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Determinants and Welfare Impacts of Rural Electrification in Ghana

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Abstract

Electricity is considered one of the basic attributes of modern life. This study examines why some rural households and communities remain without power despite Ghana's progress in rural electrification. The objectives are to analyze the role of socio-economic factors in household electrification and to also examine the welfare impacts of one of Ghana's flagship rural electrification programs. Using the most recent two household datasets constructed from two nationwide household surveys (GLSS VI and GLSS VII samples) combined with other community datasets, the following results were obtained. First, household expenditure, employment status, and gender of the head of the household are significant predictors of rural household electrification in Ghana. Second, these robust predictors tend to persist over the two sample periods. Third, using one of Ghana's flagship rural electrification programs called the Self-Help Electrification Programme (SHEP) as a proxy for public policy, the results indicate that SHEP correlates with improvements in electrification rates of rural communities. Lastly, although rural electrification improves community welfare, its impact is skewed towards rural communities with higher average household expenditure.

Keywords: Ghana; electrification; SHEP; households; communities; welfare.

JEL Classification: D12, Q41, 013, I3.

1. Introduction

Electricity is an essential input for socio-economic development. Electricity brings improvements in health delivery, education, environmental sustainability and agricultural development (Kemausuor et al., 2014). Despite its importance, access to electricity is limited in many developing countries. In sub-Saharan Africa (SSA) alone, more than 600 million people lacked access to electricity in 2015 (International Energy Agency (IEA), 2015). In Ghana, where this study focuses, more than 7 million people do not have access to electricity (IEA, 2015). Even for communities connected to the national grid, the electricity supply is insufficient and households and businesses often endure blackouts.

Notwithstanding a serious lack of access to electricity, there have been some signs of progress in Ghana and other developing countries. Between 2000 and 2016, the percentage of people with access to electricity increased from 64% to 82% in developing countries, and from 23% to 43% in SSA (IEA, 2017). In Ghana, it increased from 45% to 84%. The trend is confirmed by Ghana's census data, which show that the percentage of households with access to electricity steadily increased from 45% in 2006 to 74% in 2017 as shown in Figure 1 (Ghana Living Standards Survey V and VII rounds). Even in rural areas where access to electricity is more limited, the figure also shows that the percentage of rural households with access to electricity increased from 23% to 61% between 2006 and 2017. Available data also indicates that an increasing number of rural communities are being connected to the grid. For instance, about 1,900 rural communities were connected to the national grid between 2009 to 2015 (Ministry of Energy, 2017).

In spite of these encouraging trends in electricity access, many questions are yet to be answered: Despite the increase in access to electricity, why do some households and communities continue to remain without electricity? Which households or communities have benefited from electricity access? What is the role of public policy in improving access to electricity? What are the impacts of rural community electrification programs on the welfare of communities?

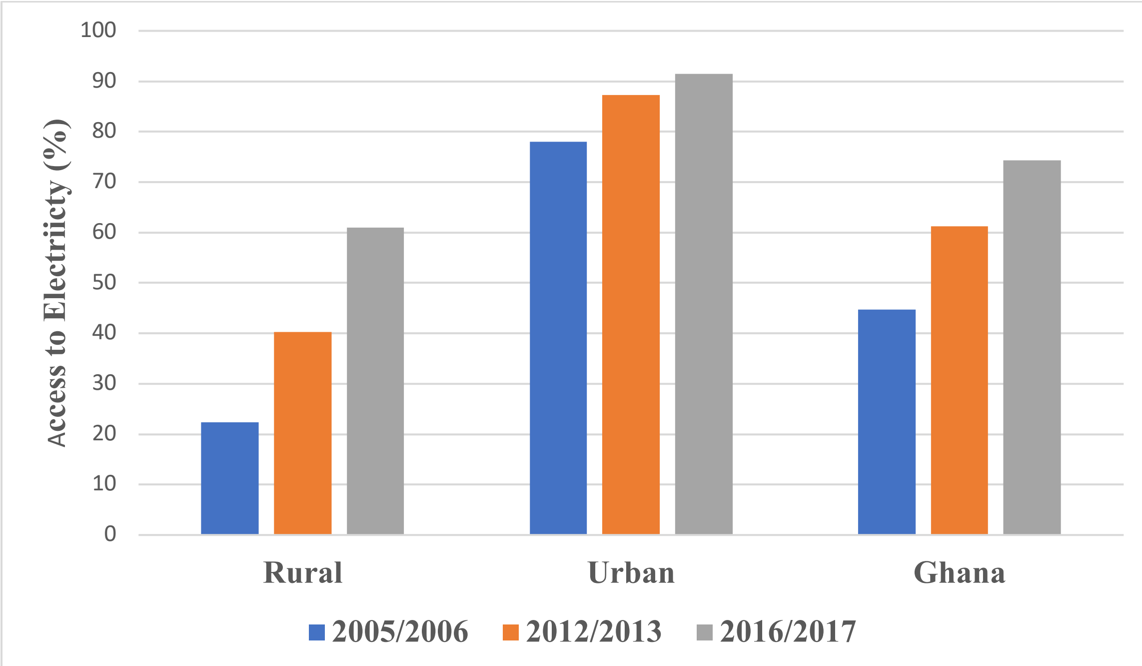

Figure 1: Access to grid electricity among households in Ghana

Source: Author's computations using GLSS V, GLSS VI and GLSS VII datasets.

This study investigates the dynamics of rural electrification in Ghana. Particularly, we focus on key determinants of electricity access for rural households in Ghana. Moreover, this study examines the role of public policy in community electrification and their impact on community welfare. To achieve this purpose, we explore how one of Ghana's flagship rural electrification programs called the Self-Help Electrification Programme (SHEP) improved electricity access and poverty alleviation.

This study contributes to extant literature in two ways. First, it introduces dynamic aspects to the study of rural household electrification in developing countries. While many previous studies on electrification (e.g. Oda and Tsujita, 2011; Onjeji et al., 2012; Kemmler, 2006; Khandker et al., 2012) is based on cross-sectional analysis and ascertain the factors explaining rural electrification at a given time, they do not show how these factors have changed over time. Building on these studies, we investigate whether factors explaining rural household electrification have changed or not from the period 2012-2017. Second, this study evaluates the impact of a public policy to increase access to electricity on the welfare of rural community. While several studies have estimated the benefits of rural electrification on employment and welfare (e.g. Grogan and Sadanand, 2012; Salmon and Tanguy 2016; Dasso and Fernandez, 2015; Adu et al., 2018), they do not directly assess the impact of rural electrification programs. Although the success of Ghana's electrification drive has been credited to programs like SHEP, no attempts have been made to empirically examine how much the program has contributed to improvements in electricity access. In directly examining the impact of SHEP, this study empirically ascertains the role of public policy in increasing access to electricity, improving welfare and reducing poverty.

