Electricity Accessibility and Household Business Start-ups in Rural Uganda: Evidence from Quasi-Experimental Analysis

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Abstract
This article examines the impact of access to electricity on rural household business startups across 3 channels: (1) access to rural electrification programmes, (2) access to power (irrespective of the source) and (3) connection to the grid. We use inverse probability weighted regression adjustment on survey data collected from the central region of rural Uganda and apply propensity score matching (PSM) as a check to the robustness of our results. Our primary results reveal substantial and significant impacts of electricity access on household business start-ups across the three channels. Our findings remain robust, and hidden bias does not affect our results. We find that access to power seems to have a more significant impact than access to the other two channels. This suggests that for a better understanding of how electricity affects rural areas, a comprehensive analysis of all power sources is crucial. Additionally, we show that access to electricity primarily influences the establishment of service-related enterprises rather than manufacturing and processing enterprises. From a policy standpoint, our results indicate that developing a rural transformation program through enhanced electrification interventions necessitates multiple support programmes beyond merely extending the grid lines to rural areas.

Keywords: Rural electrification; household enterprises; rural business start-ups; IPWRA; PSM; Uganda

JEL Classification Codes: L26, L32

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1.0 Introduction

The provision of electricity infrastructure and services in rural areas, commonly referred to as rural electrification, is increasing in sub-Saharan Africa (SSA), where there is a significant disparity in electricity accessibility between rural and urban areas (Golumbeanu & Barnes 2013). In 2008, the World Bank shifted its energy strategy to support rural electrification programs in developing countries, recognizing that electrification improves the social, environmental, and economic wellbeing of rural livelihoods. It is also believed that universal access to electricity will contribute to a reduction in global energy poverty by providing accessible, reliable, and sustainable energy to the world's population. Many countries have increased their investment in electrification initiatives, especially in clean and renewable energy systems, for the purpose of meeting Sustainable Development Goal 7 (SDG 7) by the year 2030 (IEA, 2020).

In SSA, rural areas continue to have lower levels of electricity accessibility. Rural households in SSA account for 70% of the world's unelectrified rural households (IEA, 2020). Approximately 668 million people in rural Sub-Saharan Africa have no access to electricity, half of whom live in Nigeria, the Democratic Republic of Congo (DRC), Ethiopia, Tanzania, and Uganda (IEA, 2021). Uganda has shown remarkable progress in electricity access, despite being one of the 20 countries with the largest population lacking access to electricity. According to World Bank data, as of 2019, electricity access in Uganda was 41%, with 70% in urban areas and 31% in rural areas. This marked a significant improvement from the 10% total access in 2010, where urban access was at 48% and rural access was only 3.4%.

Most of the literature that relates electricity to business outcomes in rural areas has examined the impact of rural electrification programmes on various business outcomes; for example, Chaplin *et al*. (2017) and Lee *et al.* (2020) reported improved value addition.[1] Additionally, Groth (2020) and Kooijman-van Dijk and Clancy (2010) observe the significance of electric lighting in business performance. Akpan *et al*. (2013) observed increased profitability of businesses connected to grid electricity. Kassem *et al*. (2018) reported that firms that gain access to electricity enhance their performance by reducing entry costs to businesses, fostering competition, and allowing unproductive firms to exit.

However, rural electrification can impact business outcomes through three channels. First, rural electrification[2] and various outcomes, e.g., households can start businesses once a village gains access to electricity regardless of whether they are connected to the grid or not. For instance, a given household can establish an agro-processing plant after connecting to the grid and thereby serve as an input supplier to other households, supporting them in starting or expanding their businesses.[3]

Based on these three channels, our contribution to the literature is twofold. First, we examine three channels through which access to electricity influences business start-ups by rural households. These channels are access to rural electrification programmes, access to power

[1] Chaplin *et al*. (2017) and Lee *et al*. (2020) also report reduced local crime rates resulting from electricity accessibility.

[2] Defined by access to rural electrification programme.

[3] E.g. a household that establishes a maize mill can supply maize flour to other households, thereby helping them in setting up a local alcohol brewing plant.

regardless of the source (sorted from the aggregated power accessibility indicator) and connection to the grid. Second, we examine how access to electricity impacts business start-ups, and we extend our analysis to document the types of businesses that households tend to establish when they gain access to electricity. The literature on rural electrification is focused on business start-ups, but evidence on the nature of established businesses has remained limited. To investigate this matter, we categorize businesses into two main sectors: (1) manufacturing and processing and (2) services. We employ inverse probability weighting with regression adjustment (IPWRA) to address possible selection bias and propensity score matching (PSM) techniques to test for robustness of the results. To test for hidden bias, we apply the Rosenbaum (2002) hidden bias sensitivity analysis to check the consistency of our results based on the identification assumption.

The findings indicate strong and significant impacts of access to electricity on household business start-ups across the three channels. However, access to power seems to have a greater impact than access to the other two channels. The latter result implies that to better understand how electricity impacts rural areas, a deeper analysis of all power sources is fundamentally important. We also find that access to electricity mainly influences the establishment of service-related enterprises rather than manufacturing and processing firms.

The study is structured into five parts. The first section covers the context and overview of rural electrification and business start-ups. Section 2 discusses the theoretical foundations and existing literature on rural electrification and business start-ups. Section 3 describes the methodologies employed. Section 4 details the results related to rural electrification and business start-ups. Section 5 concludes with recommendations.

2.0 Literature Review

The relationship between rural electrification and rural transformation has been widely documented (Barron and Torero 2014; Bastakoti 2003; Gertler *et al*. 2011, Kanagawa and Nakata (2008)). From a theoretical perspective, Barron & Torero (2014) and Gertler *et al*. (2011) developed a framework that provides a link between rural electrification and household economic outcomes. Specifically, both studies reported that rural electrification supports learning, improves health by reducing respiratory diseases from biomass, decreases the risk of toxic gases from kerosene lamps, and boosts income from nonagricultural activities. Kanagawa and Nakata (2008) document the positive and immediate effects of rural electrification on human and physical capital and quality of life, which leads to long-term income gains. Furthermore, Mori (2017) documents a positive and significant effect of electricity infrastructure on the value of land, houses and productive investments.

