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Socioeconomic and Behavioural Factors Influencing Electrical Appliance Adoption Among Rural Farming Households: An Endogeneity Switching Regression Analysis

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ABSTRACT

In rural areas, household agricultural income has a significant influence on the adoption of new technologies, including electrical appliances. Despite technological advancements, adoption rates remain inconsistent due to socioeconomic disparities and behavioural patterns. This study examines the impact of socioeconomic and behavioural factors, as well as agricultural income, on the adoption of electrical appliances among farming households in South Africa's Eastern Cape Province. Data were collected from 224 households using structured questionnaires and analysed through descriptive statistics and Endogeneity Switching Regression (ESR). The results show that variables such as age ($p<0.01$), years of schooling ($p<0.05$), occupation ($p<0.01$), family size ($p<0.05$), access to extension services ($p<0.05$), off-farm income activities ($p<0.05$), and distance to markets ($p<0.01$) significantly influence the likelihood of adopting electrical appliances. The ESR model confirms a statistically significant and positive relationship between adoption and household agricultural income. The Average Treatment Effect on the Treated (ATT) indicates an income gain of ZAR2,757 ($p<0.01$), while the Average Treatment Effect on the Untreated (ATU) suggests potential gains of ZAR1,765 ($p<0.01$) if non-adopters were to adopt. The study recommends targeted interventions, including expanded extension services, adult education programs, and gender-sensitive strategies to empower female-headed households. Strengthening rural

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electrification and promoting affordable, energy-efficient technologies are also crucial for enhancing energy security and improving productivity in rural farming systems.

Keywords: Energy-Efficient Technologies, Rural Electrification, Sustainable Farming Practices.

1. INTRODUCTION

In many developing countries, particularly in rural areas, poverty and food insecurity persist as significant challenges. Limited access to energy significantly impedes efforts to alleviate poverty, stimulate economic growth, and improve quality of life, particularly in agriculture (Doll & Pachauri, 2010). While electricity serves essential household functions, such as lighting and communication, its broader role in driving economic and agricultural development is profound. Access to electricity supports entrepreneurship, boosts productivity, and aligns with global development agendas such as the United Nations' Sustainable Development Goals (SDGs) (United Nations, 2015).

Agricultural production contributes directly to SDG 1 (No Poverty) and SDG 2 (Zero Hunger). Electricity access enhances food preservation, crop processing, and access to educational and health services. Lack of refrigeration, for instance, leads to spoilage of perishable goods, worsening food insecurity (Arthur, 2009). Therefore, rural electrification is crucial for enhancing agricultural productivity and overall livelihoods. Despite infrastructure development, the adoption of electrical appliances in farming households, especially in the Eastern Cape Province, remains limited. Socioeconomic disparities and behavioural constraints often hinder adoption. Understanding these influences is essential for guiding policies that promote sustainable technology use.

Adopting electrical appliances can significantly enhance agricultural productivity (Kageni, 2015; Melesse, 2015; Mekonnen, 2017). However, household decisions to adopt technology are shaped by income levels, education, access to finance, and attitudes toward innovation. Higher incomes and educational attainment typically increase the likelihood of adoption (Peters & Sievert, 2016), while financial constraints and cultural resistance can deter investment in new technologies (Mandipaza, 2022). Tailored interventions are necessary to bridge these gaps and foster inclusive rural development (Sharma & Singh, 2015; Obayelu, 2017).

Socioeconomic variables, such as income, education, and access to credit, significantly affect households' willingness and ability to invest in technology (Nkhoma, Mwale, & Ngonda, 2024). Lower-income households often lack the financial flexibility to purchase appliances, but targeted microloans, subsidies, or financial literacy programs can improve accessibility (Shi & Qamruzzaman, 2022). Bridging these disparities can support the equitable diffusion of technology.

Behavioural dimensions also shape technology adoption. Positive attitudes toward innovation increase the uptake of innovation (Akroush *et al*., 2019; Blimpo & Cosgrove-Davies, 2019). Households that recognise the utility of electrical appliances in boosting efficiency and yields are more likely to invest (Ali, Shafiq, & Andejany, 2021). Conversely, cultural norms and fear of financial risk can impede progress (Mandipaza, 2022). Community outreach, peer testimonials, and tailored education programs can counter misconceptions and resistance. External factors, including electricity reliability and market access, further influence adoption (Odhiambo, 2015; Mudi, 2020). Without a stable energy infrastructure, households cannot utilise appliances effectively. Additionally, geographic distance from suppliers or service providers adds logistical barriers. Financial incentives, policy support, and infrastructural investment are crucial for creating an enabling environment for adoption (Pothitou, Hanna, & Chalvatzis, 2017).

1.1. Problem Statement

Despite significant rural electrification efforts in South Africa, the adoption of electrical appliances among farming households in the Eastern Cape remains uneven. A complex mix of socioeconomic, behavioural, and infrastructural barriers influences this disparity. Addressing these issues is critical to unlocking the full benefits of electricity in improving agricultural productivity and rural livelihoods. This study aims to identify these key influencing factors and assess the impact of appliance adoption on household agricultural income using an Endogeneity Switching Regression approach.

