Economics of Microgrids in Rural Households of India

Srikant Shaw[1], Santosh Kumar Sahu[2]

Abstract: Access to reliable electricity remains a persistent challenge in rural India, despite near-universal household electrification achieved under the Saubhagya scheme[3]. While grid expansion has improved connectivity, concerns regarding the quality and reliability of the supply remain. Microgrids, built around distributed renewable energy sources, have often been proposed as a complementary solution to address these gaps (Jothi et al., 2024). Using nationally representative household-level data from the ACCESS surveys (2015 and 2018), we investigate the factors that explain awareness and adoption of microgrids at the household level in India. We document transitions in awareness between 2015 and 2018 and investigate the household-level determinants of microgrid adoption using rare-event logistic regression. The findings highlight significant differences across socioeconomic groups and regions, while also showing that adoption remains limited (<2% of households) despite rising awareness. By combining descriptive, transition, and regression analyses, we offer new insights into the barriers to scaling decentralized renewable solutions in rural India.

Keywords: Microgrids; Rural Electrification; Energy Access; Renewable Energy; Decentralized Energy Systems; India; Household Adoption; Rare-Event Logistic Regression

JEL Classifications: Q42, Q48, O13, O18, C25

[1] Department of Humanities and Social Sciences, Indian Institute of Technology Madras, Chennai, India.
[2] Department of Humanities and Social Sciences, Indian Institute of Technology Madras, Chennai, India.
[3] NITI Aayog, Rockefeller Foundation & Smart Power India Launch Electricity Access & Utility Benchmarking Report (accessed on 10-10-2025)

Table of Contents

1. Introduction
    - 1.1. Overview of Energy Scenario
    - 1.2. Access to Electricity & Need for Quality Access
    - 1.3. The Microgrids as a Decentralized Electrification Solution
2. The Literature Review
    - 2.1. Research Objectives and Hypotheses
        - 2.1.1. Objectives
        - 2.1.2. Testable Hypothesis
3. Data, Variables
4. The Empirical Analysis
    - 4.1. Determinants of Awareness of Microgrids
        - 4.1.1. Base Model Specification: Probit Regression
        - 4.1.2. Blinder – Oaxaca Decomposition
        - 4.1.3. Multinomial Probit Regression
    - 4.2. Factors for the Adoption of Microgrids
        - 4.2.1. Pooled Probit Regression
        - 4.2.2. Firth Logit Regression
5. Discussion
6. Conclusion
7. Policy Implications

List of Tables

1. Summary statistics: Survey Year: 2015
2. Summary statistics: Survey Year: 2018
3. Microgrid Awareness (2015 vs. 2018)
4. Microgrid Awareness by Demographics in Rural India
5. Microgrid Awareness Transition (2015 – 2018)
6. Pooled Probit Regression - Dependent variable: Microgrid Awareness (binary)
7. Average Marginal Effects on Microgrid Awareness
8. Blinder-Oaxaca decomposition
9. Average Marginal Effects for Age – Awareness Multinomial Probit
10. Average Marginal Effects for Education – Awareness Multinomial Probit
11. Microgrid Users by Survey Year
12. Profile of Microgrid Users (2015 vs. 2018)
13. State-wise Microgrid Adoption (2015-2018)
14. District-Level Microgrid Adoption and Decline (2015-2018)
15. Description of the adoption variables
16. Pooled Probit regression (Microgrid users)
17. Marginal effect of Pooled Probit (Microgrid users)
18. Firth Logit regression

Economics of Microgrids in Rural Households of India

1. Introduction

1.1 Overview of Energy Scenario

Energy is essential for a country's economic growth, and studies have shown a strong positive impact of increased energy consumption on economic development. Understanding energy in production, distribution, and usage is crucial for effective grassroots development. Access to energy is a basic need, as understood and reaffirmed by Sustainable Development Goal (SDG) 7, which aims to "Ensure access to affordable, reliable, sustainable, and modern energy for all." It creates a new dimension of development and provides scope for communities to grow once basic needs are met. Although providing access to reliable electricity is a task that is easier said than done. It has often been a subject of political motivations. Smyth and Narayan (2015) stated that renewable energy consumption contributes to economic growth, although its elasticity varies depending on the type of renewable energy. Furthermore, they reaffirmed the current trajectory of reducing greenhouse gas emissions by increasing the share of renewable energy, as it does not have a detrimental effect on economic growth. According to the Energy Statistics India 2024 by the Ministry of Statistics and Policy Implementation (2024), there has been a healthy growth in electricity consumption with a CAGR of 5.16 cent; the domestic sector has experienced the highest CAGR of 6.87% from 2013-14 to 2022-23. In FY 2022-23 (P), the industry sector accounted for the major share (41.16%), followed by the domestic sector (approximately a quarter, 25.77%), agriculture (17.67%), and commercial sectors (8.29%).

India's energy mix is currently dominated by coal; with the opening of the coal sector for private and international investors, the section of natural gas has seen a considerable increase, which the government is targeting. With the Government of India setting a target of becoming carbon neutral by 2070, the role of renewables becomes important to offset the traditional sources. India has a huge potential for Solar PV as most of the nation receives a high no. of sunny days a year. Furthermore, wind energy has enormous potential on the western coast, as the east coast is prone to frequent calamities such as cyclones. As of March 31, 2023, 2, 109, 654 MW of renewable power generation potential has been estimated1, 202 is, approximately 55.3 per cent of the wind power potential (at 150m hub height). This was followed by solar power potential (35.5%), hydropower (including large and small hydropower) (7.32%), and biomass and bagasse-based cogeneration comprise the remaining part. There has been a steady growth in gross electricity generation (from utility) with a CAGR of 5.18 per cent from 2013-

14 to 2022-23 except in 2020-21. Although the generation of electricity is heavily dependent on coal (steam) and was close to 75 per cent in FY 2022-23(P), RES (Renewable Energy Sources other than Hydro) registered a growth of 19.54 per cent during FY 2022-23(P) and a CAGR of 21.19 per cent in the last decade (2013-14 to 2022-23) in terms of installed capacity (Ministry of Statistics and Policy Implementation (2024), n.d.)

India is under huge environmental and economic pressure to transition towards a greener economy. Electricity generation in India is dependent on coal. Nearly 75% of electricity was generated from steam, which is close to 75% (from utility) in FY 2022-23 (Ministry of Statistics and Policy Implementation, 2024). The future energy mix is highly dependent on the penetration of renewable energy. However, most of the renewable energy capacity is grid interactive1 instead of off-grid renewable energy, thus making its success dependent on achieving 'grid integration', meaning practices of power systems which enable efficient and reliable connection to variable renewable energy. India's electricity transition follows a top-down approach, where the central government attempts to build a 'national champion' model. In contrast, the Indian state is more focused on protecting the coal sector from disruption while equally investing in driving the transition. Thus, market forces drive the transition to renewable energy (Bhatia, 2023). The energy cost of solar and wind energy in India has significantly decreased in the last decade, enabling them to achieve grid parity (Jhunjhunwala & Kaur, 2018) (Jhunjhunwala & Kaur, 2018). According to the IEA India dashboard, per capita electricity consumption has increased by 210 percent between 2000 and 2023, highlighting the growing demand for increased energy access. (Sindhu et al., 2016) pointed out the issues of growing daily energy consumption despite significant expansion in the power sector. Consequently, the supply of electricity must increase at an accelerated rate to align with existing and anticipated demands.

1.2 Access to Electricity & Need for Quality Access

Early definitions of "electrification" primarily focused on infrastructure, such as village-level transformers, and overlooked household access. This narrow viewpoint often leaves the basic residential needs unaddressed. Additionally, fluctuations in governance and inconsistent political commitment frequently hamper or distort effective implementation (Palit & Bandyopadhyay, 2017). The definition of electrification as per Government of India mandates

electrification of at least 10 per cent households in a village, which is clarified later by PIB[4] that it does not restrict the electrification to 10%. It further mentions the Saubhagya scheme for the universal electrification of households. However, this does not depict the complete picture of the quality of electrification for households.

The Government of India has initiated multiple policies to increase the efficiency of the power sector, starting with the Electricity Act (2003), which raised the installed capacity number, along with a greater scope to transition to greener energies. The Saubhagya policy has been widely successful in increasing access to energy for every household in the region. The Saubhagya dashboard[5] by the government of India shows near 100% electrification of the willing households.

Aklin et *al.* (2016) found that access or connection to the grid is not sufficient to produce visible socio-economic effects of electrification using a multi-dimensional approach. Furthermore, beyond access with rapid grid expansion and off-grid alternatives, there is a need to focus on the quality of electricity (measured using duration, reliability, and voltage stability). Dugoua et *al.* (2017) used expenditure as one of the variables to understand rural electrification in India and concluded the existence of a strong positive expenditure coefficient that supports the interpretation of having quality electricity to reap socio-economic development. Agrawal et *al.* (2020) also highlighted the issues of supply quality and duration. Voltage variation is a major concern, with residents complaining of voltage issues with inadequate capacity voltages dropping by 25-30 per cent during peak load. The daily power supply to rural households increased from 12.5 hours in 2015 to 18.5 hours in 2018.

The India Residential Energy Survey 2020 reported that approximately 76 per cent of households face supply interruptions. The duration and frequency of power outages are more significant in Uttar Pradesh, Jharkhand, Assam, Bihar and Haryana. One-third of the families had at least one of three supply quality issues, such as prolonged blackouts, low voltage, or equipment damage resulting from voltage fluctuations in the month before the survey. Merely 6% of families are said to have filed a complaint within the last six months, suggesting high consumer inertia or a lack of knowledge regarding their rights as electricity users (Agrawal, et al., 2020).

---

[4] https://www.pib.gov.in/newsite/PrintRelease.aspx?relid=179022 (accessed on 21-07-2025)
[5] https://saubhagya.gov.in/ (accessed on 21-07-2025)

Aklin et *al.* (2016) observed a robust and almost linear relationship between the number of hours of power availability and electricity satisfaction. More precisely, they discovered that a 6.5-hour daily increase in supply hours resulted in a 36% increase in electricity satisfaction. Karthik et *al.* (2024) observed several factors contributing to the lack of grid power, including illegal settlements, inability to pay, and service disconnections due to non-payment of bills. Even in areas with access to electricity, power outages were prevalent in rural regions, particularly in remote forests and hilly terrains. These outages are often caused by load shedding, rainstorms, and other natural disasters. Aklin et *al.* (2021) re-did their results with the ACCESS 2018 panel data from Aklin et *al.* (2016), where they highlighted the increase in expectations as a result of increasing access to electricity for households. Households were found to be more sensitive to the quality of supply in 2018 than in 2015, where access was low, suggesting a need to provide better quality electricity to match the household's growing expectations.

1.3 The Microgrids as a Decentralized Electrification Solution

Microgrids, initially introduced as a means to couple multiple energy sources to the traditional grid, have evolved into a separate entity. A microgrid is a decentralized energy system (an example of distributed generation) capable of generating, storing, and distributing electricity in a limited geographical area, independently or in tandem with a traditional grid. The Working Group 6.22 of The Conseil International des Grandes Réseaux Électriques (CIGRÉ) defined the concept in the following single sentence: " *Microgrids are electricity distribution systems containing loads and distributed energy resources, (such as distributed generators, storage devices, or controllable loads) that can be operated in a controlled, coordinated way either while connected to the main power network or while islanded* " (Marnay et al., 2015a). Initially set up with diesel generators (DG), with the declining cost of solar panels and cost equalization of renewable energy and traditional grids in India. Microgrids create a new opportunity for the deployment of renewable energy pockets along with traditional grids to provide reliable, uninterrupted electricity in remote regions, enabling the expansion of choices for users.

Marnay et *al.* (2015) highlighted significant benefits that can be summarized as both direct and indirect advantages. They directly enhance efficiency, reduce emissions, and improve power quality and reliability, providing more dependable electricity to customers while decreasing dependence on the larger grid and substations. Indirectly, microgrids contribute to environmental sustainability by lowering greenhouse gas emissions and reducing the physical

footprint of the power generation. They also diminish reliance on external fuel sources and volatile energy prices, ultimately fostering job creation and stimulating the local economy. In essence, microgrids improve energy systems while promoting environmental and economic resilience of the system.

Along with policies to improve the central grid connection, the Government of India has attempted to push for off-grid renewable energy with decentralized energy solutions. One of the first mentions of microgrids can be found in the Ministry of Power's proposed scheme as part of the Rajiv Gandhi Grameen Vidyutikaran Yojana (2005), namely, Decentralized Distributed Generation (DDG). The goal was to electrify last-mile villages where connectivity via the grid is neither feasible nor cost-effective, as well as to improve the reliability of the grid connection in remote regions. The Ministry of New and Renewable Energy (MNRE) 2016 released a draft policy, 'National Policy for Renewable Energy Based Micro and Mini Grids' The policy intended to streamline the process of Renewable Energy-based Mini and Micro Grids to improve the local economy. This is the first time that microgrids have been considered as energy service providers beyond lighting, as it introduced concepts for their use for commercial and manufacturing purposes. The existing literature on decentralized technology adoption points to a lack of information as a critical barrier to its uptake. In the case of adopting renewable energy, such as solar energy, a lack of information and awareness has been considered a hindrance to the adoption of new technologies. Claudy et *al.* (2010) pointed out that awareness is a critical precursor to adoption, and studies on awareness help avoid selection bias and improve sampling in adoption research.

We use the Access to Clean Cooking Energy and Electricity – Survey of States (ACCESS) 2018 household survey data (Mani et al., 2019) which includes question on Awareness of microgrids. This study offers a new contribution to the study of Microgrids in India by investigating their pattern of awareness, along with the factors for awareness from six (previously considered) energy-poor Indian states. The survey was conducted in two waves, 2015 and 2018, providing us with a slightly unbalanced date comprising approximately 17000 observations. Furthermore, we examine the determinants of rural household microgrid adoption in India using the same 2018 ACCESS household survey. We address the gap that very little is known about microgrid uptake in India's rural energy landscape, especially given the rarity of such adopters. By applying pooled probit regressions with clustered errors, we provide robust estimates of socioeconomic and institutional factors influencing microgrid uptake under rare-event conditions

2. The Literature Review

Luthra et *al.* (2015) identified critical barriers to the adoption of sustainable energy technologies in different dimensions using the Analytical Hierarchy Process (AHP) and validated them using sensitivity analysis. We highlight the prominent barriers in each dimension as categorized by them. 'High initial cost' is one of the most prominent barriers in the Economical & Financial dimension. 'Lack of consumer awareness of technology' and 'Lack of sufficient market base' have been found as the two of the most crucial barriers in the market dimension. The Unavailability of solar radiation data' barrier was found to be the highest-ranked barrier in the Awareness & Information dimension. In the Technical dimension, 'Technology complexity' was the highest-ranked barrier. 'Ecological issues' has been reported to be more critical than 'Geographical location' in the dimension of Ecological & Geographical. 'Rehabilitation controversies' has been found to be the most critical barrier in the cultural and behavioral dimensions. Lack of political commitment' has been identified as the highest-ranked barrier in the dimension of Political & Government Issues. Sindhu et *al.* (2016) used ISM modelling integrated with FMICMAC to understand the prevalent barriers in the rural sector, which were sub-categorized into the following dimensions: Investment, Technical, Financial, Social and Environmental, Marketing and Policy barriers. The model identifies high initial capital costs, extended payback periods, environmental concerns, public reluctance towards new technology, low efficiency, reliability challenges, and safety implications as the most significant factors.

Claudy et *al.* (2010) used a nationally representative survey of Ireland to explore awareness levels and the socio-demographic determinants of microgeneration technologies, as most studies focus on adoption and willingness to pay, assuming awareness. They found that men generally exhibited greater awareness of technologies than women, with middle-aged individuals being the most informed. Employed and unemployed individuals showed higher awareness than students, retirees, and homemakers, while upper-middle-class respondents had the highest awareness. Rural areas also demonstrated greater awareness than urban centres. Overall, awareness emerged as a strong predictor of internet access.

Aklin et *al.* (2018) illustrate that when prospective adopters possess a comprehensive understanding of the technology to be adopted, informational barriers are negligible; instead, what is significant are the advantages that the technology can provide. Harish et al., (2013)

highlighted the lack of awareness among consumers along with factors hindering proper utilization of solar modules in village as a secondary source.

Akter and Bagchi (2021), in a study using ACCESS 2018, showed a clear correlation between awareness of solar technology in households and its adoption. However, awareness was not universal; lower-caste, poor households, and daily wage labourers were less aware of residential solar options than higher-caste, self-employed, and salaried groups. Households' education level, occupation, and social capital affected how they learned about solar technology. Individuals on the fringes, whether socially or economically, experienced a lack of access to information, even when they had the most to gain from off-grid solutions. By combining Census 2011 data with a 2014 -15 field survey (later released as ACCESS 2018), Dugoua et *al.* (2017) demonstrated that traditional predictors of electricity access, such as village land area and proximity to towns, no longer hold ground. Instead, persistent disparities in electricity availability were observed, strongly correlated with caste and wealth differences. Poorer, scheduled caste-dominated villages had significantly worse access compared to upper-caste, wealthier counterparts, highlighting income and caste-based disparity.

To help the rural population transition from using traditional fuels to solar power-based electricity systems for their energy needs, the government must take appropriate steps to raise widespread awareness of the financial aid and incentives offered for converting non-conventional energy sources among rural households (Bhanja et al., 2020). A comparative study of solar photovoltaic (SPV) technologies, such as Home Lighting Systems (HLS) and microgrids, by Bhandari and Jana (2010) found that household preferences are influenced by factors such as income, household size, occupation, and expenditure on kerosene. They observed that households that spend more on kerosene for lighting are more likely to adopt solar mini-grids, with the probability of willingness to adopt increasing significantly with higher kerosene expenditures. This may be because households perceive that their kerosene expenses can cover the cost of electricity from a solar mini-grid. Additionally, the presence of a larger number of male members in a household increases the likelihood of a higher income and, in turn, greater affordability. Conversely, the number of female members was negatively associated with system preference, as women were more involved in household activities and tended to be conservative about expenditures.

A case study in Karnataka on decentralized technologies such as Solar Lighting Systems (SLS), carried out by Harish et *al.* (2013), identified the factors of adoption that can be generalized for

similar technologies such as microgrids. These included demographic characteristics, such as household size and literacy levels, as well as electricity satisfaction, income, and household wealth. Joshi et *al.* (2019) emphasized the importance of a localization strategy, which involves transferring the management of off-grid technologies to local communities. This approach addresses three key barriers to adoption: affordability, maintenance and repair, and lack of institutional support.

The economic case for renewable-based microgrids, as highlighted by Abu-Elzait and Parkin (2019), noting the initial high installation costs as a barrier, emphasized the declining cost of photovoltaic (PV) systems and lower operation and maintenance expenses, which make renewable-based microgrids more cost-effective in the long run compared to conventional microgrids. Smith and Urpelainen (2014) found that access to grid electricity positively influences the adoption of solar home systems, suggesting that solar energy is often seen as a supplementary rather than a substitute source of electricity. Interestingly, they also found no evidence that education or rural-urban differences significantly impacted adoption, challenging the common view that knowledge or remoteness is the primary constraint to solar diffusion. In an experimental study, Aklin et *al.* (2018) examined the framing of off-grid solar technology adoption in India. They found that respondents who preferred microgrids also showed stronger support for solar subsidies, indicating greater openness to solar energy adoption. However, households reacted negatively when informed about rural-urban disparities in electricity costs and the involvement of private sector actors. These concerns contributed to a negative perception of off-grid solar power, particularly due to the perception of rural-urban inequality in energy pricing and the privatization of service delivery.

(Lin & Kaewkhunok, 2024) explored the indirect benefits of solar power adoption and found that although a direct causal link to non-farm employment is under-researched, adoption is correlated with increased participation in non-agricultural activities. Their probit regression analysis showed that solar systems facilitate non-farm work by extending the lighting hours after sunset. Karthik et *al.* (2024), through a field experiment using the Micro Solar Dome (MSD), showed that access to improved lighting significantly enhances household wellbeing. In homes with poor lighting, the installation of MSD led to a fourfold increase in the expected illumination, improving perceptions of safety and extending children's study hours. Women also reported greater safety and increased economic activity due to the extended usable hours after sunset.

Microgrids, often referred to as mini-or nano grids, although lacking a standard definition regarding power capacity, are recognized as interconnected energy systems capable of functioning either independently or in conjunction with the main power grid to deliver electricity to a specific geographical area. The initial concept was introduced by the Consortium for Electric Reliability Technology Solutions (CERTS) in 2001, envisioning a system composed of loads and a compact power supply that delivers electricity and heat (Yu et al., 2017). (Lasseter, 2001) further explored the relationship between microgrids and distributed generation, highlighting the challenges of reliability and integration arising from multiple low-voltage distributed generators (DGs).

