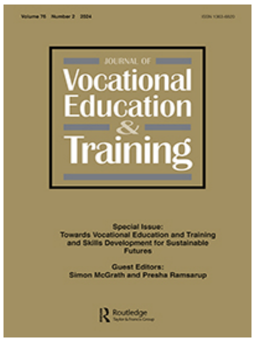

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ABSTRACT

We use new survey data from 1,203 households in rural Eastern India to estimate cross-sectional models of overall energy use and embedded emissions. Findings indicate that the primary driver of household energy use is household size and affluence. This is unsurprising and consistent with findings from the engineering literature on energy demand. However, there is also a substantial and significant moderating influence of skills on energy use. For emissions, we observe a bifurcated relationship in line with educational attainment. For those that have completed secondary education or more, skills are negatively associated with energy use and emissions, whereas for those with lesser qualifications more skills are associated with more energy use and emissions. The results are consistent with the environmental Kuznets curve, which implies that a critical level of affluence is required before environmental impacts start lessening. The results also echo a sociological critique of human capital theory – that individual abilities are not productive in and of themselves, but rather in relation to socially determined opportunity structures. Our findings show that this could also hold for greenhouse gas emissions.

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1 Introduction

As documented by a sequence of reports by the United Nations Intergovernmental Panel on Climate Change, there is scientific consensus that increasing concentration of Carbon Dioxide, Methane, and other Green House Gases (GHGs) that results from human activities is resulting in rising average temperatures of the Earth's climate.[1] This in turn risks ecological and societal degradation (Magnan et al. 2021) and is potentially an existential threat to humanity. To reduce the risk of catastrophic climate change, the intergovernmental Paris Accord agreed by 196 signatories in 2015, aims to keep the global average temperature rise this century as close as possible to 1.5 degrees Celsius above pre-industrial levels (UNFCCC– United Nations Framework Convention on Climate Change 2015). In order to achieve this, the UNFCCC argues GHG emissions must peak before 2025 at the latest and decline 43% by 2030.[2] Materially, GHG emissions are a simple phenomenon, with the IPCC estimating that these can mostly (86%) be attributed to the use of fossil fuels (Masson-Delmotte et al. 2021, 80). However, as exemplified by the carbon footprint concept, this use of fossil fuels is embedded in complex supply-chains satisfying demand from end users (see for instance Hermannsson and McIntyre 2014). Reducing GHG emissions therefore requires diverse actions throughout the global economy and society. For instance, Foley et al (2020) identify 76 specific solutions including changes to energy production, material use and efficiency, as well as consumer behaviours such as shifting to more vegetable-based diets.

This paper examines the role of skills in household energy use and resulting emissions. We build on a substantial engineering literature estimating empirically the influence of household attributes on energy use and emissions (see Chen et al (2022) for an overview). Building on theoretical and empirical arguments that skills can affect both environmental attitudes and behaviours (see Section 2), we extend this approach by including in our model terms for skills and education and test whether these factors moderate household energy use and emissions. Focussing on households, in rural villages in the state of Odisha in Eastern India.

Contributing to the economy-ecology domains of the political-economy-ecology triad of Lotz-Sisitka et al (2023), we pursue three objectives: 1) to analyse the association between skills and household energy use; 2) to analyse the association between skills and embedded emissions from household energy use; and 3) to appraise the potential for 'upskilling' to facilitate reduction in emissions from household energy use. Data are obtained from a household survey of energy use, attitudes and skills developed by a multidisciplinary consortium of researcher from engineering and social sciences based at HEIs and NGOs in the UK and India. The purpose of the survey was to gather information on rural households in low-income regions that are heavily dependent on agriculture for their livelihood. The focus on such contexts was driven by the observation that households there had most to gain from overcoming intermittencies in access to energy and also potential for implementing local biomass solutions, given the availability of agricultural bio-waste (Gupta, Puri, and Ramakumar 2021).