2. MATERIAL AND METHODS

2.1. Description of the Study Area

This study was conducted in Mnquma Local Municipality (MLM), located in the Eastern Cape Province of South Africa at 32° 19′ 0″ S and 28° 8′ 0″ E. MLM is part of the Amathole District

Municipality and falls within the former Transkei region, an area historically marked by high poverty levels, underdeveloped infrastructure, and heavy reliance on small-scale agriculture. The municipality has a dual economy, where urban centres, such as Butterworth, Centane, and Ngqamakhwe, have better infrastructure, while rural villages face challenges related to limited market access, poor service delivery, and energy insecurity.

According to Stats SA (2021), Mnquma has an estimated population of 252,390 people, residing in 69,732 households, spread across an area of 3,328 km². Many households in rural Mnquma depend on subsistence farming and small-scale agricultural activities as their primary source of income. However, access to modern farming technologies, including electrified equipment, remains limited due to socioeconomic disparities and infrastructure challenges. Access to electricity plays a crucial role in enhancing productivity, reducing labour intensity, and improving household well-being, making it an essential factor in rural development.

The Integrated National Electrification Programme (INEP) has expanded electricity access in rural South Africa, yet many areas still face energy insecurity and unreliable service delivery.



FIGURE 3.1: Map of the Study Area

2.2. Research Design and Unit of Analysis

This study employed a quantitative cross-sectional research design, collecting data at a single point in time to analyse various demographic and socioeconomic factors influencing the

adoption of electrical appliances following rural electrification. Data was gathered through questionnaires administered to selected households. Proper research planning was crucial for selecting appropriate variables, determining the types of data required, and establishing realistic means of data collection and interpretation (Leedy & Ormrod, 2010).

The unit of analysis, defined as the person or object from whom data is collected (Bless *et al*., 2016), comprised rural agricultural households from three electrification stages in three purposively selected villages. The household representative in Mnquma Local Municipality was surveyed on behalf of all household members, with a focus on those who shared the same electricity budget. This approach minimised costs and time by questioning only one member per household rather than every member.

2.3. Sampling Procedure

The sampling procedure involved selecting a representative subset of the population that accurately reflects the characteristics of the entire population. To assess the impact of electrification on household agricultural income and the adoption of electrical appliances, this study focused on three villages at different stages of electrification within the Mnquma area.

Mgomanzi (electrified village): Households in this village have had access to electricity for an extended period, allowing for the sustained adoption of appliances. Qobo-qobo (recently electrified village): Households here gained access to electricity only recently, providing an opportunity to examine early adoption trends. Qina (non-electrified village): Households in this village still rely on alternative energy sources such as firewood, paraffin, and solar power, making it a useful comparison group for understanding barriers to appliance adoption. These villages were selected to represent different stages of electrification and appliance adoption, allowing for a comparative analysis of how access to electricity, agricultural income, and socioeconomic factors influence technology adoption. Out of the total 854 households in these villages (Stats SA, 2011), 313 households were electrified, 260 were recently electrified, and 281 remained non-electrified.

A sample of the study was determined using Yamane's formula, ensuring a 95% confidence level. The total population of households across these three villages was 854, according to the 2011 census data. To achieve the desired sample size, simple random sampling was employed. This technique ensured that each household had an equal chance of being included in the study,

thereby minimising selection bias. The sampling frame was provided by the local authorities, who supplied lists of households for each village (Bless *et al*., 2016). The application of Yamane's formula is as follows (1967):

$$n= \frac{N}{1+Ne^2}$$

Where n = sample size; N = number of households, 854 (total number of households of the three selected villages obtained from the census 2011) and e = degree of precision (95%)

$$=\frac{N}{1+Ne^2}$$

$$= \frac{854}{1+854\times0.05^2}$$

n=272

This calculated sample size of 272 households provided a robust basis for the study, ensuring that the findings would be generalisable to the broader population of the three villages. However, due to the limited number of farmers, the study was able to conduct a survey on 224 farming households, which was also significant enough to draw conclusions that represented the entire population.

2.4. Data Collection

The study utilised a structured questionnaire as the primary data collection tool to ensure the systematic gathering of relevant information from respondents. Face-to-face survey interviews were conducted to improve response accuracy by allowing interviewers to clarify questions, probe for details, and address any misunderstandings. This method was particularly beneficial in rural settings where literacy levels may vary, ensuring that all respondents fully understood the questions before answering (Leedy & Ormrod, 2010). The survey targeted household heads, as they are typically responsible for decision-making regarding agricultural activities, income allocation, and the adoption of technology. However, in cases where the household head was unavailable, a close relative or next of kin was interviewed to maintain data consistency. This approach helped minimise information gaps while ensuring that responses accurately reflected the household's circumstances. The questionnaire incorporated both closed-ended and open-ended questions to provide a balanced approach to data collection. Closed-ended questions facilitated easy quantification and comparison of responses, while open-ended questions

allowed respondents to elaborate on specific issues, providing deeper insights into their experiences and perceptions of electrification and agricultural income.