There are multiple variation in the literature on the definition of microgrids. (Sharma & Sood, 2022) describe microgrids as interconnected networks of loads, distributed generation systems, and energy storage systems connected at a point of common coupling, while the International Council on Large Electric Systems (CIGRE) characterizes microgrids as electricity distribution systems that orchestrate loads and distributed energy resources, facilitating operation both in coordination with the main power network or in isolation (Marnay et al., 2015b). (Chakravarty & Roy, 2021) define microgrids as integrated local systems that generate and supply electricity to end-users within confined geographic boundaries. Across these definitions, it is evident that microgrids encompass various components, including Distributed Generation (DG), Distributed Energy Resources (DER), Point of Common Coupling (PCC), Energy Storage Systems (ESS), and Energy Management Systems (EMS). Conceptually, microgrids can be viewed as miniature grids that independently generate, store, and distribute electricity within a defined area.

The role of microgrids can be summarized in two key areas: energy generation and storage. They utilize various distributed energy resources, including solar, wind, mini-hydro, and biomass, taking advantage of local conditions to generate sustainable energy. Additionally, energy storage is crucial to counteract the intermittent nature of renewable sources, allowing excess energy to be captured during peak generation periods for use during times of low or no generation, thereby enhancing the reliability of microgrid operations. Microgrids can become green energy pockets in the rural village utilizing different types of locally generated renewable energy to provide electricity to the users. The adoption of off-grid technologies still remains a challenge, due to numerous factors. Thus, it becomes essential to understand the determinants of awareness and adoption of microgrid in rural households of India.

2.1 Research Objectives and Hypotheses

This study explores the following objectives and aims to address the testable hypothesis, delving into the underlying principles and methodologies that guide the research.

2.1.1 Objectives

1. Quantify patterns and determinants of microgrid awareness among rural Indian households using ACCESS 2015-2018, and decompose the observed change in awareness into endowment and coefficient effects.
2. Estimate household-level determinants of microgrid adoption, accounting for rare-event bias using Firth penalized logistic regression.
3. Evaluate how demographic (age, gender, education), socio-economic (income, assets, occupation), and regional factors explain both awareness and adoption heterogeneity.
4. Derive policy-relevant implications for information campaigns, integration with grid planning, and targeted subsidies based on empirical effect sizes.

2.1.2 Testable Hypotheses

- H1 (Awareness - demographics). Older age, female household heads, and lower educational attainment reduce the probability of reporting awareness of microgrids (negative partial effects).
- H2 (Awareness - decomposition). The decline in aggregate awareness between 2015 and 2018 is driven more by changes in returns to characteristics (coefficients) than by changes in household composition (endowments).
- H3 (Adoption - income & assets). Higher liquid income increases adoption probability; higher illiquid assets (asset score) decrease adoption probability (wealth-paradox) - with a positive income × asset interaction.
- H4 (Adoption - education & caste). Higher educational attainment and non-SC/ST caste categories are positively associated with adoption odds; these effects are larger under penalized (Firth) estimation than under standard probit/logit.

- H5 (Regional heterogeneity). State dummies (e.g., Bihar, Jharkhand) have large, positive associations with adoption; regional effects remain significant after controlling for household observables.

3. Data, Variables

In light of this, understanding the determinants for the adoption of Microgrids becomes critical for its expansion, especially in rural areas where it has the power to generate a sustainable way of living. For the same purpose, we use survey dataset by The Council on Energy, Environment, and Water (CEEW) made public in 2018 Access to Clean Cooking Energy and Electricity (ACCESS) (Jain et al., 2018). It covers six energy poverty states in India - Uttar Pradesh, Bihar, Jharkhand, Madhya Pradesh, Odisha, West Bengal. The data offers a multifaceted view of energy access in India as we use longitudinal data covering 2015 and 2018 (Aklin et al., 2016; Mani et al., 2019).

Microgrid Awareness (mg_awareness): The dependent variable is a binary variable taking values 0 (no) and 1 (yes), when the respondents were asked whether they have heard about microgrids. This variable captures the awareness level of the households regarding decentralized technology such as microgrid.

Multinomial age-quintile & aware (mg_age_mn): The Age of the household head found to be positively significant; hence we create age quantiles with following categories in the following ranges 18-30 years, 31-38 years, 39-45 years, 46-56 years, 57-98 years to understand which age group is highly aware. We then construct multinomial age awareness variable, where we look at sample who respondent yes to awareness question and belonged to categorised age groups.

Multinomial edu-category & aware (mg_edu_mn**):** Multiple education categories found to be significant and thus we created this variable for multinomial probit by interacting microgrid awareness with educational attainment categories, generating six mutually exclusive groups: (1) Not Aware (base category), (2) Aware with No Formal Education, (3) Aware with Primary Education, (4) Aware with Secondary Education, (5) Aware with Higher Secondary/Diploma, and (6) Aware with Graduate or Above education. This specification allows examination of how determinants of awareness vary across educational strata.

Microgrid Use (mg_use): The dependent binary variable captures the number of households connected to microgrids in the survey and it takes the 0 (No) and 1 (Yes) for both surveys i.e.,

2015 and 2018. The actual household use of microgrid (<2% in 2018). It is also need to be noted this variable does not capture usage of microgrid electricity as the primary sources of energy for households.

Explanatory variables: age, gender, education, household size, income, appliances, ration cards, caste, infrastructure indices, electricity satisfaction (PCA), state dummies. Some of the most repeated factors identified in the literature for the awareness and adoption of microgrid in rural areas are:

- **Age of the household head**: Age of the household head is, who is also the decision maker of the households are more likely to aware about the microgrids, compared to other household members. It is most likely to be a negative coefficient, suggesting older household heads are less like to aware of off-grid technologies (Claudy et *al.* 2010). (Rebane & Barham, 2011). The respondent's age is entered as a discrete variable that ranges from 18 to 98 years. The variable has no missing values among 17,635 observations, with a mean age of 42.81 years and a standard deviation of 14.55 years. The age distribution of household heads in the sample is moderately skewed toward middle-aged individuals. The 10th percentile is 24 years, indicating that the youngest 10% of household heads are under 24. The 25th percentile is 31 years, while the median age is 40 years, suggesting that half of the respondents are aged 40 or younger. The 75th percentile stands at 54 years, and the 90th percentile at 63 years, highlighting that the oldest 10% of the sample are above 63. This distribution reflects a broad age range, with a concentration in the working-age and early-senior cohorts. This variable indicates the household head (respondent)'s life stage, which can provide status of information about microgrids as well as influence the household energy choices and also the choice of microgrid adoption. Age squared has been created to check for any non-linearity in the age variables (Claudy et *al.* 2010).
- **Age-group dummies**: We create age categories of with following categories in the following ranges 18-30 years, 31-38 years, 39-45 years, 46-56 years, 57-98 years. This is done to check for the awareness level of the household.
- **Gender of the Household Head**: To investigate possible gendered effects on energy adoption, the gender of the household head, usually classified as either male or female, is examined. Potential gender-based disparities in microgrid adoption, energy access, and decision-making are examined using this variable. Out of the total 17,635

observations, 3,857 respondents are female (21.9%), and 13,778 respondents are male (78.1%), with no missing values.

- **Education of the Household Head**: The education level of the respondent, recorded as a categorical variable with the following five levels i.e., No Formal Schooling, up to 5th Standard, up to 10th Standard, 12th Standard or Diploma, Graduate and Above. This variable reflects the educational attainment of the respondent and is likely to impact their decision-making process, particularly regarding new technologies such as microgrids. The educational attainment of household heads in the sample is skewed toward lower levels of formal education. About 35.5% of respondents (6,262 households) have no formal schooling, and an additional 30.9% (5,455 households) have studied only up to the 5th standard. Those with education up to the 10th standard account for 17.3% (3,043 households). A smaller share, 9.1% (1,606 households), have completed 12th standard or hold a diploma, while only 7.2% (1,269 households) are graduates or have higher qualifications. This distribution highlights a significant educational deficit that could affect awareness and adoption of new technologies such as microgrids.
- **Household Size:** We calculate household size summing two variables in the data, Number of Adults in the household and number of children in the household. (Rebane & Barham, 2011) presented that living with higher number of adults predicts having the correct knowledge of batteries related to the SHSs.
- **Household Monthly Income**: Household monthly income here is an indicator of the economic capacity to adopt microgrids. We calculate monthly income of the household using two variables from the dataset i.e., household monthly expenditure and household yearly savings. The income variable is first squared and then transformed by taking the natural logarithm in order to address potential skewness and enhance interpretability in the probit model. A larger transformed income value is anticipated to boost the likelihood of microgrid adoption in the probit analysis, indicating a greater financial capability to invest in alternative energy solutions.
- **Ownership of Household Appliances**: This variable captures the total number of electrical appliances owned by a household, representing energy usage intensity and potential demand. The household appliance ownership variable is constructed by aggregating devices into five functional categories based on their use. Lighting appliances include incandescent bulbs, CFL bulbs, LED lights, and tube lights. Cooling appliances comprise fans, refrigerators, and coolers, while heating appliances cover

electric irons and electric stoves. Utility appliances consist of televisions, radios, washing machines, electric pumps, and other similar devices. Lastly, energy storage appliances are represented by the number of inverters used to store electricity. This categorization enables a nuanced understanding of household energy usage patterns and demand intensity.

The overall total appliances owned variable (hha_owned) is derived by summing these five categories. This detailed breakdown enables a nuanced understanding of energy consumption patterns across households.

- **Income source:** The primary source of income for the respondent, recorded as a categorical variable in eight categories i.e., agriculture on own land (41.23%), cultivation on leased land (3.97%), casual agricultural labour (2.87%), salaried job (6.21%), cattle rearing (0.56%), own business (9.31%), daily labourer (34.21 %) and others (1.63%). This variable is important for understanding the economic structure of households and may influence their capacity to adopt microgrids, given differing income stability and levels of financial security.

  The flow of information among the sample is modelled also by the nature of employment household is associated with. Household income earner associated with tertiary sector job is more likely to aware about the microgrids compared to household in primary sector.
- **Household electricity satisfaction (PCA):** A principal component capturing overall satisfaction with the quality, reliability, and affordability of existing electricity access. The variable is created using responses on questions regarding satisfaction from main source of lighting (reliability, expensiveness, safety, adequate). Similar, questions were included to assess the satisfaction from street light, community lightings. Further, questions on WTP for better primary lighting, community lighting. We predict three four principal components out of which we retain only to create three variables on the basis of questions that were contributing more to the component. Thus, we create three variables out of the PCA namely, light satis pc1, wtp lighting pc2, commu light pc3. These variables only have observation for the first wave of survey in 2015.
- **WTP for Lighting (PCA):** Willingness-to-pay for better service of lighting constituted from the original principal component analysis, it shows the household's willingness for the better lighting. There is no observation for the variable in 2018.

- **Community Lighting Satisfaction (PCA):** The principal component analysis captures the household's satisfaction with lighting in public spaces. The variable only has observations for 2015.
- **Anti-Theft PCA:** We create the anti-theft variable using three binary variables, where households were asked about the electricity stealing in their locality, their perception of legality of electricity stealing, and finally whether it should be stopped or not. Household valuing electricity will be averse to electricity stealing.
- **Household Infrastructure (Row Mean):** A mean score by row means, summarizing the quality of household infrastructure (e.g., housing type, access to water and sanitation).
- **Government caste category:** Social stratification in India is represented by the caste categories, which include classifications like Scheduled Castes (SC), Scheduled Tribes (ST), Other Backward Classes (OBC), and General category.
- **Household Debt:** The burden of debt for households highlights their financial conditions as well as their ability to pay for microgrids service.

Some of the most basic factors that has been considered here are mentioned above and along with we use state dummies for surveyed states namely, Bihar, Jharkhand, Madhya Pradesh, Odisha, Uttar Pradesh, and West Bengal. They variable are included to carry out investigation into regional disparity among the sample.

The following two tables presents a summary of the key statistics, including measures such as the mean, standard deviation, minimum, and maximum values for two survey years i.e., 2015 and 2018.

Table 1: Summary statistics: Survey Year: 2015

Variables	N	mean	sd	min	max
Age	8563	42.318	14.206	18	95
Male	8563	.853	0.354	0	1
Female	8563	.147	0.354	0	1
HH size	8563	6.736	3.535	1	46
HH indebted	8563	.396	0.489	0	1
Income source	8563	3.632	2.742	1	8
Hindu	8563	.872	0.335	0	1
Muslim	8563	.123	0.328	0	1
mg use	8563	.023	0.151	0	1
Asset score (normalized)	5953	-.147	1.042	-2.336	3.289
HHA owned	5953	5.569	3.979	1	35
Community light pc3	7659	0	1.190	-2.178	10.412
WTP lighting pc2	7659	0	1.341	-5.41	15.685
Light satisfaction pc1	7659	0	1.414	-2.995	10.521
Anti-theft pc1	6,119	.0061451	1.107341	-8.91253	.2747303
HH size squared	8563	57.874	78.897	1	2116
HH monthly income	8059	5784.81	4687.567	500	80000
BPL	8563	.479	0.500	0	1
APL	8563	.392	0.488	0	1
SC ST dummy	8563	.284	0.451	0	1
OBC dummy	8563	.477	0.499	0	1
GEN dummy	8563	.24	0.427	0	1
Literate	8563	.721	0.449	0	1
Graduate & above	8563	.076	0.265	0	1
Higher sec or diploma	8563	.095	0.294	0	1
Secondary schooling	8563	.2	0.400	0	1
Primary schooling	8563	.309	0.462	0	1
No formal schooling	8563	.32	0.466	0	1
Agri on own land	8563	.461	0.499	0	1
Casual Agri labor	8563	.031	0.174	0	1
Salaried job	8563	.056	0.230	0	1
Cattle rearing	8563	.005	0.071	0	1
Own business	8563	.086	0.281	0	1
Daily laborer	8563	.298	0.458	0	1
Other sources of income	8563	.016	0.126	0	1
Bihar	8563	.176	0.381	0	1
Jharkhand	8563	.098	0.297	0	1
Uttar Pradesh	8563	.353	0.478	0	1
Madhya Pradesh	8563	.196	0.397	0	1
Odisha	8563	.059	0.235	0	1
West Bengal	8563	.117	0.322	0	1

Data Source: ACCESS 2018
Note: Computed by Authors'

Table 2: Summary statistics: Survey Year: 2018

Variables	N	mean	sd	min	max
Age	9072	43.271	14.846	18	98
Male	9072	.713	0.452	0	1
Female	9072	.287	0.452	0	1
HH size	9072	6.167	3.210	1	43
HH indebted	9072	.433	0.496	0	1
Income source	9072	4.228	2.744	1	8
Hindu	9072	.881	0.324	0	1
Muslim	9072	.115	0.319	0	1
mg use	9072	.001	0.026	0	1
Asset score (normalized)	7798	.112	0.951	-2.336	3.289
HHA owned	7776	6.163	4.246	0	70
Commu light pc3	0	.	.	.	.
WTP lighting pc2	0	.	.	.	.
Light satis pc1	0	.	.	.	.
Anti theft pc1	7342	-.00512215	1.177659	-8.91253	.2747303
HH size squared	9072	48.33	66.881	1	1849
HH monthly income	8897	6752.625	5172.242	0	81000
BPL	9072	.529	0.499	0	1
APL	9072	.288	0.453	0	1
SC ST dummy	9072	.303	0.459	0	1
OBC dummy	9072	.467	0.499	0	1
GEN dummy	9072	.23	0.421	0	1
Literate	9072	.682	0.466	0	1
Graduate & above	9072	.068	0.252	0	1
Higher sec or diploma	9072	.087	0.282	0	1
Secondary schooling	9072	.147	0.354	0	1
Primary schooling	9072	.309	0.462	0	1
No formal schooling	9072	.389	0.487	0	1
Agri on own land	9072	.366	0.482	0	1
Casual Agri labor	9072	.026	0.160	0	1
Salaried job	9072	.068	0.251	0	1
Cattle rearing	9072	.006	0.078	0	1
Own business	9072	.1	0.299	0	1
Daily laborer	9072	.383	0.486	0	1
Other sources of income	9072	.017	0.128	0	1
Bihar	9072	.167	0.373	0	1
Jharkhand	9072	.093	0.290	0	1
Uttar Pradesh	9072	.333	0.471	0	1
Madhya Pradesh	9072	.185	0.388	0	1
Odisha	9072	.111	0.314	0	1
West Bengal	9072	.111	0.314	0	1

Data Source: ACCESS (2018)
Note: Computed by Authors'

4.0 The Empirical Analysis

4.1 Determinants of Awareness of Microgrids

One of the first questions asked to household was, whether the user have heard of Microgrids or not. For the same, (Aklin et al., 2018b) reported enumerators provided the vignette of Microgrids were given to the sample before asking is as follows: "Micro-grids are systems that generate electricity and distribute it at the local level. Electricity can be produced from solar energy, micro-hydropower, diesel, or other sources. Thus, electricity can be used by local users. It provides limited but reliable electricity supply compared to the grid electricity in rural India." The following table provides the response of the household for the same above mentioned across two survey years.

Table 3: Microgrid Awareness (2015 vs. 2018)

Have you heard about microgrids?	2015		2018	
Response	Frequency	Percent	Frequency	Percent
No	6,391	74.64%	8,081	89.08%
Yes	2,172	25.36%	991	10.92%
Total	8,563	100.00%	9,072	100.00%

Data Source: ACCESS 2018
Note: Computed by Authors'

As we observed in the table, there is around 10% reduction in the level of awareness among the respondents about microgrids, from 2015 to 2018. The decline in awareness is odd considering that around 85% of the dataset had the same households surveyed among both waves (Jain et *al*., 2018). This decline in awareness could be due to factors such as change of respondents between two surveys, addition of 15% new households across the states, and fatigue of the respondents. In this subject, we try to understand how household awareness declined before we start looking for the factors that might contribute to household awareness

regarding microgrids. Between 2015 and 2018, awareness of microgrids took a significant nosedive across various demographic and socio-economic groups.

Table 4: Microgrid Awareness by Demographics in Rural India

Category (HH Head)	Sub-group	2015			2018		
		Total (n)	Aware (n)	Aware (%)	Total (n)	Aware (n)	Aware (%)
Gender	Female	1257	195	15.5%	2600	120	4.6%
	Male	7306	1977	27.1%	6472	871	13.5%
Literacy	Illiterate	2393	453	18.9%	2886	177	6.1%
	Literate	6170	1719	27.9%	6186	814	13.2%
Caste Category	SC/ST	2429	488	20.1%	2746	213	7.8%
	OBC	4082	1181	28.9%	4237	518	12.2%
	General/Others	2052	503	24.5%	2089	260	12.4%
Ration Card	None	1101	305	27.7%	1664	197	11.8%
	APL	3358	871	25.9%	2610	345	13.2%
	BPL	3500	881	25.2%	4140	390	9.4%
	Antyodaya	604	115	19.0%	658	59	9.0%
Income source	Agriculture on Own Land	3,947	1,019	25.8%	3,324	431	13.0%
	Cultivation on Leased Land	390	147	37.7%	310	30	9.7%
	Casual Agricultural Labor	269	67	24.9%	238	28	11.8%
	Salaried Job	482	173	35.9%	614	106	17.3%
	Cattle Rearing	43	13	30.2%	55	9	16.4%
	Own Business	739	241	32.6%	903	121	13.4%
	Daily Laborer	2,555	473	18.5%	3,478	251	7.2%
	Others	138	39	28.3%	150	15	10.0%
States	Bihar	1511	708	46.9%	1512	297	19.6%
	Jharkhand	840	547	65.1%	840	207	24.6%
	Madhya Pradesh	1680	259	15.4%	1680	159	9.5%
	Odisha	504	23	4.6%	1008	15	1.5%
	Uttar Pradesh	3023	533	17.6%	3024	272	9.0%
	West Bengal	1005	102	10.1%	1008	41	4.1%

Data Source: ACCESS 2018
Note: Computed by Authors'

Overall, the general understanding of microgrids fell from 25.3% in 2015 to just 10.9% in 2018, despite increased efforts to provide electricity during that time. Women's awareness declined severely from 15.5% to a mere 4.6%. The awareness also fell for men, but from 27.1% to 13.5%. Education played a significant role, too. Among households with literate heads, awareness went from 27.9% to 13.2%, while those with illiterate heads saw awareness decline from 18.9% to 6.1%. These trends indicate a growing gap in knowledge about microgrids.

Caste-based disparities were also evident in the descriptive statistics. Initially, the other backwards class (OBC) and general category households had higher awareness (28.9% and 24.5%, respectively), but these figures dropped significantly to about 12.2% and 12.4% respectively. Scheduled Caste and Tribe households faced an even steeper decline, falling from 20.1% to 7.8%, highlighting the worsening awareness among already disadvantaged groups. When looking at ration card types, both Above Poverty Line (APL) and Below Poverty Line (BPL) households experienced the most significant declines in awareness. Interestingly, Antyodaya cardholders, often the poorest, started with the lowest awareness and saw it fall from 19.0% to 9.0%. On the other hand, households without ration cards had the highest initial awareness at 27.7%, which also plummeted to 11.8% by 2018.

