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Non-farm entrepreneurship, caste, and energy poverty in rural India

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ABSTRACT

This study examines how non-farm entrepreneurship influences rural household energy poverty and explores caste-based heterogeneities in outcomes in India. The study used different quasi-experimental econometric methods to analyse panel data from the waves 1 and 2 (2015 and 2018) of the Access to Clean Cooking Energy and Electricity Survey of States (ACCESS) in India. The overall results across all estimation methods show that households' engagement in non-fam entrepreneurship significantly contributes to a reduction in their energy poverty levels and the probability of being energy poor. The sizes of the reduction vary across the four castes (General Caste, Scheduled Tribe, Scheduled Caste, and Other Backward Caste). The energy poverty reducing effect of non-farm entrepreneurship is particularly high among members of the Scheduled Tribe. Further mediation analyses reveal that non-farm entrepreneurship potentially affects rural households' energy poverty through their accumulation of financial (savings) and durable assets which possibly enable them to access cleaner energy sources for lighting and cooking. We encourage governments to pay attention to policies that promote non-farm entrepreneurship which has the potential to enhance asset accumulation and reduce rural energy poverty in the process.

1. Introduction

Energy poverty refers to the lack of access to sustainable, safe, and affordable, cheap and environmentally friendly energy products and services needed to advance economic growth and human capital development (Koomson and Danquah, 2021; Reddy et al., 2000). Deprivations in energy access have negative implications on many aspects of people's lives, including education, health, social inclusion, subjective wellbeing, nutrition (Awaworyi Churchill and Smyth, 2021; González-Eguino, 2015). Indoor pollution related to energy poverty kills over 4.3 million people annually, with women and children accounting for 60% of the fatalities (World Health Organization, 2016). In 2019, 2.6 billion and 759 million of the global population did not have access to clean cooking fuels and electricity respectively (IEA, IRENA, UNSD, World Bank, WHO, 2021). Despite being a global menace, energy poverty is more prevalent in developing countries, notably in Asia and Africa (Khanna et al., 2019), where >60% of those who depend on traditional biomass for cooking can be found (Khanna et al., 2019). Beyond regional disparities, energy poverty is more prevalent in rural locations, with rural-urban gap in access to clean cooking fuels and technologies being 42 percentage points (IEA, IRENA, UNSD, World Bank, WHO, 2021).

Among the many potential drivers of energy poverty, recent studies have identified factors such as affordability, accessibility, income, energy inefficiency, climate change and others (see e.g., Boardman, 2013; Khanna et al., 2019; Koomson and Danquah, 2021; Rao and Pachauri, 2017). Emerging strands of the literature have also linked energy poverty to race and ethnicity (Awaworyi Churchill and Smyth, 2020; Ngarava et al., 2022; Paudel, 2021; Wang et al., 2021). To alleviate energy poverty, several policy options have been considered to accelerate households' transition to cleaner and contemporary cooking and lighting fuels—especially rural-located homes due to their lower purchasing power and main reliance on relatively low income (Akter and Bagchi, 2021; Koomson and Danquah, 2021; Tiwari et al., 2022).

Non-farm entrepreneurship (NFE) or employment generating activities outside of farming are also referred to as off-farm enterprises. NFE can involve a variety of income-producing activities, such as income from self-employment in the manufacturing and service sectors (P. Lanjouw and Lanjouw, 1999; Tacoli, 2017). Non-farm entrepreneurship is crucial to the economic development of emerging nations like India, where the bulk of people live in rural areas. For instance, over 900

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people (or around 65% of the country's population) live in rural India (Government of India, Ministry of Finance, 2022). Likewise, NFE sector is widespread in African countries, and accounts for up to 36% of rural income. By engaging the rural population into various non-farm activities, this sector contributes to economic growth by enhancing employment and income generation outside farming activities (Haggblade et al., 2007; Reardon et al., 2000).

Despite the significant role of non-farm entrepreneurship (NFE) in alleviating income and consumption poverty and enhancing several indicators of rural household welfare through its income effect (Bui and Hoang, 2021; Ferreira and Lanjouw, 2001; Hoang et al., 2014; Zereyesus et al., 2017), researchers are yet to empirically explore the NFE-energy poverty nexus. Premised on the evidence above, and the global agenda to promote NFE as a viable policy tool for rural poverty alleviation (J. O. Lanjouw and Lanjouw, 2001; Zereyesus et al., 2017), it is imperative to explore whether the income/consumption poverty reducing effect of NFE extends to energy poverty. This interest is informed by Amin et al. (2020) assertion that income/consumption poverty and energy poverty are conceptually similar, and that income poverty worsens deprivations in energy access. Since interest in the ethnic and racial dimensions of energy poverty is at the burgeoning stage (Awaworyi Churchill and Smyth, 2020; Paudel, 2021), many undiscovered narratives exist in other geographical areas. In India, the country of focus for this study, the persistent inter-caste hierarchy and significant intra-caste inequality have been identified as critical factors in determining poverty and other forms of economic deprivation (Tiwari et al., 2022) but less is known about how caste-based disparities in access to resources influence energy poverty. Also, although financial inclusion (Koomson and Danquah, 2021) and access to off-grid solar power have the potential to decrease rural energy poverty, there are inequalities in financial inclusion and access to energy, especially among Scheduled Castes and Scheduled Tribes (Akter and Bagchi, 2021; Tiwari et al., 2022). Given the caste-based inequalities in access to resources, it is important to explore whether caste-based differences exist in the potential NFE-energy poverty nexus.

This study contributes to the literature by answering the research question: Can NFE be promoted as a policy tool to alleviate energy poverty in rural households? We embark on this line of inquiry by examining the association between NFE and energy poverty in rural India using panel data from waves 1 and 2 of a rural-based survey—Access to Clean Cooking Energy and Electricity Survey of States (ACCESS) in India. Informed by the caste-based inequality in access to resources in India, we engage in subsampled modelling to ascertain the heterogeneities in the effect of NFE on energy poverty across different caste groups. We further explore whether financial and durable asset accumulation serve as potential pathways through which NFE transmits to energy poverty in rural India. To address the widely acknowledged endogeneity problem inherent in the NFE-household welfare nexus, we follow existing studies by employing NFE operational networks as an instrument in a two-stage least squares procedure.

Addressing these questions is timely and relevant since energy transition and energy poverty remain central to the Sustainable Development Goal 7 (SGD 7) which seeks to ensure access to affordable, reliable, sustainable, and modern energy by 2030. These questions are also pertinent to the SDG 11 (sustainable cities and communities), 12 (responsible consumption and production), 13 (climate action) and 15 (life on land) which are in turn linked to the SDG 10 (reduced inequality). The results of this analysis may stimulate further discourse on NFE as a pathway to these SDGs in India and other multi-racial and multi-ethnic developing countries. Our overall finding indicates that engagement in NFE reduces household energy poverty in rural India. Across the different Caste groups, the role of NFE in reducing energy poverty is most prevalent among members of the Scheduled Tribe which is significantly relevant for policy due to the levels of deprivation faced by members of the Scheduled Tribe. We further find that financial and durable asset accumulation serve as potential pathways through which NFE influences energy poverty in rural India.

The remainder of the paper proceeds as follows. Section 2 provides the background and explains the conceptual link between NFE and energy poverty. The data and variables used are described in Section 3 while the empirical procedure is presented in Section 4. Section 5 presents the results while Section 6 concludes.