The collected data focused on four key aspects: household demographics, electricity availability, adoption of electrical appliances, and the perceived benefits of electricity. Demographic data covered age, gender, education level, household size, income sources, and farming activities, providing a socioeconomic profile of respondents. Information on electricity availability helped classify households into three categories: electrified, recently electrified, and non-electrified. The section on electrical appliance adoption assessed the types of appliances owned, their usage patterns, and factors influencing adoption decisions. Lastly, the study examined the perceived benefits of electricity, specifically its role in enhancing agricultural productivity, generating income, and improving household well-being. By integrating both qualitative and quantitative elements, the questionnaire was designed to capture comprehensive data, aligning with the study's objective of examining the relationship between agricultural income, electrification, and the adoption of electrical appliances in Mnquma Local Municipality.

2.5. Data

This section presents data which was collected from smallholder farmers. Table 1 below illustrates the collected data from smallholder maize farmers.

TABLE 1: Data Collected from Maize Farmers

Variables	**Variable description**	**Expected sign**
Adoption outcome variables	**Outcome indicator**	
Binary adoption variable	Dummy = 1 for electricity appliance adopters, 0 otherwise	
Household characteristics		
Sex	Dummy =1, if a farmer is the male household head, 0 otherwise	+/-
Age	Age of the household head (years)	+

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Household monthly income	Total household monthly income (actual amount)	+
Farm size	The actual size of the farm (actual hectares)	+
Family size	Total family size (in adult-equivalent)	+/-
Years spent in school	Total number of years of schooling of the household head (years)	+/-
Asset ownership	The initial value of assets owned by the household	+/-
Off-farm employment	Dummy = 1 if the farmer participates in off-farm income-generating activities; 0 otherwise	+
Extension visits	Dummy = 1 if the farmer accessed the extension service; 0 otherwise	+/-
Access to credit	Dummy = 1 if the farmer accessed credit; 0 Otherwise	+
Member of farm organization	Dummy = 1 if the farmer is a member of a farm organization. 0 otherwise	+
Access to electricity appliances	Dummy = 1 if the farmer has access to electricity appliances in the village; 0 otherwise	+
Market access	Dummy = 1 if a village has access to the primary market	+

3. DATA ANALYSIS

Data analysis is a crucial component of this study, enabling the examination of patterns, testing of hypotheses, and drawing of inferences from the sample to the broader population (Bless *et al*., 2016). This study utilised three key methods: descriptive statistics, binary logistic regression (BLR), and endogeneity switching regression (ESR). Each of these methods was chosen based on the nature of the research questions and the data, with justifications for their use provided below.

3.1. Descriptive Statistics

Descriptive statistics were employed to summarise key household characteristics, electrification status, and appliance adoption rates. This involved calculating frequencies, percentages, means, and standard deviations to represent the demographic and household data. The data were presented using graphs and tables for clarity and easy interpretation. SPSS version 24 was used for the descriptive analysis. Descriptive statistics are helpful in presenting an overview of the data, particularly when working with large datasets of household data. They help to identify patterns and trends, such as the distribution of electrification status and appliance adoption. Studies such as Matinga and Annegarn (2013), which focused on the adoption of modern energy sources in South Africa, and Tucho and Nonhebel (2017), who analysed energy consumption patterns in rural Ethiopia, have also employed descriptive statistics in similar contexts. These studies demonstrate the utility of descriptive methods in exploring energy access and adoption patterns in rural areas.

3.2. Binary Logistic Regression Model

3.2.1. Model Specification

Binary choice models, such as the logit or probit models, are appropriate for analysing models with binary response-dependent variables. These models assume both deterministic utility and probabilistic decision processes (Mdoda *et al*., 2022; Greene, 2012) and are commonly used in adoption decision studies involving binary choices. The study employed a binary logistic regression model, which was found to perform better than the multinomial logit model (Nontu & Taruvinga, 2021; Mdoda *et al*., 2019), to analyse factors influencing household adoption of new electrical appliances based on electricity availability.

Binary logistic regression analyses data and explains the relationship between a binary dependent variable and one or more independent variables at the nominal, ordinal, interval, or ratio level. The dependent variable, energy security status, was coded as 1 if the household was energy-secured and 0 otherwise. The logistic model is expressed as:

According to Greene (2012), the logistic model takes the form:

$$\log(P_i\ /(1-P_i)\ = logP_i = \beta_0 + \beta_1 X_1 \ldots\ldots\ldots\

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The probability of the occurrence of an event relative to non-occurrence is called the odds ratio and given by the following equation:

$$P_i\ /(1-P_i)\ = \exp(\beta_0 + \beta_1 X_1) \ldots\ldots\ldots\

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- y_0, y_1,……., y_n are the coefficients.