The remainder of this paper is composed as follows: Section 2 gives a brief overview and history of electrification in Ghana. Section 3 describes the data used in this study. Section 4 presents the econometric models employed. Section 5 discusses the results. Finally, Section 6 concludes and provides some policy implications.

2. Overview and History of Electrification in Ghana

In the colonial days of the Gold Coast (before Ghana's independence in 1957), electricity was mostly supplied from isolated diesel generation plants dispersed across the country (Kumi, 2017). The plants were owned by industries and institutions such as hospitals, schools, municipalities, and factories. In 1914, the first public electricity generation system was set up by the Gold Coast Railway Administration in Sekondi (Institute of Statistical, Social and Economic Research (ISSER), 2005). Although the goal was to supply electricity only to the railways sector in Sekondi, it was extended to some major cities in the country including Takoradi, Accra, Nsawam, Kumasi, Tema, Tamale, and Bolgatanga by 1955.

Ghana began to move away from these diesel generation plants to hydroelectricity in 1972 with the completion of the Akosombo Dam Project over the Volta River that provides a total installed capacity of 912 MW for electricity generation. Although the primary goal of the project was to supply electricity only to the aluminum industry in Ghana, electricity supply was extended to neighboring countries including Togo and Benin (Kumi, 2017). The Kpong Hydroelectric Power Station was commissioned in 1982 to supplement the supply from the Akosombo Dam Project, increasing the installed generation capacity from 912 MW to 1072 MW.

Ghana experienced its first electricity crisis in 1984, when a severe drought in the previous year caused a 15% reduction in the expected long-term inflow into the Akosombo Dam. The crisis called for an immediate action, as the country could not rely solely on hydropower. As a result, several thermal power plants were introduced into Ghana's generation mix. The first of these was a 550 MW facility (Tapco and Tico) at the Takoradi Thermal Plant completed in 2000. Since then, the total installed capacity of thermal power plants has increased to 2,785 MW as of the end of 2017 (Energy Commission of Ghana, 2018). Currently, the electricity generation mix in Ghana is mainly dominated by hydro and thermal sources. Figure 2 depicts the historical electricity generation mix from 2000 to 2017. It shows that hydro had been the main source of electricity until 2015, when thermal sources took over. By the end of 2016, the share of thermal power in the generation mix stood at 57.21% while hydro stood at 42.79%. Although Ghana introduced renewable energy sources such as solar in 2013, they have yet to play a significant role in the generation mix. Presently, renewable energy sources contribute less than 1% to the total power supply (Figure 2).

Electricity access of rural residents has improved considerably, increasing from 6% in 1990 to 60% in 2015 (World Bank, 2016). This is a testament to Ghana's commitment to achieving universal access to electricity, a journey that began with the establishment of the National Electrification Scheme (NES) in 1989 (Ministry of Energy, 2010). This scheme serves as the key instrument to extend electricity to all parts of the country by 2020. Within the first ten years of the NES, about 2,350 communities were connected to the national grid (Kemausuor and Ackom, 2017). Although the universal access target will not be achieved by 2020, judging from the annual growth in electricity access of 2.6% over the period, it is likely that this scheme has contributed to a rapid increase in electricity access. The two pillars of the NES are the National Electrification Program (NEP) and SHEP. Under the first phase of the NEP, electricity was extended to all district capitals in the country. Under the second phase, plans to electrify communities were based on the most economically viable projects.

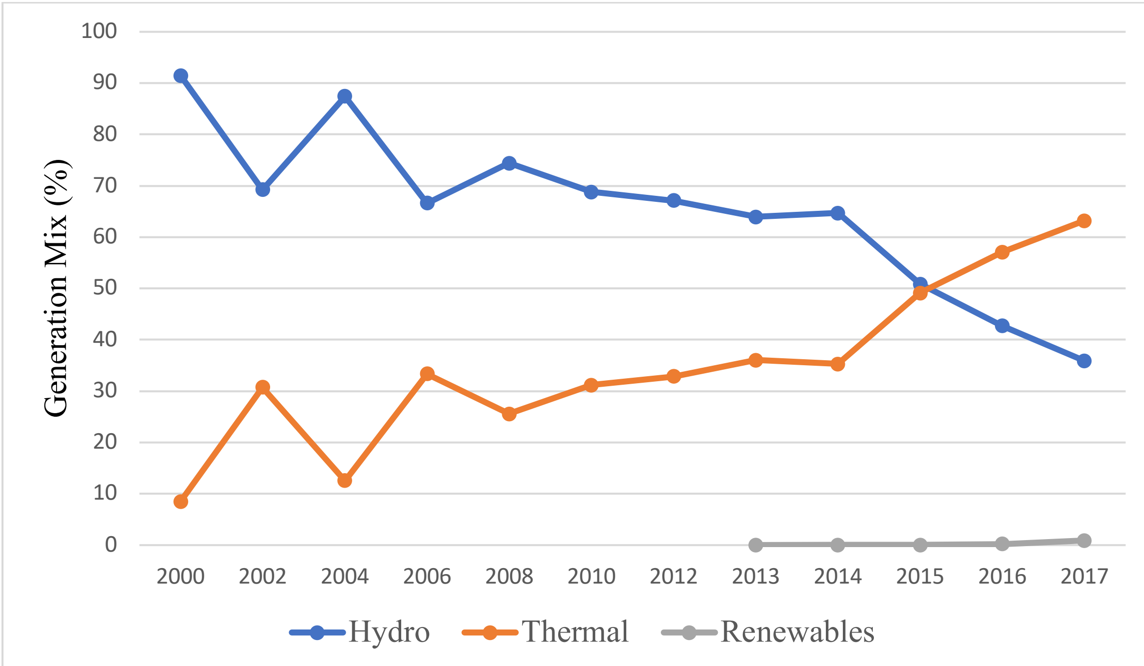

Figure 2: Historical electricity generation mix from 2000-2017

Sources: Energy Commission of Ghana, 2017; Energy Commission of Ghana, 2018.

SHEP was established to support the NES and encourage community participation with the goal of accelerating the country's electrification process. Under SHEP, households in communities without electricity were expected to mobilize resources to provide a number of utility poles, with the government providing the remaining poles, transmission equipment, materials, and construction work. Rural communities within 20 kilometers from an existing 33kV or 11kV sub-transmission line qualified for electrification if they were willing to pay for the cost of standard low- voltage poles needed for the distribution network in the community. Unelectrified communities that could not afford to pay for the low-voltage poles could request financial assistance from their respective local governments (Kemausuor and Ackom, 2017).[1] Figure 3 shows the number of communities connected to the national grid under SHEP from the year 2009 to 2016. The figure shows an increasing number of communities under SHEP although the number of new communities joining SHEP has been declining after 2012 due to financial challenges.