Khandker *et al*. (2009) observe that the absence of electricity in rural areas impedes development. Hernández-Escobedo *et al.* (2017) reported that the installation of solar energy systems enhances sustainable manufacturing in Mexico. Additionally, access to electricity in rural areas also contributes to women's empowerment. Grogan and Sadanand (2013) reported a 23% increase in the likelihood of rural Nicaraguan women working outside their homes because of electricity accessibility. The correlation between rural electrification and women's empowerment is also corroborated by Dinkelman (2011), Kanagawa & Nakata (2008), Khandker *et al*. (2009), Khandker *et al.* (2014), and Rathi & Vermaak (2018).

Access to electricity in rural areas can impact business outcomes, especially small-scale business start-ups and other income-generating activities beyond agriculture (see Burney *et al*., 2017; de Groot *et al*., 2017; Hossain & Samad, 2021; Khandker *et al*., 2009; Kumar Sedai *et* *al*., 2022; Vernet *et al.*, 2019). Bastakoti (2003) reported increased growth of local enterprises, employment creation and smooth entrepreneurship development systems resulting from increased electricity accessibility, while Chaplin *et al*. (2017) and Lee *et al.* (2020) reported improved value addition.[4] Additionally, Groth (2020) and Kooijman-van Dijk and Clancy (2010) observe the significance of electric lighting in business performance. Specifically, Groth (2020) and Kooijman-van Dijk (2010) suggested that under conditions of small business premises where light only enters through the door, electric lighting provides increased visibility through which business performance can be enhanced and new customers can be attracted (Vernet *et al*. 2019).

Kariuki (2016) used a two-stage least squares estimation to evaluate the relationship between rural electrification and microenterprises in Muranga County, Kenya. The results reveal that electricity adoption has a positive and significant relationship with business performance. This is supported by Kassem *et al*. (2018), who report that firms that gain access to electricity enhance their performance by reducing entry costs to businesses, fostering competition, and allowing unproductive firms to exit.

Furthermore, access to electricity lowers the cost of production and increases the profitability of enterprises. Akpan *et al*. (2013) noted that on average, enterprises in communities connected to an electricity grid are 16.2% more profitable than enterprises in communities without grid connections. The study attributes this difference to the ability of electricity to reduce business costs. Regarding the gendered impacts of rural electrification and the profitability of businesses, Olanrewaju and Olanrewaju (2020) document the increased profitability of women-owned microenterprises when they access electricity.

In relation to business start-ups, Kooijman-van Dijk and Clancy (2010) demonstrated the emergence of businesses in Bolivia and Tanzania. This study reports the increased emergence of businesses in agro-processing, tailoring, metalworks, communication services, and ice cream-making in the two countries, and specifically, in Tanzania, there were also increased establishments in lighting and grain milling.

Akpandjar & Kitchens (2017) indicated that providing electricity in Ghana increased the likelihood of rural men starting small businesses. These findings are supported by Carlowitz (2021), who reports positive effects of rural electrification on firm creation in Ghana. Vernet *et al*. (2019) document a positive and significant effect on the creation of female-owned microenterprises in Kenya.[5]

Furthermore, Khurana and Sangita (2022) used a two-stage Heckman identification model to examine the impact of electricity accessibility in rural India. The results show a positive impact on households' decisions to establish nonfarm enterprises, especially those that operate within their home premises. The decision to establish businesses within home premises is attributed to the current bleak employment scenario, where Indians consider small-scale nonfarm entrepreneurship to be a significant occupation for generating income.

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[4] Chaplin *et al*. (2017) and Lee *et al*. (2020) also report reduced local crime rates resulting from electricity accessibility.

[5] The increase in the creation of female-owned microenterprises is attributed to the reduction in time spent on home production activities by women.

Studies that have examined the impact of electrification on businesses in Africa, for example, Chaplin *et al*. (2017), Lee *et al.* (2020), Groth (2020), Kariuki (2016), and Kooijman-van Dijk and Clancy (2010), have emphasized the impact on business performance with limited focus on business startups. Those that have documented business startups, such as Akpandjar & Kitchens (2017), Carlowitz (2021), and Vernet *et al.* (2019), do not distinguish access channels, but access to electrification may have both external and internal impacts. The challenge in many developing countries is now to create a clear picture of what happens when electricity infrastructure is extended. It is important to answer whether extending the power line to the village (external effect) is enough to trigger business startups or if connection to the grid at the household level (internal effect) is necessary. The impact on businesses when a rural area gains access to electricity may differ from that when a household connects to the grid. In addition to the previous studies documenting the impact on business startups, they do not focus on household businesses, let alone the different sectors affected by access to electricity. Other studies, such as Kirubi *et al.* (2009) and Khandker *et al*. (2014), rely on the correlation between electrification and business activities without controlling for selection bias, particularly in rural electrification program placements. We contribute to the literature in two ways: first, we examine electricity access through three channels when the village gains access to electricity, access to power regardless of the source and, when a household connects to electricity. Second, we analyse the business sectors affected by electrification in rural areas to provide clarity for policy interventions on which business sectors are triggered by electrification. We also address selection bias in rural electrification program placements by using double robust propensity score matching techniques to highlight causation rather than just correlation between electrification and business startups.

3.0 Data and Methods

This study uses cross-sectional data collected from 5 randomly selected districts in the central region of Uganda, i.e., Kalungu, Kayunga, Mityana, Mukono, and Wakiso districts. The central region is Uganda's most populous region with the highest rural electrification rates. The data were collected through face-to-face interviews in a single wave during the months of February and March 2023. A total of 932 respondents were randomly selected from two villages per district[6], i.e., one village that benefited from the rural electrification programme and another village that did not. In total, 40 villages were recruited for the study, with 20 from treated villages (499 respondents) and 20 from control (433 respondents). Table 1 presents the descriptive statistics of the treatment, outcome and explanatory variables.