In the second stage, the outcome equation assesses the impact of appliance adoption on agricultural income:

Income Equation: $Y_i = \alpha_0 + \alpha_1 Adopt_i + \alpha_2 Z_i + \epsilon_i$

Where:

- Y_i is the agricultural income for household iii,
- $Adopt_i$ is the adoption status of appliance iii (from the first stage),
- Z_i represents control variables (e.g., household size, education),
- ϵ_i is the error term.

ESR corrects for endogeneity by considering the simultaneous relationship between appliance adoption and agricultural income, ensuring unbiased estimates. Studies such as Di Falco *et al*. (2011), who used ESR to assess the impact of climate change adaptation on farm productivity, and Mekonnen *et al*. (2021), who applied ESR to evaluate the impact of improved cooking stoves on household welfare, illustrate the model's effectiveness in evaluating the causal impact of adoption decisions in agriculture and rural settings.

The Endogeneity Switching Regression (ESR) model was selected for this study due to its suitability in addressing the complex relationship between appliance adoption and agricultural income, particularly in the presence of selection bias and potential endogeneity. In this context, the decision to adopt electrical appliances is not random; rather, it is likely influenced by both observed and unobserved characteristics of the household. These factors may include income levels, education, and household composition, as well as latent traits such as risk preferences, time preferences, or exposure to information—variables that cannot always be directly measured but may influence both the likelihood of adoption and agricultural income outcomes.

Traditional estimation techniques, such as Ordinary Least Squares (OLS) or Propensity Score Matching (PSM), may fail to provide unbiased estimates under these circumstances. OLS assumes exogeneity and homogeneity, whereas PSM can only control for observable covariates and does not correct for selection bias due to unobservable variables. In contrast, ESR allows for a more rigorous approach by jointly modelling the selection into adoption and the outcome (agricultural income), explicitly accounting for the possibility that the two processes are correlated through unobserved factors.

The ESR model operates in two stages. The first stage involves estimating a selection equation using a probit model to determine the probability that a household adopts electrical appliances. This step helps to isolate the factors influencing the adoption decision. The second stage consists of estimating separate income equations for adopters and non-adopters, thereby allowing the analysis to capture heterogeneity in outcomes based on adoption status. The ESR model corrects for endogeneity by incorporating the correlation between the error terms of the selection and outcome equations, ensuring that the estimated impact of adoption on income is not biased by self-selection.

This modelling framework has been widely applied in agricultural and rural development studies where treatment assignment is non-random. For example, Di Falco *et al*. (2011) employed ESR to evaluate the impact of climate change adaptation strategies on agricultural productivity, while Mekonnen *et al*. (2021) used the model to assess the welfare effects of adopting improved cooking technologies. Following this tradition, the application of ESR in this study is both methodologically sound and contextually appropriate, as it enables a credible estimation of the causal effect of adopting electrical appliances on agricultural income in rural settings.

4. RESULTS AND DISCUSSION

4.1. Socio-Demographic Characteristics of Smallholder Farmers

Table 2 outlines key differences between adopters and non-adopters of electrical appliances. Electrified households were more often female-headed (64% vs. 52%) and married (52% vs. 48%), suggesting that access to electricity supports proactive, stable household structures. Though access to credit was limited across both groups, electrified households tended to have larger families (5 members), larger farms (2 hectares), and were located closer to markets (average distance of 20.16 km), facilitating adoption and maintenance of technologies (Mdoda *et al*., 2023; Makamane *et al*., 2023).

Education and income levels were notably higher among electrified households, with an average of 13 years of schooling and a monthly income of ZAR 6,234.14. These factors enhance the ability to invest in and manage new technologies. Although the average age across households was 54 years, older farmers tended to adopt less due to risk aversion (Mdoda *et al*., 2024). Non-electrified households, meanwhile, relied more heavily on social grants and

agriculture (58%), indicating traditional income sources that may limit their ability to adopt technological change (Qange *et al*., 2024; Nontu *et al*., 2024).

TABLE 2: Demographic Characteristics Between New Technology Adopters and Non-Adopters of Farming Rural Households

Variables	**Electrified**	**Non-electrified**	**Overall**	**T-test**
Gender: Female	0.64	0.52	0.58	0.015**
Access to credit: No	0.28	0.26	0.27	0.008***
Marital status: Married	0.52	0.48	0.50	0.14**
Occupation: pensioner and farmer	0.34	0.44	0.39	1.234
Source of income: social security and agricultural activities	0.54	0.58	0.56	0.003***
Access to information: Yes	0.52	0.37	0.45	0.024**
Cooperative membership	0.44	0.28	0.36	0.009***
Variable	**Electrified**	**Non-electrified**	**Overall**	**Chi-squared**
Age	52.3	56.4	54.4	0.004***
Family size	5.3	3.9	4.6	0.015**
Farm size	2.4	1.9	2.2	0.000***
Years spent in school	13.4	9.4	11.4	0.028**
Household monthly income	6 234.14	4 689.58	5 461.86	0.045**
Distance to markets	20.16	34.26	27.21	0.018**

Note: ** $p < 0.05$ and *** $p < 0.01$ represent the significant levels, respectively.