[1] Ghana is a constitutional republic with two spheres of government: national and local. At the highest levels of local government, there are three types of assemblies: metropolitan, municipal and district. The local government assemblies are responsible for the setting and collecting of local revenue, public health, environmental protection and sanitation and the provision of basic education.

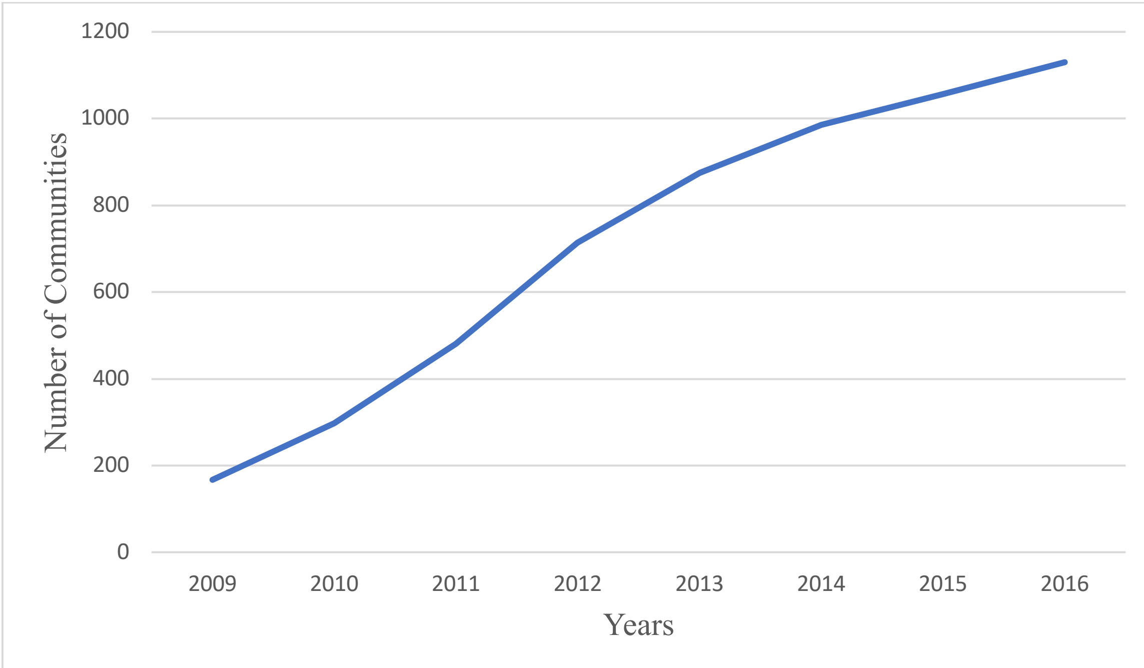

Figure 3: Number of communities under SHEP (2009-2016)

Source: Ministry of Energy Database (2017).

3. Data and Descriptive Statistics

Data were extracted from the sixth and seventh rounds of the Ghana Living Standards Survey (GLSS VI and GLSS VII) conducted by the Ghana Statistical Service (GSS) in 2012/2013 and 2016/2017, respectively. These are nationwide household surveys designed to collect detailed information including demographic characteristics, education, health, employment, migration, tourism, fuel use, housing conditions, household agriculture, access to financial services, and asset ownership (GSS 2014, 2018). The sampling frame for the survey was people living in private households[2] in Ghana and was divided into primary and secondary sampling units. Census enumerated areas (EAs) were defined as the primary sampling unit and households within each EA constituted the secondary sampling unit. According to the population in each administrative region, the EAs were first stratified into Ghana's ten administrative regions.

In the 2012/2013 sample, the GSS adopted a two-stage stratified random sampling design in which 1,200 EAs were considered in the first stage to cover a nationally representative sample of 18,000 households. In the 2016/2017 sample, however, 1,000 EAs were considered in the

[2] Private households are defined in GLSS as excluding institutional populations such schools and hospitals.

first stage to cover a nationally representative sample of 15,000 households. This study also uses data from the Ghana Ministry of Energy that contains electrified and unelectrified communities, years of connection, and the number of people in the community.[3] The data extracted from the 2012/2013 and 2016/2017 samples are matched with the data from the Ghana Ministry of Energy. Because this study focuses on rural households living in electrified communities, a final sample used is 2,235 (out of 9,214 households) and 3,807 (out of 7,651) rural households from the 2012/2013 and 2016/2017 samples, respectively. Data on communities on SHEP were collected from the Ghana Energy Development and Access Project (GEDAP) of the Ministry of Energy.

Table 1 lists all the variables used in this study and their respective definitions. Table 2 provides the descriptive statistics of all the variables used in the study. Using the 2012/2013 sample, 76% of the household heads are male and their average age is approximately 47 years old. In the 2016/2017 sample, 70% of the household heads are male and the average age is the same. The average household size in both samples is approximately five members. Merging communities from the 2012/2013 sample and 2016/2017 sample yields a total of 415 communities common to both samples. Of this number, 144 communities were connected to the national grid through SHEP during 2012-2017.

[3] http://gheatoolkit.energycom.gov.gh/Energydatabase/Database

Variables	Definition
Household	
Gender of household head	Dummy (male=1, female=0)
Age of household head	Continuous
Log annual household expenditure[4]	Continuous
Household size	Continuous
Electricity	Dummy (yes=1, no=0)
Employment status	Dummy (Employed=1, otherwise=0)
Community	
SHEP	Dummy (community received SHEP between 2012-2016=1, otherwise=0)
Years on SHEP	Years communities have been on SHEP
Electrification rate	Continuous (average HH electrification rate in the community)
Average HH size in a community	Continuous
Average annual HH expenditure	Continuous
Population	Continuous (number of people in the community)
Poverty	Continuous (percentage of poor rural households in a community)

Table 1: List of variables and definitions

[4] Household electricity expenditure is deducted from the total annual household expenditure.