Understanding the drivers of energy use and emissions in low-income settings is crucial for reducing the GHG impact of improving material well-being in such settings. India, is a useful context to examine, being the host to many low-income households which are likely to experience relatively rapid income growth in coming years in line with India's projected economic growth (Corbridge 2018; Datt, Ravallion, and Murgai 2016). Other things being equal, income growth is likely to increase the GHG emissions of these households, especially given the reliance on coal fire power stations for the Indian national grid (Roy and Schaffartzik 2021), unless they are able to access greener sources of energy.

The paper is structured as follows: The next section provides a brief summary of preceding work and the third section introduces the survey. The fourth section presents findings from descriptive analyses and estimates for cross-sectional models of energy use and emissions by households, estimated using multiple regression. In the fifth section, we briefly discuss potential for education to influence GHG emissions based on our findings, before concluding.

2 Prior research

An immediate challenge to the ambition of the Paris agreement to reduce global GHG emissions from 2025 is the urgent need to improve material living standards of a rapidly expanding global population.[3] As Grunewald et al (2017) summarise, raising the lowest incomes and minimising climate change are concurrent global challenges. An ideal scenario would be for lower- and middle-income countries to be able to increase the economic output available to its citizens, whilst reducing or, ideally, eliminating altogether, the GHGs embedded in the production of outputs, thereby achieving what's been termed 'Green growth' (see Bowen and Hepburn 2014 for a discussion). From an optimist's vantage point, the prospect of decoupling economic output and GHG emissions is arguably more plausible now than it is ever been in the past, with the cost of renewable energy technologies dropping rapidly as global production is scaled up (Stern 2022). Conversely, the historical record suggests that whilst economic growth has lifted hundreds of millions of individuals out of poverty in recent decades, not least in China (Page and Pande 2018), it has also coincided with increased GHG emissions (Masson-Delmotte et al. 2021).,

The Environmental Kuznets Curve hypothesises a development pattern, where, starting from a low base, economies pollute more as they become more prosperous, until a critical point is reached, where output and environmental harm are decoupled, with increasing prosperity now associated with reduced environmental impacts (Dasgupta et al. 2002; Dinda 2004; Grossman and Krueger 1995). The term is adapted with reference to the hypothesised inverse U-shape relationship of economic development and inequality in the 20th century (Kuznets 1955). Empirical evidence on the relationship between GHG emissions and income level is consistent with the prediction that emissions intensities don't start falling until a critical threshold is reached (Grunewald et al. 2017; Wan et al. 2022).

Could education and skills play a role in decoupling economic output and environmental impacts? McMahon (McMahon 2009, Ch. 9) sets out a neoclassical framework of the economy to analyse the channels through which education may impact on the environment. The model specifies individuals as utility maximisers that value environmental benefits and for which education increases productivity via the human capital stock (Becker 1994), which is a homogenous input in production (i.e. no differentiation between types of skills). In this framework, a key environmental benefit of education is increasing the input of human capital in production, which can substitute for raw materials. Education also impacts on the environment in indirect ways, through increased awareness that can influence regulation and through impacts of education on reducing population growth, which reduces the need to expand output for any desired output per capita target. This education-population-environment channel is discussed by UNESCO (2020, Ch. 20), who argue education investment could be among the most cost-effective measures to reduce GHG emissions.

The notion that education leads to more pro-environmental behaviours is articulated in a simple conceptual model by Kreft et al (2021) who argue that skills play a double role of enabling individuals to better understand environmental challenges and help individuals adopt more pro-environmental behaviours. Based on a small sample of farmers in Switzerland, they argue that the psychological concepts of self-efficacy and locus of control, which they label as non-cognitive skills, are positively associated with a substantially higher adoption of climate change mitigation measures.