4.2. Energy Security Status Dimension for Farming Rural Households

Figure 2 below illustrates the energy security status in the farming households. The findings from the figure indicate a significant disparity in energy security among the surveyed households. Specifically, 68% of these rural farming households are classified as energy-secure, while 32% are deemed energy-insecure. This distribution highlights that most

households rely on reliable energy access, which is essential for sustaining their agricultural activities and maintaining their daily living standards. Sixty-eight percent of households categorised as energy secure are positioned to leverage stable energy sources effectively. This access is likely to enhance their agricultural productivity and overall quality of life by enabling the use of modern farming tools, improving operational efficiency, and supporting various household needs.

In contrast, 32% of households identified as energy insecure face significant challenges related to energy access. These challenges may hinder their agricultural productivity, limit their use of modern technologies, and adversely affect their overall well-being. The gap between energy-secure and insecure households highlights a critical area for targeted intervention.

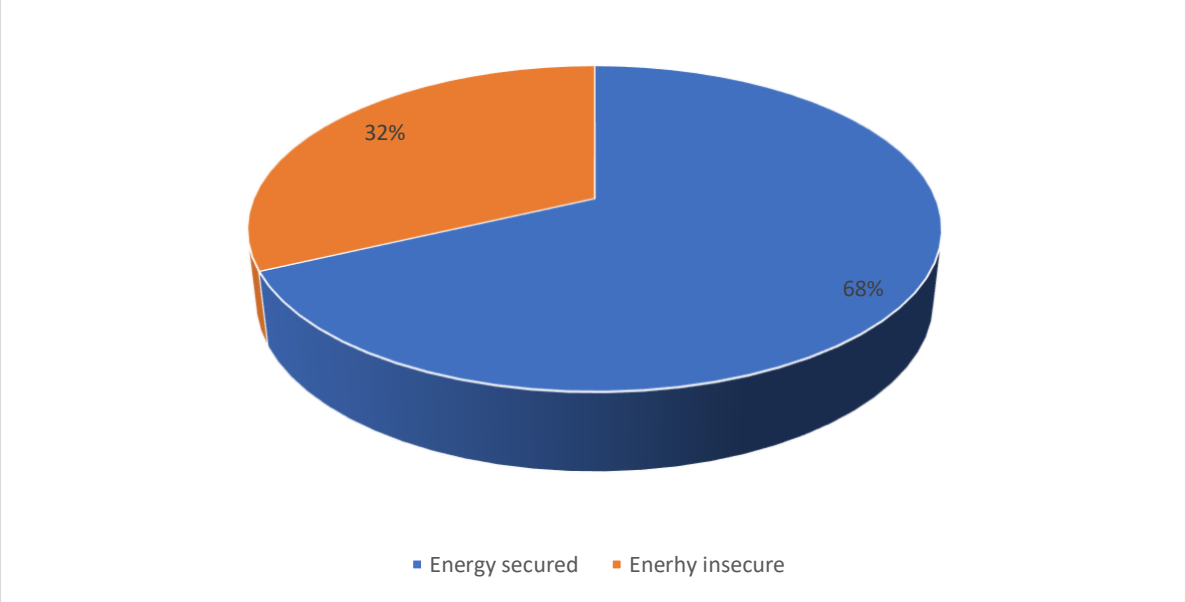


FIGURE 2: **Energy Security Status Dimension for Farming Rural Households**

4.3. Total Household Energy Expenditure of the Farming Households

Table 3 compares energy expenditure across sources for electrified and non-electrified households, categorised into four brackets (0–100, 101–200, 201–300, and >300 units). Among electrified households, 51% spend between 101 and 200 units on electricity, with 23% spending over 300 units, indicating both widespread use and potential financial strain for some. Non-electrified households exhibit high spending on gas, with 34% falling within the 101–200 units range and 21% exceeding 300 units, reflecting their dependence on gas for cooking and heating. Paraffin use is also prevalent: 59% spend 0–100 units and 36% spend 101–200 units, underlining its role as a key energy source. Candle usage, with 34% spending 0–100 units,

highlights the lack of reliable lighting. Some non-electrified households also rely on firewood, with 23% spending between 201 and 300 units. Other sources primarily fall within the lower expenditure brackets, offering varied but limited alternatives. Overall, energy spending patterns reveal the cost burden and inefficiencies faced by households without electricity. These findings emphasise the need for targeted electrification and affordable energy solutions to reduce dependency on less efficient and more costly sources.