Variable	Obs.	Mean	SD	Max	Min
Household					
Male head (GLSS VI)	2235	0.76	0.43	1	0
Male head (GLSS VII)	3807	0.70	0.46	1	0
Age of household head (GLSS VI)	2235	47.44	16.43	98	15
Age of household head (GLSS VII)	3807	47.02	16.27	99	17
Annual HH expenditure (GLSS VI)	2235	6506.84	6298.64	146345.4	31.2
Annual HH expenditure (GLSS VII)	3807	8196.56	7251.99	111002.9	86.25
Household size (GLSS VI)	2235	4.74	2.97	29	1
Household size (GLSS VII)	3807	4.50	3.05	28	1
Employment status (GLSS VI)	2235	0.84	0.33	1	0
Employment status (GLSS VII)	3807	0.79	0.41	1	0
Community					
SHEP	415	0.35	0.44	1	0
Electrification rate (GLSS VI)	415	42.34	40.48	100	0
Electrification rate (GLSS VII)	415	61.09	37.23	100	0
Average household size	415	4.73	1.39	10.93	1.8
Average annual HH expenditure	415	6722.042	3703.458	38735.92	1460.838
Population	415	1387.819	1381.629	4990	29
Years on SHEP	144	5.17	2.37	6	1
Poverty (GLSS VI)	415	90.04	14.20	100	14.29
Poverty (GLSS VII)	415	37.64	32.57	100	0

Table 2: Descriptive Statistics

Note: SD denotes standard deviation, Obs. represents number of observations, and Min and Max are minimum and maximum.

4. Econometric Models

4.1 Household Model

This study estimates a model of household choice on electrification by assuming that a household's decision to connect to the electricity grid is influenced by their characteristics such as expenditure (expenditure), age of household head (age), household size (size), gender of household head (gender), and employment status of the household head(job). The household choice of connecting to the electricity grid (A) in general is expressed as:

$$A = A(expenditure, age, size, gender, job) \tag{1}$$

Suppose representative household i has to choose between j alternatives (where $j = 1,2$; the first alternative is having access to grid electricity and the second is the use of private generator, solar and rechargeable battery for lighting as well as households without electricity. The indirect utility derived from not having access to grid electricity is defined by M_{ij}. M_{ij} is composed of two parts; an observable part, $x_i'\beta^j$, and an unobservable part $\varepsilon_{i,j}$, where x_i is a vector of all the variables in Eq. (1) and β^j is a vector of parameters to be estimated. The indirect utility function for alternative j for household i can then be expressed as:

$$M_{ij} = x_i'\beta^j + \varepsilon_{i,j} \tag{2}$$

The unobserved part, $\varepsilon_{i,j}$, is assumed to be jointly normally distributed with mean 0, and variance $\sum$]. i.e. $\varepsilon \sim N\ [0, \sum]$.

Then, the probability that household i chooses the first alternative (i.e., chooses to have access to grid electricity) is:

$$P_{i1} = Pr(\varepsilon_{i2} - \varepsilon_{i1} < x_i'\beta_1 - x_i'\beta_2) = \Pr\ [\dot{\varepsilon}_{i,21} < x_i'(\beta_1 - \beta_2)] \tag{3}$$

where $\dot{\varepsilon}_{i,21} = \varepsilon_{i2} - \varepsilon_{i1}$.

A similar expression can be obtained for the probability, P_{i2} that household i chooses the second alternative (i.e. chooses not to have access to grid electricity). It is assumed that ε_{ij} has a joint normal density function defined as $f(\varepsilon_{ij}) = f(\varepsilon_{i1}, \varepsilon_{i2})$. Let y_{ij} denote a discrete choice outcome variable that takes a value of 1 if household i has access to grid electricity and 0 otherwise. The cumulative probability for the choice of the first alternative (having access to grid electricity) for household i can now be expressed as:

$$P_{i1} = pr[y_i = 1] = \int_{-\infty}^{\dot{V}_{i,12}} f(\dot{\varepsilon}_{i,21}) d\dot{\varepsilon}_{i,21} \tag{4}$$

where $\dot{V}_{i,12} = x_i'(\beta_1 - \beta_2)$. The expression in Eq. (4) is specific to the first alternative. In a more general case, the choice probability for household i choosing alternative j is given by $P_{ij} = pr[y_i = j] = h_j(x_i'\beta_j)$, where $h_j(x_i'\beta_j)$ takes a similar expression as in Eq. (4). The log likelihood function for a sample of N independent households with j alternatives can then be expressed as:

$$l = LnL = \sum_{i=1}^{N} \sum_{j=1}^{N} y_{ij}\, Ln(\hat{P}_{ij}) \tag{5}$$

where $\hat{P}_{ij}$ is estimated with a similar expression to that in Eq. (4) using a simulation method that is substituted into the log likelihood function, which is then maximized to obtain the parametric estimates for the β's.

The primary statistical methods are linear fixed effects regressions and logistic regressions. We estimate both ordinary least squares (OLS) regressions (with community fixed effects) and logistic regressions (with conditional community fixed effects).

4.2 Community Model

At the community level, we are interested in (1) the impact of SHEP on improvements in community electrification and (2) the impact of SHEP on community welfare.

The linear regression specification for (1) is given as:

$$Y_{jk} = \alpha_k + \gamma_1 SHEP_{jk} + \gamma_n \theta_{jk} + \varepsilon_{jk} \tag{6}$$

where j denotes communities and k denotes districts. The primary outcome variable of interest Y_{jk} is the change (percentage points) in electrification rates between 2012/2013 sample and the 2016/2017 sample. Communities j are grouped under districts k, implying that α_k is the district fixed effect. γ_1 is the coefficient for the main explanatory variable, SHEP. SHEP takes the value of 1 if a rural community is on SHEP between 2013 and 2016, and 0 otherwise. γ_n is a vector of coefficients for control variables, θ_{jk}. ε_{ij} is the error term that is clustered by district.

We also construct a two-period community panel dataset using the 2012/2013 and 2016/2017 samples to examine the impact of SHEP on community welfare. We exploit the difference-in-difference (DID) method to identify the impact of SHEP on community welfare. Treatment communities are defined as communities on SHEP between 2013 and 2016, while control communities are those without electricity connection. This study assumes that the period 2016/2017 is the post-intervention period because SHEP data covers 2012-2017. We use two outcome variables: average annual household expenditure in a community and the percentage of poor households in a community.[5] Given the relatively short period (about four years) between the two data samples, we expect that trends between the control and treatment groups have not changed significantly in the absence of SHEP. The average treatment effect on treated (ATT) is the counterfactual mean difference in the average gains in both treated and control communities which is defined as follows:

$$\text{ATT} = E(Y_1 - Y_0|X, D = 1) = E(Y_1|X, D = 1) - E(Y_0|X, D = 1) \tag{7}$$

where $E(.)$ denotes the expectation operator, X is a vector of control variables, D is an indicator variable that takes the value of 1 if a community is treated and 0 otherwise, and Y_1 and Y_0 are the outcome variables for treated and control communities.

[5] Poverty in Ghana is focused on consumption poverty. In the 2012/2013 and 2016/2017 samples, the upper poverty lines of GH¢1314 and GH¢1760 per adult equivalent per year are calculated, respectively (GSS: 2014, 2018). Rural households with annual HH expenditure below the upper poverty line are classified as poor.

