	0.939**
Divorced	222	2.498	0.705	0.808	4.717	2.815	2.181	-0.633***
Widowed	222	4.847	1.301	1.426	8.108	5.364	4.330	-1.033***
Buddhist	222	95.503	13.180	6.732	100	95.126	95.880	0.754
Muslim	222	1.617	4.251	0	31.651	1.501	1.733	0.232
Christian	222	0.374	1.026	0	11.507	0.409	0.338	-0.070
Ln of district population	222	8.076	0.573	6.385	9.267	7.919	8.234	0.314***
Ln of distance to nearest provincial town (base year)	111	3.492	0.874	0.405	4.867	-	-	-

Located along the national border (base year)	111	0.216	0.413	0	1	-	-	-
Located in mountainous or plateau areas (base year)	111	0.180	0.386	0	1	-	-	-

Note: The total number of observations in each time period is 111. "-" represents information not applicable.

***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.