Overall, empirical findings on the relationship between education, awareness, attitudes, and behaviours towards the environment paint a complex picture. Liu, Teng and Han (2020) analyse just under 2,500 responses to the 2010 Chinese General Social Survey and find that environmental knowledge is strongly associated with awareness of environmental problems. However, they caution that this does not automatically lead to pro-environmental behaviours as this is mediated by environmental attitudes. Paço, and Lavrador (2017) caution based on a survey of 800 Portuguese university students that a higher level of environmental knowledge does not necessarily lead to more positive attitudes and behaviours towards energy saving. Pothitou, Hanna, and Chalvatzis (2016) argue based on a small sample of household ($n = 249$) in Peterborough, England, that there is a positive relationship between knowledge, environmental predisposition and energy efficiency activities (such adoption of low energy lightbulbs). Empirically, it is difficult attributing behaviours to skills or education, given confounding effects where education and skills measures are typically strongly correlated with income and socioeconomic background. Powdthavee (2020) addresses these challenges by using compulsory schooling changes in England as a natural experiment and finds that whilst more schooling facilitated better understanding of climate changes, a causal link could not be established from education to pro-environmental behaviours.

As the IPCC (Masson-Delmotte et al. 2021, 80) has pointed out, global GHG emissions can mostly (86%) be attributed to the use of fossil fuels. To the extent that this is embedded within the overall structure of the economy, the opportunity for individuals or households to influence this are at best indirect through political influence or purchase choices. The most direct link between households and GHG emissions is through a household's own energy use, although it should be noted from the outset that this is also constrained by structural features, such as the composition of generation feeding into the electrical grid. In the case of India, electricity supply relies predominantly on coal-fired power stations (Roy and Schaffartzik 2021) and therefore electricity from the grid is highly emissions intensive. A reminder that context matters for determining what behaviours are pro-environmental.

Shen et al (2022) point out that for rural households in China, domestic energy use per householder increased by 50% in the 20 years from 1992 to 2012, with higher income households typically using cleaner sources of energy. Studying the same Rural Residential Energy Survey (1992–2012), Zhu et al. (2019) point out that whilst overall rural households in China are transitioning to cleaner energy sources progress is highly uneven between regions, indicating the influence of specific local factors. Tesfamichael et al (2020) argue based on an energy cultures framework and fieldwork in rural Kenya, that cost and income are not the only determinants of energy use and that communal attitudes also play a role. Twumasi et al (2020) find from a survey of rural Ghanaian households that level of education and access to non-farm employment are positively associated with the use of clean energy, whilst age and household size are negatively associated. Ravindra et al (2019) show based on nationally represented survey that for India, the use of clean fuels for cooking is associated with rising incomes. Based on a case study in the Punjab region, they argue that socio-cultural, economic, and behavioural factors influenced household fuel choice and therefore there is potential to speed up the transition to clean fuels for rural household energy consumption with targeted support.

3 Data and methods

A household survey was conducted to collect information from a sample of 13 villages in 6 identified districts in the state of Odisha: Jajpur (Kuanar pur and Bindhan), Dhenkanal (Kaisiadihi and Balaram pur), Angul (Sarangapur and

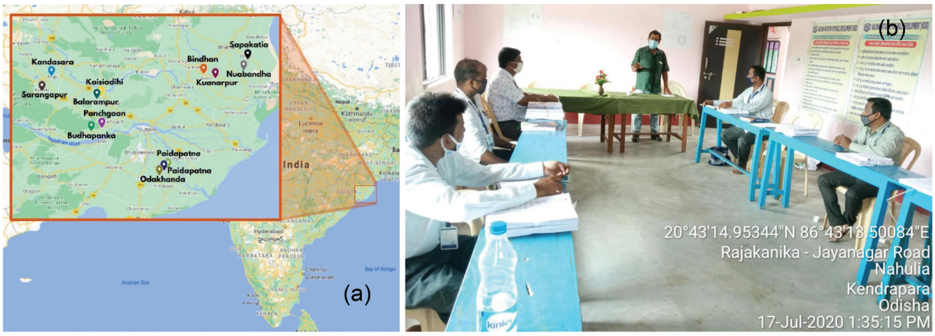

Figure 1. a) Location of the 13 surveyed villages. (b) Gram Utthan survey staff training.