[6]During the analysis, one respondent was dropped out due to missing data on several variables.

Table 1: Descriptive statistics (N=931)

Variable	Description	Mean	S. D
Treatment			
Access to rural electricity programme	1 if a household is in village with access to rural electricity programme, 0 otherwise	0 .535	0.499
Connection to the grid	1 if a household is connected to grid electricity ,0 otherwise	0 .260	0.439
Access to power	1 if a household has access to power irrespective of the type/source, 0 otherwise	0.309	0.462
Outcome			
Household business start-up	1 if a household owns a homebased business enterprise, 0 otherwise.	0 .230	0.421
Manufacturing and processing business	1 if a household is running a manufacturing or agro-processing business enterprise, 0 otherwise	0.059	0 .235
Service business	1 if a household is running a service enterprise,0 otherwise	0.126	0.332
Explanatory Variables			
Age of the household head	Age of the household head in complete years	48.967	14.53
Male headed household	1 if a household head is male, 0 otherwise	0.63	0.482
Education of household head	1 if a household head education level is post primary and 0 otherwise	0.261	0.439
Modern House	1 if a house is iron roofed and plastered,0 otherwise	0.353	0.478
Number of Children	Total number of Children below 18 years currently staying within the household	3	2
Number of Rooms	Number of rooms used for sleeping in the household	3	1
Number of Female Household member	Number of female members residing in the household	3	1.85
Distance from the main road	Distance from the main road in Kilometres	1.85	4.194
Age of the Wife of Household head	Age of the wife of household head in complete years	45.43	14.66
Land size	Land in acres owned by the household	1.790	2.527
Land ownership status	1 if the Household owns a piece of land and otherwise 0 otherwise	0.851	0.355
Knowledge of REP	Dummy= 1 if the Household head has knowledge about rural electrification programme, otherwise 0	0.679	0.467

On average, 53.5 percent of households are in villages with access to rural electrification programme, 26 percent are connected to the grid, and 31 percent have access to power regardless of the source. Additionally, 23% of households own a business, 12.6% of which are service businesses, and approximately 6% of which are agro-processing businesses. Household heads are, on average, aged 49; 63% of the household heads are males, while 26% of such household heads have attained postprimary education. Approximately 35% of the respondents owned a permanent house. The average number of children per family was 3, which was the same as the average number of female members in the household and the number of rooms used for sleeping. On average, households were located 1.8 km from the main road and owned approximately 1.8 acres of land, and 85% of the households owned land. Approximately 68% of the household heads provided hand information about the rural electrification programme.
In Table 2, we present the results of the mean differences between the treated households across the three experimental arms households in villages with access to the rural electrification programme, households with access to power irrespective of source, households with connection to grid and their respective controls.

Table 2: Mean differences between the treated and control households (N=931)

	Rural Electrification			Access to Power			Connection to Grid		
Variable	**Treatment (Access to Grid)**	**Control (No Access to Grid)**	**Mean difference**	**Treatment (Access to Grid)**	**Control (No Access to Grid)**	**Mean difference**	**Treatment (Access to Grid)**	**Control (No Access to Grid)**	**Mean difference**
Household business start-ups	0.265	0.191	0.073**	0.461	0.142	0.318***	0.4032	0.184	0.218***
Manufacturing and processing business	0.056	0.062	-0.006	0.097	0.041	0.055**	0.074	0.053	0.020
Service business	0.158	0.090	0.068**	0.291	0.052	0.238***	0.222	0.092	0.129***
Land ownership Stuts	0.855	0.847	0.008	0.840	0.857	0.016	0.843	0.854	0.011
Age of the household head	48.675	49.304	-0.629	47.87	49.45	1.586	47.913	49.339	- 1.42
Male Headed Households	0.649	0.614	0.034	0.673	0.614	0.058*	0.679	0.616	0.062
Education of the household head	0.286	0.233	0.053*	0.312	0.239	0.073*	0.333	0.236	0.096**
Distance from Main Road (km)	0.919	2.348	-1.428***	0.862	2.038	- 1.17**	0.841	2.631	- 1.78***
Land Size (Acres)	1.775	1.807	-0.032	1.852	1.741	0.011	1.757	1.793	-0.036
Number of Children	3.458	3.247	0.211	3.645	3.232	0.142**	3.650	3.258	0.391**
Females	3.274	2.993	0.281**	3.350	3.051	0.299**	3.399	3.053	0.281**
Number of Rooms	3.419	3.491	-0.072	3.773	3.310	0.462***	3.793	3.333	0.459***
Age of the Wife of the household head	44.905	46.503	-1.597*	43.31	46.38	-3.067*	43.580	46.3773	-2.797*

*Significant at 10%; ** significant at 5%; *** significant at 1%.
Source: Author's calculations

The results in Table 2 suggest that the households in all treatment and control arms are not homogeneous across several variables, with the treatment group outperforming the control group. This suggests that there could be unobservable characteristics that may have influenced the performance of households in the treated villages or a potential selection bias during respondent selection. These differences can impact our results, particularly when employing linear estimation techniques in the analysis. To address this issue, we adopted the inverse probability weighting with regression adjustment (IPWRA) and propensity score matching (PSM) techniques to enhance the reliability of the results.

3.1 Empirical Strategy

To estimate the impact of rural electrification, it is essential to understand how the rural electrification programme was implemented. It is illogical to assume that the implementation was random. The selection of villages to benefit from the program may have been influenced by political factors, donors' and other stakeholders' interests, or proximity to an existing gridline. Another potential reason for choosing villages to benefit from rural electrification could be based on economic feasibility results available at the time of selection. These factors impact the likelihood of certain villages being selected to benefit from the programme.