This study follows the specifications of Angrist and Pischke (2009) and Saing (2018) to estimate the equation below:

$$Y_{jt} = \alpha + \gamma Treat_j + \lambda Post_t + \beta TreatPost_{jt} + \sigma X_{jt} + v_j + \omega_t + \varepsilon_{jt} \tag{8}$$

where Y_{jt} represents the outcome variables of community j at time t. $Treat_j$ is a dummy variable of community j being treated, taking the value of 1 if treated and 0 otherwise. $Post_t$ is the time dummy indicating post-treatment period, taking the value of 1 if the period is post-treatment and 0 otherwise. $TreatPost_{jt}$ is the interaction term between the treatment and time dummies with β as the ATT. X_{jt} , v_j and ω_t are vectors of community-level controls, community and time-specific fixed effects, respectively. ε_{jt} is an idiosyncratic error term.

This paper uses observational non-randomized data. As a result, we cannot directly observe the counterfactual outcome $E\ (Y_1 - Y_0)$. Thus, the simple mean value comparisons between the treated and untreated communities could result in biased estimates. Nilsson (2017) argues that estimating ATT using fixed-effects panel estimations can reduce any selection bias resulting from time-invariant heterogeneity. As a robustness check, this study uses Coarsened Exact Matching (CEM) to assign subjects to treatment and control groups before employing the fixed-effects panel estimations that help reduce model dependence (Ho et al., 2007). The matching procedure generates weights that are used in the subsequent weighted fixed-effects panel regressions.

Gains of electricity access might be heterogenous. To consider the distributional consequence across all expenditure groups and poverty classes of communities, we employ unconditional DID quantile panel fixed effect regression. More specifically, this technique is applied to specific welfare quantiles at 25%, 50%, and 75% by estimating a similar equation in Eq. (8) below with q denoting the quantile.

$$Y_{jt}^{(q)} = \alpha^{(q)} + \gamma^{(q)} Treat_j + \lambda^{(q)} Post_t + \beta^{(q)} TreatPost_{jt} + \sigma^{(q)} X_{jt} + v_j^{(q)} + \omega_t^{(q)} + \varepsilon_{jt}^{(q)} \tag{9}$$

5. Empirical Results

5.1 Household Electrification in Ghana

This sub-section explores the determinants of electrification at the household level. Table 3 and Table 4 report the regression results using the 2012/2013 and the 2016/2017 samples, respectively. The dependent variable in the results presented in Tables 3 and 4 is a dummy variable for whether or not a rural household has access to grid electricity in an electrified community. To account for the sampling structure and disproportionate sampling, standard errors are clustered at the community level and sampling weights are applied. Results in models (1) and (3) are results from logistic regressions (conditional community fixed effects) and results from models (2) and (4) are from OLS regressions (community fixed effects) using both Tables 3 and 4.

Overall, the marginal effects are correctly signed and the statistical significance is typically strong. The household head often controls household decisions especially in the case of expenditures. Having a male as a household head increases the probability of having electricity by 0.3%‒0.6% (Table 3) and 0.50%‒1.60% (Table 4). Electricity access is a key household decision, because of not only the many uses of electricity in the household but also because of the monetary costs involved. Most household decisions in Ghana are made by the head of the household, who is male in many cases, as shown in Table 2.

The tables also reveal that an employed household head is 7%‒15% (Table 3) and 10%‒21% (Table 4) more likely to have an electricity connection compared to an unemployed one. This is not surprising, since most unemployed household heads do not have enough financial resources needed to electrify their households. Tables 3 and 4 also show that household expenditure is the strongest predictor of rural electrification in Ghana, which is to be expected, since the use of electricity is associated with connection costs and monthly electricity bills. Also, higher expenditure households are more likely to migrate from unelectrified rural communities to electrified rural communities than those with lower household expenditures. This result is consistent with the findings of Dugoua et al. (2017), who showed that an increase in household expenditure by one percent is associated with a 11%‒20% point increase in household electricity access rate in rural India. Hence, expenditure plays a vital role in the decision to electrify a household.

The predictors of rural household electrification persist over the two samples, as both Tables 3 and 4 indicate that expenditure, employment status and gender of the household head are significant predictors of household electrification in Ghana. Also, the size of each of the significant marginal effects in Table 4 (2016/2017 sample) is larger than those in Table 3 (2012/2013 sample). The implication of these larger marginal effects is to increase positive signed marginal effects or decrease negative signed marginal effects. For instance, comparing models (1) of Tables 3 and 4, employed household heads have an approximately 14% probability of having an electricity connection in the 2012/2013 sample, while the probability increases to 15% in the 2016/2017 sample.

Variables	(1) Logit	(2) Linear	(3) Logit	(4) Linear
Age of HH head	0.95	0.28	0.08	0.01
	(0.153)	(0.035)	(0.046)	(0.050)
Expenditure (log)	23.62***	11.30***	20.01***	9.18***
	(0.084)	(0.091)	(0.033)	(0.005)
Household size	-0.20	-0.40	-0.14	-0.23
	(0.018)	(0.020)	(0.012)	(0.120)
Male head	0.62*	0.59**	0.41**	0.34*
	(0.002)	(0.004)	(0.003)	(0.002)
Employment status	14.26***	8.33**	15.24***	7.34**
	(0.013)	(0.014)	(0.021)	(0.013)
Observations	2235	2235	2235	2235
District FE	No	No	Yes	Yes
Community FE	No	No	Yes	Yes
Clustered SE	No	Yes	No	Yes
R-squared		0.304		0.392

Table 3: Regression results (dependent variable: dummy for whether or not a rural household has access to grid electricity in an electrified community) using GLSS VI

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Logistic regressions are estimated with conditional fixed effects at the community level; robust standard errors are clustered by community and reported in parentheses. Marginal effects are multiplied by 100 to convert to percentage points.

Variables	(1)	(2)	(3)	(4)
	Logit	Linear	Logit	Linear
Age of HH head	1.30	0.30	0.09	0.02
	(0.301)	(0.040)	(0.020)	(0.030)
Expenditure (log)	26.80***	12.40***	26.50***	10.90***
	(0.043)	(0.005)	(0.031)	(0.004)
Household size	-0.87	-0.69*	-0.19	-0.30
	(0.076)	(0.002)	(0.015)	(0.02)
Male head	1.60**	1.30**	1.10***	0.50**
	(0.006)	(0.004)	(0.007)	(0.001)
Employment status	14.70**	9.70***	20.80***	11.50***
	(0.019)	(0.028)	(0.013)	(0.031)
Observations	3807	3807	3807	3807
District FE	No	No	Yes	Yes
Community FE	No	No	Yes	Yes
Clustered SE	No	Yes	No	Yes
R-squared		0.163		0.281

Table 4: Regression results (dependent variable: dummy for whether or not a rural household has access to grid electricity in an electrified community) using GLSS VII

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Logistic regressions are estimated with conditional fixed effects at the community level; robust standard errors are clustered by community and reported in parentheses. Marginal effects are multiplied by 100 to convert to percentage points.