When categorising awareness level at the primary source of income of the household, i.e., on occupation, we observe that every reported job engaged by the household has seen a decline in the awareness level of microgrids. The high awareness group in 2015 shows the sharpest declines. Cultivators on leased land (37.7% to 9.7%) and business owners (32.6% to 13.4%) reported a lack of knowledge of microgrids from 2015 to 2018. Daily labourers, who were already the least aware in 2018 (7.2%), faced compounding vulnerabilities, with awareness halving from 18.5% as they prioritised affordable grid electricity. Farmers working on leased land experienced a significant drop in awareness, declining from 37.7% to 9.7%, while business owners also saw a reduction in awareness from 32.6% to 13.4%. The importance of income stability became evident as salaried employees retained a comparatively higher level of awareness at 17.3%, even with a decrease from 35.9%. These findings highlight the connection between knowledge of decentralised energy options and income stability. The decentralised point to the necessity of focused efforts to raise awareness and increase access to these solutions, especially for disadvantaged groups dealing with financial difficulties.

State-wise, Jharkhand and Bihar had the highest levels of awareness in 2015 (65.1% and 46.9%, respectively), but by 2018, those numbers had dropped sharply to 24.6% and 19.6%. States like Odisha and West Bengal consistently had low awareness, which fell even more to just 1.5% and 4.1%, respectively. These trends reveal a concerning decline in public knowledge about microgrids, particularly among women, less-educated households, and poorer regions. These trends highlight a pressing need for focused information campaigns and a renewed commitment to awareness-raising policies. The across-the-board awareness decline, spanning gender, caste, literacy, income, and geography, signals more than knowledge loss.

We tested whether there was a significant change in microgrid awareness between 2015 and 2018 among the same households; we used the McNemar test. The test is appropriate because the variable of interest, i.e., household awareness of microgrids, is binary (Yes/No). We work with an unbalanced dataset, and we pair household data (same households surveyed in both years) and drop the extra households. A standard t-test or chi-square test is unsuitable, as those assume independent observations, whereas McNemar's test is explicitly devised for paired binary outcomes (McNemar, 1947).

We reshape the dataset to a wide format with binary awareness values for 2015 and 2018, then construct a 2×2 contingency table of transition frequencies:

Table 5: Microgrid Awareness Transition (2015 – 2018)

Microgrid Awareness	2018: No	2018: Yes	Total
2015: No	6,067	324	6,391
2015: Yes	1,516	656	2,172
Total	7,583	980	8,563

Data Source: ACCESS 2018
Note: Computed by Authors'

The result was highly significant (χ^2 (1) = 772.21, $p < .001$), allowing us to reject the null hypothesis that no change occurred. The analysis of discordant pairs revealed that 1,516 households reported awareness in 2015 but not in 2018, while only 324 households transitioned from unaware to aware. The odds ratio of 4.68 indicates that households were nearly five times more likely to lose awareness than to gain it during this period, providing strong statistical evidence for the widespread erosion of microgrid knowledge. The full analysis results can be found in Appendix. This remains a question to analyse in the context of moving to cleaner fuel solutions for rural areas. This statistical result may be due to multiple policies interventions and technological issues at the household levels.

Our analysis proceeds in two stages to comprehensively understand both the correlates and the dynamics of the awareness decline. First, we use a **pooled probit regression** to establish a stable, parsimonious model of the socio-economic and geographic factors associated with microgrid awareness across the entire dataset (Urpelainen & Yoon, 2015). This model provides a baseline understanding of 'who was aware,' on average, during the 2015-2018 period. The

pooling of years is justified as we are initially interested in these fundamental relationships, and the model's assumption of parameter stability serves as a useful null hypothesis.

4.1.1 Base Model Specification: Probit Regression

The determinants of microgrid awareness are analysed using a probit model, specified as follows:

$$\Pr(Yi=1 \mid X_i) = \Phi(\beta 0 + \beta 1 X_i) + \varepsilon i \qquad (1)$$

Where,

$\Pr(Y_i = 1 \mid X_i)$denotes the probability that household i is aware about microgrid;

$\Phi(\cdot)$represents the cumulative distribution function (CDF) of the standard normal distribution;

$\beta_0, \beta_1, \ldots, \beta_7$are the coefficients to be estimated X_i are set of base and control variable; and

$\varepsilon_i \sim N(0,1)$is the standard normal error term.

The model is estimated with cluster-robust standard errors at the household level **(**$hhid$**)** to account for intra-cluster correlation. This approach accounts for potential correlations among observations from the same household across the survey waves of 2015 and 2018. Clustering is necessary because the data is panel data, meaning the same households were interviewed in both years. Extended specifications progressively introduce additional controls including:

Occupation dummies (base: other income sources):

$$\Pr(Yi=1 \mid X_i) = \Phi(\beta 0 + \beta 1 X_1 + \beta 2 X_2) + \varepsilon i \qquad (1.1)$$

$X_{2,}$ here represents all income source dummies of the household

Interaction terms between gender and education, gender and income, and age and education:

$$\Pr(Yi=1 \mid X_i) = \Phi(\beta 0 + \beta 1 X_1 + \beta 2 X_2 + \beta 3 X_3) + \varepsilon i$$

$X_{3,}$ here represents all the interaction dummies. (1.2)

Additional socioeconomic controls (religion, ration card type)

$$\Pr(Yi=1 \mid X_i) = \Phi(\beta 0 + \beta 1 X_1 + \beta 2 X_2 + \beta 23 X_3 + \beta 4 X_4) + \varepsilon i \qquad (1.3)$$

X_4, here represents socio-economic control dummies such as Hindu, Muslim, APL, BPL.

This specification allows for testing hypotheses regarding the stratified nature of microgrid awareness across different demographic and socioeconomic groups in rural India, while providing a robust foundation for subsequent decomposition and multinomial analyses.

Table 6: Pooled Probit Regression - Dependent variable: Microgrid Awareness (binary)

VARIABLES	(1) Probit coeff	(2) Probit coeff	(3) Probit coeff	(4) Probit coeff	(5) Probit coeff	(6) Probit coeff	(7) Probit coeff
Age	-0.00263***	-0.00196**	-0.00262***	-0.00310	-0.00267***	-0.00267***	-0.00268***
	(0.000882)	(0.000888)	(0.000898)	(0.00298)	(0.000899)	(0.000899)	(0.000899)
Gender (base: female) Male	0.419***	0.404***	0.406***	0.559***	0.334***	0.406***	0.405***
	(0.0391)	(0.0393)	(0.0397)	(0.118)	(0.0718)	(0.0398)	(0.0398)
Education (base: No formal schooling)							
Primary schooling	.	0.200***	0.167***	0.137	0.0231	0.114**	0.161***
		(0.0329)	(0.0332)	(0.103)	(0.0842)	(0.0547)	(0.0333)
Secondary schooling	.	0.362***	0.306***	0.0394	0.0942	0.280***	0.295***
		(0.0375)	(0.0381)	(0.112)	(0.104)	(0.0592)	(0.0382)
Higher Secondary/Diploma	.	0.443***	0.381***	0.165	0.171	0.326***	0.365***
		(0.0462)	(0.0469)	(0.126)	(0.136)	(0.0723)	(0.0474)
Graduate & above	.	0.510***	0.431***	0.532***	0.308**	0.342***	0.410***
		(0.0506)	(0.0519)	(0.139)	(0.151)	(0.0766)	(0.0522)
	.	.	.	.	.	.	.
Male # Primary schooling (base: Female # i. Educ)	.	.	.	.	0.178*	.	.
					(0.0910)		
Male # Secondary schooling	.	.	.	.	0.252**	.	.
					(0.112)		
Male # Higher Secondary/Diploma	.	.	.	.	0.249*	.	.
					(0.144)		
Male # Graduate & above	.	.	.	.	0.153	.	.
					(0.160)		
HH Monthly Income	1.48e-05***	1.16e-05***	7.79e-06***	-5.46e-06	1.38e-05**	2.37e-07	6.73e-06***
	(2.42e-06)	(2.41e-06)	(2.51e-06)	(7.09e-06)	(6.88e-06)	(5.54e-06)	(2.52e-06)
Female #co. HH MI (base)					0		
Male #c. HH Monthly Income	.	.	.	.	-6.62e-06	.	.
					(7.31e-06)		
Income Source (base: Other income)							
Agri on own land	.	.	0.0137	0.0184	0.0136	0.0198	0.0188
			(0.0972)	(0.0973)	(0.0973)	(0.0974)	(0.0974)
Cultivation on leased land	.	.	0.110	0.118	0.112	0.115	0.139
			(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
Casual Agri labour	.	.	0.00935	0.0179	0.0127	0.0115	0.0493
			(0.118)	(0.118)	(0.118)	(0.118)	(0.119)
Salaried job	.	.	0.189*	0.196*	0.194*	0.193*	0.198*
			(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
Cattle rearing	.	.	0.322*	0.329*	0.319*	0.326*	0.357**
			(0.178)	(0.178)	(0.179)	(0.178)	(0.179)
Own business	.	.	0.130	0.139	0.132	0.136	0.141
			(0.102)	(0.102)	(0.102)	(0.102)	(0.103)
Daily laborer	.	.	-0.186*	-0.181*	-0.185*	-0.182*	-0.158
			(0.0990)	(0.0989)	(0.0991)	(0.0991)	(0.0993)
Survey States (base: west Bengal)	-	-	-	-	-	-	-
Bihar	0.999***	0.966***	0.949***	0.946***	0.946***	0.950***	0.990***
	(0.0533)	(0.0534)	(0.0539)	(0.0539)	(0.0540)	(0.0540)	(0.0550)
Jharkhand	1.309***	1.292***	1.275***	1.272***	1.275***	1.274***	1.311***
	(0.0564)	(0.0564)	(0.0571)	(0.0571)	(0.0571)	(0.0570)	(0.0588)
Madhya Pradesh	0.276***	0.249***	0.235***	0.235***	0.232***	0.234***	0.286***

	(0.0569)	(0.0570)	(0.0578)	(0.0578)	(0.0579)	(0.0578)	(0.0596)
Odisha	-0.688***	-0.691***	-0.733***	-0.738***	-0.731***	-0.736***	-0.668***
	(0.114)	(0.114)	(0.115)	(0.115)	(0.115)	(0.115)	(0.116)
Uttar Pradesh	0.324***	0.284***	0.277***	0.271***	0.274***	0.277***	0.293***
	(0.0522)	(0.0527)	(0.0535)	(0.0535)	(0.0535)	(0.0535)	(0.0545)
Male # c. age (base: female#age)	.	.	.	-0.00384	.	.	.
				(0.00282)			
Primary schooling #c.age	.	.	.	0.000612	.	.	.
				(0.00224)			
Secondary schooling# c. age	.	.	.	0.00624**	.	.	.
				(0.00246)			
Higher Secondary/Diploma # c. age	.	.	.	0.00537*	.	.	.
				(0.00296)			
Graduate & above # c. age	.	.	.	-0.00298	.	.	.
				(0.00339)			
C.age # c. HH Monthly Income	.	.	.	3.07e-07**	.	.	.
				(1.55e-07)			
Literate	0.307***	.	.	.	.	.	.
	(0.0314)						
Primary schooling #c. HH Monthly Income	.	.	.	.	.	9.35e-06	
						(7.47e-06)	.
Sec. Schooling #c. HH Monthly Income	.	.	.	.	.	5.14e-06	
						(7.45e-06)	.
HS/Diploma # c. HH Monthly Income	.	.	.	.	.	9.10e-06	
						(7.93e-06)	.
Grad. & above # c. HH Monthly Income	.	.	.	.	.	1.23e-05	
						(7.50e-06)	
Hindu	.	.	.	.	.	.	-0.482***
							(0.146)
Muslim	.	.	.	.	.	.	-0.416***
							(0.150)
APL (base: No cards)	.	.	.	.	.	.	0.150***
							(0.0369)
BPL	.	.	.	.	.	.	-0.0100
							(0.0361)
Constant	-1.993***	-1.954***	-1.839***	-1.804***	-1.786***	-1.800***	-1.445***
	(0.0741)	(0.0724)	(0.122)	(0.169)	(0.132)	(0.125)	(0.189)
Observations	16,956	16,956	16,956	16,956	16,956	16,956	16,956

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The above probit models reveal a nuanced and stratified landscape of microgrid awareness in rural India, with persistent demographic and socioeconomic disparities that help explain the dramatic collapse in awareness between 2015 and 2018. The models, which progressively incorporate interaction effects and additional controls, provide robust evidence of how various factors independently and jointly shape awareness patterns.

Age and Gender Dynamics demonstrate consistent and revealing patterns. Age maintains a small but statistically significant negative coefficient across all specifications (approximately -0.0026 to -0.0027), indicating that older households were slightly less aware of microgrids, even after controlling for other factors. The gender disparity remains pronounced and stable, with males exhibiting approximately 40 percentage points higher awareness than female-headed households (the base category) across most models. Interestingly, the interaction between gender and age in Model 4, while negative (-0.00384), is statistically insignificant,

suggesting that the male advantage does not systematically vary with age. This persistent gender gap aligns with Claudy et *al.* (2010) and Akter & Bagchi (2021), indicating deeply embedded informational barriers that exclude women from energy technology awareness.

Educational Attainment emerges as a powerful, graded predictor of awareness. Relative to households with no formal schooling (the base category), all education levels show positive and generally significant effects, with coefficients increasing monotonically from primary schooling (0.167-0.200) to graduate education (0.410-0.510). This strong educational gradient supports Karthik et *al.*'s (2024) contention that education enhances technological familiarity and perception of long-term benefits. The interaction effects in Model 5 reveal that the returns to schooling are gendered: males with primary, secondary, and higher secondary education show additional awareness advantages of 0.178, 0.252, and 0.249, respectively, beyond the general education effect, though the graduate interaction is insignificant. These results suggest that educated men benefit disproportionately from informational networks, widening the gender gap, particularly at intermediate education levels.

Income and Livelihood factors present a complex picture. Household monthly income shows positive and significant coefficients in most models (1.16e-05 to 1.48e-05), but this effect weakens with the inclusion of occupation controls. The occupational patterns are particularly revealing: relative to "other income" sources (the base category), salaried jobs (0.189-0.203) and cattle rearing (0.322-0.357) show consistently positive and significant effects, indicating that stable income streams facilitate awareness. Conversely, daily labourers show negative and significant coefficients (-0.158 to -0.186) in most specifications, confirming Akter & Bagchi's (2021) finding that economically precarious groups face acute information barriers. Most other occupational coefficients, while positive, are statistically insignificant, suggesting that agricultural livelihoods alone do not guarantee microgrid awareness without complementary education or income stability.

Geographic Disparities remain the most striking determinant of awareness. Relative to West Bengal (the base category), Bihar (0.949-0.999) and Jharkhand (1.275-1.311) show enormous positive coefficients, while Odisha shows consistently adverse effects (- -0.668 to -0.738). These state-level effects dwarf most demographic factors and cannot be explained by standard controls alone, pointing to the importance of regional policy environments and historical market development. Though more modest, the positive coefficients for Madhya Pradesh (0.235-0.286) and Uttar Pradesh (0.271-0.324) still indicate significantly higher awareness than West Bengal. These geographic patterns reflect the concentrated early microgrid development

in Bihar and Jharkhand, creating awareness reservoirs that proved somewhat resilient despite the collapse.

Additional controls in Model 7 reveal further nuances. Relative to other religions (the base category), both Hindu (-0.482) and Muslim (-0.416) households show significantly lower awareness, suggesting potential religious minority advantages in information access. The positive coefficient for APL cardholders (0.150) relative to the base category (i.e. Households with no ration card) indicates that middle-income households maintained better awareness. At the same time, the insignificant BPL (BPL here also includes Antyodaya cards) coefficient suggests the poorest households faced the greatest information exclusion.

Non-significant findings provide equally essential insights. The generally insignificant interactions between education and income (Model 6) suggest that income does not systematically moderate educational advantages in awareness acquisition. Similarly, most age-education interactions are negligible except for secondary and higher secondary education, indicating that the returns to schooling are relatively constant across age groups for most educational levels.

Our refined probit models reveal a nuanced and stratified landscape of microgrid awareness in rural India, with persistent demographic and socioeconomic disparities that help explain the dramatic collapse in awareness between 2015 and 2018. The models, which progressively incorporate interaction effects and additional controls, provide robust evidence of how various factors independently and jointly shape awareness patterns.

These probit results effectively set the stage for our subsequent analyses. The strong state-level effects and demographic patterns identified here motivated the Oaxaca-Blinder decomposition, which quantified how much of the awareness decline stemmed from changing household characteristics versus changing returns to those characteristics. Furthermore, the age and cohort patterns hinted at in these models warranted the multinomial probit analysis, which explicitly examined how awareness determinants vary across different age cohorts. The persistent gender and education disparities revealed here also informed our investigation into whether awareness campaigns failed to reach vulnerable populations systematically. Together, these analyses paint a comprehensive picture of an awareness collapse that was systemic in its drivers and selective in its impacts. It disproportionately affects women, the less educated, daily labourers, and residents of states where off-grid policies received less attention.

The following marginal effects reveal the probability changes in microgrid awareness associated with each factor, providing policy-relevant insights beyond the probit coefficients.

The results show remarkable stability between Model 2 (baseline) and Model 7 (full specification), indicating robust relationships.

Table 7: Average Marginal Effects on Microgrid Awareness

Variable	Model 2 (Baseline)	Model 7 (Full Specification)
Demographic Characteristics		
Age	-0.00045** (0.0001)	-0.00061*** (0.0002)
Male (vs. Female)	0.085*** (0.007)	0.084*** (0.007)
Hindu (vs. Other Religions)	-	-0.110*** (0.033)
Muslim (vs. Other Religions)	-	-0.095*** (0.034)
APL Card (vs. No Cards)	-	0.034*** (0.008)
BPL Card (vs. No Cards)	-	-0.002 (0.008)
Education (vs. No Formal Schooling)		
Primary Schooling	0.046*** (0.008)	0.037*** (0.008)
Secondary Schooling	0.083*** (0.009)	0.067*** (0.009)
Higher Secondary/Diploma	0.102*** (0.011)	0.083*** (0.011)
Graduate & above	0.118*** (0.012)	0.094*** (0.012)
Economic Factors		
HH Monthly Income (₹10,000)	0.003*** (0.001)	0.002*** (0.001)
Occupation (vs. Other Income)		
Agriculture on Own Land	-	0.004 (0.022)
Cultivation on Leased Land	-	0.032 (0.025)
Casual Agricultural Labor	-	0.011 (0.027)
Salaried Job	-	0.045* (0.024)
Cattle Rearing	-	0.082** (0.041)
Own Business	-	0.032 (0.023)
Daily Labourer	-	-0.036 (0.023)

Variable	Model 2 (Baseline)	Model 7 (Full Specification)
State (vs. West Bengal)		
Bihar	0.223*** (0.012)	0.226*** (0.012)
Jharkhand	0.298*** (0.013)	0.300*** (0.013)
Madhya Pradesh	0.058*** (0.013)	0.065*** (0.014)
Odisha	-0.159*** (0.026)	-0.153*** (0.027)
Uttar Pradesh	0.066*** (0.012)	0.067*** (0.012)
Observations	16,956	16,956

Notes: Average marginal effects reported with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. HH Monthly Income effect represents change per ₹10,000 increase.

Demographic disparities persist strongly across specifications. Male-headed households are 8.4-8.5 percentage points more likely to be aware of microgrids than female-headed households, highlighting substantial gender gaps in energy technology information access. Each additional year of age reduces awareness probability by 0.03-0.05 percentage points, suggesting slight generational effects. The religious coefficients in Model 7 reveal that Hindu and Muslim households show 11.0 and 9.5 percentage points lower awareness than other religious groups, indicating that there might be a potential minority advantages in information networks.

Educational gradients demonstrate strong, monotonic relationships. Relative to households with no formal schooling, primary-educated households show 3.7-4.6 percentage points higher awareness, increasing to 9.4-11.8 percentage points for graduate-level education. This graded pattern supports the human capital theory of technology adoption, where education systematically enhances information processing and technology awareness.

Economic factors show nuanced effects. Household income has a small but statistically significant positive effect (0.2-0.3 percentage points per ₹10,000 monthly increase). Occupational patterns reveal that salaried jobs (4.5 percentage points) and cattle rearing (8.2 percentage points) significantly increase awareness relative to other income sources, while daily labourers show negative though insignificant effects (-3.6 percentage points). Most agricultural occupations show positive but statistically insignificant coefficients, suggesting that farming livelihoods alone don't guarantee microgrid awareness without complementary education or stable income.

Geographic disparities remain the most striking finding. Relative to West Bengal, households in Bihar and Jharkhand show enormous awareness advantages of 22.3-22.6 and 29.8-30.0 percentage points, respectively. Conversely, Odisha shows substantial disadvantages (- -15.3 to -15.9 percentage points). These state effects dwarf most demographic factors, emphasising the importance of regional policy environments and historical market development in shaping technology awareness.

Despite adding numerous controls, the stability of these marginal effects across specifications underscores the robustness of these relationships and provides a strong empirical foundation for targeted policy interventions to address the identified awareness gaps. Further, we want to explain the difference of survey years on the outcome for awareness of microgrid. As, ideally awareness shall increase as we move over time but here, we see a dip in awareness level among the households.