To counteract issues that can lead to endogeneity problems and potentially impact our results, a randomized control trial would be instrumental. However, due to the absence of baseline data, we chose to use the matching technique in our analysis. This method has been used in various studies related to rural electrification programmes for example (Bensch *et al*., 2011; Djoumessi *et al*., 2021; Rathi & Vermaak, 2018; Samad & Zhang, 2019). Matching methods have been widely used in this field to address endogeneity issues by establishing a counterfactual group for comparison with the treated group. These techniques do not rely on a parametric model and can assess the impact of the treatment without making arbitrary assumptions about the error distribution or functional form (Caliendo and Kopeinig, 2008). Other studies examining the impact of electrification have used instrumental variable (IV) approaches, using variables such as the distance between villages and power plants, as well as the gradient and proximity to electric poles. Unfortunately, our dataset did not include information on these variables. In addition, instrumental variables present their own set of challenges, as highlighted by Kassie *et al.* (2011).

We measure the average treatment effect on the treated (ATT), which is defined as the average treatment effect on individuals who received the treatment compared to those who did not receive it. According to Caliendo and Kopeinig (2008), the average treatment effect on the treated (ATT) can be calculated as follows.

$$\text{ATT}=E\{Y_{1i}-Y_{0i}\,|\,D_i=1\}=\ E\{Y_{1i}-Y_{0i}\,|\,D_i=1\}-E\{Y_{0i}\,|\,D_i=1\} \qquad (1)$$

where $E(\bullet)$ is the expected value and Y_{1i} is an outcome of interest; in our case, $\langle i\rangle$ is a household that has access to electricity. Y_{0i} is the outcome for the same household if that household had not accessed electricity. Di is a binary treatment indicator that equals 1 if household i received electricity and 0 otherwise. The challenge we face in measuring equation (1) is that we cannot observe the same household in two different situations, one with electricity access and one without. We can only observe one situation: either with electricity or without access to electricity, but not both. With this paradox, the only way to measure the impact of treatment is to compare households with access to electricity to those without access to electricity.

$$E\{Y_{1i} - Y_{0i} \mid D_i = 1\} = E\{Y_{1i} - Y_{0i} \mid D_i = 1\} = \text{ATT} = (E\{Y_{0i} \mid D_i = 1\} \text{-} E\{Y_{0i} \mid D_i = 0\} \quad (2)$$

Takahashi and Barrett (2014) note that the left-hand side of equation (2) measures the average difference in outcomes between actual users of the treatment and nonusers, while the right-hand side of the same equation shows the extent of bias from the true ATT due to differential outcomes. To effectively address this issue within our analysis, we employ the inverse probability weighted regression adjustment (IPWRA) method. This estimation approach, known as IPWRA, involves utilizing the inverse of the estimated treatment probability weights. These inverse probability weights serve to amplify the impact of treated individuals who may have initially seemed unlikely to choose the treatment.

In the same way, they magnify individuals in the control group who appear to be similar to those who would have selected the treatment (Caldera, 2019). The IPWRA estimator uses these weights to produce robust estimates of ATET. The inverse probability weighted regression adjustment is a double robust estimator. It allows for the modelling of both the outcome and treatment equations, ensuring that even if one of the models, either the treatment model or the outcome model, is misspecified, the estimator remains consistent (Caldera, 2019). The weights of the IPWRA are calculated based on the treated and control groups. The assumption is that for all covariates, the probability of receiving the treatment is strictly positive, as defined by Rosenbaum and Rubin (1983) and presented below.

$$e(x) = \Pr(Y_i = 1|X) = F[g(x) = \text{E}(Y_i|X) \qquad (3)$$
$$0 < e(x) < 1 \text{ , } \forall = X$$

where X is a vector of covariates based on observable characteristics and $F(\bullet)$ is a cumulative distribution. According to (Rosenbaum & Rubin, 1983), the X vector contains all variables that affect both the treatment and outcome. According to equation (3) (Hirano and Imbens, 2001; Khonje *et al*., 2018), the weights can be defined as 1 for the treatment group and $\frac{p(x)}{1-p(x)}$ for the control group. These can be combined into one weighting equation below.

$$W_i = Y_i + (1 - Y_i)\frac{p(x)}{1-p(x)} \qquad (4)$$

where $p(x)$ is the estimated propensity score.

To calculate the average treatment effect, the IPWRA uses a linear regression model that is based on two processes. The inverse probability weighting (IPW) process focuses more on the treatment model when calculating the effects. The regression adjustment process focuses more on the outcome. Following Khonje *et al*. (2018) and Wooldridge (2007), the regression adjustment process can be stated as

$$ATT_{ra} = N_t^{-1} \sum_{t=1}^{N} Y_i [t_a(X\phi_a) - (t_n(X\phi_n)] \qquad (5)$$

N_t is the number of treated individuals in sample $T_a(x)$ and is assumed to be the treatment model, while $T_n(x)$ is assumed to be the control. X represents the observable characteristics, and $\phi \quad =(\alpha_i, \beta_{i)})$. The IPWRA estimator is constructed by combining the weights in equation (4) and the regression adjustment process in equation (5), as indicated in equation (6).

$$ATT_{IPWRA} = N_t^{-1} \sum_{t=1}^{N} Y_i[t_{a*}(X\phi_{a*}) - (t_{n*}(X\phi_{n*})] \quad (6)$$

where ϕ_{a*}= (α_t^* β_t^*) is obtained from the weighted linear regression

$$\min_{\alpha_t^*\beta_t^*} \sum_{=1}^{N} \frac{Y_i(y_{i-}\alpha_t^* - X\beta_t^*)^2}{pr(X,\lambda)} \quad (7)$$

where ϕ_{a*}= (α_n^* β_n^*) is obtained from the weighted linear regression

$$\min_{\alpha_n^*\beta_n^*} \sum_{=1}^{N} \frac{Y_i(y_{i-}\alpha_n^* - X\beta_n^*)^2}{1-pr(X,\lambda)} \quad (8)$$

Like other matching methods, the IWPRA relies on two assumptions that must hold for a robust ATET. The first assumption is the conditional independence assumption, which states that assignment to the treatment is based on observable characteristics and is independent of the outcome. This assumption is very strong, as it can be interpreted that unobservable characteristics did not influence the treatment. However, this may not be the case because it is possible for unobservable characteristics to influence self-selection (Wooldridge, 2007). The second assumption is the common support assumption, which states that, given the set of observable characteristics, all individuals have an equal probability of being in either the treatment or control group. Once these assumptions are satisfied, the treatment and control groups in the sample are comparable.