5.2 Impact of Rural Electrification Program on Community Electrification

This subsection extends the analysis from the household level to the community level and seeks to answer an important question: Does public policy improve rural community electrification rates in Ghana? To measure public policy, SHEP data taken from GEDAP covering 2009-2017 is used. The dataset is combined with the 2012/2013 and 2016/2017 samples using community names to arrive at a final number of 415 communities common to both samples. Of these, 144 were on SHEP between 2013 and 2016.

First, we investigate whether SHEP targeted rural communities with low electrification rates. In other words, we test whether a correlation exists between SHEP and a community's electrification rate. To achieve this objective, a dummy variable is created which is equal to 1 if a rural community joined SHEP between 2013 and 2016 (between 2012/2013 and 2016/2017 samples), and 0 otherwise. The key independent variable is electrification rate defined as the percentage of rural households with access to electricity in a community. This variable is constructed using the 2012/2013 sample. Table 5 reports the estimated results of OLS and logistic regressions. Standard errors are clustered at the district level throughout the analysis to control for intra-district error correlation. Models (1) and (2) are first estimated without controls using logit and OLS regressions, respectively. In models (3) and (4), control variables such as log average expenditure, average household size and log population are included.

The coefficient estimates of electrification rate from models (1) and (2) in Table 5 are strongly negative, indicating that the lower the electrification rate of a rural community, the higher the probability that it will be selected for SHEP. The negative relationship holds with the inclusion of the control variables as reported in models (3) and (4). The smaller coefficient estimates (in absolute terms) in models (3) and (4) compared to models (1) and (2) suggest the importance of taking into account key control variables to prevent the coefficient estimates from being overstated. Specifically, a 1% point decrease in the electrification rate of a community will lead to a 0.2%–1.6% points increase in the probability of been selected to SHEP on average. In terms of the control variables, only population (used as a proxy for the size of a community) was found to be statistically significant. The coefficient estimates indicate that the smaller the population of a community, the higher the chances that it will be selected to SHEP.

Variables	(1)	(2)	(3)	(4)
	Logit	Linear	Logit	Linear
Electrification rate (0-100)	-1.02***	-1.62***	-0.23***	-0.28***
	(0.003)	(0.002)	(0.001)	(0.0004)
Average expenditure (log)			0.22	0.05
			(0.037)	(0.037)
Average household size			-0.05	-0.05
			(0.015)	(0.014)
Population (log)			-4.35**	-4.55*
			(0.022)	(0.024)
Observations	415	415	415	415
District FE	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes
R-squared		0.455		0.381

Table 5: Regression results (dependent variable: dummy for whether or not a rural community implemented SHEP between 2013 and 2016)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Robust standard errors are clustered by district and reported in parentheses. Marginal effects are multiplied by 100 to convert to percentage points.

Based on the above results, we further examine the impact of SHEP on community electrification-rate improvements. In other words, it tests whether SHEP correlates with actual improvements in electricity access. Improvement in electricity access is defined as the difference in community electrification rates between 2016/2017 and 2012/2013 samples. This definition implies that a community's electrification rate has improved if the difference is positive. On the other hand, if a community's electrification rate decreased from the 2012/2013 sample to the 2016/2017 sample, then the negative difference implies that the community's electrification rate has worsened. The key independent variable is the SHEP dummy variable. The results are shown in Table 6.

Models (1) and (2) are estimated without controls while models (3) and (4) include all control variables. The estimated coefficients of SHEP from models (1) and (2) are strongly positive, indicating that the program positively correlates with actual improvements in electricity access. The positive relationship holds with the inclusion of the control variables reported in models (3) and (4). Specifically, rural communities on SHEP between the period 2012 and 2017 improved their community electrification rates by about 15%–17% on average. Because the rural electrification rates increased by 21% from 2013 to 2017 (Figure 1), the results suggest that this increase is largely explained by SHEP.

As a robustness check, CEM is used to confirm the results.[6] The CEM algorithm allows both control and treated communities to be matched according to various community-level characteristics. Two different sets of community-level characteristics are matched First, communities are matched on average expenditure, average household size, community electrification rate and the logged population. The results are shown in model (5) of Table 6 with a matched sample size of 289. Second, they are matched on average expenditure, average household size, community electrification rate, the logged population and district fixed effects. The results with matching are also shown in model (6) of Table 6 with a sample size of 204. The smaller sample size in model (6) is a result of the more covariates used in the matching as compared with model (5). The results in both models (5) and (6) support the positive relationship between SHEP and improvements in community electrification rates found in models (1) – (4). Specifically, rural communities on SHEP between the period 2012-2017 improved their community electrification rates by about 11%–12% on average, suggesting that coefficients obtained without matching are slightly overstated.

A further robustness check is conducted by using the number of years a community has been on SHEP as the key independent variable instead of the dummy variable representing implementation of the program. The same models are estimated applying the same matching techniques as in Table 6. The results are shown in Table 7. Once again, we found that the effect is positive and statistically significant. Evidence shows that SHEP has improved community electrification rates.

[6] This study used the Stata cem library as described by Blackwell et al. (2010) to implement the CEM.

Variables	(1)	(2)	(3)	(4)	(5) CEM1	(6) CEM2
SHEP	17.42**	16.33***	15.51***	14.61***	11.23***	12.30**
	(4.867)	(5.196)	(4.305)	(4.468)	(5.096)	(4.107)
Average expenditure (log)			9.95***	7.76***		
			(3.394)	(3.748)		
Average household size			-3.63	-2.99		
			(4.498)	(4.806)		
Population (log)			19.17***	18.89***		
			(2.330)	(2.344)		
Observations	415	415	415	415	289	204
District FE	No	Yes	No	Yes	No	No
Clustered SE	Yes	Yes	Yes	Yes	No	No
R-squared	0.023	0.035	0.179	0.191	0.015	0.017
Overall imbalance					0.793	0.849
					(0.839)	(0.942)

Table 6: Regression results (dependent variable: difference in community electrification rates between 2016/2017 and 2012/2013 samples)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Robust standard errors are clustered by district and reported in parentheses. In model (5), the control and treatment groups are matched on logged average expenditure, average household size, electrification rate and logged population. In model (6), however, the control and treatment groups are matched on logged average expenditure, average household size, electrification rate, logged population and district fixed effects.