4.1.2 Blinder – Oaxaca Decomposition

Acknowledging the significant aggregate decline shown by the McNemar test, we employ a Blinder-Oaxaca decomposition to directly test this assumption and diagnose the causes of the decline. The decomposition explicitly tests whether the drop is due to changes in household characteristics (endowments) or changes in the influence of those characteristics (coefficients), thus building upon and interrogating the results of the pooled model.

This method allows for breaking down the overall mean difference into components that are explained and unexplained (Blinder, 1973; Oaxaca, 1973), facilitating a deeper understanding and highlighting the sources of disparities between two groups. We employ a non-linear Blinder-Oaxaca decomposition using a probit model to account for the binary nature of our dependent variable (Yun, 2004). The relax[6] option was necessary to handle perfect prediction issues with some state dummy variables across survey years, particularly for Jharkhand and Odisha, where sampling frames differed between 2015 and 2018.

The Linear Blinder – Oaxaca model decompositions yield qualitatively similar results, though with greater emphasis on structural factors (85% unexplained vs 66% in probit). We prefer the probit specification for theoretical consistency with our binary outcome variable.

---

[6] Note: State dummy variables for Jharkhand and Odisha exhibited zero variance in some survey years due to sampling design. The decomposition proceeds by assuming zero coefficients for these variables in affected years, following standard practice for handling perfect prediction in non-linear decomposition models.

The analysis employs a non-linear Blinder-Oaxaca decomposition using a probit specification to account for the binary nature of microgrid awareness, with the total sample comprising 16,956 household observations (8,059 from 2015 and 8,897 from 2018). The decomposition follows the pooled coefficients approach; utilizing coefficient estimates from a probit model that pools both survey years while including a group dummy variable. The formal decomposition structure is expressed as:

$$\text{Overall Gap} = \text{Explained Component} + \text{Unexplained Component} \quad (2)$$

Where the specific components are defined as:

$$\text{Explained Component} = (X_1 - X_2) * \hat{\beta} \quad (2.1)$$

$$\text{Unexplained Component} = X_1 * (\hat{\beta}_1 - \hat{\beta}) + X_2 * (\hat{\beta} - \hat{\beta}_2) \quad (2.2)$$

Here, X_1 and X_2 represent the mean characteristic vectors for 2015 and 2018, respectively, $\hat{\beta}_1$ and $\hat{\beta}_2$ denote the group-specific probit coefficient estimates, and $\hat{\beta}$ indicates the coefficients from the pooled probit model. The explained component quantifies the portion of the awareness gap attributable to differences in observable household characteristics between periods, evaluated at the pooled coefficients. The unexplained component captures the differential returns to these characteristics, consisting of two subcomponents: the difference between 2015 and pooled coefficients, and the difference between pooled and 2018 coefficients, each weighted by their respective group means. This decomposition structure provides a neutral reference point that avoids the index number problem of choosing either group's coefficients as the benchmark, while maintaining methodological consistency with the binary outcome variable through the probit functional form.

Table 8: Blinder-Oaxaca decomposition

		Robust				
Mg Awareness	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
overall						
group_1	0.267	0.005	55.880	0.000	0.258	0.277
group_2	0.111	0.003	33.480	0.000	0.104	0.117
difference	0.157	0.006	26.910	0.000	0.145	0.168
explained	0.053	0.004	12.270	0.000	0.045	0.062
unexplained	0.103	0.006	17.250	0.000	0.092	0.115
cons	0.531	0.072	7.360	0.000	0.390	0.673

Note: The full table with explained and unexplained section can be found in Appendix.

The non-linear Blinder-Oaxaca decomposition reveals a more nuanced explanation for the 15.7 percentage point decline in microgrid awareness between 2015 and 2018 than suggested by linear probability models. The decomposition attributes approximately 34% of the total gap (0.053 / 0.157) to differences in household characteristics (the explained component), while the remaining 66% (0.103 / 0.157) stems from structural changes in how these characteristics

translate into awareness (the unexplained component). This distribution shows that while differences in composition across survey periods were significant, the fundamental changes in the awareness generation process have mainly caused the decline in microgrid awareness.

The explained component demonstrates that differential household endowments contributed meaningfully to the awareness gap. Male-headed households, which were more prevalent in 2015, accounted for a 1.37 percentage point advantage in awareness, while educational disparities particularly in secondary (0.48 percentage points) and higher education (0.14 percentage points) further amplified the gap. Geographic composition also proved significant, with state distribution differences contributing substantial explanatory power. Conversely, income differences between periods exerted a negative influence (-0.42 percentage points), partially offsetting other characteristics' effects.

The substantial unexplained component, however, reveals the profound structural deterioration in microgrid awareness determinants. Catastrophic declines in state-level coefficients dominate this component, with Uttar Pradesh (-12.5 percentage points), Madhya Pradesh (-7.6 percentage points), and West Bengal (-4.2 percentage points) experiencing the most severe deteriorations in awareness returns. Demographic factors also showed markedly reduced predictive power, with age (-7.0 percentage points) and gender (-4.9 percentage points) becoming significantly less determinative of awareness. The negative coefficient for household income (-1.5 percentage points) further indicates that economic status became a weaker predictor of awareness acquisition over time.

This pattern strongly suggests that national electrification policies expanded grid access and fundamentally reconfigured the institutional and informational landscape for decentralised energy technologies. State-level effects demonstrate how initial policy environments that supported microgrid awareness generation systematically eroded. The persistence of substantial unexplained variance even after accounting for detailed household characteristics underscores that the awareness collapse transcended demographic shifts, instead reflecting systemic changes in energy technology discourse, market structures, and information channels during India's rapid grid expansion era.

4.1.3 Multinomial Probit Regression

The analysis employs a multinomial probit model to examine the determinants of microgrid awareness across different age cohorts. The model specification follows the random utility

framework where household *i* chooses among *j* age-awareness categories, with the latent utility for category j given by:

$$U_{ij} = X_i \beta_j + \varepsilon_{ij} \quad (3)$$

Where U_{ij} represents the utility household *i* derives from belonging to age-awareness category *j*, X_i is a vector of household characteristics including demographic, educational, economic, occupational, and geographic variables, β_j are category-specific parameters to be estimated, and ε_{ij} follows a multivariate normal distribution with zero mean and covariance matrix Σ. The probability that household *i* chooses category *j* is:

$$P(Y_i = j \mid X_i) = \Phi(X_i \beta_j) \quad (3.1)$$

Where $\Phi(\cdot)$ denotes the multivariate normal cumulative distribution function.

The model was estimated using maximum likelihood with households which are not aware as the base outcome ($\beta_1 = 0$) for identification. The estimation converged with a final log pseudolikelihood of -11744.664, and the Wald chi-square statistic of 1908.77 ($p<0.000$) indicates strong joint significance of the explanatory variables. Standard errors were clustered at the household level (9071 clusters) to account for intra-household correlation in the panel data structure, and the model automatically handled perfect collinearity by omitting the West Bengal dummy variable. The comprehensive specification includes controls for gender, religion, ration card status, educational attainment, household income, occupational categories, and state fixed effects to isolate the independent associations between these factors and age-based awareness patterns. We here present the average marginal effect table of the age-awareness multinomial probit and the probit results can be found in the Appendix.

Table 9: Average Marginal Effects for Age – Awareness Multinomial Probit

Dependent VARIABLES	Aware & 18-30 Years M.E. coeff	Aware & 31-38 Years M.E. coeff	Aware & 39 - 45 Years M.E. coeff	Aware & 46 - 56 Years M.E. coeff	Aware & 57 - 96 Years M. E. coeff
Gender (base: female) Male	0.0144***	0.0093***	0.0084**	0.0191***	0.0307***
	(0.0043)	(0.0036)	(0.0036)	(0.0029)	(0.0028)
Religion (base: Others)					
Hindu	-0.0405**	-0.0130	-0.0295***	-0.0122	-0.0148
	(0.0170)	(0.0144)	(0.0113)	(0.0151)	(0.0165)
Muslim	-0.0376**	-0.0074	-0.0387***	-0.0040	-0.0080
	(0.0176)	(0.0149)	(0.0122)	(0.0155)	(0.0169)
Ration Cards Holder (base: No cards)					
APL	-0.0046	0.0091**	0.0052	0.0059	0.0180***
	(0.0048)	(0.0043)	(0.0043)	(0.0042)	(0.0041)
BPL	-0.0103**	-0.0026	0.0024	0.0049	0.0027
	(0.0048)	(0.0042)	(0.0041)	(0.0040)	(0.0040)
Education (base: No formal schooling)					
Primary schooling	0.0318***	0.0093**	0.0009	-0.0032	0.0026
	(0.0050)	(0.0038)	(0.0037)	(0.0036)	(0.0038)
Secondary schooling	0.0412***	0.0196***	0.0048	0.0015	0.0052
	(0.0055)	(0.0043)	(0.0043)	(0.0040)	(0.0041)

Higher Secondary/Diploma	0.0641***	0.0173***	0.0140***	0.0071	-0.0143**
	(0.0062)	(0.0053)	(0.0050)	(0.0049)	(0.0057)
Graduate & above	0.0825***	0.0156***	0.0061	0.0079	-0.0185***
	(0.0066)	(0.0059)	(0.0057)	(0.0052)	(0.0063)
HH Monthly Income	2.61e-10	-8.08e-07**	6.43e-07**	5.56e-07**	8.61e-07***
	(3.12e-07)	(3.21e-07)	(2.97e-07)	(2.52e-07)	(2.44e-07)
Income Source (base: Other income)					
Agri on own land	0.0271*	0.0442**	-0.0027	0.0047	-0.0380***
	(0.0156)	(0.0187)	(0.0115)	(0.0108)	(0.0088)
Cultivation on leased land	0.0368**	0.0578***	0.0125	0.0074	-0.0523***
	(0.0173)	(0.0197)	(0.0127)	(0.0119)	(0.0108)
Casual Agri labour	0.0263	0.0405*	0.0070	0.0049	-0.0386***
	(0.0187)	(0.0207)	(0.0137)	(0.0128)	(0.0112)
Salaried job	0.0422**	0.0517***	0.0006	0.0060	-0.0245**
	(0.0163)	(0.0193)	(0.0123)	(0.0118)	(0.0098)
Cattle rearing	0.0191	0.0599**	0.0220	0.0104	-0.0076
	(0.0290)	(0.0251)	(0.0196)	(0.0205)	(0.0162)
Own business	0.0336**	0.0550***	0.0058	0.0093	-0.0398***
	(0.0162)	(0.0191)	(0.0120)	(0.0113)	(0.0094)
Daily laborer	0.0272*	0.0416**	-0.0035	-0.0112	-0.0582***
	(0.0159)	(0.0189)	(0.0117)	(0.0110)	(0.0091)
Survey States (base: West Bengal)					
Bihar	0.0557 ***	0.0334***	0.0346***	0.0336***	0.0739***
	(0.0080)	(0.0060)	(0.0064)	(0.0063)	(0.0086)
Jharkhand	0.0884 ***	0.0510***	0.0523***	0.0390***	0.0737***
	(0.0083)	(0.0063)	(0.0067)	(0.0067)	(0.0087)
Madhya Pradesh	0.0273***	0.0040	0.0045	0.0052	0.0311***
	(0.0086)	(0.122)	(0.0071)	(0.0069)	(0.0090)
Odisha	-0.0670***	-0.0321**	-0.0439**	-0.0386**	0.0176
	(0.0251)	(0.0160)	(0.0186)	(0.0171)	(0.0137)
Uttar Pradesh	0.0213***	-0.0005	0.0070	0.0062	0.0388***
	(0.0080)	(0.0061)	(0.0065)	(0.0063)	(0.0084)
Observations	16,956	16,956	16,956	16,956	16,956

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Building upon the patterns identified in the pooled probit and Blinder-Oaxaca decomposition, the marginal effects from the multinomial probit analysis reveal nuanced probability changes in microgrid awareness across age cohorts, with "Not Aware" households now serving as the reference category. This refined specification provides clearer insights into the actual magnitude of demographic and socioeconomic factors on awareness probabilities across different age groups.

The marginal effects reveal a complex educational pattern where higher education consistently increases the probability of being in the youngest aware cohorts while showing neutral or negative effects for older groups. Primary education increases the probability of being in the 18-30 aware cohort by 3.18 percentage points ($p<0.01$), while graduate education shows an even stronger effect of 8.25 percentage points ($p<0.01$) for the same group. However, these educational advantages diminish or reverse for older cohorts, with graduate education actually reducing the probability of being in the oldest aware group by 1.85 percentage points ($p<0.01$). This pattern suggests that educational advantages in microgrid awareness were concentrated

among younger households, revealing a distinct generational divide in how education facilitated information acquisition.

Gender effects demonstrate a striking age-dependent progression. Male-headed households show progressively stronger positive marginal effects across older cohorts, increasing from 1.44 percentage points ($p<0.01$) for the 18-30 group to 3.07 percentage points ($p<0.01$) for the 57-96 cohort. This indicates that the gender gap in awareness not only persists but intensifies with age, with older male-headed households being significantly more likely to maintain awareness compared to their female counterparts.

Household income exhibits statistically significant but economically small effects across cohorts, with the largest impact observed for the oldest group (0.000086 percentage points, $p<0.01$). Occupational patterns reveal that agricultural occupations (own land, leased land, casual labour) show positive effects for younger cohorts but strongly negative effects for the oldest group, ranging from -3.80 to -5.23 percentage points ($p<0.01$). Daily labourers face particularly severe disadvantages in older cohorts, with a -5.82 percentage point effect ($p<0.01$) for the 57-96 group, indicating that economic vulnerability compounds with age in awareness retention. State-level marginal effects demonstrate consistent geographic patterning aligned with historical microgrid development. Bihar and Jharkhand show strong positive effects across all age cohorts, with the largest impacts observed for the oldest group (7.39 and 7.37 percentage points respectively, $p<0.01$). This suggests persistent awareness retention in states with early microgrid initiatives. Conversely, Odisha exhibits consistently negative effects across most cohorts, reaching -6.70 percentage points ($p<0.01$) for the non-aware category, confirming the state's limited microgrid penetration.

The marginal effects analysis substantiates the Blinder-Oaxaca decomposition findings by quantifying how demographic characteristics translated into actual probability differences across age cohorts. The results reveal that the awareness collapse documented between 2015-2018 was not uniform but followed pre-existing demographic fault lines. The concentration of educational advantages among younger households, coupled with compounding gender and economic disparities in older cohorts, suggests that awareness campaigns and market development failed to achieve intergenerational knowledge transfer. The strong state-level effects further emphasize the enduring impact of regional policy environments, with early-adopting states maintaining awareness advantages even amid systemic collapse. These patterns underscore that the microgrid awareness ecosystem was vulnerable precisely because it had

failed to build inclusive foundations across age, gender, and educational dimensions before the grid expansion policy shock.

We also run multinomial probit with mg_edu_mn as the dependent variable. It was created by interacting microgrid awareness with educational attainment categories, generating six mutually exclusive groups: (1) Not Aware (base category), (2) Aware with No Formal Education, (3) Aware with Primary Education, (4) Aware with Secondary Education, (5) Aware with Higher Secondary/Diploma, and (6) Aware with Graduate or Above education. This specification allows examination of how determinants of awareness vary across educational strata.

Table 10: Average Marginal Effects for Education – Awareness Multinomial Probit

Dependent variable: mg_edu_mn	(1) Aware & No Formal Education	(2) Aware & Primary Education	(3) Aware & Secondary Education	(4) Aware & Higher Educ. or Diploma	(5) Aware & Graduate or above
VARIABLES	M.E. coeff	M.E. coeff	M.E. coeff	M. E. coeff	M.E. coeff
Age	0.00044***	-0.0001	-0.0002*	-0.0006***	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.00009)	(0.0001)
Gender (base: female) Male	-0.0022	0.0334***	0.0294***	0.0196***	0.0167***
	(0.0044)	(0.0038)	(0.0031)	(0.0023)	(0.0022)
Religion (base: Others)					
Hindu	-0.0478***	-0.0080	-0.0287*	0.0039	-0.0163
	(0.0156)	(0.0160)	(0.0150)	(0.0128)	(0.0136)
Muslim	-0.0261*	0.0048	-0.0490***	-0.0080	-0.0208
	(0.0161)	(0.0167)	(0.0159)	(0.0134)	(0.0140)
Ration Cards Holder (base: No cards)					
APL	-0.0010	0.0124**	0.0065	0.0078**	0.0109***
	(0.0051)	(0.0054)	(0.0042)	(0.0035)	(0.0031)
BPL	0.0071	0.0045	-0.0154***	-0.0021	-0.0042
	(0.0047)	(0.0052)	(0.0044)	(0.0036)	(0.0033)
HH Monthly Income	-1.85e-06***	-2.03e-07	5.89e-07**	8.93e-07***	1.29e-06***
	(5.19e-07)	(4.55e-07)	(2.66e-07)	(1.92e-07)	(1.78e-07)
Salaried job	0.0021	0.0069	0.0001	0.0108**	0.0191***
	(0.0071)	(0.0075)	(0.0060)	(0.0044)	(0.0034)
Cattle rearing	0.0008	0.0431**	0.0165	0.0109	-0.0075
	(0.0203)	(0.0196)	(0.0181)	(0.0133)	(0.0171)
Own business	0.0039	0.0135**	0.0099**	0.0052*	-0.0072*
	(0.0055)	(0.0057)	(0.0047)	(0.0038)	(0.0040)
Daily labourer	0.0111***	-0.0101**	-0.0331***	-0.0158***	-0.0194***
	(0.0036)	(0.0042)	(0.0043)	(0.0031)	(0.0035)
Survey States (base: West Bengal)					
Bihar	0.0558***	0.0706***	0.0420***	0.0299***	0.0346***
	(0.0068)	(0.0081)	(0.0067)	(0.0061)	(0.0072)
Jharkhand	0.0623***	0.1031***	0.0569***	0.0363***	0.0426***
	(0.0073)	(0.0086)	(0.0070)	(0.0064)	(0.0074)
Madhya Pradesh	0.0041	0.0210**	0.0056	0.0115*	0.0250***
	(0.0077)	(0.0089)	(0.0071)	(0.0064)	(0.0074)
Odisha	-0.0566***	-0.0341*	-0.0580***	-0.0164	0.0026
	(0.0190)	(0.0187)	(-0.0580)	(0.0144)	(0.0121)

Uttar Pradesh	0.0103	0.0240***	0.0002	0.0144**	0.0244***
	(0.0069)	(0.0081)	(0.0067)	(0.0060)	(0.0071)
Observations	16,956	16,956	16,956	16,956	16,956

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The marginal effects from the education-awareness multinomial probit indicate clear stratification patterns in microgrid awareness across different educational levels, with "Not Aware" households serving as the reference category. Age exhibits a transparent educational gradient, showing positive impacts for households without formal education that are aware (0.00044, $p<0.01$), but increasingly adverse effects for those with higher education levels, reaching -0.0006 ($p<0.01$) for graduate-level awareness. This suggests that while older age predicts awareness for the least educated, it becomes a disadvantage for those in highly educated households. Gender differences reveal a significant educational pattern, with male-headed households not showing any notable advantage regarding awareness without formal education but demonstrating considerable positive effects for all educated categories, ranging from 3.34 percentage points ($p<0.01$) for primary education to 1.67 percentage points ($p<0.01$) for awareness among graduates. This indicates that the gender gap in awareness is most significant among those with intermediate educational levels.

Economic factors demonstrate systematic stratification: household income has adverse effects for aware non-educated households (-1.85e-06, $p<0.01$) but shows positive and increasingly beneficial effects for those with higher education groups (1.29e-06, $p<0.01$ for graduates). Occupational trends indicate that daily labourers experience considerable disadvantages at all educational levels, worsening effects at higher education strata (-1.94 percentage points for graduates, $p<0.01$). In comparison, salaried employment only benefits the highly educated (1.91 percentage points for graduates, $p<0.01$). Geographical disparities remain notably consistent, with Bihar and Jharkhand exhibiting strong positive effects across all educational categories (3.46-10.31 percentage points, $p<0.01$). In contrast, Odisha demonstrates ongoing adverse effects, particularly among less-educated populations (-5.66 percentage points for individuals without formal education, $p<0.01$).

The analyses of education-awareness and age-awareness using multinomial probit reveal complementary stratification patterns that jointly clarify the decline of microgrid awareness. The age-based model displays that younger households tend to concentrate their awareness, while the education-based analysis reveals that higher educational attainment provides specific

socioeconomic advantages to aware households. Both models consistently highlight expanding gender disparities and significant state-level influences. However, the education-focused approach more effectively captures how economic vulnerability compounds with limitations in human capital. The persistent disadvantages faced by daily labourers across both models, alongside the concentration of awareness within educated male households in high-aware areas, suggest that microgrid awareness has not reached beyond privileged demographic groups, thereby rendering the whole ecosystem susceptible to failure during grid expansion.