4.0 Empirical Results

In this section, we present the results of the inverse probability weighted regression adjustment (IPWRA) and use propensity score matching (PSM) for a robustness check. We also present the results of the identification assumptions for both IPWRA and PSM. We examine the three channels through which access to electricity influences business start-ups by rural households. We start with the rural electrification programme as the first channel and assess what happens to business start-ups when a village accesses electricity. Second, we investigate the impact of access to power (regardless of the source) on business start-ups. We argue that rural electrification programmes can complement other energy sources, such as generators and solar panel batteries, or act as a motivating factor for households without grid connections to opt for alternative energy sources. This could be for the purpose of withstanding competition or a need to match connected households. The second channel is derived from the argument that access to power in rural areas surpasses access to grid connectivity or access to rural electrification programs. In this case, households with access to power regardless of the source (treatment 2) are compared to those without power accessibility (control 2). Third, we investigate the impact of the conventional channel (grid connectivity) on business start-ups. We follow Khandker *et al*. (2009), who demonstrated the positive and significant impacts of grid connectivity on household welfare. To test this hypothesis, we compare business start-ups for households that are connected to the grid (treatment 3) to those that are not (control 3).

4.1 Factors associated with the rural electrification programme

We first report probit regression estimates of the inverse probability weighted regression adjustment model (Table 3) and the ATET in Table 4. In Model 1, we present the factors used to estimate the outcome mean for households in villages with access to the rural electrification programme and for households in villages without access to the programme. We also report the factors for the treatment model. In Model 2, we present the same factors associated with the establishment of manufacturing and processing firms. For services, the factors are reported in Model 3. The results in Table 3 indicate that the distance to the main road is negatively and significantly associated with business start-ups and the establishment of manufacturing or processing firms. A possible explanation for these results is that, in the context of Uganda, power lines are mainly located on the roadside. This implies that connection to the grid becomes expensive with distance from the pole, which can translate into a reduced probability of households connecting to the grid and consequently affecting the establishment of businesses. Furthermore, the treatment model also shows negative and significant associations between the number of female household members and access to the rural electrification programme. These negative results can be attributed to the inherent fear associated with the use of electricity by Uganda's households (Ogwok *et al.,* 2022).

Table 3: Probit regression results from the inverse probability weighted regression Adjustment

	Model 1 Household Business Start-up	Model 2 Manufacturing & Processing business	Model 3 Services business
Variable	**Coef**	**Coef.**	**Coef.**
OME (0)			
Age of the Respondent	-0.007	-0.003	-0.006
	(0.005)	(0.007)	(0.007)
Number of Children	0.004	0.036	-0.039
	(0.027)	(0.036)	(0.031)
Male Headed Households	-0.288	-0.302	-0.067
	(0.188)	(0.285)	(0.215)
Land Ownership Status	0.020	0.336	-0.026
	(0.215)	(0.361)	(0.237)
Distance from the Main Road	-0.104*	-0.268**	-0.024
	(0.058)	(0.121)	(0.121)
Land size	-0.025	0.004	-0.075
	(0.027)	(0.219)	(0.062)
_cons	-0.010	-0.109	-0.793
	(0.369)	(0.558)	(0.414)
OME (1)			
Age of the wife of Household head	-0.029***	-0.011	-0.030
	(0.005)	(0.009)	(0.005)
Number of Children	0.040	0.052	0.130
	(0.026)	(0.040)	(0.029)
Male Headed Households	0.124	-0.258	0.173
	(0.157)	(0.277)	(0.178)
Land Ownership Status	0.205	0.062	0.421*
	(0.192)	(0.313)	(0.227)
Distance from the Main Road	0.022	-0.182	0.508*
	(0.033)	(0.148)	(0.029)
Land size	0.030	-0.039	0.032
	(0.025)	(0.043)	(0.305)
_cons	0.066	-0.854	-0.475
	(0.290)	(0.415)	(0.339)
TME (1)			
Male Headed Households	-0.037	-0.037	-0.037
	(0.089)	(0.089)	(0.089)
Age of the Household Head	0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)
Distance from the Main Road	-0.102**	-0.102**	-0.102**
	(0.040)	(0.040)	(0.040)
Females	-0.056**	-0.056**	-0.056**
	(0.023)	(0.023)	(0.023)
Land Size	0.002	0.002	0.002
	(0.017)	(0.017)	(0.017)
Number of Rooms	-0.038	-0.038	-0.038
	(0.319)	(0.319)	(0.319)
Education_HH Head	0.159	0.159	0.159
	(0.098)	(0.098)	(0.098)
_cons	0.175	0.175	0.175
	(0.212)	(0.212)	(0.212)

*Significant at 10%; ** significant at 5%; *** significant at 1%.
Notes: Estimated using the Inverse Probability of the Weighted Regression Adjustment

4.2 Access to rural electrification programme and business start-ups

Next, we estimate the ATET of the rural electrification programme on business start-ups and estimate the sector-specific average treatment effects on the treated. The results in Table 4 show positive and significant effects on overall business start-ups (Model 1) and on service-related businesses. Specifically, the number of business start-ups among matched households that accessed electricity was 5.8 percentage points greater than that among matched households without access to electricity. This difference is statistically significant at the 5% level. The positive and significant impact of the rural electrification programme on business start-ups is supported by the potential outcome mean, which also indicates a greater number of business start-ups among households in villages with access to rural electrification programmes. In relation to service-related business start-ups, the results indicate that the number of matched households with access to electricity is 7.0 percentage points greater than that of matched households without access to electricity. This difference is statistically significant at the 1% level. We find no effect on the establishment of manufacturing and processing firms. These findings align with earlier findings by Akpandjar & Kitchens (2017) and Kooijman-van Dijk and Clancy (2010).

Table 4: ATET results of access to rural electrification programme and business start-ups.