2. Background and conceptual link

2.1. The state of energy poverty in India—rural predominance and policy

The most common way to examine energy poverty is via an energy ladder, which is frequently used to compare the main sources of household energy for lighting and cooking at various income levels (Sovacool and Drupady, 2016). Energy poverty is influenced by socioeconomic and cultural factors, especially in developing economies (Awaworyi Churchill and Smyth, 2020; Koomson et al., 2022a). The acute energy poverty in India, which affects all social groups but more pronounced among the lower classes, provides an intriguing viewpoint and generally illustrates asymmetrical traits in terms of scale, socioeconomic space, and sociocultural space. Most of the poor rely on traditional energy fuels (such as dung and crop residues) since they cannot afford to spend a larger portion of their income on efficient energy fuels like kerosene and gas. For instance, Gupta et al. (2019) estimated that more than two-thirds of rural households in Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh use the traditional firewood stoves called Chulha.

The majority of India's energy comes from conventional sources including firewood, cow dung cake, crop waste, and other polluting fuels (kerosene) (Sharma and Dash, 2022). Using rural energy poverty in India as an example, it is local in terms of scale but micro level in terms of socioeconomic, sociocultural, and political sphere. India's rural energy consumption landscape is diversified, and rural people's unique cultural spaces of functional existence related to energy are represented in their unique consumption habits. As a result, the demand for an energy mix in rural India is complicated and varied, necessitating a thorough evaluation of the energy supplies that are locally accessible and their aggregation. Consequently, it is crucial to take these aspects into account when measuring the local energy poverty. India is an unequally distributed country in terms of energy consumption, and socioeconomic position (such as caste system) is closely linked to energy poverty (Akter and Bagchi, 2021; Tiwari et al., 2022). Compared to upper class houses (such as General Castes) who are connected to grids, poor households belonging to lower castes (such as scheduled castes and tribes) are more likely to consume off grids (Akter and Bagchi, 2021). Caste-based injustices/inequalities can be associated with the discrepancies in grid access.

India is the third-largest energy user in the world, but traditional energy sources like coal, oil, and solid biomass supply 80% of the country's needs (IEA, IRENA, UNSD, World Bank, WHO, 2021). As a significant source of income, India's energy industry generated tax revenues of USD 92 billion, or around 17% of all government receipts. Petroleum and gas are highly subsidized sources of energy in India to ensure energy access and affordability, particularly, for people below the poverty line. Oil and gas subsidies have increased in recent years. In the year 2020, total subsidies on oil and gas reached USD 7.8 billion (Aggarwal et al., 2022). Most of these subsidies were directed to benefits transfer (in cash form) to ensure affordability for consumers. India's current energy policies aim to substantially reduce its reliance on coal in energy mix by 2040 and stimulating clean energy investment (International Energy Agency, 2021). In recent years, there has been a significant reduction in fossil fuels subsidies to promote clean energy as an alternative source. On the hand, subsidies for renewable energy sources nearly doubled in the year 2022 (Aggarwal et al., 2022). Despite a significant drop in fossil fuel subsidies in India, the coal, oil, and gas sectors received more in subsidies in 2021 than the clean energy sector

(Aggarwal et al., 2022). The prevalence of heavy subsidies for coal and fossil fuels partly aimed to achieve certain policy objectives such as ensuring the affordable access to energy for consumers.

India has implemented several policies and programmes to guarantee its population's access to energy during the past few decades. To give rural and marginalised populations access to clean energy, the Indian government has launched several programmes. To improve the infrastructure for electricity in rural regions, for instance, three rural electrification programmes were combined in 2005 under the Rajiv Gandhi Vidyutiaran Yojana (RGGVY) initiative (Chaurey et al., 2012). Similar to this, the Ujjwala 2.0 scheme was introduced in 2016 to ensure that rural residents had access to energy, but only 30% of the subsidies' benefits was received by the bottom 40% of the population who lived in rural areas (Merrill et al., 2019), forcing rural households to use firewood and other forms of traditional cooking fuels, which leads to indoor pollution and related health problems.

2.2. The caste system—access to resources, poverty, and inequality

Based on social and economic hierarchy, the caste system in India has a nearly three-thousand-year-old history. India is known for its widespread practise of caste segregation, which is broken down into four categories: Scheduled Castes, Scheduled Tribes, Backward Castes, and General Caste (Saxena and Bhattacharya, 2018). Scheduled Caste individuals frequently refer to themselves as "Dalits" or "untouchables". On the other hand, marginalised groups are categorised as Scheduled Tribes or Backward Classes. Other ethnic groups, such as Muslims and Sikhs, are included in the General Caste category.

There are widespread disparities in rural-urban access to energy among different segments of the population in India (Akter and Bagchi, 2021). Access to energy is available to various caste classes through both formal and informal sources. Members of higher Caste hierarchies generally appear to have more access to resources and benefits than less privileged social groups. For instance, in rural areas, the majority of landowners and business people are from upper castes like Brahmins, Kshatriyas, and Banias, while members of lower castes like Lodhs and Sainis work in menial jobs (e.g., carpentry, farm labour). The most marginalised communities in India include Scheduled Caste and Scheduled Tribe, who mostly rely on employing traditional energy sources like dung cake, firewood, and crop wastes (Akter and Bagchi, 2021; Pradhan et al., 2022). This leads to prevalent inequalities in energy access and trapping the marginalised communities into energy poverty. It will be interesting to look at discrepancies and inequalities in energy access in India given its complex caste-based culture. The inequitable distribution of resources and the lack of access to electricity highlight the need for better policy design to provide rural marginalised groups with appropriate access to energy.

2.3. NFE in India and its dynamics

The ever-increasing global population is putting pressure on agrarian economies like India to create non-farm employment opportunities by promoting rural enterprises to ensure sufficient income and livelihoods for the rural communities. On the other hand, the developing economies, particularly, in South Asia like Pakistan, India, Bangladesh, and Sri Lanka have seen a significant decline in farm size over the period. For instance, in India, marginal and small farmers account for 86.2% of all land holdings (Palsaniya et al., 2022) while about 65% of farmers in Pakistan hold <5 acres (Ahmad et al., 2021). According to World Census of Agriculture, the average farm size in India in the year 2010 was just over one acre (Yamano et al., 2021). Diversification in rural income is pre-requisite for rural transformation. The rural non-farm economy can generate a positive impact on rural income and livelihood. Non-farm activities such as agro-processing, transporting, marketing, retailing, and other associated activities (e.g., handicrafts, baking) create self-employment activities to support rural livelihoods and generate additional income sources which can be channelled into accessing reliable energy, but researchers have yet to empirically examine this relationship.

The dynamics of NFE in India can be attributed to many "push" (e.g., population growth, diminishing farm productivity) and "pull" (e.g., lower risks farm activities, higher return on investment) factors (J. O. Lanjouw and Lanjouw, 2001). Low farm productivity and limited off farm activities in semi-arid areas have forced the workers into non-farm sectors such as pottery and construction work (Mehta and Shah, 2003). In addition, limited access to finance and technologies coupled with low capital investment which result in low income and high poverty incidence are leading factors which push farmers into non-farm activities (Chandrasekhar and Mehrotra, 2016). As a result, NFE is emerging due to adaptation of non-farm activities, which seems to help increase income of household due to change in means of livelihood and climate change.

2.4. Conceptual link between NFE and energy poverty

According to estimates, between 35 and 50% of rural income in developing nations comes from non-farm sources. Marginalised and landless individuals are particularly able to supplement their income by working in related non-farm industries (Independent Evaluation Group, 2017). NFE has a positive effect on welfare through job creation, income generation, and asset accumulation (Duong et al., 2021; Lanjouw and Lanjouw, 2001). The expansion of non-farm rural businesses has been shown to have a major impact on rural GDP, employment, family income, food security, dietary diversity, and social welfare (Dzanku, 2019; Hoang et al., 2014; Mishra et al., 2015; Nagler and Naudé, 2017). NFE may contribute directly or indirectly to economic expansion and development.