4.2. Determinants of Adoption of Microgrids in India

Building on the insights gained from awareness, the subsequent sections explore the factors affecting microgrid adoption in India. The clear stratification in awareness patterns, especially the educational divides, gender-related access, and regional disparities, provides a vital basis for comprehending barriers to adoption. Given that awareness is unevenly distributed across demographic and geographic lines, it is reasonable to conclude that adoption will face significant structural obstacles. The next phase examines whether the same elements limiting awareness also restricted adoption, or if additional barriers arose at the adoption stage. This analysis seeks to determine if the previously identified awareness gaps chiefly hindered microgrid adoption or if separate economic, technical, and institutional challenges independently obstructed household decisions regarding adoption, thereby offering a comprehensive view of the microgrid ecosystem's decline from awareness to adoption.

Across the pooled sample of 17,635 households, only 207 households (1.17%) reported microgrid usage. Adoption was far more prevalent in 2015 (201 households, 2.35%) than in 2018 (6 households, 0.07%). This is due to their complete discontinuation of diesel-based microgrid systems, and increase in regular grid connectivity at these households. The reliance on diesel microgrids and diesel generators has drastically decreased, falling from 13 per cent of households in 2015 to only 0.3 per cent by 2018. There has been a rise in grid electricity consumption, which also significantly lowered the number of households relying on kerosene for lighting, dropping from 68 per cent in 2015 to just 16 per cent in 2018. Conversely, the adoption of solar home systems and solar lanterns for lighting has risen from 7 to 16 per cent during the same period (Jain et al., 2018).

Table 11: Microgrid Users by Survey Year

Survey Year	Total Households	Microgrid Users	Adoption Rate (%)
2015	8,563	201	2.35
2018	9,072	6	0.07
Total	17,635	207	1.17

Data Source: ACCESS 2018
Note: Computed by Authors'

In 2015, 90% of adopters were from male-headed households (181 of 201), and this skew persisted in 2018 (5 of 6 adopters). While this reflects the male dominance in household headship, the marginal presence of female adopters suggests gendered constraints in energy decision-making or financing access. Among 2015 adopters, 70.1% of household heads were literate, and 29.9% were not. In 2018, adopters were evenly split (3 literate, 3 non-literate). This slight trend may indicate that literacy facilitates awareness and trust in decentralized technologies, though adoption was still present among illiterate households.

Table 12: Profile of Microgrid Users (2015 vs. 2018)

Characteristic	**Category**	**2015 (% of Users)**	**2018 (% of Users)**
Gender (HH Head)	Male	90.0	83.3
	Female	10.0	16.7
Literacy	Literate	70.1	50.0
	Illiterate	29.9	50.0
Caste	SC/ST	9.4	16.7
	OBC	64.7	66.7
	General	25.9	16.7
Ration Card	BPL	53.7	33.3
	APL	29.9	16.7
	Antyodaya	4.5	33.3
	None	11.9	16.7
Income Source	Agriculture	36.8	16.7
	Daily Wage Labour	22.4	16.7
	Own Business	14.4	66.7
	Salaried Job	8.0	0.0
Wealth Category	Rural Poor	57.2	33.3
	Rural Middle	15.9	16.7
	Rural Upper/Affluent	13.4	50.0

Note: Due to the very small number of adopters in 2018 (n = 6), percentages may not generalize and should be interpreted with caution.

In 2015, OBC households accounted for 64.7% of adopters, while SC/ST households made up just 9.4% and General/Others 25.9%. In 2018, out of 6 adopters, 4 were OBC, reinforcing the pattern. This skew suggests possible targeting or awareness concentration within certain social groups, particularly OBCs, or unequal access among SC/STs.

In 2015, more than half of adopters held BPL cards (53.7%), followed by APL (29.9%) and Antyodaya (4.5%). The presence of adopters across card types, especially APL and even some without cards, implies economic heterogeneity and a non-exclusive targeting of low-income people. In 2018 the distribution was more uniform, but the sample size was too small to generalize.

The Wealth category has been created using Asset score where households were categorized into Rural Affluent, Rural Upper, Rural Lower, Rural Middle and Rural Poor based on data about the house, house ownership, vehicle ownership and other variable related to quality of living. In 2015, adopters were concentrated in the Rural Poor (57.2%) and Rural Middle (15.9%) categories, but some adoption was also observed among the Rural Upper and Affluent groups. This reflects need-based adoption (among people with low incomes) and possible proactive or reliability-driven adoption (among better-off households). In 2018, the six adopters were from middle to upper wealth categories, suggesting a shift in access or targeting.

Among 2015 adopters, agriculture (36.8%), daily labor (22.4%), and own business (14.4%) were the dominant income sources. Salaried workers (8%) and others formed a smaller share. In 2018, 4 of the six adopters reported their own business as their income source. This suggests that irregular or self-employed households may have more substantial incentives to invest in alternative, reliable power sources like microgrids.

The adoption of microgrids varied significantly across different states, with Bihar standing out as the leading adopter in 2015, accounting for 77.6% of all users (156 out of 201). Uttar Pradesh also showed some adoption with 35 users, while Jharkhand and West Bengal had only minor participation. Notably, Madhya Pradesh and Odisha reported zero adoption during both years, indicating either a lack of interventions or inadequate reporting.

Table 13: State-wise Microgrid Adoption (2015-2018)

State	2015 Users	2015 Surveyed HHs	2015 Rate (%)	2018 Users	2018 Surveyed HHs	2018 Rate (%)
Bihar	156	1,511	10.3	4	1,512	0.26
Jharkhand	8	840	0.95	2	840	0.24
Uttar Pradesh	35	3,023	1.16	0	3,024	0.00
West Bengal	2	1,005	0.20	0	1,008	0.00
Madhya Pradesh	0	1,680	0.00	0	1,680	0.00
Odisha	0	504	0.00	0	1,008	0.00
Total	201	8,563	2.35	6	9,072	0.07

By 2018, there was a substantial decline in microgrid adoption across all states, with just 6 users remaining - 4 in Bihar and 2 in Jharkhand. No new states emerged on the adoption map, and previously engaged states like Uttar Pradesh and West Bengal experienced complete attrition. This trend suggests a significant withdrawal, failure, or replacement of microgrid infrastructure, likely due to the rapid expansion of the main grid, insufficient maintenance, or changing user preferences.

A closer look at the district-level distribution reveals extreme geographic concentration of adoption in 2015. The top three districts i.e., Purwa Champaran, Kishanganj, and Khagaria (all in Bihar) - counted for over 50% of all adopters, underscoring the role of localized interventions, such as pilot projects or developer activity.

Table 14: District-Level Microgrid Adoption and Decline (2015-2018)

State	**District**	**Users in 2015**	**Users in 2018**	**Change (Δ)**
Bihar	Purwa Champaran	56	1	-55
	Khagaria	20	0	-20
	Kishanganj	33	0	-33
	Samastipur	17	1	-16
	Siwan	13	2	-11
	Nawada	9	0	-9
	Patna	1	0	-1
	Bhagalpur	7	0	-7
	Supaul	0	0	0
Jharkhand	Sahibganj	4	2	-2
	Saraikela-Kharsawan	2	0	-2
	Garhwa	2	0	-2
	Bareilly	9	0	-9

Uttar Pradesh	Bijnour	4	0	-4
	Gorakhpur	1	0	-1
	Gonda	1	0	-1
	Siddharthnagar	14	0	-14
	Sitapur	5	0	-5
	Aligarh	1	0	-1
	Pratapgarh	0	0	0
West Bengal	North 24 Parganas	1	0	-1
	Malda	1	0	-1
	Paschim Medinipur	0	0	0
Madhya Pradesh	All districts	0	0	0
Odisha	All districts	0	0	0

Note: Only districts with users in 2015 or 2018 are included. Δ = Users 2018 - Users 2015.

Between 2015 and 2018, only four districts retained any adopters, with Purwa Champaran, Samastipur, Sahibganj, and Siwan each reporting 1-2 users. All other districts that had adopters in 2015 saw complete attrition. The sharpest declines were recorded in Purwa Champaran (-55 users), Kishanganj (-33), and Khagaria (-20). This concentrated rise and subsequent decline reinforce the idea that microgrid adoption in rural India has so far been project-driven and un-sustained, lacking broader diffusion or integration into stable service delivery models.

Table 15: Description of the adoption variables

Variable	Description / Construction	Measurement Type	Expected Sign	Justification / Rationale
Age	Age of household head in years	Continuous	(–)	Older heads are more risk-averse towards new technology.
Age^2	Square of age	Continuous	(–)	Captures non-linear effects of age.
Male	1 = Male-headed household	Binary	(+)	Male-headed households have higher income and decision power.
OBC	1 = OBC, 0 otherwise	Binary	(+)	Higher socioeconomic status than SC/ST.
Gen	1 = General caste, 0 otherwise	Binary	(+)	Better resource access and connectivity.
Hindu	1 = Hindu household, 0 otherwise	Binary	(+)	Represents religious/cultural regions.
Muslim	1 = Muslim household, 0 otherwise	Binary	(+)	Represents religious/cultural regions
APL / BPL Dummies	Ration card category based on poverty status	Binary	(±)	Proxy for household economic class; BPL (includes Antyodaya) expected negative.
Literate	1 = Literate household head	Binary	(+)	Reduces information gap for technology adoption.
Primary schooling	Completed up to 5th grade	Binary	(+)	Improves awareness and comprehension.

Variable	Description / Construction	Measurement Type	Expected Sign	Justification / Rationale
Secondary schooling	Completed 6th–10th grade	Binary	(+)	Improves cost–benefit evaluation skills.
Higher secondary / diploma	Completed 12th or diploma	Binary	(+)	Enhances technology perception and adoption capacity.
Graduate and above	Graduate or higher education	Binary	(+)	Indicates higher income potential and innovation receptivity.
Occupation dummies	Agriculture, salaried, business, etc.	Binary	(+/–)	Captures livelihood-based energy needs and ability to pay.
HH monthly income	Monthly household income (₹)	Continuous	(+)	Higher income increases affordability.
HH indebted	1 = Household in debt	Binary	(–)	Financial constraints reduce adoption likelihood.
HH size	Number of household members	Continuous	(+)	Larger families have higher energy demand.
HH size²	Square of HH size	Continuous	(–)	Captures diminishing returns to energy needs.
HH assets (PCA)	Asset index constructed via PCA	Continuous	(+)	Proxy for wealth and affordability.
HH Appliances (HHA_Owned)	Aggregate of number of electrical appliances owned by the household (includes lighting, cooling, heating, etc.)	Continuous	(–)	Higher number of appliances have energy demand.
Electricity satisfaction (PCA1)	Composite satisfaction index for lighting reliability	Continuous	(–)	Dissatisfied households are more likely to adopt microgrids.
Willingness to pay (PCA2)	PCA index for WTP for improved lighting	Continuous	(+)	Captures demand-driven motivation for microgrid adoption.
Community lighting satisfaction (PCA3)	PCA index for perceived adequacy of community lighting	Continuous	(–)	Poor community lighting spurs alternative adoption.
Anti-theft (PCA4)	PCA index for perceived safety/anti-theft measures	Continuous	(+)	Reflects improved trust and local governance factors.
State dummies	Bihar, Jharkhand, Uttar Pradesh, Madhya Pradesh, Odisha (base: West Bengal)	Binary	Contextual	Controls for state-level policy and electrification variation.

4.2.1 Pooled Probit Regression

We run a Probit regression model in order to determine what factors constitute to microgrid adoption among the households. Since, the sample is repeated in two years i.e., 2015 and 2018, we run a pooled probit regression as there is not a significant gap to observe any year effects. We also cluster standard errors at the household level to account for correlation between observations from the repeated household across years. To account for the repeated observation

with households, we compare the standard error with the non-clustered model to ensure they are underestimated.

We do not include Madhya Pradesh, Odisha and West Bengal dummies as they are omitted due to non-existent of microgrid users in the data. The pooled probit models analyse how socio-demographic, economic, and infrastructural factors influence the probability of microgrid adoption across rural Indian households. The coefficients are consistent across model specifications, with several statistically significant predictors.

Table 16: Pooled Probit – Microgrid Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Probit coeff: Demographics	Probit coeff: +Educ caste & Region	Probit coeff: +Economic & Livelihood	Probit coeff: +HH Structure	Probit coeff: Interaction	Probit coeff: 2015 PCA
Age	-0.00317*	-0.00414**	-0.00322	0.0248*	0.0241*	-0.0260
	(0.00189)	(0.00198)	(0.00224)	(0.0136)	(0.0137)	(0.0195)
Age Square				-0.000310**	-0.000303**	0.000262
				(0.000147)	(0.000147)	(0.000206)
Gender (base: female) Male	0.389***	0.253***	0.261**	0.267**	0.260**	-0.284*
	(0.0835)	(0.0941)	(0.103)	(0.105)	(0.105)	(0.153)
Caste Category (base: SC & ST)						
OBC	0.467***	0.310***	0.325***	0.326***	0.325***	0.444**
	(0.0884)	(0.101)	(0.111)	(0.113)	(0.114)	(0.178)
GEN	0.367***	0.243**	0.280**	0.349***	0.353***	0.492**
	(0.0983)	(0.114)	(0.126)	(0.130)	(0.131)	(0.202)
Religion (base: Others)						
Hindu	2.840***	3.063***	2.765***	2.737***	2.744***	2.872***
	(0.0686)	(0.161)	(0.154)	(0.203)	(0.183)	(0.404)
Muslim	3.160***	3.411***	3.141***	3.119***	3.137***	3.213***
	(0.0864)	(0.168)	(0.168)	(0.212)	(0.192)	(0.421)
HH Monthly income			1.32e-05**	1.40e-05**	1.16e-05*	2.57e-05**
			(5.88e-06)	(6.53e-06)	(6.69e-06)	(1.02e-05)
HH indebted			-0.172**	-0.173**	-0.172**	-0.307***
			(0.0701)	(0.0722)	(0.0723)	(0.116)
Asset score (normalized)			-0.470***	-0.201***	-0.277***	-0.0399
			(0.0503)	(0.0629)	(0.0731)	(0.0905)
HH size				0.0788***	0.0847***	0.0630**
				(0.0298)	(0.0294)	(0.0308)
HHA owned				-0.163***	-0.167***	-0.143***
				(0.0281)	(0.0281)	(0.0381)
Literate	-0.0842					
	(0.0631)					
Education dummies (base: No formal schooling)		✓	✓	✓	✓	✓
State Dummies		✓	✓	✓	✓	✓
Income Source Dummies (base: Other income)			✓	✓	✓	✓
HH size squared				✓	✓	✓
light_satis_pc1						-0.115**
						(0.0560)

wtp_lighting_pc2						0.143***
						(0.0493)
commu_light_pc3						-0.257***
						(0.0784)
anti_theft_pc1						0.0281
						(0.0543)
Monthly Income – Assest Score Interact					1.17e-05**	
					(5.31e-06)	
Constant	-5.645***	-6.851***	-6.812***	-6.963***	-6.981***	-5.827***
	(0.128)	(0.297)	(0.313)	(0.474)	(0.464)	(0.711)
Observations	17,635	17,635	13,237	13,180	13,180	4,213

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Full Model in Appendix

The pooled Probit models examine how socio-demographic, economic, infrastructural, and perception-based factors influence microgrid adoption among rural Indian households, with updated specifications that refine our understanding of key determinants.

Age plays a complex role in adoption. Initial models show that younger household heads are likelier to adopt microgrids, indicating a consistent adverse linear effect. However, when we introduce age squared in Models 4-5, we uncover a significant non-linear pattern: the probability of adoption initially increases with age, peaking during middle age before declining. This finding suggests that middle-aged household heads, who blend experience with a willingness to take risks, are the most likely adopters. Interestingly, in Model 3, age becomes statistically insignificant once we introduce economic controls, which indicates that financial factors primarily influence the relationship between age and adoption rather than reflecting lifecycle preferences. Gender remains a strong and consistent predictor, with male-headed households showing significantly higher adoption rates across all pooled models. The persistent gender gap indicates that male household heads may concentrate economic agency, risk tolerance, and decision-making authority in the context of energy technology investments.

Religious affiliation shows strong effects, though the revised specifications somewhat attenuated the coefficients. Hindu and Muslim households maintain substantially higher adoption probabilities than other religious groups, underscoring the role of spiritual community networks in facilitating technology adoption, potentially through information sharing or collective action mechanisms. Caste dynamics reveal persistent structural advantages that remain robust across specifications. OBC and General caste households maintain significantly higher adoption probabilities than SC/ST households throughout all models, with coefficients

showing remarkable stability. Social hierarchies influence energy access, even with policy interventions to reduce disparities.

Educational attainment shows a more precise pattern in the updated models, with secondary and higher secondary education demonstrating statistically significant positive effects in Models 3-5. Intermediate educational levels may significantly influence microgrid adoption by equipping individuals with the technical literacy needed to evaluate new energy technologies while ensuring they remain connected to local community networks.

Economic factors reveal nuanced relationships. Monthly income consistently predicts adoption across Models 3-6, confirming the importance of financial capacity. However, asset scores show a significant negative relationship in most specifications, creating an interesting paradox where liquid income promotes adoption while illiquid wealth discourages it. Wealthier households may already have satisfactory energy alternatives or perceive microgrids as inferior to grid connections. The interaction term in Model 5 confirms that income and assets work together synergistically; higher income has a greater positive effect for households with more assets. Financial constraints hinder adoption, as household indebtedness consistently shows adverse effects across various specifications.

Household structure demonstrates predictable patterns, with household size showing a positive association, while the possibility of non-linearity remains unconfirmed. The consistent adverse effect of electrical appliance ownership suggests that microgrids may not meet the power requirements of households with numerous electrical devices, or that appliance-rich households are already well-served by existing energy sources. Regional disparities remain pronounced, with Bihar, Uttar Pradesh, and Jharkhand showing significantly higher adoption rates across all models. These strong state effects likely reflect regional policy initiatives, implementation effectiveness, or particular infrastructural gaps that make microgrids more attractive alternatives.

We excluded the ration card categories (APL/BPL) from the final analysis because they consistently showed statistical insignificance in predicting microgrid adoption patterns. This exclusion suggests that poverty classifications based on ration cards do not effectively capture the factors influencing energy adoption, as they lack the detailed information provided by continuous economic variables such as income and assets.

The sixth model focuses on a specialised analysis based solely on 2015 data, incorporating perception-based Principal Component Analysis (PCA) variables unique to that year. It serves

two primary purposes: testing hypotheses about energy satisfaction and community perceptions in adoption decisions and providing robustness through alternative measurement approaches. The key findings from the 2015 PCA model reveal several essential insights regarding lighting satisfaction and energy adoption behaviours. First, a significant negative relationship exists between lighting satisfaction and adoption; households dissatisfied with grid quality seek alternative energy sources. Additionally, the willingness to pay for better lighting is a strong positive predictor, indicating considerable demand for improved energy services. Interestingly, community lighting satisfaction is negatively associated with adoption decisions, suggesting that community dissatisfaction may influence individual choices. Furthermore, the gender effect observed in pooled models has reversed, with male-headed households exhibiting a lower probability of adoption in 2015. Lastly, changes in occupational patterns have emerged, showing positive associations with salaried jobs and cattle rearing, which reflect diverse energy needs and varying levels of exposure to promotional efforts. While limited to 2015, the analysis offers valuable insights into perceptual and attitudinal factors that enhance the understanding of microgrid adoption.

These results emphasise that a complex interplay of social identity, economic capacity, structural factors, and perceptual elements drives microgrid adoption. The consistent advantages for certain social groups highlight the need for targeted inclusion strategies to ensure equitable energy access. The strong economic effects underscore the importance of financial mechanisms, particularly for addressing indebtedness constraints. The regional variations suggest that policy learning from high-adoption states could benefit other regions, while the perception-based drivers indicate that addressing service quality concerns could significantly boost adoption rates.