Kandasara), Bhadrak (Sapakatia and Nuabandha), Cuttack (Budhapanka and Panchgaon), and Khordha (Paidapatna Balipatana, Paidapatna Banamalipur, and Odakhanda). In total, the responses of 1,203 households were collected. Figure 1, panel (a) shows the location of the surveyed villages.

The overarching aim of the survey was to assess the feasibility of expanding the use of bioenergy to supply electricity, cooking fuel and soil additives to rural households. The survey gathered household-level information on household composition, total income, assets, dwelling, energy, expenditures on energy and household waste production. Then based on the survey respondent, the survey gathered information about attitudes to household energy use, interest in adopting bioenergy solutions, employment status, highest qualification attained, language use and skills across four domains: numeracy, literacy, computer use and soft skills (see more detailed discussion below).

Field work was carried out in July 2020 by the NGO Gram Utthan, which was a partner in the consortium. The survey was administered using paper-based questionnaires. Gram Utthan trained field workers (Figure 1 (b)). Ethical approval was sought by the University of Glasgow, College of Science and Engineering Ethics Committee. Approval was granted in January 2020 (approval reference 300,190,093). All participants provided informed consent based on a plain language statement and consent forms that were approved by the ethics committee.

3.1 Surveying for skills and derivation of skills index

The questionnaire module for skills was an adapted from the OECD Survey of Adult Skills and the World Bank's STEP (Skills Towards Employability and Productivity) programme, which developed survey instruments tailored to collect data on skills in low- and middle-income country contexts. The skills module was based on 34 individual questionnaire items. Preceding a list of activities for each domain listed in Table 1, respondents were asked 'Do you ever in your work or home life undertake any of the following activities?' This is an example

Table 1. Questionnaire items on skills.

Numeracy	Literacy	Computer use	Soft skills
Do you ever in your work or home life undertake any of the following activities?			
Calculate prices, costs, or budgets? (1)	Read directions or instructions? (1)	Better understand issues related to your work? (1)	Cooperating or collaborating with others including co-workers? (1)
Use or calculate fractions, decimals, or percentages? (2)	Read books or articles in newspapers, magazines, or newsletters? (2)	Conduct transactions on the internet, e.g. buying or selling products or services, or banking? (2)	Sharing work-related information with others including co-workers? (2)
Use a calculator - either hand-held or computer based? (3)	Read articles in professional journals or scholarly publications? (3)	Use spreadsheet software, for example Excel? (3)	Instructing, training or teaching people, individually or in groups? (3)
Prepare charts, graphs or tables? (4)	Read manuals or reference materials? (4)	Use a word processor, for example Word? (4)	Making speeches or giving presentations in front of five or more people? (4)
Use simple algebra or formulas? (5)	Read diagrams, maps or schematics? (5)	Use a programming language to program or write computer code? (5)	Selling a product or selling a service? (5)
Use more advanced maths or statistics such as calculus, complex algebra, trigonometry, or use of regression techniques? (6)	Read bills, invoices, bank statements or other financial statements? (6)	Participate in real-time discussions on the internet, for example online conferences, social media, or chat groups? (6)	Advising people? (6)
	Write letters, memos or e-mails? (7)		Planning your own activities? (7)
	Write articles for newspapers, magazines or newsletters? (8)		Planning the activities of others? (8)
	Write reports? (9)		Organising your own time? (9)
	Fill in forms? (10)		Persuading or influencing people? (10)
			Negotiating with people either inside or outside your firm or organisation? (11)
			Working with children? (12)
			Working with animals? (13)

of an indirect method for assessing skills (for a discussion see Palczyńska and Rynko 2021). Asking respondent an explicit question on skills is likely to gauge self-efficacy that may not always reflect actual aptitude. Instead, the questionnaire asks respondents about experience of a range of tasks. The assumption being that if a person has done a task, they possess the skills implicit in the task. Positive responses are coded as 1 whilst negative responses are coded as 0.