Rural non-farm activities have been crucial to the economic growth of nations over the past few decades (J. O. Lanjouw and Lanjouw, 2001; Liang, 2006) and continue to contribute to economic development of nations in several ways. They enhance job creation, reduce rural unemployment, and influence several moving factors in rural areas. Some salient features of these activities have been highlighted by Lanjouw and Lanjouw (2001). Market access, communication and information technology, financial resources, pre-set skills, robust infrastructure, and transportation, and diversified rural non-farm enterprises are among the essential success factors (Carletto et al., 2007; Davis, 2006; Gajigo, 2013). For instance, creative non-farm activities can support the agricultural industry, improve neighbourhood communication, and reduce rural poverty by facilitating the exchange of labour and goods. According to Kazungu and Guuroh (2014), a substantial financial component of rural non-farm revenue sources is the transformation of rural crude produces or agro handling, through processing, building, or wrapping. Whereas indirect routes primarily rely on non-farm businesses as a possible source of employment and livelihood, direct channels heavily rely on links between the agricultural sector and export markets (Farooq and Younais, 2018).

2.4.1. Household income

The emphasis on non-farm enterprises has resulted in a more comprehensive understanding of rural development through income diversification for better livelihood and access to better and more dependable resources, such as energy (Khurana and Sangita, 2022). Possibilities exist for non-agricultural jobs and off-farm business ventures to produce NFE income (Davis, 2001; Pattayat et al., 2022). NFE has received widespread recognition for its capacity to raise household income (Nagler and Naudé, 2014; Xiaoping et al., 2007). For instance, according to a study by Farooq and Younais (2018), >50% of Pakistan's rural labour force is employed in non-farm activities to support their livelihood. According to Himanshu et al. (2013), rural non-farm income in India increased by up to 62% and rural employment by up to 31.5% between 2004 and 2005. Non-farm diversification in India has also lowered obstacles to economic mobility and made it possible for rural households to enhance their standard of living (Birthal et al., 2014; Himanshu et al., 2013). Related to this, because cleaner cooking and lighting fuels are more expensive, a similar body of literature indicates that households' switch to them depends heavily on greater purchasing power (Akter and Bagchi, 2021; Koomson and Danquah, 2021; Tiwari et al., 2022). Hence, by hastening their energy transition process, households' greater purchasing power from NFE-related improved incomes can contribute to the reduction in energy poverty.

2.4.2. Financial and durable asset accumulation

Non-farm activities also result in the accumulation of material goods, which provide farmers more power by allowing them to diversify their sources of income and hence improve their spending patterns (Briggeman, 2011). There are two types of asset accumulation: productive assets and non-productive assets. For instance, productive assets include human capital, physical capital (equipment), and financial capital, and non-productive assets include consumables like refrigerators, vehicles, and real estate. Duong et al. (2021) assessed the effects of off-farm employment and firm activities on the accumulation of both productive and non-productive assets. They observed that a rise in non-farm sector employment resulted in a considerable increase in durable assets. A similar positive association between NFE activities and asset accumulation was discovered by Olugbire et al. (2012), demonstrating that activities that generate income off-farm contribute to the accumulation of productive and non-productive durable assets which can provide the financial resources required for households to transition to the use of cleaner cooking and lighting energy sources.

2.4.3. Health and socioeconomic status

Non-farm enterprise activities play an important role in improving quality of life through increased income and consumption patterns such as clean energy consumption. Researchers have investigated the impact of NFE employment and income on energy transition (*P.* Wang et al., 2023). Higher income and employment opportunities may help to get better access to healthcare, schooling, and greater social prestige, and clean energy, which ultimately will have a positive impact on mental health of households (Zimmerman and Katon, 2005). The empirical evidence demonstrates that participation in NFE leads to better consumption options (such as dietary, energy, and health facilities), transmitted through increased employment and income opportunities (Danquah and Iddrisu, 2018). In sum, NFE plays a crucial role in improving the wellbeing of households through various channels such as better increased income, asset accumulation, and healthy diet. Improved health is associated with enhanced productivity and incomes which can reduce energy poverty by increasing rural households' purchasing power towards cleaner energy sources for lighting and cooking.

Based on insights drawn from the extant literature, Fig. 1 depicts the theoretical connections between NFE, asset accumulation and energy poverty. These are empirically tested in Section 5.4.

3. Data and measurement of variables

This study makes use of panel data from both waves 1 and 2 (2015 and 2018) of the Access to Clean Cooking Energy and Electricity Survey of States (ACCESS) in India (Jain et al., 2015). The ACCESS is Indian's largest energy access survey and covers >9000 rural households across 756 villages in 54 districts. The selected districts are spread across six states—Bihar, Jharkhand, Madhya Pradesh, West Bengal, Uttar Pradesh, and Odisha. Implemented by the Council on Energy, Environment and Water (CEEW) and the Columbia University, the ACCESS uses a random sampling approach to select rural households to be part of the study. In respective terms, waves 1 and 2 of the cleaned data included 8563 and 9072 households which sum up to 17,635 observations. Apart from the detailed information on household's access to and use of energy, the survey provides information on demographic characteristics, farm and non-farm economic activities, lighting and cooking satisfaction and many others. Despite the workable sample of 17,635 observations in both waves, our regression analysis included 15,391 observations due to missing observations.

3.1. Non-farm entrepreneurship (NFE)

Consistent with previous studies (Peprah and Koomson, 2015; Zereyesus et al., 2017), we measure NFE status of the household as a binary variable. We assign the value 1 to the household if it owns or operates a non-farm business activity (other than agriculture) and 0 if otherwise.

3.2. Caste membership

Caste membership in this paper is based on the groupings of households grounded on Indian government's caste categories and as applied in the ACCESS data (Jain et al., 2015). The caste categories captured in this paper are General Caste, Other Backward Caste, Scheduled Caste and Scheduled Tribe. Membership to each of these caste groups is measured using a dummy variable (1 = Yes; 0 = No). Considering General Caste, for example, a household is assigned 1 if it is a member of the General Caste and 0 if otherwise. The same approach is used to capture the remaining three caste group memberships.

The religious, social, cultural, and economic position of a person are just a few of the aspects that support the caste system in India (Agte and Bernhardt, 2023; Munshi, 2019). The caste system in India is primarily divided into four groups, as detailed in Section 2.2: Scheduled Castes, Scheduled Tribes, Backward Castes, and General Caste. Most Indians (about 68%) identified themselves as belonging to lower castes, such as Scheduled Castes or Scheduled Tribes (34%) and Backward castes (35%), while 30% were categorised as belonging to the General category, according to a recent survey conducted in India by the Pew Research Centre of 30,000 adults living in 26 states across the country (Sahgal et al., 2021). Only a very small percentage (4%) is thought to be a part of the upper castes.

3.3. Energy poverty

We use the multidimensional energy poverty index (MEPI), which incorporates both objective and subjective indicators of energy poverty. The MEPI is frequently utilised in developing country research because of its conceptualization and how it reflects economic conditions and the

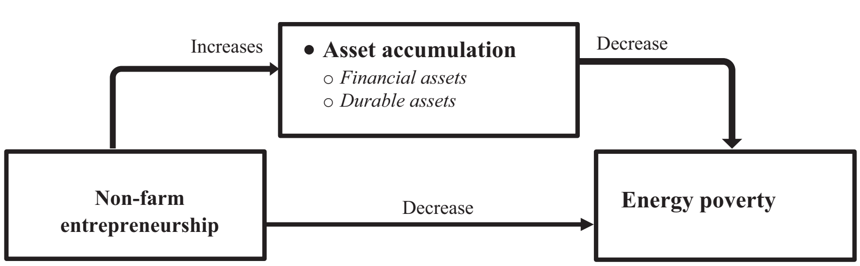

Fig. 1. Conceptual relationship between NFE, asset accumulation and energy poverty (Source: Authors' Construct).

adoption rate of renewable energy in developing nations (Awaworyi Churchill and Smyth, 2020; Koomson and Danquah, 2021; Nussbaumer et al., 2013).