TABLE 3: Total Household Energy Expenditure on Energy Sources for Farming Rural Households

	Electrified				**Not-electrified**			
Source	**0-100**	**101-200**	**201-300**	**>300**	**0-100**	**101-200**	**201-300**	>300
Electricity	13	51	13	23	0	0	0	0
Gas	0	5	1	6	0	34	10	21
Paraffin	29	0	0	0	59	36	1	0
Candles	31	0	0	0	34	0	0	0
Firewood	0	0	0	0	0	0	23	3
Other energies	0	0	0	0	17	20	1	0

4.4. Benefits of Electricity with Electric Appliances on Farming Rural Households

Figure 3 below shows the various benefits of electricity and electrical appliances for rural farming households in Mnquma Local Municipality. The most cited benefit is enhanced knowledge, with 90% of respondents reporting improved access to educational resources. This is followed by increased farm productivity (86%), as electricity enables the use of advanced equipment and technology, leading to higher yields and improved agricultural practices.

Improved operational efficiency is recognised by 80% of households, while 78% noted income diversification through new business opportunities. Enhanced food storage, cited by 76%, reduces post-harvest losses and boosts food security. Additionally, 74% of respondents acknowledged an improved quality of life due to better lighting, hygiene, and modern conveniences. Environmental and financial benefits, although slightly less emphasised (74% and 70%, respectively), remain notable, reflecting a reduced reliance on unsustainable energy sources and potential cost savings. While immediate gains, such as productivity and efficiency,

are prioritised, the findings suggest that increased awareness of long-term benefits could further promote adoption.

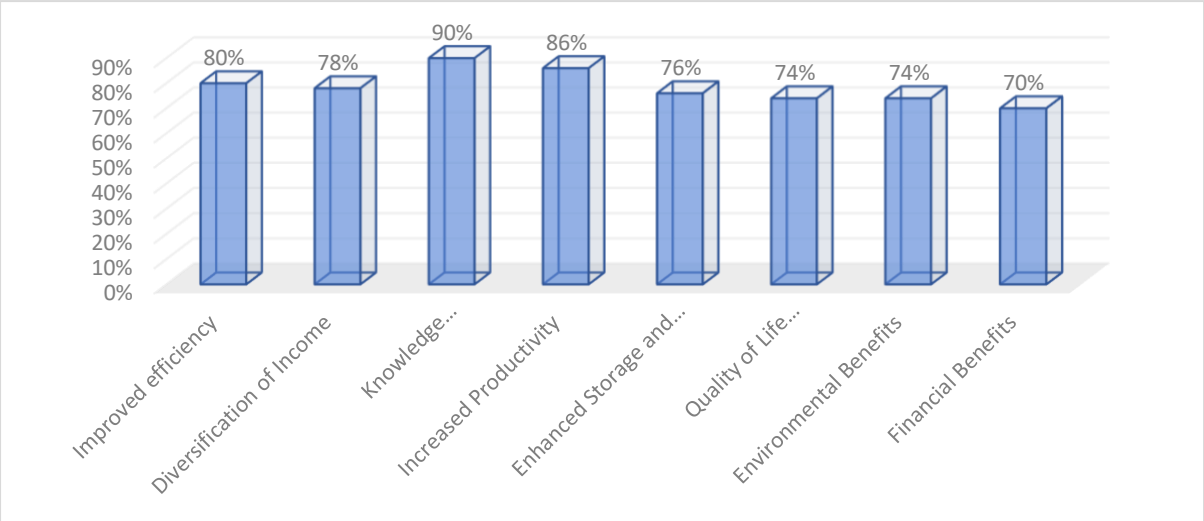


FIGURE 3: **Benefits of Electricity with Electric Appliances on Farming Rural Households**

4.5. Contribution of Electricity to Electricity Appliances on the Socioeconomic Status of Farming Households

Figure 4 illustrates the socioeconomic benefits of electricity and appliance use among farming households. The findings reveal varied impacts, with security and safety being the most recognised, cited by 40% of respondents. Electricity improves household safety, likely through better lighting and the use of security systems. Farming-related benefits were acknowledged by 32%, reflecting the role of electricity in enhancing productivity through improved tools and infrastructure. Business benefits were noted by 18%, highlighting electricity's support for entrepreneurship and small-scale economic ventures.

Only 10% of respondents identified environmental benefits, indicating limited awareness of electricity's role in reducing reliance on unsustainable energy sources. While immediate socioeconomic benefits are widely recognised, environmental impacts are often underappreciated. Overall, the data highlight the transformative impact of electricity on rural development. However, there is a clear need to enhance communication and awareness about its broader environmental advantages. The study affirms electricity's multifaceted contributions to socioeconomic well-being and highlights the need for targeted outreach to amplify less visible benefits such as environmental sustainability.