We create a simple arithmetic index of all skills by adding up the positive responses, which can be used to identify more and less skilled respondents in the sample. For intuitive interpretation, this is rescaled to range from 0 to 100. There are several methods for constructing an index of skills use, we opt for this because of the transparency of the approach and because we do not have any prior information on the relative importance of the different skills domain. However, implicit in the simple addition is a skewed weighting towards skills domains with more questionnaire items (in this case literacy and soft skills).

We analyse the survey data by estimating through Ordinary Least Squares (OLS) regression, a cross-sectional model for energy expenditures and emissions. The analysis is cross-sectional in the sense that the survey only collects data from households at one point in time and observations of diverse households are used to calculate model coefficients using the OLS algorithm, which estimates a 'line of best fit' through the data points. The model builds on an engineering tradition of estimating household energy use functions. Chen et al (2022) survey this literature and conclude that energy use can be explained through four domains: 1) Dwelling factors, 2) Technical factors (appliance ownership); 3) Socio-demographic and geographic factors; and 4) Behavioural factors. The variables used in our analysis are listed in Table 2 below. It goes without saying that the more detailed information available for each factor the more precise the model is likely to be. Our survey captures important detail about the first three factors. However, behavioural factors are by their nature hard to observe via a survey and we do not have direct information on behaviour. Such unobserved features will influence parameter estimates for independent variables if correlated with these and/or will be captured in the residual of the estimate.

The dependent variables are log-transformed, that is to say we calculate the natural logarithm of the underlying variable and use this in the regression. This a commonly used functional form for modelling skewed distributions, which enables the linear OLS approach to model non-linear phenomena. Therefore, a unit change in a coefficient should be interpreted as approximately a % change in the dependent variable. Moreover, we log transformed the skills use index and therefore a unit % change in skills suggests a % change in the dependent variable.

Data on embedded GHG emissions for energy use were calculated separately for each energy use category identified in the survey. Respondents were asked about how much they spent on each of fine energy use categories per year: 1) LPG, 2) Electricity, 3) Kerosene, 4) Biofuels (Wood/Straw/Dunk) and 5) Charcoal. Publicly available information from a range of sources was used to obtain coefficients for a) the quantity of energy source obtained per Indian Rupiah and b) the embedded GHS emissions per unit.

Table 2. Variables used in analyses.

Variable	Description	N	Mean/ %	Std. Dev.	Min	Max
Total energy expenditure	Annual household expenditure on energy in Indian Rupiah based on respondents recall.	1,148	3,104	1,964	9	36,000
Log energy expenditure	Natural logarithm of annual energy expenditure.	1,148	7.9	0.5	2.2	10.5
Emissions	Carbon footprint of energy use. Kgs CO^2.	1,148	123,152	82,863	14,396	434,108
Log emissions	Natural logarithm of CO^2 carbon footprint.	1,148	11.5	0.8	9.6	13.0
Postcode	Postcode of village where survey was administered	1,148	756,203	2,403	752,102	759,145
Household size	Number of children and adults living in household.	1,148	5.4	2.1	1.0	10.0
Type of dwelling (binary variables)	No response	1,148	3%			
	Separate house	1,148	27%			
	Semi-detached house	1,148	27%			
	Flat/apartment	1,148	1%			
	Compound	1,148	3%			
	Huts/buildings	1,148	30%			
	Makeshift, improvised or temporary dwelling	1,148	0%			
	Other	1,148	9%			
Income categories (binary variables)	No response	1,141	7%			
	0–20,000 INR	1,141	2%			
	20,000–30,000 INR	1,141	9%			
	30,000–40,000 INR	1,141	49%			
	>40,000 INR	1,141	34%			
Bank account	Respondent has a bank account. Binary variable coded 1 for yes.	1,148	61%			
Skills index	Aggregate index of all skills. Normalised between 0 (least skilled) and 100 (most skilled)	1,148	34	23	0	100
Log skills	Natural logarithm of skills index	1,081	3.4	0.7	1.2	4.6
Highest qualification completed (binary variables)	No response	1,148	6%			
	Below primary	1,148	36%			
	Primary	1,148	22%			
	Secondary	1,148	33%			
	Tertiary	1,148	4%			