Following previous studies, we generate the MEPI using six indicators spread across five dimensions with their respective weights assigned to them (Adusah-Poku and Takeuchi, 2019; Koomson and Danquah, 2021; Nussbaumer et al., 2013). These five dimensions are cooking, lighting, connected household appliances, entertainment/education, and communication (see Table A1 for indicators and weights). The MEPI was developed based on the multidimensional poverty measure by Alkire and Foster (2011) which was also influenced by Amartya Sen's ideas of deprivations.

Although each of MEPI's five dimensions can be allocated an equal weight of 0.2, the cooking and lighting dimensions are assigned bigger weights than the other three due to their relative importance in the conceptualization of energy poverty (Adusah-Poku and Takeuchi, 2019; Nussbaumer et al., 2013). Between cooking and lighting, cooking is given more weight than lighting since it continues to be a major energy demand for households in resource-poor countries. Specifically, the cooking dimension is assigned a weight of 0.41, while the lighting dimension is assigned a weight of 0.20. The remaining three dimensions are all given a weight of 0.13 each. The indicators in Table A1 are all coded to indicate deprivations and are used to compute the energy deprivation scores for which a unit increase reflects an increase in energy poverty. Each household's multidimensional energy poverty/deprivation score, which is a weighted sum of deprivations ranging from 0 to 1, is computed using eq. (1).

$$d_i = w_1 I_1 + w_2 I_2 + \cdots + w_n I_n \tag{1}$$

where d_i is the household energy deprivation or MEPI score, $I_i = 1$ if a household is deprived in indicator i and $I_i = 0$ if otherwise. w_i is the weight attached to indicator i with $\sum_{i=1}^{n} w_i = 1$. The MEPI score ranges from 0 to 1, with a unit increase reflecting an increase in energy poverty. Consistent with previous studies (Koomson and Danquah, 2021), we use the dual cut-off of 0.5 to obtain a binary measure of energy poverty which means that a household assumes an energy poor status if its MEPI score is greater or equal to 0.5. Cut-offs of 0.33 and 0.2 are also used to identify energy poor households to enrich the robustness checks. We employ the MEPI score as our main measure of energy poverty in the analysis while the binary versions of MEPI (MEPI status) are used for robustness check.

3.4. Financial and durable assets

To empirically assess potential channels of influence we assess the roles of financial and durable assets accumulation.

We measure financial asset accumulation using savings balances or the total monetary value that was saved by the household head in a year. Due to heterogeneities associated with household savings ability, we use the log version of the savings balance to smooth the values in order to avoid producing biased estimates.

Apart from financial assets, we measure durable asset accumulation using the approach proposed by Ferreira and Lanjouw (2001) which is applied in creating the wealth index in the Demographic and Health Surveys (DHS) (Rustein and Johnson, 2004; Rutstein, 2015). In doing this, we employed principal component analysis to create an asset accumulation index (i.e., wealth index) using various forms of durable assets owned by each household. These include fan, cooler, washing machine, inverter, and others. To avoid reverse causality in our mediation analyses, we excluded appliances that are conceptualised as indicators of energy poverty such as radio, television etc.

4. Estimation procedure

To estimate the association between NFE, Caste membership and energy poverty, we employ ordinary least squares (OLS) while controlling for key control variables because our outcome variable is continuous. Our baseline model of interest is specified as shown in eq. 2.

$$EPov_{it} = \alpha + \beta \widehat{NFE}_{it} + \gamma Caste_{it} + \lambda X_{it} + \varphi_s + \delta_t + \varepsilon_{it} \tag{2}$$

where $EPov_{it}$ is the energy poverty score of household i at time t. Time represents the period of each wave of the ACCESS data; NFE_{it} is a binary which captures the non-farm entrepreneurship status of household i at time t; *Caste* represents the caste membership status of household. X is a set of control variables that have been identified in earlier studies as drivers of energy poverty. These variables include gender, age, household size, bank account ownership, educational status, and religious affiliation (Awaworyi Churchill and Smyth, 2020; Koomson and Danquah, 2021; Prakash and Munyanyi, 2021). φ_s and δ_t represent wave and state fixed effects while ε is a random error term.

4.1. Potential endogeneity

Existing studies that have explored the link between NFE and socioeconomic outcomes have identified endogeneity to be associated with non-farm employment (see e.g., Bui and Hoang, 2021; Zereyesus et al., 2017). In previous studies, the sources of endogeneity have been explained as emanating from omitted variable bias, measurement error or reverse causality between non-farm employment and the outcome variable of interest (Bui and Hoang, 2021; Ferreira and Lanjouw, 2001; Zereyesus et al., 2017). In this study, we suspect the endogeneity to emanate from omitted variable bias or reverse causality and not from measurement error since NFE is a binary variable and households are unlikely to make errors in recalling whether they own or operate a non-farm business.

With regard to reserve causality, NFE can increase income and savings of a household (Peprah and Koomson, 2015; Zereyesus et al., 2017) which will in turn enhance the household's ability to spend on modern energy sources for lighting and cooking, thereby reducing energy poverty (Koomson and Danquah, 2021). On the other hand, energy poverty can also have a negative effect on NFE since the income and savings needed for non-farm business venturing can be drained by energy poverty. This is because energy poverty has a negative effect on health and can cause households to divert financial resources to cater for healthcare (Awaworyi Churchill and Smyth, 2021), thereby leaving little to be invested in non-farm business. This is also because most households rely on personal savings as their source of capital for NFE venturing (Peprah and Koomson, 2015). Regarding omitted variables, they include contextual factors, which we are unable to account for in our model but are likely to impact both NFE and energy poverty. Previous studies have resolved endogeneity using instrumental variable estimation (IV) or two-stage least squares (2SLS) which employ external instruments. Although many instruments have been employed in the literature to resolve endogeneity associated with non-farm employment, the most widely used is non-farm networks due to its high level of validity (see e.g., Bui and Hoang, 2021; Hoang et al., 2014; Oseni and Winters, 2009).

Consistent with the widely used instrument (see e.g., Bui and Hoang, 2021; Hoang et al., 2014; Oseni and Winters, 2009), we obtain a measure of non-farm networks which is the average number of neighbours who operate NFEs. On the basis of validity, research has shown that the stronger a household's non-farm network, the higher its chances of being engaged in a non-farm activity. Put differently, households are more likely to discover and diversify their income portfolios into non-farm activities if many of their neighbours are engaged in it (Kajisa, 2007). Non-farm networks, on the other hand, are unlikely to have a direct impact on household energy poverty unless they do so indirectly via a family's discovery and eventual participation in NFE.

In addition to utilizing the standard IV method, other quasi-experimental approaches such as Lewbel (2012) 2SLS and propensity score matching (PSM) methods are employed as robustness checks. These approaches are described in depth in Subsection 5.3, where they are used.

4.2. Summary statistics

The descriptive statistics which indicate dynamics in NFE and energy poverty between Waves 1 and 2 of the survey are presented in Table A2. As reported, Waves 1 and 2 included 7558 and 7833 rural households, respectively. For the purpose of consistency, the proportion of households engaged in NFE was 17% while those not involved in it was 83% in both waves of the survey. Nonetheless, rural households experiencing multidimensional energy poverty reduced from 87.1% (2015) to 63.4% (2018) as shown in Table A2. In respective terms, the rates of energy poverty among rural households not engaged in NFE were 88.7% and 65.5% in 2015 and 2018. Conversely, the rates of energy poverty among rural households involved in NFE were 79.4 and 52.8% in 2015 and 2018, respectively. Although, we can deduce that NFE is associated with lower rates of energy poverty, this correlation analysis does not account for other control variables that can affect energy poverty. Since stronger inferences can be drawn after accounting for such controls, we apply multiple regression analysis which accommodates such controls and discuss the results in Section 5.