Table 17: Marginal Effects at Mean for Pooled Probit

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables	ME coeff: Demographics	ME coeff: +Educ caste & Region	ME coeff: +Economic & Livelihood	ME coeff: +HH Structure	ME coeff: Interaction	ME coeff: 2015 PCA
Age	-0.000094* (0.000056)	-0.000106** (0.000051)	-0.00010 (0.00007)	0.00071** (0.00039)	0.00069* (0.00039)	-0.00009 (0.00015)
Age squared				-8.84e-06** (4.25e-06)	- 0.00000865** (0.00000425)	
Gender (base: Female) Male	0.01151*** (0.00255)	0.00647*** (0.00239)	0.00779** (0.00306)	0.00762** (0.00297)	0.00742** (0.00296)	-0.01049* (0.00591)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	ME coeff: Demographics	ME coeff: +Educ caste & Region	ME coeff: +Economic & Livelihood	ME coeff: +HH Structure	ME coeff: Interaction	ME coeff: 2015 PCA
OBC	0.01382***	0.00793***	0.00972***	0.00930***	0.00926***	0.01683**
	(0.00271)	(0.00256)	(0.00331)	(0.00320)	(0.00321)	(0.00691)
GEN	0.01085***	0.00621**	0.00835**	0.00996***	0.01006***	0.01838**
	(0.00296)	(0.00290)	(0.00377)	(0.00371)	(0.00372)	(0.00787)
Hindu	0.08408***	0.07827***	0.08259***	0.07813***	0.07826***	0.11091***
	(0.00628)	(0.00613)	(0.00765)	(0.00833)	(0.00803)	(0.01874)
Muslim	0.09353***	0.08717***	0.09383***	0.08906***	0.08946***	0.12388***
	(0.00693)	(0.00660)	(0.00838)	(0.00892)	(0.00862)	(0.01988)
Literate	-0.00249					
	(0.00187)					
Primary schooling		0.00008	0.00200	0.00142	0.00150	0.00060
		(0.00205)	(0.00277)	(0.00264)	(0.00264)	(0.00554)
Secondary schooling		0.00167	0.00609*	0.00544*	0.00564*	-0.00066
		(0.00232)	(0.00319)	(0.00309)	(0.00310)	(0.00642)
Higher sec or diploma		0.00177	0.00660*	0.00770**	0.00772**	-0.00237
		(0.00275)	(0.00373)	(0.00361)	(0.00361)	(0.00758)
Graduate & above		-0.00091	0.00495	0.00702	0.00690	-0.00802
		(0.00313)	(0.00421)	(0.00436)	(0.00440)	(0.00917)
HH monthly income			3.93e-07**	4.01e-07**	1.22e-07	9.78e-07**
			(1.77e-07)	(1.87e-07)	(2.44e-07)	(3.82e-07)
HH indebted			-0.00512**	-0.00493**	-0.00491**	-0.01214***
			(0.00210)	(0.00493)	(0.00207)	(0.00444)
HH size				0.00225***	0.00242***	0.00243**
				(0.00085)	(0.00084)	(0.00118)
HH size squared				-0.0000543	-0.0000605	-0.000052
				(0.0000389)	(0.0000381)	(0.000043)
HH Appliances owned				-0.00465***	-0.00478***	-0.00542***
				(0.00078)	(0.00078)	(0.00139)
Asset-score (normalized)			-0.01405***	-0.00574***	-0.001**	-0.00148
			(0.00157)	(0.00180)	(0.000)	(0.00348)
Agri on own land			-0.00020	-0.00080	-0.00060	-0.00060
			(0.00356)	(0.00345)	(0.00344)	(0.00344)
Casual Agri labor			-0.00112	-0.00003	-0.00043	-0.00043
			(0.00554)	(0.00542)	(0.00539)	(0.00539)
Salaried job			0.00170	0.00453	0.00395	0.00395
			(0.00475)	(0.00476)	(0.00481)	(0.00481)
Cattle rearing			-0.00171	-0.00304	-0.00292	-0.00292
			(0.01397)	(0.01411)	(0.01435)	(0.01435)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	ME coeff: Demographics	ME coeff: +Educ caste & Region	ME coeff: +Economic & Livelihood	ME coeff: +HH Structure	ME coeff: Interaction	ME coeff: 2015 PCA
Own business			0.00601	0.00810**	0.00839**	0.00839**
			(0.00417)	(0.00409)	(0.00410)	(0.00410)
Daily laborer			-0.01012	-0.00927	-0.00918**	-0.00918**
			(0.00373)	(0.00360)	(0.00359)	(0.00359)
Light satisfaction pc1						-0.00444**
						(0.00213)
WTP lighting pc2						0.00551***
						(0.00183)
Community light pc3						-0.00987 ***
						(0.00299)
Anti-theft PC1						0.00112
						(0.00208)
Bihar		0.00313***	0.05588***	0.05023***	0.05061***	0.07028***
		(0.00546)	(0.05588)	(0.00663)	(0.00670)	(0.01048)
Jharkhand		0.02354***	0.02608***	0.02252***	0.02264***	0.03075**
		(0.00611)	(0.00764)	(0.00754)	(0.00759)	(0.01210)
Uttar Pradesh		0.02320***	0.03672***	0.03035***	0.03048***	0.03769***
		(0.00532)	(0.00681)	(0.00668)	(0.00673)	(0.00999)
Observations	17,635	17,635	13,237	13,180	13,180	4,213

The analysis of rare events data presents several significant challenges, particularly when investigating the dependent variable mg_use, which exhibits an exceedingly low prevalence of 2.3% in 2015 and 0.1% in 2018. This low occurrence can lead to biased maximum likelihood estimates, as they tend to skew toward zero. Furthermore, the phenomenon of complete or quasi-complete separation is often encountered with such rare outcomes. In this scenario, predictors may perfectly predict either failure or success, resulting in infinite parameter estimates that complicate interpretation.

4.2.2 Firth Logit regression

To address these issues, Firth's logit (Firth, 1993) offers a valuable approach by reducing small-sample bias, which is particularly pronounced in logistic regression frameworks dealing with imbalanced outcome distributions. This technique improves the reliability of estimates and confidence intervals, especially when the number of events per variable is limited, thus providing better finite sample properties and enhancing the robustness of the analysis.

Table 18: Firth Logit regression

VARIABLES	(1) Firth logit Coeff: Demographics	(2) Firth logit Coeff: +Educ & Region	(3) Firth logit Coeff: +Economic & Livelihood	(4) Firth logit Coeff: +HH Structure	(5) Firth logit Coeff: Interaction
Age	-0.00824*	-0.00839*	-0.00591	0.0432	0.0412
	(0.00494)	(0.00487)	(0.00516)	(0.0318)	(0.0317)
Age Square				-0.000540	-0.000523
				(0.000350)	(0.000350)
Gender (base: female) Male	1.019***	0.671***	0.624**	0.614**	0.603**
	(0.233)	(0.237)	(0.244)	(0.248)	(0.248)
Ration Cards Holder (base: No cards)					
APL			0.275	0.143	0.167
			(0.249)	(0.253)	(0.254)
BPL			0.171	-0.00730	0.0170
			(0.232)	(0.236)	(0.237)
Caste Category (base: SC & ST)					
OBC	1.275***	0.779***	0.725***	0.722***	0.717***
	(0.242)	(0.244)	(0.253)	(0.254)	(0.254)
GEN	1.042***	0.633**	0.608**	0.732**	0.741**
	(0.269)	(0.279)	(0.293)	(0.296)	(0.296)
Religion (base: Others)					
Hindu	-0.0222	-0.358	-0.266	-0.477	-0.529
	(1.428)	(1.449)	(1.461)	(1.468)	(1.467)
Muslim	0.766	0.339	0.472	0.263	0.244
	(1.435)	(1.456)	(1.472)	(1.479)	(1.478)
Education (base: No formal schooling)					
Primary schooling		0.0309	0.166	0.152	0.157
		(0.187)	(0.199)	(0.201)	(0.201)
Secondary schooling		0.144	0.471**	0.395*	0.411*
		(0.207)	(0.226)	(0.231)	(0.231)
Higher Secondary/Diploma		0.250	0.599**	0.680**	0.675**
		(0.250)	(0.273)	(0.278)	(0.279)
Graduate & above		-0.0204	0.355	0.466	0.441
		(0.289)	(0.315)	(0.321)	(0.324)
HH Monthly income			2.99e-05**	3.06e-05**	2.89e-05**
			(1.46e-05)	(1.55e-05)	(1.41e-05)
HH indebted			-0.394***	-0.362**	-0.365**
			(0.153)	(0.156)	(0.156)
Asset score (normalized)			-1.074***	-0.444***	-0.649***
			(0.109)	(0.135)	(0.157)
Income Source (base: Other income)					
Agri on own land			-0.0109	-0.0521	-0.0351
			(0.255)	(0.259)	(0.259)
Cultivation on leased land			0.0146	0.0923	0.0577
			(0.396)	(0.405)	(0.407)
Casual Agri labour			0.190	0.348	0.292
			(0.350)	(0.362)	(0.366)
Salaried job			0.276	0.0831	0.0585
			(0.898)	(0.923)	(0.929)
Cattle rearing			0.346	0.490*	0.522*
			(0.290)	(0.295)	(0.295)
Own business			-0.779***	-0.687**	-0.676**
			(0.268)	(0.272)	(0.272)
HH size				0.159**	0.168**
				(0.0657)	(0.0658)
HH size squared				-0.00352	-0.00377
				(0.00294)	(0.00293)
HHA owned				-0.408***	-0.418***
				(0.0506)	(0.0508)

Bihar		4.833***	4.723***	4.410***	4.432***
		(0.639)	(0.641)	(0.643)	(0.642)
Jharkhand		2.741***	2.505***	2.253***	2.236***
		(0.706)	(0.708)	(0.709)	(0.709)
Uttar Pradesh		2.679***	3.280***	2.858***	2.855***
		(0.656)	(0.657)	(0.660)	(0.660)
Literate	-0.221				
	(0.160)				
c.hh_monthly_income#c.asset_score_norm					2.97e-05**
					(1.20e-05)
Constant	-5.875***	-8.407***	-8.917***	-8.381***	-8.375***
	(1.449)	(1.600)	(1.638)	(1.798)	(1.795)
Observations	17,635	17,635	13,237	13,180	13,180

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The Firth logit specification reveals more pronounced demographic patterns than the standard probit approach. While both methods identify male-headed households as significantly more likely to adopt microgrids, the Firth correction amplifies this gender disparity substantially. Male-headed households show 83% higher odds (exp (0.603) = 1.83) of adoption in the Firth specification, compared to the more modest effects detected by probit. This suggests that standard methods may have underestimated the gender gap in energy technology adoption due to the rare-events bias suppressing the actual effect size.

The age-adoption relationship shows similar non-linear patterns across both methods, but Firth logit coefficients are approximately twice as significant, indicating a more substantial life-cycle effect where middle-aged household heads demonstrate the highest adoption propensity. This enhanced detection power likely stems from Firth's better handling of the imbalanced outcome distribution. Perhaps the most striking difference emerges in the caste-based disparities. The Firth logit reveals substantially larger disadvantages for marginalized groups than detected by probit. OBC households show 105% higher odds and General caste households 110% higher odds of adoption compared to SC/ST households in the Firth specification, versus only 37% and 41% higher odds respectively in probit models. This dramatic amplification suggests that standard methods significantly underestimated the role of social hierarchies in energy access.

While significant in probit models, the effects of religious affiliation become statistically insignificant in Firth logit specifications. This indicates that the apparent religious differences detected by probit may have been artifacts of the rare-events bias, and that caste rather than religion is the primary social identity factor influencing adoption decisions. The Firth correction provides clearer insights into economic determinants. Household income shows a more substantial, more statistically significant positive effect on adoption, with Firth logit

coefficients approximately 2.5 times larger than probit estimates. This suggests that affordability constraints are even more binding than previously estimated.

The wealth paradox - where higher asset ownership correlates with lower adoption - intensifies in Firth specifications. The negative coefficient for asset score nearly triples in magnitude, strengthening the hypothesis that wealthier households may already have satisfactory grid connections or alternative energy sources, reducing their incentive for microgrid adoption. The income-asset interaction remains positive and significant in both specifications, confirming that the complementary relationship between liquid income and illiquid wealth is robust to methodological choices.

Firth logit uncovers a clearer education-adoption gradient than probit models. While probit detected only marginal effects for secondary education, Firth logit reveals strong, statistically significant benefits: secondary education holders show 51% higher odds and higher secondary graduates 96% higher adoption odds. This enhanced detection suggests that education's role in overcoming information barriers and technical competence requirements for microgrid adoption was underestimated in standard models.

The most substantial methodological differences emerge in regional effects. Firth logit coefficients for state dummies are 2-4 times larger than probit estimates, revealing dramatically stronger regional patterns. Bihar shows an astounding 83-fold higher odds (exp (4.432) = 84.1) of adoption compared to the reference category in Firth logit, versus only 6.4-fold in probit.

The massive amplification observed suggests that policy effectiveness in high-adoption states may be substantially greater than what the probit estimates indicate. Furthermore, it implies that geographical targeting could yield even more significant impacts than previously thought. Additionally, the analysis highlights that regional infrastructure and governance factors play a more decisive role than detected by standard methods. Both methods converge on similar occupational patterns: daily labourers face significant adoption barriers while business owners show higher adoption rates. This consistency across methodological approaches strengthens confidence in these livelihood effects as robust findings rather than statistical artifacts.

The comparative analysis indicates that standard regression methods may significantly underestimate effect sizes in rare-events contexts, such as the adoption of energy technology. Specifically, the Firth correction highlights several key findings. First, social and structural barriers, particularly those related to caste and region, are found to be more severe than

suggested by probit estimates. Additionally, economic constraints appear to be more binding than what standard models indicate. Furthermore, the role of education in overcoming adoption barriers is revealed to be more substantial than previously thought. Lastly, the impacts of policy in regions where adoption is successful could be much larger than the estimates provided by traditional methods.

The consistency in significance patterns and coefficient signs across methods provides strong evidence for the core theoretical framework, while the amplified effect sizes in Firth's logit offer a more accurate quantification of the true relationships. This suggests that energy adoption researchers working with rare technologies should strongly consider penalized likelihood methods to avoid underestimating the importance of key determinants. For policy purposes, the Firth logit results imply that targeted interventions addressing caste disparities, regional infrastructure gaps, and economic constraints could yield even larger adoption gains than previously estimated from standard regression models.

5. Discussion

Our empirical investigation provides robust econometric evidence on the socioeconomic and regional factors influencing microgrid awareness and adoption in rural India, using nationally representative data from the ACCESS surveys (2015–2018). The multidimensional complexity of behavioral and informational limitations that underlie decentralized energy transitions is made clear by the models. We discuss each hypothesis (H1–H5) based on the decomposition results, marginal effects, and calculated coefficients.

H1 (Awareness – Demographics).

The Probit results consistently show that age exerts a small but statistically significant negative influence on microgrid awareness, confirming that older household heads are less informed about decentralized technologies. Gender remains one of the most persistent sources of disparity, and male-headed households are 35 - 40 percent more likely to be aware of microgrids than female-headed ones, even after controlling for education, occupation, and income. This gap persists across all model specifications, underscoring the informational exclusion of women in household energy decision-making. Education exhibits a transparent gradient: the probability of awareness increases monotonically with schooling level, with the marginal effect nearly tripling between households with no formal education and those with tertiary qualifications. These results confirm H1, and establish a systematic stratificication of awareness by age, gender, and education.

H2 (Awareness – Decomposition of Decline).

The McNemar test and Oaxaca–Blinder decomposition jointly reveal a statistically significant microgrid awareness erosion between 2015 and 2018. Households were nearly five times more likely to lose awareness than to gain it, a striking asymmetry that rejects the null of no change. Decomposition results show that roughly two-thirds of the decline is attributable to changes in coefficients, returns to characteristics rather than compositional changes in household attributes. In other words, even if demographic and income structures had remained constant, the same observable traits translated into weaker awareness outcomes in 2018 than in 2015. The outcomes supports H2 and suggests a systemic weakening of information channels—likely due to the policy emphasis on rapid grid expansion under Saubhagya, which diverted attention from off-grid options. The result demonstrates how large-scale infrastructure policy can inadvertently alter the informational equilibrium of rural energy markets.

H3 (Adoption – Income and Assets).

The Firth Logit results indicate a positive and significant association between household income and microgrid adoption, confirming that financial capacity remains a prerequisite for participation in decentralized systems. Yet, the asset score shows a negative coefficient for wealthier households, as measured by durable goods or housing quality, are less likely to adopt microgrids. This inverse relationship suggests a "wealth–paradox": households with higher fixed assets may prefer grid electricity, viewing microgrids as inferior substitutes rather than complements. The positive interaction between income and assets further refines this finding that households with higher liquidity but moderate asset bases are the most likely adopters. This pattern validates H3, emphasizing that liquidity and expenditure flexibility matter more than static wealth in shaping decentralized technology uptake.

H4 (Adoption – Education and Caste).

Education plays a decisive role in shaping adoption, mirroring its impact on awareness. Firth estimates show that households with secondary or higher education exhibit significantly greater odds of adoption than those with no schooling. The penalized likelihood method reveals stronger coefficient magnitudes than the standard Probit model, implying that conventional estimators understate the effect of education under rare-event conditions. Caste-based stratification is also pronounced: Scheduled Caste and Scheduled Tribe households are markedly less likely to adopt microgrids, even after controlling for income, education, and occupation. This pattern is consistent with long-standing evidence of social exclusion in

technology diffusion (Dugoua et al., 2017). These results confirm the hypothesis that H4 educational attainment and social hierarchy jointly determine adoption outcomes, operating through both information access and social capital mechanisms.

H5 (Regional Heterogeneity).

State-level differences remain the single most potent predictors of both awareness and adoption. Relative to West Bengal, households in Bihar and Jharkhand show odds ratios exceeding 2 in the adoption model and significant positive coefficients in awareness regressions. In contrast, Odisha consistently records negative coefficients in both outcomes. These results persist across specifications and are not attenuated by socioeconomic controls, confirming strong regional effects. They reflect historical variation in the presence of microgrid operators, state-level renewable policies, and donor-funded pilots. The regional dummies demonstrate their econometric significance, confirming H5 and establishing that state-specific policy environments and infrastructure ecosystems, rather than household characteristics alone, condition household adoption behaviour.

Overall, the econometric evidence depicts a two-stage diffusion bottleneck. Awareness, an informational precondition for adoption has not only stagnated but regressed over time, while adoption remains confined to a narrow subset of households with stable income and educational advantage. The results collectively illustrate that microgrid diffusion is constrained not by a lack of access to technology per se, but by a breakdown of informational, institutional, and economic linkages that connect rural households to decentralized solutions.

6. Conclusion

This paper contributes new empirical evidence on the micro-level determinants of microgrid awareness and adoption in rural India during a phase of rapid grid expansion. Using the nationally representative ACCESS 2015–2018 panel, it quantifies how information, economic capacity, and institutional context jointly influence decentralized energy diffusion. The results highlight that, despite near-universal electrification, awareness of microgrids declined sharply between 2015 and 2018, with households nearly five times more likely to lose awareness than gain it. Decomposition analysis shows that this regression is driven by declining *returns to key characteristics,* such as education and income rather than changes in household composition, suggesting a structural erosion of the information environment surrounding decentralized renewables.

At the adoption stage, less than two percent of households reported using microgrids in 2018. Employing Firth penalized logistic regression to correct for rare-event bias, the study finds that income, education, and state-level policy environments significantly increase adoption odds, while asset accumulation and caste disadvantages reduce them. By juxtaposing these findings with conventional Probit estimates, the paper demonstrates that standard models systematically underestimate the influence of socioeconomic and institutional factors under rare-event conditions. Thus, methodologically, the study contributes by validating Firth Logit as a robust approach for analyzing rare adoption phenomena in energy-access research, offering a framework applicable to other low-prevalence innovations in development economics.

From a policy perspective, the results bridge micro-level behavior with macro-level governance structures. The consistent regional effects—strongly positive for Bihar and Jharkhand and negative for Odisha—mirror differences in state-level policy implementation following the MNRE's 2016 National Microgrid Policy draft. These findings reinforce that policy clarity, exit options for developers, and hybrid grid–microgrid integration mechanisms directly shape household adoption incentives. The study thus complements the existing policy literature by grounding macro-level frameworks in microeconometric evidence, demonstrating how structural and informational asymmetries persist despite regulatory progress.

Together, these findings advance the empirical understanding of the interaction between central grid expansion and decentralized energy diffusion, illustrating that universal electrification can inadvertently suppress off-grid innovation if policies do not integrate both systems coherently. Reintegrating microgrids into India's energy-access framework—as *complementary*, not *competing*, infrastructures—could enhance system reliability, stimulate rural enterprise, and support the national net-zero trajectory.

Future research should deepen this work along three key fronts. First, data integration is essential; linking household-level data with supply-side datasets—such as developer operations, tariff structures, and project lifecycles—would facilitate causal identification of institutional and market constraints that are currently inferred from cross-sectional variation. Second, methodological innovation is crucial. Expanding the rare-event modeling framework to include panel or spatial econometric structures can help capture dynamic diffusion patterns and neighborhood spillovers in awareness and adoption. Finally, policy experimentation needs to be prioritized. Implementing randomized or quasi-experimental interventions, such as information campaigns targeting women or income-linked financing pilots, should be designed

to test whether the behavioural and financial barriers identified can actually be relaxed in practice. By combining these directions, future work can move beyond documenting the decline of microgrid diffusion to designing evidence-based policies that align affordability, awareness, and institutional coherence., ensuring decentralized renewable systems remain integral to India's equitable and resilient energy transition.

7. Policy Implications

The econometric results presented in this study demonstrate that informational asymmetries, liquidity constraints, and regional policy heterogeneity continue to shape the trajectory of microgrid adoption in rural India. These micro-level findings must be interpreted within the broader institutional and policy context that has evolved since the 2016 MNRE draft of the National Policy for Renewable Energy-Based Mini and Micro Grids. The 2016 draft marked a crucial conceptual shift, positioning microgrids as energy service providers rather than temporary substitutes for grid electricity. By encouraging commercial and productive use applications, it opened a pathway to improve financial viability and local economic linkages. However, our results indicate that, despite this policy intent, awareness and adoption remain highly unequal, suggesting that implementation and outreach have not effectively penetrated household-level decision processes.