4 Analyses of survey findings

Data analysis proceeds in two stages. First, descriptive statistics are calculated to get an overall sense of the data and stylised patterns. Second, multivariate regression models are used to assess the relative influence of different factors.

4.1 Descriptive statistics

Table 3 below calculates the mean and standard deviation for energy expenditures, CO2 emissions and household size, grouped by the highest level of education attained by the respondent. This reveals that emissions rise with education level while expenditures do not seem to follow a similar pattern. Therefore, it is plausible that more education is associated with affluence, which in turn is associated with expenditures, which in turn drive emissions.

Table 3. Energy expenditures, emissions, and household size by education level.

Education	Summary statistic	Energy expenditures, log	CO^2 emissions, log	Household size
No response	mean	8.67	11.88	4.75
	sd	0.61	0.71	3.41
Below primary	mean	8.47	11.36	5.31
	sd	0.62	0.79	2.08
Primary	mean	8.57	11.49	5.47
	sd	0.43	0.79	2.09
Secondary	mean	8.28	11.43	5.16
	sd	0.70	0.76	2.08
Tertiary	mean	8.59	11.67	5.26
	sd	0.58	0.76	2.07
Total	mean	8.45	11.45	5.25
	sd	0.62	0.78	2.22

Table 4. Energy expenditures, emissions, household size and education level by skill quintile.

Skill quintile	Summary statistic	Energy expenditures, log	CO^2 emissions, log	Household size	Education level
1	mean	8.53	11.59	5.51	1.65
(lowest)	sd	0.50	0.79	2.24	1.05
2	mean	8.48	11.57	5.47	1.84
	sd	0.48	0.70	2.01	0.96
3	mean	8.61	11.35	5.57	1.88
	sd	0.41	0.80	2.18	0.89
4	mean	8.70	11.29	6.01	2.25
	sd	0.39	0.83	2.14	0.93
5	mean	8.14	11.44	4.40	2.21
(highest)	sd	0.90	0.71	1.56	1.13
Total	mean	8.47	11.47	5.38	1.94
	sd	0.60	0.78	2.11	1.03

Conversely, it is possible that education has some moderating influence on emissions through emissions intensities, even if the overall trajectory is upwards. This requires more in-depth examination.

Table 4 examines averages by skill quintiles (1 least skilled, 5 most skilled), which reveals a mixed picture. On the one hand, for energy expenditures, an inverted U-shape, (as per the Kuznets curve) where expenditures rise and then fall again. Conversely, for emissions, the least skilled (quintile 1) and most skilled (quintile 5) emit the most also combining the lowest household size among the categories reported.

4.2 Multiple regressions

To identify the drivers of energy expenditures at a household level, we estimate a series of progressively more elaborate cross-sectional regression models in Table 5 below. The first model only has one variable, household size. This reveals that for each additional household member, energy expenditures increase by approximately 8%. Model 2 also contains coefficients for dwelling- and income categories. With respondents in flats/apartments being treated as a reference

Table 5. Regression models for total energy expenditures (natural logarithm).