The sample distribution of castes ladder for rural India used in our analysis is described in Table A3. Scheduled Caste and Scheduled Tribes combined composed of 28.5% of the sample data whereas the backward Castes, on the other hand, makes 48% of the sample. The descriptive and summary statistics of all other variables included in the analysis are presented in Table A3. The pairwise correlation between the variables employed in the study are displayed in Table A4.

To examine the geographic differences in farming and non-farm activities, we create percentages of rural households involved in farming vis-à-vis NFEs across different states. The sampled households' participation in farming and NFE activities at the state level is shown in Table A5 in the Appendix. The highest rates of farming activity are found in Madhya Pradesh, Jharkhand, and Uttar Pradesh, where 50% of the sampled population is involved in farming. Conversely, the engagement in NFE activities ranges from 10.8 to 21.8%. Beyond the purview of this study, several factors, including household income diversification, agricultural infrastructure, and proximity to urban regions, may be contributing to differences in farming versus non-farm participation.

5. Results

This section which presents and discusses the econometric results is divided into four subsections. An explanation of the baseline results opens the section, which is then followed by endogeneity-corrected estimates, results of the analysis across different caste categories, and a robustness check.

5.1. Baseline results

The estimates of the association between NFE and energy poverty based on the pooled and waves 1 and 2 data are respectively reported in Columns 1 to 3 of Table 1. To establish that the subsampled estimates are statistically different from each other, we apply the Chow test of differences to the estimates reported in Columns 2 and 3 (Chow, 1960; Kofinti et al., 2023; Koomson et al., 2022b; Nunoo et al., 2018). At the 1% alpha level, the Chow test is statistically significant, suggesting that the NFE coefficients are statistically different in waves 1 and 2. We observe that that holding other factors constant, households engaged in NFE experience 0.053 to 0.068 reduction in energy poverty than households that do not engage in NFE. As suggested in an earlier study on income disparities of farm and non-farm activities in Africa, Asia, and Latin America (Reardon et al., 2000), these significant estimates can be largely explained by the distribution of households' capacity to make

Table 1
NFE, Caste, and energy poverty (Baseline results).

	(1)	(2)	(3)
MEPI score	All	Wave1	Wave2
Non-farm entrepreneurship	−0.061***	−0.053***	−0.068***
	(0.005)	(0.006)	(0.007)
Female	−0.030***	−0.043***	−0.024***
	(0.004)	(0.006)	(0.006)
Age	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)
Household size	−0.003***	−0.004***	−0.001
	(0.000)	(0.001)	(0.001)
Bank account	−0.055***	−0.054***	−0.042**
	(0.005)	(0.006)	(0.017)
Educational level (Base = No education)			
Up to 5th Standard	−0.057***	−0.052***	−0.063***
	(0.004)	(0.005)	(0.006)
Up to 10th Standard	−0.106***	−0.093***	−0.120***
	(0.005)	(0.006)	(0.008)
12th Standard/Diploma/graduate	−0.152***	−0.149***	−0.156***
	(0.005)	(0.007)	(0.008)
Caste (Base = General)			
Other Backward Caste	0.042***	0.047***	0.037***
	(0.005)	(0.006)	(0.007)
Scheduled Caste	0.064***	0.065***	0.062***
	(0.005)	(0.007)	(0.008)
Scheduled Tribe	0.100***	0.094***	0.107***
	(0.006)	(0.008)	(0.009)
Hindu	0.005	0.017**	−0.004
	(0.005)	(0.007)	(0.008)
Wave 2	−0.126***		
	(0.004)		
State fixed effects (Base = Bihar)			
Jharkhand	0.035***	0.003	0.071***
	(0.006)	(0.008)	(0.010)
Madhya Pradesh	−0.012**	−0.034***	0.012
	(0.005)	(0.007)	(0.008)
Odisha	−0.000	−0.005	0.013
	(0.007)	(0.010)	(0.010)
Uttar Pradesh	−0.067***	−0.089***	−0.041***
	(0.005)	(0.006)	(0.007)
West Bengal	−0.132***	−0.150***	−0.112***
	(0.008)	(0.013)	(0.009)
Observations	15,391	7558	7833
R-squared	0.249	0.203	0.160
Chow test: LR chi2 (16): (2) = (3)			254.30***

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$

investments in non-farm assets and the relative scarcity of low capital entry barrier to NFE. The findings of this study support the assertion of Reardon et al. (2000) that public investments and policy must prioritise an increase in the access of poor households to assets that enable them to overcome non-farm employment entry barriers.

In addition to this key variable, it appears from the results that energy poverty is approximately 0.02 to 0.04 lower in a female-headed households. This result is intuitive because females are mostly responsible for cooking and performing other household activities. However, the result has more implications for male and female's income and expenditure pattern. The literature suggests that on average, females spend greater share of their relatively lower income on household consumption including expenditure on energy (Orkoh, 2018). It can be inferred from this result that female-headed households perform better than male-headed households in terms of energy poverty, but this is dependent on the type of energy (efficient or inefficient) and the distribution of the level of income of the two households.

Like the gender of the household head, age of the household head and size of the household are both negatively associated with energy poverty. While age may be interpreted from the perspective of its positive association with experience and earnings, the negative effect of increased household sizes on energy poverty may be explained by households' arrangements including the frequency of cooking and size of income contributions by other household members towards expenditure on cooking fuel. A larger household may help to reduce energy poverty if the majority of the individuals are wage earners and contribute to the cost of cooking fuel, however, it may be challenging to infer the energy's efficiency from these findings.

Confirming the implications of household income for energy poverty is the ownership of bank account which could be an indirect measure of households' income/wealth status. In Table 1, ownership of bank account is associated with a statistically significant reduction in household energy poverty. Although it can be argued that households' ownership of bank account does not necessarily mean they have enough income in the account to enable access to fuel for cooking, it puts them in a better position to access funding and other banking services necessary for accessing fuel for cooking. This is consistent with previous studies which have shown that financial inclusion reduces energy poverty (Koomson and Danquah, 2021).

Consistent with the conceptual link (Zimmerman and Katon, 2005), higher levels of education of household heads are associated with significant reduction in energy poverty. Energy poverty score reduces by no $<$0.05 and 0.10 in a household where the head has completed at most Standard 5 or Standard 10 compared to a household where the head has no education. Education, ownership of bank account and entrepreneurship status provide some information about the living standard of households and their resilience or susceptibility to energy poverty. However, in a developing country like India where population growth rate outstrips the rate of job creation, higher levels of education may not always guarantee gainful employment, especially among the youth due to factors including skills shortages and skill mismatch (Almeida and Faria, 2014). The literature suggests that on average, economic returns to education are positive and high (Colclough et al., 2010).

Aside education and other household configuration, caste plays an important role at every stage of people's economic life, including their experience in the labour market and access to public resources in India (Munshi, 2019; Thorat and Neuman, 2012). In this study, we argue that due to such a strong link between peoples' caste and their economic status, caste must equally be a key determinant of households' access to efficient and sustainable sources of cooking fuel. As can be seen in Table 1, energy poverty is higher within a households belong to Other Backward Caste (0.04), Scheduled Caste (0.06) or Scheduled Tribe (0.10) compared to the General Caste. These results suggest that progress towards global effort to reduce energy poverty, bridge the energy gap and improve the use of efficient energy is highly interwoven with caste and ethnicity which are in turn influenced by social norms and cultural practices.