Regional differentiation and state policy response: The econometric evidence of strong regional effects is consistent with the staggered rollout of state-level policies following the MNRE draft. Uttar Pradesh's 2016 Mini-Grid Policy, the first state-level implementation, capped microgrid capacity at 500 kW and offered a 30% capital subsidy for projects developed on identified sites. By providing clear exit options when the central grid expands—parallel operation, partial feed-in, or complete grid sale, the policy directly addressed the uncertainty faced by private developers. The significant positive coefficients for Bihar and Jharkhand in the adoption model echo this institutional clarity: both states formalized microgrid frameworks (BREDA, 2017; JREDA, 2022) that reduced investor risk and signalled long-term regulatory stability. In contrast, Odisha's 2022 renewable energy policy, though recognizing microgrids for remote electrification, has yet to establish such operational or financial clarity—consistent with the negative state coefficients in our regression.

Aligning policy design with household-level constraints: Our Firth Logit results show that income, not asset wealth, drives adoption, underscoring that liquidity, not static wealth, determines household capacity to invest in decentralized energy. Future state schemes should

thus prioritize income-linked financing mechanisms rather than asset-based eligibility. Soft loans or pay-as-you-go models tied to rural livelihoods programs (e.g., MGNREGA or self-help group financing) can effectively target liquidity-constrained households. Moreover, the observed educational gradient in both awareness and adoption underscores the need for information campaigns embedded within local governance structures. Panchayats and Village Energy Committees (VECs), already recognized in municipal frameworks, can play a central role in organizing community-level energy literacy drives, especially for women and marginalized caste groups.

Institutional coordination and grid–microgrid coexistence : The regression evidence that awareness declined over time, despite policy expansion suggests a weakening institutional interface between grid expansion and microgrid visibility. While central and state policies have clarified developer exit options, they remain less explicit on coexistence mechanisms. To prevent crowding-out effects observed empirically, regulators such as JSERC, BERC, and UPERC should operationalize hybrid grid microgrid models, where microgrids remain active even after grid arrival. The Jharkhand Power Policy (2023) sets an important precedent by mandating the deployment of microgrids in disaster-prone zones with automatic islanding capability. Policymakers could adopt similar provisions at the national level to ensure that microgrids enhance resilience and reliability, not just improve access. Strengthening institutional and market frameworks

At the meso level, the creation of Energy Service Companies (ESCOs) and their integration with DISCOMs remains essential. DISCOMs should be mandated to procure surplus power from microgrids at pre-determined feed-in tariffs under the National Tariff Policy. The econometric evidence that regional dummies dominate household-level predictors underscores that adoption hinges on institutional coherence—where regulatory clarity and commercial pathways coexist. Institutionalizing such coherence can transform microgrids from donor-driven experiments into economically sustainable infrastructure.

Toward a new policy paradigm: Future microgrid policy must address both sides of the diffusion equation: information and affordability. National and state governments should adopt a dual-track approach:

1. Information deepening: integrate microgrid awareness campaigns within existing electrification and livelihood programs, explicitly targeting the demographic groups

found to have the lowest awareness (women, older individuals, less-educated households).

2. Market and financial deepening: provide risk guarantees and blended-finance instruments to attract private capital in underperforming states.

Finally, policy vision should expand beyond electrification to include productive-use microgrids, aligning with MNRE's original 2016 intent to promote rural industrialization and employment generation. By linking our empirical evidence of adoption constraints with these design principles, future microgrid policy can evolve from a welfare-oriented model to a sustainable, market-integrated, and socially inclusive energy system—one that reinforces India's commitment to net-zero emissions by 2070 while ensuring that decentralized renewables remain an active part of its energy-access architecture.

8. Summary

The econometric results validate that informational barriers (H1–H2), financial constraints (H3), socio-cultural inequalities (H4), and institutional asymmetries (H5) jointly shape the diffusion of microgrids in India. Policy must therefore shift from a one-dimensional focus on connectivity to a multidimensional strategy encompassing information, inclusion, and institutional support. By integrating these dimensions, decentralized renewable energy systems can achieve sustained diffusion alongside India's grid expansion.

9. References

Abu-Elzait, S., & Parkin, R. (2019, April). Economic and Environmental Advantages of Renewable-based Microgrids over Conventional Microgrids. *2019 IEEE Green Technologies Conference(GreenTech)*. 2019 IEEE Green Technologies Conference(GreenTech), Lafayette, LA, USA. https://doi.org/10.1109/greentech.2019.8767146

Agrawal, S., Mani, S., Jain, A., & Ganesan, K. (2020). *State of electricity access in India. Insights from the India Residential Energy Survey.* https://www.ceew.in/sites/default/files/ceew-research-on-state-of-electricty-access-and-coverage-in-india.pdf

Agrawal, S., Mani, S., Jain, A., & Ganesan, K. (2020). *State of electricity access in India. Insights from the India Residential Energy Survey.* Council on Energy, Environment and Water. ceew-research-on-state-of-electricty-access-and coverage-in-india.pdf

Aklin, M., Cheng, C., Urpelainen, J., Ganesan, K., & Jain, A. (2016). Factors affecting household satisfaction with electricity supply in rural India. *Nature Energy*, *1*(11). https://doi.org/10.1038/nenergy.2016.170

Aklin, M., Cheng, C.-Y., & Urpelainen, J. (2018a). Social acceptance of new energy technology in developing countries: A framing experiment in rural India. *Energy Policy*, *113*, 466–477. https://doi.org/10.1016/j.enpol.2017.10.059

Aklin, M., Cheng, C.-Y., & Urpelainen, J. (2018b). Social acceptance of new energy technology in developing countries: A framing experiment in rural India. *Energy Policy*, *113*, 466–477. https://doi.org/10.1016/j.enpol.2017.10.059

Aklin, M., Chindarkar, N., Urpelainen, J., Jain, A., & Ganesan, K. (2021). The hedonic treadmill: Electricity access in India has increased, but so have expectations. *Energy Policy*, *156*, 112391. https://doi.org/10.1016/j.enpol.2021.112391

Akter, S., & Bagchi, K. (2021). Is off-grid residential solar power inclusive? Solar power adoption, energy poverty, and social inequality in India. *Energy Research & Social Science*, *82*, 102314. https://doi.org/10.1016/j.erss.2021.102314

Bhandari, A. K., & Jana, C. (2010). A comparative evaluation of household preferences for solar photovoltaic standalone and mini-grid system: An empirical study in a costal village of Indian Sundarban. *Renewable Energy*, *35*(12), 2835–2838. https://doi.org/10.1016/j.renene.2010.05.006

Bhanja, A., Kumar, A., Gupta, A. K., Gupta, A. K., Ghosal, A., Mukherjee, S., & Chaudhury, S. (2020). Developing a Framework for Rural Electrification in India- Analysis of the Prospects of Micro-grid Solutions. *International Journal of Sustainable Development and Planning*, *15*(8), 1341–1350. https://doi.org/10.18280/ijsdp.150821

Bhatia, P. (2023). India's state-led electricity transition: A review of techno-economic, socio-technical and political perspectives. *Energy Research & Social Science*, *102*, 103184. https://doi.org/10.1016/j.erss.2023.103184

Bihar Renewable Energy Development Agency (2017). (2017). *Bihar Policy for Promotion of Bihar New and Renewable Energy Sources.* Energy Department, Government of Bihar. https://www.breda.bih.nic.in/Uploads/Policies%20_Act%20_%20Regulations/RENEWABE_ENERGY_POLICY_2017.pdf

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, *8*(4), 436. https://doi.org/10.2307/144855

Chakravarty, D., & Roy, J. (2021). Solar Microgrids in Rural India: A Case Study of Household Benefits. *Ecology, Economy and Society–the INSEE Journal*, *4*(2), 65–93. https://doi.org/10.37773/ees.v4i2.140

Claudy, M. C., Michelsen, C., O'Driscoll, A., & Mullen, M. R. (2010). Consumer awareness in the adoption of microgeneration technologies. *Renewable and Sustainable Energy Reviews*, *14*(7), 2154–2160. https://doi.org/10.1016/j.rser.2010.03.028

Dugoua, E., Liu, R., & Urpelainen, J. (2017). Geographic and socio-economic barriers to rural electrification: New evidence from Indian villages. *Energy Policy*, *106*, 278–287. https://doi.org/10.1016/j.enpol.2017.03.048

Firth, D. (1993). Bias reduction of maximum likelihood estimates. *Biometrika*, *80*(1), 27–38. https://doi.org/10.1093/biomet/80.1.27

Harish, S. M., Iychettira, K. K., Raghavan, S. V., & Kandlikar, M. (2013). Adoption of solar home lighting systems in India: What might we learn from Karnataka? *Energy Policy*, *62*, 697–706. https://doi.org/10.1016/j.enpol.2013.07.085

Jain, A., Tripathi, S., Mani, S., Patnaik, S., Shahidi, T., & Ganesan, K. (2018). *Access to Clean Cooking Energy and Electricity: Survey of States 2018*. CEEW. https://www.ceew.in/sites/default/files/CEEW-Access-to-Clean-Cooking-Energy-and-Electricity-11Jan19_0.pdf

Jhunjhunwala, A., & Kaur, P. (2018). Solar Energy, dc Distribution, and Microgrids: Ensuring Quality Power in Rural India. *IEEE Electrification Magazine*, *6*(4), 32–39. https://doi.org/10.1109/MELE.2018.2871277

Joshi, L., Narayanan, N., Venkateswaran, J., Solanki, C. S., & Kumar, P. (2019). Adoption of solar photovoltaic lighting in rural India: Role of localization strategy. *Energy and Buildings*, *202*, 109370. https://doi.org/10.1016/j.enbuild.2019.109370

Jothi, E., Abbas, A. H. R., Bisht, D., Mani, A., Velusudha, N. T., & Dhabliya, D. (2024). Distributed Generation Planning in Multi-Energy Microgrids. *E3S Web of Conferences*, *540*, 10017. https://doi.org/10.1051/e3sconf/202454010017

JREDA. (2022). *Jharkhand Solar Policy 2022*. Government of Jharkhand. https://api.jreda.com/all-uploaded-img/img/6360e972de5e0.pdf

Karthik, R., Behera, R. R., Shankar, U., Patnaik, P., & Pradhan, R. P. (2024). Transforming Energy Access: The Role of Micro Solar Dome in Providing Clean Energy Lighting in Rural India. *Nature Environment and Pollution Technology*, *23*(2), 935–946. https://doi.org/10.46488/nept.2024.v23i02.028

Lasseter, B. (2001). Microgrids [distributed power generation]. *2001 IEEE Power Engineering Society Winter Meeting. Conference Proceedings (Cat. No.01CH37194)*. Proceedings of 2001 Winter Meeting of the IEEE Power Engineering Society, Columbus, OH, USA. https://doi.org/10.1109/pesw.2001.917020

Lin, B., & Kaewkhunok, S. (2024). From fields to markets: Solar power adoption impact on Nepali farmers' livelihoods. *Energy for Sustainable Development*, *82*, 101537. https://doi.org/10.1016/j.esd.2024.101537

Luthra, S., Kumar, S., Garg, D., & Haleem, A. (2015). Barriers to renewable/sustainable energy technologies adoption: Indian perspective. *Renewable and Sustainable Energy Reviews*, *41*, 762–776. https://doi.org/10.1016/j.rser.2014.08.077

Mani, S., Shahidi, T., Patnaik, S., Jain, A., Tripathi, S., Ganesan, K., Aklin, M., Urpelainen, J., Chindarkar, N., Council On Energy, Environment And Water, Initiative For Sustainable Energy Policy, & National University Of Singapore. (2019). *Access to Clean Cooking Energy and Electricity: Survey of States in India 2018 (ACCESS 2018)* (Version 1.0, pp. 10011910, 17582158, 20289049, 266112) [Text/tab-separated-values,text/tab-

separated-values,text/tab-separated-values,application/pdf]. Harvard Dataverse. https://doi.org/10.7910/DVN/AHFINM

Marnay, C., Chatzivasileiadis, S., Abbey, C., Iravani, R., Joos, G., Lombardi, P., Mancarella, P., & Von Appen, J. (2015a). Microgrid Evolution Roadmap. *2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST)*, 139–144. https://doi.org/10.1109/SEDST.2015.7315197

Marnay, C., Chatzivasileiadis, S., Abbey, C., Iravani, R., Joos, G., Lombardi, P., Mancarella, P., & Von Appen, J. (2015b). Microgrid Evolution Roadmap. *2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST)*, 139–144. https://doi.org/10.1109/SEDST.2015.7315197

McNemar, Q. (1947). Note on the Sampling Error of the Difference Between Correlated Proportions or Percentages. *Psychometrika*, *12*(2), 153–157. https://doi.org/10.1007/BF02295996

Ministry of Statistics and Policy Implementation (2024). (n.d.). *Energy Statistics India 2024*. Government of India. https://mospi.gov.in/publication/energy-statistics-india-2024-1

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review*, *14*(3), 693. https://doi.org/10.2307/2525981

Palit, D., & Bandyopadhyay, K. R. (2017). Rural electricity access in India in retrospect: A critical rumination. *Energy Policy*, *109*, 109–120. https://doi.org/10.1016/j.enpol.2017.06.025

Rebane, K. L., & Barham, B. L. (2011). Knowledge and adoption of solar home systems in rural Nicaragua. *Energy Policy*, *39*(6), 3064–3075. https://doi.org/10.1016/j.enpol.2011.02.005

Sharma, S., & Sood, Y. R. (2022). Microgrids: A Review of Status, Technologies, Software Tools, and Issues in Indian Power Market. *IETE Technical Review*, *39*(2), 411–432. https://doi.org/10.1080/02564602.2020.1850367

Sindhu, S., Nehra, V., & Luthra, S. (2016). Identification and analysis of barriers in implementation of solar energy in Indian rural sector using integrated ISM and fuzzy MICMAC approach. *Renewable and Sustainable Energy Reviews*, *62*, 70–88. https://doi.org/10.1016/j.rser.2016.04.033

Smith, M. G., & Urpelainen, J. (2014). Early Adopters of Solar Panels in Developing Countries: Evidence from T anzania. *Review of Policy Research*, *31*(1), 17–37. https://doi.org/10.1111/ropr.12061

Yu, B., Guo, J., Zhou, C., Gan, Z., Yu, J., & Lu, F. (2017). A Review on Microgrid Technology with Distributed Energy. *2017 International Conference on Smart Grid and Electrical Automation (ICSGEA)*, 143–146. https://doi.org/10.1109/ICSGEA.2017.152

Yun, M.-S. (2004). Decomposing differences in the first moment. *Economics Letters*, *82*(2), 275–280. https://doi.org/10.1016/j.econlet.2003.09.008

10. Appendix

A. McNamer Test

The test statistic is: $\chi 2 = \frac{(|b-c|-1)^2}{b+c}$

Where, b=324 (No to Yes) and c=1516 (Yes to No).

	Controls		
Cases	Exposed	Unexposed	Total
Exposed	656	1516	2172
Unexposed	324	6067	6391
Total	980	7583	8563

McNemar's chi2(1) = 772.21 Prob > chi2 = 0.0000
Exact McNemar significance probability = 0.0000
Proportion with factor

Cases	**.2536494**		
Controls	.1144459	[95% Conf. Interval]	
difference	.1392036	.1297217	.1486854

ratio	2.216327	2.09222	2.347795
rel. diff.	.1571937	.1470153	.1673721
odds ratio	4.679012	4.147353	5.291744 (exact)

B. Binder-Oaxaca Decomposition

a. Linear Binder-Oaxaca Decomposition

The Blinder-Oaxaca decomposition provides a nuanced quantification of the factors driving the dramatic 15.6 percentage point decline in microgrid awareness between 2015 and 2018. It decomposes the difference

Blinder-Oaxaca decomposition — Number of obs = 16,956
Model = linear
Group 1: survey_year = 1 — N of obs 1 = 8,059
Group 2: survey_year = 2 — N of obs 2 = 8,897
endowments: (X1 - X2) * b2
coefficients: X2 * (b1 - b2)
interaction: (X1 - X2) * (b1 - b2)
(Std. Err. adjusted for 9,071 clusters in hhid)

		Robust				
mg_awareness	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
overall						
group_1	0.267	0.005	54.130	0.000	0.257	0.276
group_2	0.111	0.003	33.280	0.000	0.104	0.117
difference	0.156	0.005	31.290	0.000	0.146	0.166
endowments	0.021	0.002	10.150	0.000	0.017	0.026
coefficients	0.186	0.006	30.650	0.000	0.174	0.197
interaction	-0.051	0.004	-12.910	0.000	-0.059	-0.043
			endowments			
Age	-0.001	0.000	-2.760	0.006	-0.001	-0.000
Male	0.008	0.001	9.240	0.000	0.007	0.010
Hindu	0.003	0.001	2.340	0.019	0.000	0.006
Muslim	-0.003	0.001	-2.430	0.015	-0.005	-0.001
APL	0.003	0.001	2.640	0.008	0.001	0.006
BPL	-0.000	0.000	-0.760	0.449	-0.001	0.001
Primary schooling	-0.000	0.000	-0.480	0.629	-0.000	0.000
Secondary schooling	0.004	0.001	5.330	0.000	0.002	0.005
Higher sec. or diploma	0.001	0.000	2.480	0.013	0.000	0.002
Graduate & above	0.001	0.000	2.860	0.004	0.000	0.002
HH Monthly Income	-0.004	0.001	-4.890	0.000	-0.006	-0.003
Agri on own land	0.001	0.002	0.580	0.564	-0.003	0.006
Cultivation on leased land	-0.000	0.000	-0.030	0.976	-0.001	0.001
Casual Agri labor	0.000	0.000	0.920	0.355	-0.000	0.000
Salaried job	-0.001	0.000	-1.590	0.111	-0.001	0.000
Cattle rearing	-0.000	0.000	-0.830	0.409	-0.000	0.000
Own business	-0.000	0.000	-1.160	0.246	-0.001	0.000
Daily laborer	0.000	0.002	0.200	0.843	-0.004	0.005
Bihar	-0.001	0.000	-3.270	0.001	-0.002	-0.000
Jharkhand		0		(omitted)		
Madhya Pradesh	-0.003	0.000	-8.270	0.000	-0.004	-0.002
Odisha	0.024	0.002	13.070	0.000	0.021	0.028

Uttar Pradesh	-0.006	0.001	-9.770	0.000	-0.008	-0.005
West Bengal	-0.005	0.000	-10.260	0.000	-0.006	-0.004
			coefficients			
Age	-0.092	0.016	-5.710	0.000	-0.123	-0.060
Male	-0.019	0.009	-2.160	0.031	-0.037	-0.002
Hindu	0.053	0.074	0.710	0.477	-0.093	0.199
Muslim	0.010	0.010	1.070	0.284	-0.009	0.030
APL	-0.000	0.005	-0.090	0.926	-0.011	0.010
BPL	-0.013	0.009	-1.460	0.144	-0.031	0.005
Primary schooling	0.009	0.004	2.230	0.026	0.001	0.016
Secondary schooling	-0.001	0.002	-0.630	0.530	-0.006	0.003
Higher sec. or diploma	0.001	0.002	0.340	0.734	-0.003	0.004
Graduate & above	0.000	0.002	0.110	0.916	-0.003	0.004
HH Monthly Income	-0.018	0.009	-2.020	0.043	-0.035	-0.001
Agri on own land	-0.004	0.016	-0.270	0.789	-0.035	0.027
Cultivation on leased land	0.001	0.002	0.790	0.431	-0.002	0.005
Casual Agri labor	-0.002	0.001	-1.380	0.167	-0.005	0.001
Salaried job	0.000	0.003	0.040	0.965	-0.006	0.007
Cattle rearing	0.000	0.001	0.230	0.819	-0.001	0.001
Own business	0.003	0.005	0.720	0.469	-0.006	0.012
Daily laborer	-0.008	0.017	-0.460	0.647	-0.040	0.025
Bihar	-0.019	0.004	-4.750	0.000	-0.027	-0.011
Jharkhand		0		(omitted)		
Madhya Pradesh	-0.063	0.004	-15.040	0.000	-0.071	-0.055
Odisha	0.024	0.002	13.070	0.000	0.021	0.028
Uttar Pradesh	-0.103	0.007	-14.450	0.000	-0.117	-0.089
West Bengal	-0.034	0.003	-13.320	0.000	-0.039	-0.029
_cons	0.460	0.095	4.830	0.000	0.273	0.646
			interaction			
Age	0.003	0.001	4.320	0.000	0.001	0.004
Male	-0.004	0.002	-2.150	0.032	-0.007	-0.000
Hindu	-0.001	0.001	-0.710	0.478	-0.004	0.002
Muslim	0.001	0.001	1.060	0.287	-0.001	0.004
APL	-0.000	0.002	-0.090	0.926	-0.005	0.004
BPL	0.001	0.001	1.440	0.150	-0.000	0.003
Primary schooling	-0.000	0.000	-0.480	0.629	-0.000	0.000
Secondary schooling	-0.001	0.001	-0.630	0.531	-0.002	0.001
Higher sec. or diploma	0.000	0.000	0.340	0.736	-0.000	0.001
Graduate & above	0.000	0.000	0.110	0.916	-0.000	0.001
HH Monthly Income	0.003	0.001	2.010	0.045	0.000	0.005
Agri on own land	-0.001	0.004	-0.270	0.789	-0.009	0.007
Cultivation on leased land	0.001	0.001	0.780	0.437	-0.001	0.002
Casual Agri labor	-0.000	0.000	-1.040	0.298	-0.001	0.000
Salaried job	-0.000	0.000	-0.040	0.965	-0.001	0.001
Cattle rearing	-0.000	0.000	-0.220	0.824	-0.000	0.000
Own business	-0.000	0.001	-0.710	0.479	-0.002	0.001
Daily laborer	0.002	0.004	0.460	0.647	-0.006	0.009
Bihar	-0.002	0.000	-4.670	0.000	-0.003	-0.001
Jharkhand		0		(omitted)		
Madhya Pradesh	-0.008	0.001	-12.980	0.000	-0.009	-0.006
Odisha	-0.024	0.002	-13.070	0.000	-0.028	-0.021
Uttar Pradesh	-0.012	0.001	-12.780	0.000	-0.014	-0.010
West Bengal	-0.008	0.001	-11.510	0.000	-0.009	-0.007

b. Non-Liner Blinder-Oaxaca (Probit)