	Model 1 Household Business Start-up	Model 2 Manufacturing & Processing business	Model 3 Services business
ATTE	**0.058****	**-0.002**	**0.070*****
(Rural Electrification (1 Vs 0)	**(0.030)**	**(0.019)**	**(0.022)**
POmean	**0.206*****	**0.082*****	**0.087*****
(Rural electrification programme)	**(0.022)**	**(0.017)**	**(0.014)**

*Significant at 10%; ** significant at 5%; *** significant at 1%.

Notes: Estimated using the inverse probability of the weighted regression adjustment.

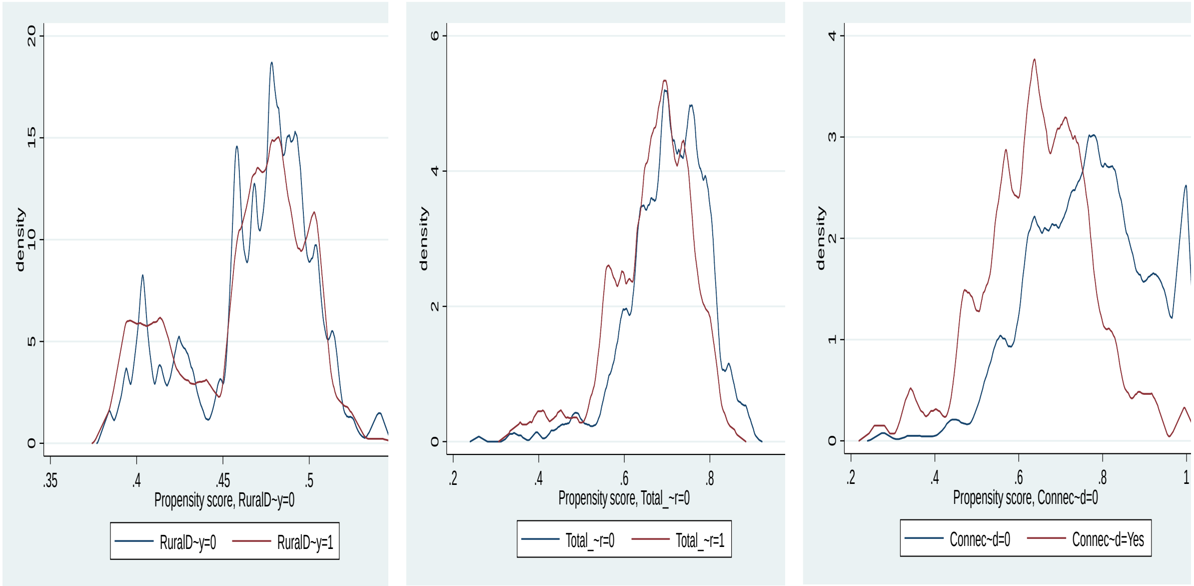
4.3 Balance checks for IPWRA on access to rural electrification

We conduct postestimation checks of the IPWRA to verify two crucial assumptions: conditional independence and common support. We assess the balance of covariates, which is important for ensuring that the conditional independence assumption holds. The weighted standardized differences are close to 0, and the weighted variance ratios are close to 1, indicating the success of the IPWRA and that a balance of variables was achieved (Caldera, 2019). Furthermore, we performed an overidentification test, and our results show that we cannot reject the null hypothesis (p value = 0.906).

Subsequently, we examine whether the common support assumption is satisfied by assessing whether all individuals in the treatment and control groups have an equal and positive probability. We find that the common support assumption is equally satisfied (refer to Figure 1, panel A).

Figure 1: IPWRA Convariate Overlap Assumption test results

Panel A: Access to rural electrication **Panel B: Access to power** **Panel C: Connection to the grid**



**Significant at 10%; **significant at 5%; ***significant at 1%. Matching was performed by using the psmatch2 program in STATA software. We use the Kernel Matching Algorithm Std. error in parentheses. The standard error for the ATT is the bootstrapped standard error of 50 replications.*

Table 5: PSM ATT results for access to rural electrification programme and business start-ups[7].

Outcome	Matching algorithm	ATT (SE)
Household Business Start-ups	Kernel Matching (bandwidth =0.04)	0.052* (0.031)
Manufacturing & Processing business	Kernel Matching (bandwidth =0.04)	-0.024 (0.019)
Services business	Kernel Matching (bandwidth =0.04)	0.071** (0.023)

4.5 Assessing the matching quality of the PSM

For the propensity score matching results to be valid, we need to evaluate the quality of the matching. Matching eliminates the differences in observables between households in villages with access to the rural electrification programme and those in villages without access to the programme. To be more specific, it is important to assess whether the two important assumptions of the PSM estimator are met. The first assumption is the conditional independence assumption. Under this assumption, we assess whether the variables used for matching are not significantly different between the treated and control groups. The results before and after matching, as well as the chi-square for the joint significance of all variables in the model, are presented in Table 6. These results show that all variables are balanced after

[7] The associated logistic model results are available on request

matching. In Table 6, we report the PseudoR2 and chi-square results. The chi-square test indicated that all variables used in propensity score matching were not significantly different after matching ($\chi 2 = 1.000$) compared to before matching ($\chi 2 = 0.000$). This was further confirmed by the PseudoR2 of the fitted model. Since there was no significant difference in the variables in the model, the PseudoR2 decreased from 10.9% before matching to 0.3% after matching. This confirms that there is no significant difference in the matched variables.