In the pooled analysis, the wave fixed effect which captures the year of the survey shows that overtime, energy poverty has reduced. Compared to the wave 1, energy poverty score has reduced by approximately 0.13 during the wave 2. This shows that overtime, the Indian government's efforts to expand rural electrification through the Rajiv Gandhi Vidyutiaran Yojana (RGGVY) initiative (Chaurey et al., 2012) and the Ujjwala 2.0 scheme (Merrill et al., 2019) have contributed to the reduction in energy poverty. Differences in development across state have implications for households' access to cooking fuel. To account for these differences, we include the state fixed effects in the models. Compared to Bihar, energy poverty is higher in Jharkhand but lower in Madhya Pradesh, Odisha, Uttar Pradesh, and West Bengal.

5.2. Endogeneity-corrected results

The baseline analysis does not consider the potential endogeneity between NFE and energy poverty. However, the results in Table 2 account for this endogeneity with non-farm network (neighbours who own NFE) as the instrument for NFE. Consistent with the proposition in Section 4.1, the first stage results (see Table 2) of the instrumental variable estimation approach show that at the 1% significance level, an increase in a household head's network of non-farm entrepreneurs is associated with an increase in his/her likelihood of engaging in NFE. From Columns 1 to 3, we see that households engaged in NFE experience reductions in energy poverty ranging from 0.251 to 0.342 compared to their non-NFE counterparts. The magnitudes of the coefficients further reveal that the endogeneity problem caused the OLS estimates of NFE be downwardly biased.

Table 2
NFE, Caste, and energy poverty (IV results).

	(1)	(2)	(3)
MEPI score	All	Wave 1	Wave 2
Non-farm entrepreneurship	−0.298***	−0.251***	−0.342***
	(0.028)	(0.036)	(0.043)
Caste (Base = General)			
Other Backward Caste	0.052***	0.058***	0.044***
	(0.005)	(0.007)	(0.007)
Scheduled Caste	0.061***	0.063***	0.058***
	(0.006)	(0.008)	(0.009)
Scheduled Tribe	0.090***	0.083***	0.098***
	(0.007)	(0.009)	(0.010)
Control variables	Yes	Yes	Yes
Wave fixed effect	Yes	No	No
State fixed effect	Yes	Yes	Yes
First stage			
Neighbours who own non-farm ent.	0.308***	0.338***	0.284***
	(0.015)	(0.023)	(0.021)
F-stochastic	394.18	214.20	186.26
Observations	15,386	7558	7828
Chow test: LR chi2 (16): (2) = (3)			258.40***

Robust standard errors in parentheses.
*** $p < 0.01$.
ent.: enterprise.

5.3. Outcomes across different castes

This section presents the results of the inter-caste effect of NFE on energy poverty, and we can observe heterogenous outcomes among the four castes in Table 3. With the Chow test being significant, we can infer that the effect of NFE on energy poverty is statistically different across the four caste groups. The sizes of the effects are high among the Scheduled Tribe (0.50) and General Caste (0.36) but low among the other Backward Caste (0.19). The magnitudes of the estimates are consistent with those presented in Table 2 where affiliation with the scheduled tribe has the highest effects on energy poverty. It is important to note that higher estimate of effect of NFE among a particular caste

Table 3
NFE and energy poverty across Castes.

	(1)	(2)	(3)	(4)
MEPI score	General Caste	Other Backward Caste	Scheduled Caste	Scheduled Tribe
Non-farm entrepreneurship	−0.355***	−0.255***	−0.186**	−0.504***
	(0.053)	(0.037)	(0.081)	(0.159)
Control variables	Yes	Yes	Yes	Yes
Wave fixed effect	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes
First stage				
Neighbours who own non-farm ent.	0.361***	0.333***	0.218***	0.205***
	(0.032)	(0.024)	(0.033)	(0.046)
F-statistic	131.47	199.82	44.04	20.29
Observations	3568	7431	2844	1543
Chow test: LR chi2 (16): (1) = (2) = (3) = (4)				3299.56***

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$.
ent.: enterprise.

does not necessarily mean that energy poverty is higher among that caste. Rather, it implies that engagement in NFE contributes to a higher reduction in energy poverty within the particular caste. Since members of the Scheduled Tribe face greater socioeconomic disadvantage, with majority of them consuming off grids, we can infer that engagement in NFE which provides them with financial resources is able make the biggest difference in reducing energy poverty among its members. The implication of this outcome is that NFE can be employed as a pro-poor policy to markedly reduce energy poverty among people belonging to lower castes.

5.4. Robustness checks

As a robustness check on the IV regression estimates, the Lewbel two-stage Least Squares (2SLS) regression analysis was conducted. The results of this analysis (see Table 4) are presented in two panels. Panel A presents the estimates which are based on internally generated instrument while Panel B presents the results of a combination of internally and externally generated instruments (non-farm network). The internal instrument is generated from the heteroskedasticity in the data. Having been used in different fields of study such as health, agriculture, and education, the Lewbel 2SLS addresses potential instances of weak instruments (Belfield and Kelly, 2012; Kofinti et al., 2022; Koomson and Danquah, 2021). The results in both panels consistently show that engagement in NFE is significantly associated with a reduction in energy poverty, but the sizes of the effects are relatively smaller than the standard IV estimates, although bigger than the OLS results. Also, the results in panel A which are based on the internal instrument are lower than those in panel B where the combined instrument is statistically significant. This confirms the reliability and robustness of the external instrument (non-farm networks) in addressing the observed endogeneity.

As this study asserts causality between NFE and energy poverty using observational data rather than perfectly designed true experiment, the propensity score matching (PSM) estimation technique is used to validate the results of the IV regression (see Table 5). The PSM has remained one of the methods used to promote causality in studies that do use random assignment (Ansong et al., 2023; Kofinti et al., 2022). The results of the different matching techniques (presented in Table 5) are consistent with those of the IV regression. On average, energy poverty is approximately 0.05 to 0.07 lower within households engaged in NFE compared to households not engaged in NFE. These sizes of the effect of the PSM analysis confirm our proposition that households' engagement in non-farm activities enable them to earn sufficient income to escape energy poverty. However, socio-cultural practices and economic advantages or disadvantages associated with households' affiliation with a particular caste influence the extent of effect of NFE.

Table 4
NFE and energy poverty (Lewbel 2SLS).

	(1)	(2)	(3)
MEPI score	All	Wave 1	Wave 2
Panel A: Internal-only instruments			
Non-farm entrepreneurship	−0.103***	−0.082***	−0.095***
	(0.017)	(0.019)	(0.025)
Control variables	Yes	Yes	Yes
Wave fixed effect	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes
First stage			
F-Statistic	14.11	10.13	12.190
J *p*-value	0.132	0.129	0.250
Observations	15,391	7558	7833
Panel B: Internal & external instruments			
Non-farm entrepreneurship	−0.157***	−0.122***	−0.159***
	(0.015)	(0.017)	(0.022)
Control variables	Yes	Yes	Yes
Wave fixed effect	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes
First stage			
Neighbours who own non-farm ent.	0.272***	0.301***	0.246***
	(0.016)	(0.023)	(0.021)
F- Statistic	41.18	27.45	22.98
Observations	15,386	7558	7828

Robust standard errors in parentheses.
*** $p < 0.01$.
ent.: enterprise

Table 5
PSM results with different matching methods.