Variables	(1)	(2)	(3)	(4)	(5) CEM1	(6) CEM2
Years on SHEP	4.81***	4.50***	4.44***	4.17***	3.06***	3.25**
	(1.577)	(1.491)	(1.377)	(1.327)	(1.472)	(1.250)
Average expenditure (log)			12.71***	10.346***		
			(3.783)	(3.395)		
Average household size			-4.96	-3.77		
			(5.802)	(5.507)		
Population (log)			18.88**	18.62***		
			(2.345)	(2.360)		
Observations	415	415	415	415	289	204
District FE	No	Yes	No	Yes	No	No
Clustered SE	Yes	Yes	Yes	Yes	No	No
R-squared	0.023	0.036	0.177	0.189	0.037	0.022
Overall imbalance					0.794	0.849
					(0.839)	(0.942)

Table 7: Robustness results (dependent variable: difference in community electrification rates between 2016/2017 and 2012/2013 samples)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Robust standard errors are clustered by district and reported in parentheses. In model (5), the control and treatment groups are matched on logged average expenditure, average household size and logged population. In model (6), however, the control and treatment groups are matched on logged average expenditure, average household size, electrification rate, logged population and district fixed effects.

5.3 Impact of Rural Electrification Program on Community Welfare

Rural electrification programs can affect household and community welfare through channels such as expenditure and poverty. In this sub-section, the impact of SHEP on community welfare is estimated. Community welfare is measured using two variables: average annual household expenditure in a community and the percentage of poor households in a community. Table 8 presents the results for the former. Results in columns (1) – (4) are from panel DID fixed effects regressions; results from column (5) are obtained by employing panel DID weighted fixed effects regression to the matched data using CEM. Across all models, the results suggest that household expenditure is 12%–22% higher on average for communities on SHEP than for those without grid connection. These results remain robust after adding other control variables as well as varying district fixed effects.

Obtained results are consistent with previous studies (Khandker et al. 2013; Saing 2018; and Adu et al., 2018). For example, Khandker et al. (2013) finds that rural electrification increased household expenditure by approximately 23% in Vietnam. Saing (2018) also finds that rural electrification increased daily per capita consumption by approximately 17%. In terms of the control variables, population, which is used as a proxy for community size, is positive and statistically significant, suggesting that rural communities with larger populations tend to benefit more in terms of welfare than communities with smaller populations. This is intuitive because connecting large communities to the grid directly benefits larger number of households.

Rural electrification via SHEP generates outcomes through multiple channels. The initial impact is that households in communities with electricity access begin to purchase electrical appliances such as television sets, light bulbs, and business equipment. These initial impacts could also produce various outputs such as increased quality of lightening, access to non-agricultural activities, modernization of agriculture, attraction of infrastructure (such as health facilities, roads and water supply), access to information, and knowledge to enhance education (Adu et al., 2018). In the medium term, these outputs also lead to more hours for studying, extended work time for shops and businesses, and greater access to knowledge and information that has the potential to improve community welfare in the long run.

All of the above suggest that rural electrification eventually leads to poverty reduction. Thus, this sub-section estimates the impact of SHEP on poverty using panel DID fixed effects regressions and panel DID weighted fixed effects regression. The results are shown in Table 9. With the exception of model (1), the average treatment effect of rural electrification is negative and statistically significant. Specifically, connecting a community to the grid through SHEP reduces the percentage of poor rural households by 8% – 10% on average. The results show that policy makers can substantially reduce poverty through rural electrification projects such as SHEP.

Variables	(1)	(2)	(3)	(4)	(5)
	DID-FE	DID-FE	DID-FE	DID-FE	CEM-DID-FE
Treat	-0.032	0.021	0.027	-0.116*	0.055
	(0.080)	(0.106)	(0.107)	(0.069)	(0.054)
Post	0.178***	0.265***	0.273***	0.162***	0.059
	(0.065)	(0.062)	(0.063)	(0.058)	(0.076)
Treat × Post	0.124*	0.221**	0.116*	0.202*	0.168***
	(0.072)	(0.017)	(0.069)	(0.026)	(0.0451)
Average household size			0.012	0.016	
			(0.017)	(0.085)	
Population (log)			0.230**	0.202***	
			(0.108)	(0.005)	
Observations	830	830	830	830	784
District FE	No	Yes	No	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
R-squared	0.530	0.520	0.450	0.456	0.322

Table 8: Impact of SHEP on community welfare (measured by average household expenditure in a community in log)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Robust standard errors are clustered by district and reported in parentheses. In model (5), the control and treatment groups are matched on average household size and population. CEM-DID-FE is a weighted fixed-effects model with the pre-estimated CEM weights constant within the panel.

Variables	(1)	(2)	(3)	(4)	(5)
	DID-FE	DID-FE	DID-FE	DID-FE	CEM-DID-FE
Treat	1.645	1.674	1.632	-0.903***	1.074***
	(1.060)	(1.091)	(1.089)	(0.348)	(0.348)
Post	-1.126***	-1.017	-1.152	-0.808***	-1.601
	(0.06)	(0.631)	(0.880)	(0.176)	(1.942)
Treat × Post	-8.726	-10.125*	-8.156**	-9.732**	-8.302***
	(5.502)	(5.671)	(4.822)	(4.182)	(2.245)
Average household size			-4.261***	-4.043	
			(1.087)	(4.390)	
Population (log)			5.752***	5.270***	
			(1.606)	(1.715)	
Observations	830	830	830	830	784
District FE	No	Yes	No	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
R-squared	0.321	0.557	0.566	0.531	0.452

Table 9: Impact of SHEP on poverty (measured as the percentage of poor households in a community [0-100])

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Robust standard errors are clustered by district and reported in parentheses. In model (5), the control and treatment groups are matched on average household size and population. CEM-FE is a weighted fixed-effects model with the pre-estimated CEM weights constant within the panel.

5.4 Distributional Impacts of Rural Electrification Program on Community Welfare

The results presented in Tables 8 and 9 show that rural electrification through SHEP improves welfare. However, it is still unclear if SHEP has the same benefits for various rural community quantile groups. Therefore, this sub-section employs unconditional DID quantile panel fixed effect regression to assess the heterogeneous impacts of SHEP across groups. Three quantiles – the 25^{th}, 50^{th} and 75^{th} – are created to examine whether communities with higher average household expenditures and lower percentage of poor households benefit more from rural electrification. Our expectations are that communities with higher average household expenditure will benefit more from rural electrification since they are better able to take advantage of economic opportunities. The results for the average annual household expenditure in a community are presented in Table 10.

The estimation results suggest that the impact of SHEP are heterogeneous: the impact of the program is stronger for quantiles of higher expenditure levels. For instance, the impact of SHEP at the 50^{th} percentile of the welfare distribution is 32%. At the upper quartile, the average treatment effect increases to about 0.42, implying that the impact of SHEP at the 75^{th} percentile of the welfare distribution is 42%. Although the average treatment effect for the bottom 25% of the welfare distribution is not statistically significant, the above results generally show that the welfare impacts increase as a rural community on SHEP moves up the welfare distribution from lower quantile to upper quantile. The results also suggest that welfare impacts of SHEP are not uniform but skewed towards rural communities with higher average household expenditures.