Mg Awareness	Coef.	Robust Std.Err.	z	P>z	[95%Conf.	Interval]
overall						
group_1	0.267	0.005	55.880	0.000	0.258	0.277
group_2	0.111	0.003	33.480	0.000	0.104	0.117
difference	0.157	0.006	26.910	0.000	0.145	0.168
explained	0.053	0.004	12.270	0.000	0.045	0.062
unexplained	0.103	0.006	17.250	0.000	0.092	0.115
			explained			
Age	0.001	0.000	1.610	0.108	-0.000	0.001
Male	0.014	0.002	7.810	0.000	0.010	0.017
Hindu	0.003	0.001	2.380	0.017	0.000	0.005
Muslim	-0.002	0.001	-2.160	0.031	-0.004	-0.000
APL	0.002	0.001	1.620	0.106	-0.001	0.005
BPL	0.001	0.001	1.610	0.108	-0.000	0.002
Primary schooling	-0.000	0.000	-0.440	0.663	-0.001	0.001
Secondary schooling	0.005	0.001	5.710	0.000	0.003	0.006
Higher sec or diploma	0.001	0.001	2.200	0.028	0.000	0.002
Graduate & above	0.001	0.001	2.470	0.013	0.000	0.003
HH Monthly income	-0.004	0.001	-5.110	0.000	-0.006	-0.003
Agri on own land	0.001	0.003	0.440	0.663	-0.005	0.007
Cultivation on leased land	0.001	0.000	1.130	0.258	-0.000	0.002
Casual Agri labor	0.000	0.000	0.570	0.571	-0.000	0.000
Salaried job	-0.001	0.000	-1.620	0.106	-0.002	0.000
Cattle rearing	-0.000	0.000	-0.880	0.378	-0.000	0.000
Own business	-0.001	0.001	-1.660	0.098	-0.002	0.000
Daily laborer	0.002	0.003	0.810	0.417	-0.003	0.008
Bihar	0.008	0.003	2.980	0.003	0.003	0.013
Jharkhand	0.006	0.003	2.240	0.025	0.001	0.011
Madhya Pradesh	0.005	0.001	3.270	0.001	0.002	0.008
Odisha		0		(omitted)		
Uttar Pradesh	0.008	0.002	4.280	0.000	0.004	0.012
West Bengal	0.003	0.001	2.780	0.005	0.001	0.005
			unexplained			
Age	-0.070	0.014	-4.850	0.000	-0.098	-0.042
Male	-0.049	0.011	-4.460	0.000	-0.070	-0.027
Hindu	0.036	0.048	0.750	0.454	-0.058	0.130
Muslim	0.008	0.007	1.200	0.230	-0.005	0.022
APL	-0.002	0.005	-0.310	0.758	-0.012	0.009
BPL	-0.009	0.007	-1.220	0.221	-0.023	0.005
Primary schooling	0.003	0.004	0.690	0.491	-0.005	0.011
Secondary schooling	-0.005	0.002	-2.110	0.035	-0.010	-0.000
Higher sec or diploma	-0.002	0.002	-1.450	0.146	-0.006	0.001
Graduate & above	-0.002	0.001	-1.430	0.151	-0.005	0.001
HH Monthly income	-0.015	0.006	-2.620	0.009	-0.027	-0.004
Agri on own land	-0.007	0.016	-0.470	0.638	-0.038	0.023
Cultivation on leased land	0.001	0.002	0.360	0.718	-0.003	0.004
Casual Agri labor	-0.002	0.001	-1.450	0.147	-0.005	0.001
Salaried job	-0.002	0.003	-0.590	0.555	-0.007	0.004
Cattle rearing	-0.000	0.000	-0.320	0.746	-0.001	0.001
Own business	0.000	0.004	0.070	0.941	-0.007	0.008
Daily laborer	-0.004	0.014	-0.290	0.771	-0.031	0.023
Bihar	-0.049	0.004	-13.020	0.000	-0.057	-0.042
Jharkhand	-0.023	0.002	-11.620	0.000	-0.027	-0.019
Madhya Pradesh	-0.076	0.005	-15.430	0.000	-0.086	-0.066
Odisha	0.009	0.003	3.120	0.002	0.003	0.015
Uttar Pradesh	-0.125	0.008	-15.490	0.000	-0.141	-0.109
West Bengal	-0.042	0.003	-15.110	0.000	-0.048	-0.037
_cons	0.531	0.072	7.360	0.000	0.390	0.673

The linear probability model decomposition presents a more extreme characterisation of the microgrid awareness collapse than the preferred probit specification. While both approaches confirm the dominance of structural factors, the linear model attributes a substantially larger share—85% versus 66% in the probit decomposition—to the unexplained component. This divergence stems from methodological foundations: the linear model's assumption of constant marginal effects across the probability distribution appears to overstate the role of changing returns to characteristics while understating compositional differences. Specifically, the linear model's endowments component (14%) is less than half the magnitude of the probit model's explained component (34%), suggesting it may underestimate how differential household characteristics between survey periods contributed to the awareness gap.

Notably, both decompositions identify similar patterns in structural deterioration, particularly the catastrophic declines in state-level coefficients. Uttar Pradesh, Madhya Pradesh, and West Bengal show consistently significant negative coefficients across both specifications, confirming these states experienced the most severe erosion of microgrid awareness infrastructure. However, the linear model's three-fold approach reveals complex interaction effects that partially offset the main components, particularly for geographic variables. The consistency in directional effects across methodologies strengthens the core finding that systemic factors drove the awareness collapse, though the linear model's more extreme distribution suggests it may overemphasise structural explanations at the expense of demographic compositional changes.

The decomposition analysis powerfully demonstrates that the collapse of microgrid awareness was a systemic event, not a demographic one. The decline was not because households became less educated, poorer, or more female-led. It occurred because the national policy environment, symbolized by the Saubhagya scheme, fundamentally altered the energy landscape. Microgrid information campaigns were likely scaled back, the technology was marginalized in public discourse, and the perceived value of being aware of decentralized alternatives evaporated as the centralized grid became the singular focus of electrification efforts. This result powerfully underscores Aklin et al.'s (2018) argument that when a technology is positioned as a private good in a market dominated by a heavily subsidized public good (the grid), its adoption and very awareness can collapse, regardless of its technical merit.

The methodological comparison underscores the importance of model specification in decomposition analysis. The linear model's computational simplicity comes at the cost of theoretical inconsistency with binary outcome variables, potentially distorting the relative contributions of characteristics versus structural factors. Nevertheless, both approaches concur that state-level policy environments and changing returns to demographic characteristics were the primary drivers of India's microgrid awareness collapse between 2015 and 2018, providing robust evidence for the structural transformation hypothesis despite quantitative differences in magnitude.

C. Multinomial Probit Regression: Age Cohort-Awareness

Dependent mg_age_mn	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MProbit coeff	MProbit coeff	MProbit coeff	MProbit coeff	MProbit coeff	MProbit coeff
Gender (base: female) Male		0.374***	0.356***	0.336***	0.614***	0.950***
		(0.0734)	(0.0783)	(0.0782)	(0.0877)	(0.116)
Religion (base: Others)						
Hindu		-0.730***	-0.463*	-0.725***	-0.466	-0.496
		(0.244)	(0.275)	(0.227)	(0.305)	(0.317)
Muslim		-0.663***	-0.340	-0.839***	-0.288	-0.350
		(0.253)	(0.284)	(0.241)	(0.313)	(0.325)
Ration Cards Holder (base: No cards)						
APL		0.0209	0.225***	0.161**	0.182**	0.375***
		(0.0676)	(0.0788)	(0.0783)	(0.0823)	(0.0771)
BPL		-0.129*	-0.0489	0.0325	0.0801	0.0402
		(0.0672)	(0.0777)	(0.0753)	(0.0796)	(0.0756)
Education (base: No formal schooling)						
Primary schooling		0.472***	0.246***	0.109	0.0394	0.136*
		(0.0686)	(0.0706)	(0.0672)	(0.0714)	(0.0705)
Secondary schooling		0.653***	0.484***	0.241***	0.192**	0.250***
		(0.0762)	(0.0788)	(0.0796)	(0.0790)	(0.0765)
Higher Secondary/Diploma		0.961***	0.483***	0.424***	0.323***	-0.0376
		(0.0849)	(0.0980)	(0.0931)	(0.0985)	(0.108)
Graduate & above		1.193***	0.468***	0.309***	0.348***	-0.0966
		(0.0904)	(0.110)	(0.106)	(0.106)	(0.119)
HH Monthly Income		2.77e-06	-1.02e-05*	1.32e-05**	1.26e-05**	1.72e-05***
		(4.42e-06)	(5.89e-06)	(5.47e-06)	(5.01e-06)	(4.63e-06)
Income Source (base: Other income)						
Agri on own land		0.405*	0.795**	0.0361	0.158	-0.548***
		(0.215)	(0.335)	(0.210)	(0.211)	(0.164)
Cultivation on leased land		0.583**	1.079***	0.342	0.266	-0.722***
		(0.241)	(0.354)	(0.234)	(0.234)	(0.202)
Casual Agri labour		0.406	0.748**	0.203	0.174	-0.547***
		(0.260)	(0.372)	(0.251)	(0.251)	(0.210)
Salaried job		0.676***	1.012***	0.182	0.276	-0.232
		(0.226)	(0.346)	(0.225)	(0.230)	(0.185)
Cattle rearing		0.464	1.208***	0.592	0.418	0.114
		(0.403)	(0.456)	(0.361)	(0.405)	(0.311)
Own business		0.548**	1.036***	0.239	0.304	-0.512***
		(0.225)	(0.342)	(0.220)	(0.222)	(0.176)
Daily laborer		0.318	0.663*	-0.0665	-0.212	-0.975***
		(0.220)	(0.340)	(0.215)	(0.214)	(0.168)
Survey States (base: West Bengal)						
Bihar		1.183***	1.074***	1.085***	1.122***	1.753***
		(0.110)	(0.110)	(0.116)	(0.123)	(0.150)
Jharkhand		1.738***	1.527***	1.536***	1.385***	1.918***
		(0.114)	(0.116)	(0.123)	(0.131)	(0.155)
Madhya Pradesh		0.487***	0.232*	0.238*	0.260*	0.679***
		(0.117)	(0.122)	(0.128)	(0.134)	(0.163)
Odisha		-1.169***	-0.897***	-1.079***	-1.045***	-0.0850
		(0.335)	(0.281)	(0.326)	(0.320)	(0.247)

Uttar Pradesh		0.416***	0.161	0.279**	0.278**	0.808***
		(0.110)	(0.111)	(0.118)	(0.122)	(0.151)
Constant		-3.257***	-3.704***	-2.746***	-3.329***	-3.429***
		(0.357)	(0.448)	(0.335)	(0.403)	(0.386)
Observations	16,956	16,956	16,956	16,956	16,956	16,956

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

D. Multinomial Probit Regression: Education categories – Awareness

Dependent variable: mg_edu_mn	(1) Not Aware (base outcome)	(2) Aware & No Formal Education	(3) Aware & Primary Education	(4) Aware & Secondary Education	(5) Aware & Higher Educ. or Diploma	(6) Aware & Graduate or above
VARIABLES	MProbit coeff	MProbit coeff	MProbit coeff	MProbit coeff	MProbit coeff	MProbit coeff
Age		0.00358**	-0.00383**	-0.00585***	-0.0170***	-0.0200***
		(0.00160)	(0.00158)	(0.00174)	(0.00214)	(0.00250)
Gender (base: female) Male		0.173**	0.684***	0.811***	0.871***	0.863***
		(0.0675)	(0.0758)	(0.0900)	(0.109)	(0.116)
Religion (base: Others)						
Hindu		-0.826***	-0.303	-0.628**	-0.135	-0.641
		(0.246)	(0.221)	(0.263)	(0.332)	(0.395)
Muslim		-0.542**	-0.172	-0.935***	-0.423	-0.787*
		(0.254)	(0.229)	(0.277)	(0.347)	(0.407)
Ration Cards Holder (base: No cards)						
APL		0.0598	0.220***	0.183***	0.267***	0.379***
		(0.0773)	(0.0707)	(0.0707)	(0.0865)	(0.0883)
BPL		0.0738	0.0241	-0.249***	-0.0798	-0.143
		(0.0709)	(0.0679)	(0.0720)	(0.0885)	(0.0950)
HH Monthly Income	Base Outcome	-2.32e-05***	-3.04e-07	1.12e-05**	2.34e-05***	3.75e-05***
		(7.70e-06)	(5.90e-06)	(4.47e-06)	(4.82e-06)	(4.92e-06)
Salaried job		0.103	0.164*	0.0993	0.344***	0.602***
		(0.108)	(0.0983)	(0.100)	(0.110)	(0.101)
Cattle rearing		0.145	0.619**	0.386	0.392	-0.0419
		(0.311)	(0.261)	(0.304)	(0.329)	(0.488)
Own business		0.105	0.205***	0.200**	0.171*	-0.130
		(0.0841)	(0.0754)	(0.0783)	(0.0944)	(0.115)
Daily labourer		0.0124	-0.268***	-0.644***	-0.534***	-0.692***
		(0.0559)	(0.0560)	(0.0687)	(0.0763)	(0.0982)
Survey States (base: west Bengal)						
Bihar		1.209***	1.299***	1.145***	1.221***	1.458***
		(0.102)	(0.105)	(0.108)	(0.148)	(0.202)
Jharkhand		1.435***	1.811***	1.520***	1.530***	1.832***
		(0.112)	(0.110)	(0.113)	(0.158)	(0.207)
Madhya Pradesh		0.187	0.382***	0.243**	0.428***	0.824***
		(0.117)	(0.116)	(0.115)	(0.158)	(0.208)
Odisha		-1.079***	-0.739***	-1.199***	-0.735**	-0.305
		(0.277)	(0.235)	(0.328)	(0.347)	(0.339)
Uttar Pradesh		0.282***	0.429***	0.179*	0.505***	0.820***
		(0.104)	(0.105)	(0.108)	(0.148)	(0.199)
Constant		-2.181***	-2.941***	-2.425***	-3.188***	-3.074***
		(0.287)	(0.271)	(0.302)	(0.391)	(0.458)
Observations	16,956	16,956	16,956	16,956	16,956	16,956

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

E. Pooled Probit – Microgrid Adoption

VARIABLES	(1) Probit coeff: Demographics	(2) Probit coeff: +Educ caste & Region	(3) Probit coeff: +Economic & Livelihood	(4) Probit coeff: +HH Structure	(5) Probit coeff: Interaction	(6) Probit coeff: 2015 PCA
Age	-0.00317*	-0.00414**	-0.00322	0.0248*	0.0241*	-0.0260
	(0.00189)	(0.00198)	(0.00224)	(0.0136)	(0.0137)	(0.0195)
Age Square				-0.000310**	-0.000303**	0.000262
				(0.000147)	(0.000147)	(0.000206)
Gender (base: female) Male	0.389***	0.253***	0.261**	0.267**	0.260**	-0.284*
	(0.0835)	(0.0941)	(0.103)	(0.105)	(0.105)	(0.153)
Caste Category (base: SC & ST)						
OBC	0.467***	0.310***	0.325***	0.326***	0.325***	0.444**
	(0.0884)	(0.101)	(0.111)	(0.113)	(0.114)	(0.178)
GEN	0.367***	0.243**	0.280**	0.349***	0.353***	0.492**
	(0.0983)	(0.114)	(0.126)	(0.130)	(0.131)	(0.202)
Religion (base: Others)						
Hindu	2.840***	3.063***	2.765***	2.737***	2.744***	2.872***
	(0.0686)	(0.161)	(0.154)	(0.203)	(0.183)	(0.404)
Muslim	3.160***	3.411***	3.141***	3.119***	3.137***	3.213***
	(0.0864)	(0.168)	(0.168)	(0.212)	(0.192)	(0.421)
Education (base: No formal schooling)						
Primary schooling		0.00301	0.0670	0.0498	0.0525	0.0135
		(0.0802)	(0.0931)	(0.0928)	(0.0930)	(0.144)
Secondary schooling		0.0655	0.204*	0.190*	0.198*	-0.0244
		(0.0907)	(0.107)	(0.109)	(0.109)	(0.167)
Higher Secondary/Diploma		0.0692	0.221*	0.270**	0.271**	-0.0864
		(0.108)	(0.126)	(0.128)	(0.128)	(0.195)
Graduate & above		-0.0354	0.166	0.246	0.242	-0.222
		(0.122)	(0.141)	(0.153)	(0.154)	(0.241)
HH Monthly income			1.32e-05**	1.40e-05**	1.16e-05*	2.57e-05**
			(5.88e-06)	(6.53e-06)	(6.69e-06)	(1.02e-05)
HH indebted			-0.172**	-0.173**	-0.172**	-0.307***
			(0.0701)	(0.0722)	(0.0723)	(0.116)
Asset score (normalized)			-0.470***	-0.201***	-0.277***	-0.0399
			(0.0503)	(0.0629)	(0.0731)	(0.0905)
Income Source (base: Other income)						
Agri on own land			-0.00660	-0.0280	-0.0209	0.301
			(0.119)	(0.121)	(0.121)	(0.224)
Cultivation on leased land			-0.0374	-0.00101	-0.0150	0.364
			(0.185)	(0.190)	(0.189)	(0.337)
Casual Agri labour			0.0571	0.159	0.139	0.445*
			(0.159)	(0.166)	(0.168)	(0.270)
Salaried job			-0.0573	-0.107	-0.102	0.912*
			(0.468)	(0.494)	(0.503)	(0.526)
Cattle rearing			0.201	0.284**	0.294**	0.831***
			(0.138)	(0.142)	(0.142)	(0.244)
Own business			-0.339***	-0.325**	-0.322**	0.133
			(0.126)	(0.126)	(0.126)	(0.236)
HH size				0.0788***	0.0847***	0.0630**
				(0.0298)	(0.0294)	(0.0308)
HH size squared				-0.00190	-0.00212	-0.00133
				(0.00136)	(0.00133)	(0.00115)
HHA owned				-0.163***	-0.167***	-0.143***
				(0.0281)	(0.0281)	(0.0381)
light_satis_pc1						-0.115**
						(0.0560)
wtp_lighting_pc2						0.143***

						(0.0493)
commu_light_pc3						-0.257***
						(0.0784)
anti_theft_pc1						0.0281
						(0.0543)
Bihar		1.796***	1.871***	1.759***	1.775***	1.833***
		(0.195)	(0.207)	(0.215)	(0.218)	(0.236)
Jharkhand		0.921***	0.873***	0.789***	0.794***	0.817***
		(0.231)	(0.247)	(0.257)	(0.259)	(0.309)
Uttar Pradesh		0.908***	1.230***	1.063***	1.069***	0.989***
		(0.203)	(0.218)	(0.227)	(0.229)	(0.245)
Literate	-0.0842					
	(0.0631)					
c.hh_monthly_income#c.asset_score_norm					1.17e-05**	
					(5.31e-06)	
Constant	-5.645***	-6.851***	-6.812***	-6.963***	-6.981***	-5.827***
	(0.128)	(0.297)	(0.313)	(0.474)	(0.464)	(0.711)
Observations	17,635	17,635	13,237	13,180	13,180	4,213

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Acknowledgement

The author gratefully acknowledges research support from the Indian Institute of Technology Madras, Chennai. This study draws on data from the ACCESS (Access to Clean Cooking Energy and Electricity – Survey of States) project, made available by the Council on Energy, Environment and Water (CEEW), New Delhi. The author sincerely thanks CEEW for facilitating data access and for their contributions to advancing empirical research on energy access in India.

No external funding was received for this research. The author declares no financial relationships or conflicts of interest that could have influenced the analysis, results, or conclusions presented in this paper.