MEPI score	(1)	(2)	(3)
	All	Wave 1	Wave 2
	ATT	ATT	ATT
1 – Nearest Neighbour (one-to-one)	−0.057***	−0.050***	−0.065***
	(0.010)	(0.011)	(0.013)
5 – Nearest Neighbour (one-to-five)	−0.059***	−0.050***	−0.065***
	(0.007)	(0.007)	(0.009)
Radius	−0.072***	−0.071***	−0.075***
	(0.006)	(0.005)	(0.007)
Kernel	−0.062***	−0.054***	−0.068***
	(0.004)	(0.006)	(0.006)
Local linear regression	−0.066***	−0.060***	−0.072***
	(0.005)	(0.006)	(0.007)
Observations	15,391	7558	7833

Bootstrapped standard errors in parentheses.
*** $p < 0.01$.

In addition to the above analyses which used a MEPI score based on a conventional weighting scheme, we embark on robustness check by applying alternative weighting schemes and reported the estimates in Table 6. In Column 1, our MEPI score uses an equal weighting scheme while for that used in Column 2, we assigned a bigger weight of 0.4 to the electricity indicator. In Columns 3, 4 and 5, we use binary measure of energy poverty which are derived using cut-offs of 0.5, 0.33 and 0.2 to identify households that are energy poor due to their MEPI score being higher than the thresholds. Across all analyses we consistently observe that households' engagement in NFE is significantly associated with increases in energy poverty ranging from 0.054 to 0.099. The robustness and sensitivity tests all imply that the effect of NFE in decreasing energy poverty is consistently established regardless of the quasi-experimental method used or the weighting and cut-off scheme used in measuring energy poverty.

5.5. Potential channel analysis

This section presents the results of a further analyses of the potential medium(s) through which NFE affects households' energy poverty. We explore the potential mediating roles of households' financial (savings) and durable assets (wealth index) as the potential channels. The analysis of these channels of effect is motivated by earlier studies in other developing countries which suggest that income from non-farm activities contributes to the expansions in savings and accumulation of durable assets (Briggeman, 2011; Duong et al., 2021; Olugbire et al., 2012).

We carry out our mediation analysis using the instrumental variable approach by Dippel et al. (2020). Applied widely in recent studies (Funke et al., 2023; Goodell et al., 2022; Handayani et al., 2023; Rezki, 2023), this method can resolve the potential endogeneity of the variable of interest and its mediator to produce the direct, indirect, and total effects without requiring an extra instrument for the mediator (Dippel et al., 2020). As a first step, we show in Table 7 that households' engagement in NFE is associated with improvements in their financial and durable assets accumulation (Briggeman, 2011; Duong et al., 2021; Olugbire et al., 2012).

Having established that NFE significantly improves households'

Table 6
NFE and energy poverty (Alternative cut-offs and weights for energy poverty index).

	(1)	(2)	(3)	(4)	(5)
	Alternative weights for MPI score		*MPI status with different cut-offs*		
Variables	Using equal weights	More weights on electricity (0.4)	0.5 cut-off	0.33 cut-off	0.2 cut-off
Non-farm entrepreneurship	−0.057***	−0.054***	−0.087***	−0.099***	−0.087***
	(0.004)	(0.004)	(0.008)	(0.009)	(0.008)
Control variables	Yes	Yes	Yes	Yes	Yes
Wave fixed effect	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	15,391	15,391	15,391	15,391	15,391

Robust standard errors in parentheses.
*** $p < 0.01$.

Table 7
Effect of NFE on household savings and durable asset accumulation.

	(1)	(2)
	Financial Asset	Durable asset
MEPI score	log(household savings)	Durable asset/wealth index
Non-farm entrepreneurship	1.047***	0.624***
	(0.089)	(0.039)
Control variables	Yes	Yes
Wave fixed effect	Yes	Yes
State fixed effect	Yes	Yes
Observations	14,775	15,392

Robust standard errors in parentheses.
*** $p < 0.01$.

accumulation of financial and durable assets, we proceed to the second step by including the mediators separately in the energy poverty model to produce the direct, indirect, and total effects as presented in Table 8. In Columns 1 and 2, we observe that increases in households' financial and durable asset accumulation are associated with 0.023 and 0.072 decrease in energy poverty respectively. We also see that the total effects of NFE on energy poverty are 0.085 and 0.072. The mediating/indirect effect of financial savings is 20.024 while that of durable assets accumulation is 0.045 which are both statistically significant at the 1% alpha level. These imply that financial and durable asset accumulation significantly mediate the relationship between NFE and energy poverty. Put differently, households' engagement in NFE increases financial and durable asset accumulation which increase households' purchasing power and helps them to transition to the use of cleaner sources of energy for cooking and lighting.

Table 8
Linear IV Mediation analysis with direct, indirect, and total effects.

	(1)	(2)
	Mediator: Financial Asset	Mediator: Durable asset
	log(household savings)	Durable asset/wealth index
Non-farm entrepreneurship [DE]	−0.061***	−0.027***
	(0.005)	(0.004)
log(household savings) [ME: savings]	−0.023***	
	(0.001)	
Asset/wealth index [ME: durable asset]		−0.072***
		(0.001)
Decomposed mediation outcomes		
Total effect [TE]	−0.085***	−0.072***
	(0.003)	(0.002)
Direct effect [DE]	−0.061***	−0.027***
	(0.005)	(0.004)
Indirect effect [IE = EM*ME]	−0.024***	−0.045***
	(0.003)	(0.002)
Observations	14,770	15,387

Standard errors in parentheses.
*** $p < 0.01$.
ME: Mediator effect.
EM: Effect on Mediator.

6. Conclusion

Access to clean and reliable energy remains a global policy issue, however, it is more of a challenge in developing and emerging economies where households' use of energy is closely linked to the type and nature of economic activities in which they are engaged, and the sociocultural norms associated with their ethnic and class status. There has been extensive research on class, energy poverty, and their links with other socioeconomic aspect of society, but little is known about how the nature/type of economic activity, class, and NFE interact to influence households' levels of energy poverty in developing countries. This study contributes to fill this gap in the literature from an Indian perspective. It specifically assesses how differences in socioeconomic privileges associated with India's caste structure interact with NFE to influence households' energy poverty.

This study used different estimation techniques (IV, Lewbel 2SLS and PSM) to analyse data from the waves 1 and 2 (2015 and 2018) of the Access to Clean Cooking Energy and Electricity Survey of States (ACCESS) in India. The results show that regardless of the estimation technique, households' engagement in non-farm entrepreneurship contribute to a statistically significant reduction in their energy poverty levels and their likelihood of being energy poor. The sizes of the energy poverty reduction vary across the four castes (General Caste, Scheduled Tribe, Scheduled Caste, and Other Backward Caste). The effects are particularly strong among members the Scheduled Tribe but weak among the other backward caste. Further analysis of the potential channels of effect suggests that NFE can reduce households' energy poverty through their accumulation of financial (savings) and durable (wealth) assets which enable them to access efficient and sustainable energy. This study demonstrates that NFE significantly reduces energy poverty in India across all social strata, though to varied degrees.

These findings underscore the need for government policy on energy poverty to pay close attention to non-farm entrepreneurs' unequal access to resources across India's various castes. With careful consideration for caste-related inequalities, the government is urged to focus on non-farm entrepreneurial programmes that have the potential to improve financial and durable asset accumulation and lower rural energy poverty. Moreover, provision of NFE opportunities to rural households and promoting skill development activities may help get them out of energy poverty. Although this study is conducted in India the findings and recommendations are applicable to other multi-ethnic and multi-racial developing countries and regions of the world where both energy poverty and NFE activities are prevalent and largely shaped by socio-cultural norms that determine one's socioeconomic status. Policies aimed at leveraging NFE as a tool to addressing energy poverty in these countries must give due cognisance to the influence of racial and ethnic diversity.