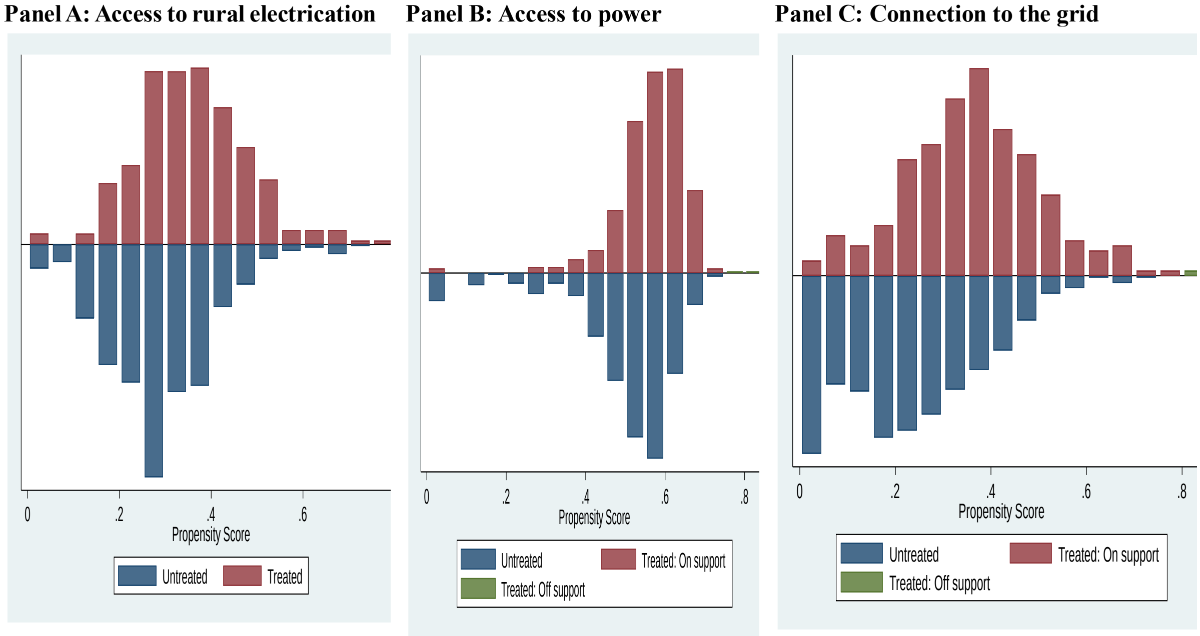
Table 6: Covariate balance tests for PSM results before and after matching

Outcome	Matching algorithm	Pseudo R^2 Unmatched	Pseudo R^2 Matched	$P>Chi^2$ Unmatched	$P>Chi^2$ Matched	Mean Bias Unmatched	Mean Bias Matched
Rural Electrification	Kernel Matching (bandwidth =0.04)	0.043	0.004	0.000	0.850	10.4	4.2
Access to power	Kernel Matching (bandwidth =0.04)	0.056	0.004	0.000	0.978	16.3	3.3
Connection to Grid	Kernel Matching (bandwidth =0.04)	0.123	0.005	0.000	0.974	18.3	3.2

Matching was performed by using the psmatch2 program in STATA software

We also check to confirm whether the second assumption of the common support condition is met to ensure that our treatment and control groups are comparable. Figure 2 panel A indicates that there is sufficient overlap among the groups, suggesting that the two groups in our study are comparable. This allows us to construct a counterfactual; households in villages with access to rural electrification programmes that are reasonably similar to households in villages without access to rural electrification programmes are selected for matching. This counterfactual can be used to estimate the average treatment effect on the treated and, consequently, the impact of the rural electrification program on business start-ups.

Figure 2: PSM Convariate Overlap Assumption test results.



4.6 Sensitivity analysis of the ATT estimates to hidden bias

The propensity score matching estimation technique may not address selection bias stemming from unobservable characteristics. The assumption is that selection into the treatment is due to observable characteristics. It is worth noting that both households in electrified villages and unelectrified villages are from the same location. They share the same geographical conditions and other institutional factors, such as schools, markets, and local administration structures. Thus, the control villages may be part of the planned rural electrification project but have not yet received the programme. This implies that they are eligible to access the programme. By implication, endogeneity concerns arising from (1) the selection of villages and (2) self-selection by households to connect may not be ruled out.

Caliendo and Kopeinig (2008) note that propensity score matching (PSM) estimators are robust to unobservable characteristics. If the bias resulting from unobservable characteristics is significant, the obtained average treatment effect (ATT) may be biased. It is necessary to check the sensitivity of the estimated results if they deviate from the identification assumptions (Becker & Caliendo, 2007). We apply Rosenbaum (2002) hidden bias sensitivity analysis to check the consistency of our results based on the identification assumption. Table 6 shows the results of the sensitivity analysis. All the average treatment effects (ATTs) are positive, indicating that the assumption of underestimating the true treatment effect is ruled out (Becker & Caliendo, 2007).

If a study were free of hidden bias, a gamma (Γ) value equal to 1 would be statistically significant at the 5% level of significance or lower. However, the critical value of gamma (Γ) at the upper bound that could invalidate our results is unknown. We set the upper bound of the critical value of gamma (Γ) to 1.5. The critical value of gamma (Γ) is set between 1 and 1.5. Subsequently, we assess the hidden bias to determine the extent to which unobservable characteristics must differ between the treatment and control groups for our results to be biased. Our findings did not reverse the treatment effect, which aligns with the conclusions of Becker & Caliendo (2007).

Table 7: Rosenbaum sensitivity test for hidden bias

Gamma(Γ)	**(p) Critical**					
	Rural Electrification		**Access to Power**		**Connection to Grid**	
	Household Business Start-up	**Service business**	**Household Business Start-up**	**Service business**	**Household Business Start-up**	**Service business**
1	0.1165	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
1.1	0.2896	0.0042	<0.0001	<0.0001	<0.0001	<0.0001
1.2	0.5108	0.0145	<0.0001	<0.0001	<0.0001	<0.0001
1.3	0.7130	0.038	<0.0001	<0.0001	0.0013	0.0010
1.4	0.8550	0.0813	<0.0001	<0.0001	0.0041	0.0026
1.5	0.9359	0.1477	<0.0001	<0.0001	0.0102	0.0057

* gamma - log odds of differential assignment due to unobserved factors. Rosenbaum bounds for gamma **(Γ) gamma (1 (0.1)1.5)** (N = 242, 287 matched pairs)

The Rosenbaum sensitivity analysis is used to address hidden bias, which is prevalent in observational studies where randomization or baseline data are often unavailable. In observational studies, variations between the treated and control groups may arise from unobserved variables, resulting in hidden bias. Sensitivity analysis assesses how much hidden bias (unobserved covariates) can impact the study outcomes. The analysis revealed the degree of hidden bias that could potentially change the study's findings.