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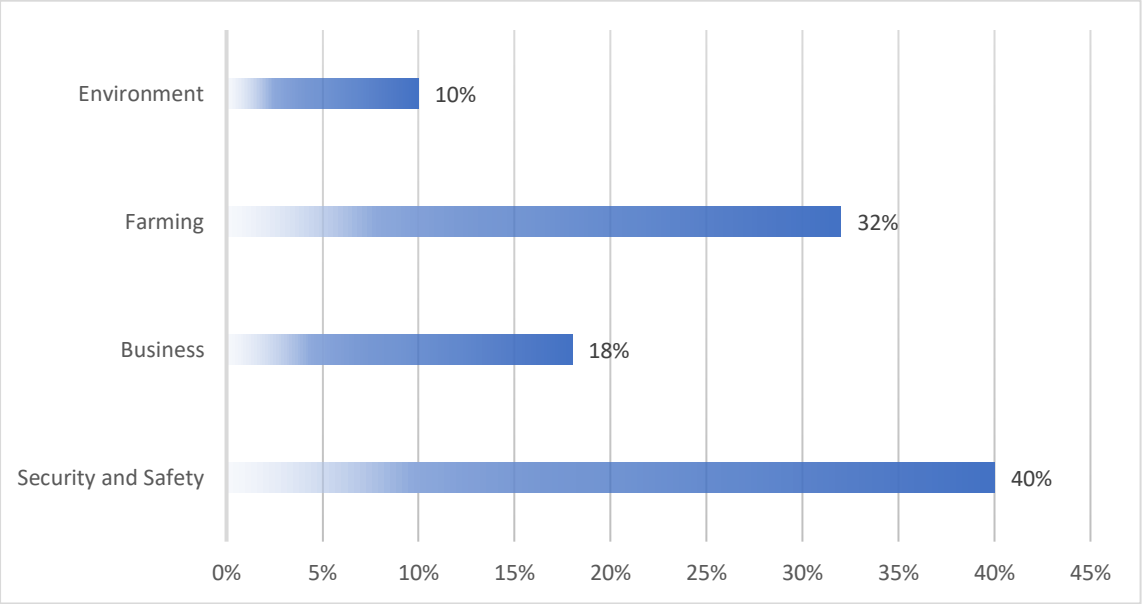


FIGURE 4: **The Additional Impact Electricity Has on Socioeconomic Factors**

Figure 4 highlights electricity's socioeconomic benefits in farming households. Security and safety were cited by 40% of respondents, emphasising the importance of improved household protection through enhanced lighting and security systems. Farming-related benefits (32%) reflect electricity's role in enhancing agricultural practices with better tools and infrastructure. Business impacts (18%) show their support for small enterprises and income generation. Only 10% recognised environmental benefits, indicating a gap in awareness about electricity's role in reducing reliance on unsustainable energy sources. Overall, electricity is valued for its safety, productivity, and contribution to livelihoods, but greater awareness is needed regarding its environmental impact.

4.6. Factors Influencing the Adoption of New Technology (Electricity Appliances) in the Rural Farming Household

Table 4 below shows the results from the model. The model used in the study employs logit regression to evaluate factors influencing the adoption of new technology (electric appliances) in rural farming households. The study results demonstrate a strong performance across key metrics. The chi-squared statistic of 30.2 with 16 degrees of freedom indicates that the model is significantly more effective at predicting the adoption outcome compared to a model with no predictors. The highly significant p-value (Prob > chi2 = 0.000) underscores that the predictors included in the model collectively have a statistically significant impact on

technology adoption. Additionally, the log-likelihood value of -154.76312 reflects substantial improvement over the null model, indicating a better fit of the model to the observed data. Most notably, the Pseudo R^2 of 0.683 suggests that approximately 68.3% of the variation in technology adoption is explained by the model's predictors, reflecting a strong explanatory power and a good fit. Collectively, these metrics confirm that the logit regression model is robust and effectively captures the factors influencing the adoption of electric appliances in rural farming households. The model's fit is supported by strong statistical evidence, highlighting the relevance and impact of the predictors included in the analysis.

TABLE 4: Factors Influencing the Adoption of New Technology (Electricity Appliances) in the Rural Farming Household

Variable	**Coef**	**Std. Err**	**P>z**	**Marginal effect**
Age	-1.986	0.182	0.006***	0.020
Years spent in school	0.547	0.253	0.018**	0.045
Occupation	1.684	0.208	0.006***	0.036
Access to extension services	0.628	0.207	0.028**	0.021
Family size	-0.749	0.351	0.012**	0.038
Off-farm activities	0.835	0.361	0.047**	0.051
Distance to market input/output	0.985	0.248	0.006***	0.055
Con_	1.191	0.543	0,016**	1.976
Observation: 320	Chi^2 (16) = 30.2, Prob > chi^2 = 0.000	Log-likelihood = -154.76312	Pesudo R^2 = 0.683	

Note: **Significant at 5% significance level; ***Significant at one percent significance level.