Table 11 presents the results for the percentage of poor households in a community. The results show that welfare impact of SHEP cannot be found beyond the 25^{th} percentile. This suggests that rural communities on SHEP with the lowest percentage of poor households benefits more from rural electrification, while such impact is not statistically significant in rural communities with higher percentage of poor households. Communities with lower percentage of poor households are more likely to have more working population than communities with higher percentage of poor households. Thus, the working population would benefit more from rural electrification through the extension of evening working hours and paid work activities. This could explain why rural communities on SHEP with the lowest percentage of poor households benefits more from rural electrification compared to those with the highest percentage of poor households.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	25th	25th	50th	50th	75th	75th
Treat	-0.051	-0.029***	-0.051**	-0.022	-0.030	-0.036
	(0.069)	(0.007)	(0.020)	(0.069)	(0.060)	(0.027)
Post	0.036***	0.084***	0.014***	0.027***	0.070***	0.049***
	(0.005)	(0.022)	(0.004)	(0.005)	(0.022)	(0.016)
Treat × Post	0.273	0.251	0.320***	0.305**	0.424***	0.396***
	(0.452)	(0.336)	(0.045)	(0.081)	(0.054)	(0.075)
Average household size		-0.022		-0.102		-0.032
		(0.171)		(0.125)		(0.080)
Population (log)		0.131***		0.194**		0.165***
		(0.016)		(0.093)		(0.039)
Observations	830	830	830	830	830	830
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.400	0.327	0.411	0.330	0.315	0.167

Table 10: Distributional impact of SHEP on community welfare (measured by average household expenditure in a community in log)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Robust standard errors are clustered by district and reported in parentheses.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	25th	25th	50th	50th	75th	75th
Treat	1.103***	1.077***	-1.304	1.074***	-1.442	-1.473
	(0.365)	(0.350)	(0.981)	(0.348)	(1.028)	(1.028)
Post	-1.254**	-1.416**	-1.075	-1.242	-1.232	-1.106
	(0.553)	(0.564)	(0.704)	(0.811)	(0.812)	(0.815)
SHEP	-9.721***	-9.366***	-7.072	-7.208	-5.681	-5.724
	(2.997)	(3.123)	(8.735)	(8.857)	(7.664)	(7.521)
Average household size		-2.925		-2.373		-2.907
		(2.009)		(2.017)		(1.903)
Population (log)		6.311***		3.630**		7.204***
		(2.481)		(1.044)		(2.734)
Observations	830	830	830	830	830	830
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.400	0.415	0.480	0.431	0.425	0.448

Table 11: Distributional impact of SHEP on poverty (measured as the percentage of poor households in a community [0-100])

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Robust standard errors are clustered by district and reported in parentheses. In reg. (5), the control and treatment groups are matched on average household size and population.

6. Conclusions

This paper has examined the role of socio-economic factors in household electrification in Ghana and assessed the welfare impact of one of Ghana's flagship rural electrification programs. Results of analysis based on the GLSS VI and GLSS VII samples, showed that at the household level, robust predictors of access to electricity are quite similar. We found that households with higher expenditures, male-headed households, and households with employed heads are more likely to have electricity connections in Ghana. Household expenditure and employment status were found to be the two strongest predictors of household electrification in Ghana. After combining the two household datasets with community data, the results suggested that rural communities with low electrification rates are more likely to be selected for SHEP. Also, the results further suggested that SHEP correlates with actual improvements in electrification rates of rural communities. By constructing a two-period community panel data using the same household datasets, we found that rural electrification through SHEP improves community welfare.

In light of these findings, some policy implications can be derived. First, the results reveal that household expenditure plays a vital role in rural household electrification. As a result, this study recommends a shift of policy efforts towards making electricity affordable, especially for low expenditure rural households. This can be achieved by employing sophisticated metering, such as encouraging households to install individual meters that is still uncommon in many parts of Ghana. It makes it easier for poorer households to pay affordable amount for electricity. Another possibility is to encourage installing prepaid meters, allowing households to pay electricity bills in small increments. Although the Electricity Company of Ghana (ECG) has outlined the processes of obtaining prepaid meters, ECG should promote the program more effectively. [7] Second, budget allocations for rural electrification projects should be complemented by introducing some incentives to attract the private sector and non-governmental organizations into funding some of these projects. Although the results suggest that policy makers can achieve substantial reduction in poverty through rural electrification projects such as SHEP, it is important to note that rural electrification is a necessary, but not a sufficient condition. Poorer communities are known to be deprived of some key amenities such as good roads, water supply, health facilities and irrigation projects. The goal of improving welfare and reducing poverty can be fully achieved if rural electrification projects are complemented with these other investment projects.

[7] https://meqasa.com/blog/electricity-prepaid-meter-acquisition-process-in-ghana/

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Appendix

	Household size	Expenditure (log)	Age of HH head	Employment status	Male head
Household size	1.0000				
Expenditure (log)	0.3627	1.0000			
Age of HH head	0.0981	-0.0415	1.0000		
Employment status	0.0177	0.0060	0.0261	1.0000	
Male head	0.2202	0.1410	-0.1491	0.0403	1.000

Table A: Correlation matrix using GLSS VI (2012/2013)

	Household size	Expenditure (log)	Age of HH head	Employment status	Male head
Household size	1.0000				
Expenditure (log)	0.3205	1.0000			
Age of HH head	0.0865	-0.0878	1.0000		
Employment status	0.0573	0.2533	0.2287	1.0000	
Male head	0.2071	0.1013	-0.1337	0.1313	1.000

Table B: Correlation matrix using GLSS VII (2016/2017)

	SHEP	Average expenditure (log)	Population (log)	Average household size
SHEP	1.0000			
Average expenditure (log)	0.0881	1.0000		
Population (log)	-0.0200	0.1340	1.0000	
Average household size	-0.1474	0.0862	-0.1392	1.0000
Poverty		-0.4766	-0.1701	0.2936

Table C: Correlation matrix (Community variables)

	Control	Treated
Algorithm 1		
All	271	144
Matched	185	104
Unmatched	86	40
Algorithm 2		
All	271	144
Matched	104	100
Unmatched	167	44
Algorithm 3		
All	830	288
Matched	539	245
Unmatched	291	43

Table D: Number of matched and unmatched observations

Note: In *Algorithm 1,* the control and treatment groups are matched on logged average expenditure, average household size, electrification rate, and logged population whiles in *Algorithm 2,* the control and treatment groups are matched on logged average expenditure, average household size, electrification rate, logged population, and district fixed effects. In *Algorithm 3,* the control and treatment groups are matched on average household size and population.