4.7 Power accessibility and household business start-ups

Next, we investigate whether access to power (irrespective of the source) influences the establishment of household business start-ups. As previously mentioned, rural electrification programmes can complement other existing power sources (such as generators, solar panels, and batteries), or households without grid connections may need to resort to alternative power sources to keep up with connected households. To examine this, we analyse our outcome variables against a binary variable that is assigned the value of 1 if a household has access to power (regardless of the source) and 0 otherwise. The average treatment effect on the treated

(ATET) results are detailed in Table 8, and the corresponding balance checks can be found in Figure 1, panel B.

Table 8: ATET Results of Power Accessibility and Business Start-ups[8]

	(1)	(2)	(3)
	Household Business Start-up	**Manufacturing & Processing business**	**Service business**
ATET	**0.326*** **	**0.038* **	**0.230*** **
(Access to Power (1 Vs 0)	**(0.033)**	**(0.021)**	**(0.029)**
POmean	**0.143*** **	**0.059*** **	**0.062*** **
(Access to Power (0)	**(0.016)**	**(0.013)**	**(0.011)**

*Significant at 10%; ** significant at 5%; *** significant at 1%.
Notes: Estimated using the inverse probability of the weighted regression adjustment estimator

The results in Table 8 indicate that the average treatment effect on the treated is 0.326, suggesting that business start-ups of matched households with access to power are 32.6 percentage points greater than those of matched households without access to power. This difference is statistically significant at the 1% level (Model 1). A quick comparison of the results in Table 4 and Table 8 (especially in the first models of both tables) reveals that access to power has a more significant impact on business start-ups than access to rural electrification. This implies that more households are engaging in businesses using power beyond what the rural electrification programme provides. In models 2 and 3, the results indicate that access to power has a positive and significant effect on the establishment of manufacturing and processing firms, as well as service-related firms. The impact is significant at the 10% and 1% levels, respectively. The results in Table 8 were also tested using PSM, remain robustly similar[9]. Assumption test of PSM are presented in Table 6, and the results of the overlap test are presented in Figure 2, panel B.

4.8 Grid connections and household business start-ups

In Table 9, we present the average treatment effect on business start-ups resulting from a household connecting to the grid. We argue that the implementation of a rural electrification programme does not always guarantee access to electricity. However, studies suggest that rural electrification positively impacts business performance (Chaplin *et al.*, 2017; Lee *et al.*, 2020) and that connecting to the grid may lead to different results. We test for this by assessing the impact of grid connections on business start-ups. To do this, we compare our outcome variables against a constructed dummy variable that is assigned a value of 1 if a household is connected to the grid and 0 otherwise. The average treatment effect on the treated (ATET) results are detailed in Table 9, and the overlap assumption test is presented in Figure 1, panel C.

Table 9: ATET Results for Connections to Grid Electricity and Business Start-ups[10]

	(1)	(2)	(3)
	Household Business-startups	**Manufacturing & Processing business**	**Service business**
ATET	**0.170*** **	**-0.002**	**0.128*** **
(Grid Connection (1 Vs 0)	**(0.036)**	**(0.022)**	**(0.302)**
POmean	**0.200*** **	**0.077*** **	**0.094*** **
(Grid Connection)	**(0.020)**	**(0.014)**	**(0.014)**

*Significant at 10%; ** significant at 5%; *** significant at 1%.
Notes: Estimated using the inverse probability of the weighted regression adjustment estimator

[8] The probit regression outcomes from the inverse probability weighted regression adjustment can be provided upon request.
[9]The PSM associated logistic regression results are available upon request
[10] The probit regression results from the inverse probability weighted regression adjustment can be provided upon request.

The results in Table 9 for Model 1 indicate that the average treatment effect on the treated is 0.170, suggesting a 17% difference in the business start-ups of households connected to the grid compared to those that are not connected. This result supports Akpandjar & Kitchens (2017) and Kooijman-van Dijk and Clancy (2010), who find increased business establishments in Ghana and Bolivia. Furthermore, we observe a positive and significant impact on the establishment of manufacturing and processing firms (Model 2). After checking for potential outcomes, even the impact of grid connectivity on business start-ups becomes positive and significant. Finally, we check the robustness of the IPWRA results on grid connections and business start-ups using PSM and observe that they remain robustly similar[11]. PSM assumption tests are presented in Table 6 and Figure 2 Panel C.

5.0 Conclusions

This study examined the impact of electricity accessibility on business start-ups in rural Uganda. We used data from 932 households in Uganda's rural areas. Our focus was to understand how access to electricity impacts business start-ups. While theory suggests that connecting rural areas to electricity is likely to increase property values and establish new businesses, the literature primarily focuses on examining the impact of access to rural electrification programmes or grid connectivity on business performance. In this study, we introduce a third channel through which rural households are impacted by access to electricity (regardless of the source). We employ inverse probability weighting with regression adjustment (IPWRA) to match treated households with those in the control group while exploring how business start-ups in rural areas are impacted by access to electricity. We investigate this impact through three channels: access to a rural electrification programme, connection to the grid, and access to power, regardless of the source.

The findings indicate strong and significant impacts of access to electricity on household business start-ups across the three channels. However, access to power seems to have a greater impact than access to the other two channels. This result suggests that for a better understanding of how electricity impacts rural areas, a deeper analysis of all power sources is fundamentally important. Additionally, we found that access to electricity mainly influences the establishment of manufacturing and processing firms rather than service-related enterprises.

As a point of caution, this study was conducted in rural areas of Uganda and may not be generalizable to urban settings and communities with greater access to electricity. For this reason, future research on this subject could explore rural and urban disparities, emphasizing profitability, sustainability, and the gender aspects of household businesses.

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[11] These results, combined with their associated logistic regression results, are available upon request.

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