The logit regression results offer critical insights into the determinants of electric appliance adoption. Age showed a significant negative effect, with a 1% increase in age reducing the likelihood of adoption by 2%. Older farmers tend to adopt less due to risk aversion or limited exposure to technology. Years of schooling positively influenced adoption. Each additional year in school raised the likelihood of adopting appliances by 4.5%. Education improves

understanding, operation, and maintenance of new technologies (Peters & Sievert, 2016). Occupation showed a positive and significant impact. Households with employment beyond farming were 3.6% more likely to adopt. Additional income and exposure through diverse jobs enhance the capacity to invest in innovation. Access to extension services also positively affected adoption. A one-day extension visit raised the likelihood of adoption by 2.1%. These services provide vital training and information (Mdoda *et al*., 2022). Family size negatively influenced adoption. A larger household reduced the probability of adoption by 3.8%, possibly due to increased resource pressure and complexity in managing new systems.

Off-farm activities significantly encouraged adoption. Households with supplementary income sources were 5.1% more likely to adopt technologies. These activities improve financial stability and openness to innovation. Surprisingly, a greater distance to markets also had a positive influence on adoption. A one-kilometre increase in distance raised adoption probability by 5.5%. This suggests that remote households may adopt technology to compensate for logistical constraints.

4.7. The Impact of Adopted Electrical Appliances on Household Agricultural Income

The study employed endogeneity switching regression to estimate the impact of adopting electrical appliances on the household agricultural income of farmers in the study area. These results are presented in Table 5 below.

TABLE 5: Effect of Adopted Electrical Appliance on Household Agricultural Income

Outcomes	**Mean outcome**		**ATT (Adoption effect)**	**ATU (Treatment Effect on the Untreated)**	**t-value**
	Adopters Electrified	**Non-electrified**			
Household agricultural income	(a) 4.782 (0.053)	(a) 2.025(0.067)	2.757 (0.068)		41.72
	(b) 5.952 (0.072)	(b) 4.187 (0.061)		1. 765(0.138)	34.22

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Note: **p<0.05 and ***p<0.01; ATT and ATU refer to the average treatment effects of farming households with and without electricity appliances, respectively.

As the outcome variables in ESR outcome equations are the logs of household agricultural income, the results of the mean outcomes of both groups and the predictions of ATT and ATU are in log forms.

The results in Table 5 reveal a substantial positive impact of adopting electrical appliances on household agricultural income by farming households in the study area. The average agricultural income for households that have adopted electrical appliances is ZAR 4,782, compared to ZAR 2,025 for those without such appliances. The Average Treatment Effect on the Treated (ATT) is ZAR2 757, with a very high t-value of 41.72, indicating a robust and statistically significant increase in income due to adoption. This substantial effect underscores the significant financial benefit that adopting electrical appliances provides to current users. These results align with those of Jena and Tanti (2023), who suggest that adopting electricity appliances can increase agricultural returns by providing farmers with various opportunities. It indicates that the adoption of new technology (such as electricity appliances) indeed increases household farm operating income.

In contrast, the Average Treatment Effect on the Untreated (ATU) estimates the potential impact on households that have not yet adopted electrical appliances. If these non-adopters were to adopt, their average agricultural income would be ZAR 5,952, compared to ZAR 4,187 if they remained non-electrified. The ATU estimate of ZAR1 765, with a t-value of 34.22, is also significant but somewhat lower than the ATT. This suggests that while there is a considerable potential benefit for non-adopters, it is less pronounced compared to the actual benefits experienced by current adopters. The discrepancy could be attributed to factors such as the initial adoption costs or the varying effectiveness of the appliances across different contexts. The high t-values for ATT and ATU confirm the statistical significance of the results, indicating that electrical appliances contribute to boosting household agricultural income. The findings show income gains for both current and potential adopters, underscoring the value of adoption in enhancing agricultural productivity and earnings.

5. CONCLUSION AND RECOMMENDATIONS

The study's findings from both the logit regression and Endogeneity Switching Regression (ESR) analyses provide strong evidence on the factors influencing the adoption of electrical appliances and their positive impact on agricultural income. Socioeconomic variables such as age, education, occupation, family size, and access to extension services significantly affect adoption. Older households were less likely to adopt, while those with higher education, diverse occupations, and access to extension services were more likely to do so. ESR results showed that adopters earned higher agricultural income (ZAR 4,782) compared to non-adopters (ZAR 2,025). The Average Treatment Effect on the Treated (ATT) revealed a ZAR 2,757 income gain for adopters, while the Average Treatment Effect on the Untreated (ATU) showed that non-adopters could gain ZAR 1,765 if they adopted. These findings confirm the economic value of technology adoption in rural areas.

Recommendations include expanding education and training to build technological literacy, particularly for older farmers. Strengthening extension services through more frequent visits and practical demonstrations is essential. Financial mechanisms such as low-interest loans, subsidies, and support for off-farm income activities can empower rural households to adopt technology. Youth-focused agricultural policies, including training and mentorship programs, should be prioritised. Enhancing rural electrification and supporting community-based initiatives can alleviate individual financial burdens and foster widespread adoption. These combined efforts can enhance productivity, increase income, and improve the overall well-being of rural households.

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