CRediT authorship contribution statement

Isaac Koomson: Conceptualization, Methodology, Data curation, Formal analysis, Resources, Writing – original draft, Writing – review & editing. **Emmanuel Orkoh:** Conceptualization, Methodology, Resources, Validation, Writing – original draft, Writing – review & editing. **Shabbir Ahmad:** Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that have no financial or non-financial interests to declare for this paper.

Appendix A. Appendices

Table A1
Dimensions, indicators, and weights for multidimensional energy poverty.

Dimension	Indicator (weight)	Variables	Deprivation cut-off (energy poor if….)
Cooking	Modern cooking fuel *(0.205)*	Type of cooking fuel	Any fuel use besides electricity, LPG, kerosene, natural gas, or biogas.
	Indoor pollution *(0.205)*	Food cooked on stove or open fire (no hood/chimney), indoor, if using any fuel beside electricity, LPG, natural gas, or biogas	True
Lighting	Electricity access *(0.20)*	Has access to electricity	False
Services provided by means of household appliances	Household appliance ownership *(0.13)*	Has a fridge	False
Entertainment/education	Entertainment/education appliance ownership *(0.13)*	Has a radio OR television	False
Communication	Telecommunication means *(0.13)*	Has a phone land line OR mobile phone	False

Source: Adopted from: (Nussbaumer et al., 2013).

Table A2
Within-group frequencies for non-farm entrepreneurship and energy poverty for waves 1 and 2.

Non-farm entrepreneurship	Energy Poverty		
	No (%)	Yes (%)	Total (%)
Panel A: Wave 1 sample			
No	706 (11.3)	5554 (88.7)	6260 (100)
Yes	267 (20.6)	1031 (79.4)	1298 (100)
Total	973 (12.9)	6585 (87.1)	7558 (100)
Panel B: Wave 2 sample			
No	2248 (34.4)	4282 (65.6)	6530 (100)
Yes	615 (47.2)	688 (52.8)	1303 (100)
Total	2863 (36.6)	4970 (63.4)	7833 (100)

Source: Authors' estimate from ACCESS data, 2015 & 2018.

Table A3
Summary statistics.

Variable	Description	Mean	Std. Dev.
MEPI score	Multidimensional energy poverty/deprivation score ranging from 0 to 1	0.483	0.232
MEPI status	Dummy variable equals 1 if household's multidimensional energy deprivation score exceeds 0.0.5	0.751	0.433
Non-farm entrepreneurship	Dummy variable equals 1 if household owns or operates a business activity	0.169	0.375
Female	Dummy variable equals 1 if household head is female	0.208	0.406
Age	Age of household head	42.918	14.649
Household size	Continuous variable for household size	6.577	3.432
Bank account	Dummy variable equals 1 if household head owns a bank account	0.919	0.273
Up to 5th Standard	Dummy variable equals 1 if respondent's highest education level is up to 5th Standard	0.306	0.461
Up to 10th Standard	Dummy variable equals 1 if respondent's highest education level is up to 10th Standard	0.178	0.383
12th Standard/Diploma/graduate	Dummy variable equals 1 if respondent's highest education level is up to 12th Standard/Diploma/graduate	0.175	0.380
General caste	Dummy variable equals 1 if household is in the General Caste category	0.232	0.422
Other backward caste	Dummy variable equals 1 if household is in the Other Backward Caste category	0.483	0.500
Scheduled caste	Dummy variable equals 1 if household is in the Scheduled Caste category	0.185	0.388
Scheduled tribe	Dummy variable equals 1 if household is in the Scheduled Tribe category	0.100	0.300
Hindu	Dummy variable equals 1 if respondent's religion is Hindu	0.883	0.321
Neighbours owning non-farm ent.	Average number of neighbours who own NFE	0.166	0.217
Log(savings)	Log of total household savings per annum	2.497	4.091
Durable asset/wealth index	Durable asset accumulation index generated using PCA on household durable assets owned	0.007	1.824

MEPI: multidimensional energy poverty index PCA: principal component analysis.
ent.: enterprise

Table A4
Correlation matrix for variables used in the analysis.

	Energy poverty	NFE	Female	Age	Household size	Bank account	Up to 5th Std	Up to 10th Std	Up to 10th Std	Other Backward Caste	Scheduled Caste	Scheduled Tribe	Hindu
Energy poverty	1												
NFE	−0.12	1											
	(0.00)												
Female	−0.06	−0.02	1										
	(0.00)	(0.00)											
Age	−0.01	−0.02	−0.11	1									
	(0.43)	(0.02)	(0.00)										
Household size	−0.05	0.05	−0.10	0.00	1								
	(0.00)	(0.00)	(0.00)	(0.92)									
Bank account	−0.20	0.04	0.02	0.03	0.05	1							
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)								
Up to 5th Std	0.02	0.02	−0.05	0.01	−0.03	0.02	1						
	(0.01)	(0.00)	(0.00)	(0.11)	(0.00)	(0.03)							
Up to 10th Std	−0.09	0.03	−0.08	−0.06	0.03	0.04	−0.31	1					
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)						
12th Std/Dip/grad	−0.20	0.04	−0.09	−0.15	0.07	0.08	−0.30	−0.20	1				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
Other Backward Caste	0.01	0.07	−0.01	−0.01	0.08	0.00	0.01	−0.01	0.00	1			
	(0.07)	(0.00)	(0.26)	(0.19)	(0.00)	(0.63)	(0.25)	(0.11)	(0.66)				
Scheduled Caste	0.05	−0.04	0.01	−0.02	−0.04	0.00	0.00	−0.04	−0.05	−0.46	1		
	(0.00)	(0.00)	(0.14)	(0.01)	(0.00)	(0.99)	(0.74)	(0.00)	(0.00)	(0.00)			
Scheduled Tribe	0.14	−0.05	−0.01	−0.04	−0.09	−0.06	0.00	−0.04	−0.09	−0.32	−0.16	1	
	(0.00)	(0.00)	(0.27)	(0.00)	(0.00)	(0.00)	(0.90)	(0.00)	(0.00)	(0.00)	(0.00)		
Hindu	0.01	−0.03	−0.05	0.01	−0.04	0.05	0.00	0.06	0.06	−0.08	0.17	0.08	1
	(0.24)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.82)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

NFE: Non-farm entrepreneurship Up to 5th Std: Up to 5th Standard 12th Std/Dip/grad: Up to 10th Standard.
12th Std/Dip/grad: 12th Standard/Diploma/graduate.
Source: Authors' estimate from ACCESS data, 2015 & 2018.

Table A5
Farm and non-farm activities across states.

State	Farming Activity			Non-farm Activity		
	No (%)	Yes (%)	Total (%)	No (%)	Yes (%)	Total (%)
Bihar	1791 (59.25)	1232 (40.75)	3023 (100)	2529 (83.66)	494 (16.34)	3023 (100)
Jharkhand	853 (50.77)	827 (49.23)	1680 (100)	1387 (82.56)	293 (17.44)	1680 (100)
Madhya Pradesh	1506 (44.82)	1854 (55.18)	3360 (100)	2855 (84.97)	505 (15.03)	3360 (100)
Odisha	937 (61.97)	575 (38.03)	1512 (100)	1182 (78.17)	330 (21.83)	1512 (100)
Uttar Pradesh	3067 (50.72)	2980 (49.28)	6047 (100)	5049 (83.5)	998 (16.5)	6047 (100)
West Bengal	1510 (75.01)	503 (24.99)	2013 (100)	899 (89.19)	109 (10.81)	1008 (100)
Total	9664 (54.8)	7971 (45.2)	17,635 (100)	13,901 (83.59)	2729 (16.41)	16,630 (100)

Source: Authors' estimate from ACCESS data, 2015 & 2018.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.107118.

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