Variables		(1)	(2)	(3)	(4)	(5)
Household size		0.0762***	0.0811***	0.0748***	0.0728***	0.0644***
	No response		0.0676	0.0821	0.0868	0.0939
Type of dwelling	Separate house		−0.165***	−0.0621	−0.0559	−0.0128
	Flat/apartment		ref.	ref.	ref.	ref.
	Semi-detached house		0.267*	0.271*	0.231	0.242
	Compound		0.212**	0.198**	0.196**	0.215**
	Huts/buildings		0.245***	0.265***	0.248***	0.231***
	Makeshift dwelling		0.281	0.296*	0.318*	0.290**
	Other		−0.157***	−0.141***	−0.160***	−0.143***
	No response		0.0455	0.0754	0.0764	0.0954
Income category	<30,000 INR		0.101*	0.0751	0.0769	0.0620
	30–40,000 INR		ref.	ref.	ref.	ref.
	>40,000 INR		0.184***	0.211***	0.211***	0.237***
Bank account			0.0515	0.0100	0.00578	−0.0436
Log skills				−0.122***	−0.112***	−0.00462
	No response				0.0257	0.330
Education	Below primary				ref.	ref.
	Primary				0.0789**	−0.214
	Secondary				−0.0630	1.465***
	Upp. Sec. & Tertiary				0.149*	0.440
	No response					−0.0876
Education × log skills	Below primary					ref.
	Primary					0.0905
	Secondary					−0.445***
	Upp. Sec. & Tertiary					−0.0940
Constant		8.027***	7.871***	8.326***	8.309***	8.034***
Observations		1,019	1,018	954	954	954
R-squared		0.122	0.247	0.234	0.245	0.308
Postcode		Ö	Ö	Ö	Ö	Ö
Adj. r-squared		0.121	0.238	0.223	0.231	0.291

***p<0.01, **p<0.05, *p<0.1

category, the results show that those living in separate houses spend approximately 16.5% less on energy and those living in semi-detached houses, compounds or huts/buildings spend between approximately 21% and 27% more on energy. For income, respondents earning 30–40,000 INR form the reference category and those that earn less than that and more than 40,000 INR spend approximately 10% and 18% more on energy, respectively. Model 2 represents a typical engineering model for household energy expenditures, containing key parameters on household composition, dwelling and income (see e.g. Chen et al. 2022). From Model 3 onwards, we augment this model with information on education and skills. Model 3 adds a term for the logarithm of the aggregate skills index. This reveals that for each unit increase in skills, energy expenditures drop by approximately 12%. It should be noted that the standard deviation of the log index is 0.7 so that for every standard deviation increase in skills, energy expenditures drop by approximately 8%. This is a substantial effect, roughly equivalent to reducing household size by one member. In Model 4, we add terms for formal qualifications. The reference category is having attained less than primary education. Findings are mixed with those having attained primary or upper-secondary/tertiary qualifications spending approximately 8% and 15% more on energy, respectively. However, those that have attained secondary qualifications spend 6% less on energy, other things being equal. Finally, in Model 5 we examine the interaction between education and skills in driving household expenditures on energy. This reveals a much more nuanced view in that the impact of skills varies considerably by education level. The overall effect for skills (−0.00462) is no longer statistically significantly different from zero and the qualification-specific terms, are only significant for secondary (−0.445).

This is an interesting result, but how should it be interpreted? A weakness of the survey data is that income categories do not capture much variation with 83% of respondents in two categories. It is therefore plausible that qualifications partially capture the effects of income levels. If that is the case, these findings are entirely consistent with an environmental Kuznets curve view, where affluence must pass a certain threshold before skills start having a moderating influence on expenditures. It should be noted that we only have a few observations in the upper-secondary/tertiary category (n = 54) and therefore any estimate for this group will be affected by larger confidence intervals and reduced statistical significance. A further weakness of the survey is that we do not have direct evidence on the nature of household livelihoods. However, all models

Table 6. Regression models for GHG emissions (natural logarithm).

Variables		(1)	(2)	(3)	(4)	(5)
Household size		0.0619***	0.0744***	0.0685***	0.0686***	0.0629***
Type of dwelling	No response		0.209*	0.174	0.189	0.191
	Separate house		0.482***	0.547***	0.540***	0.571***
	Flat/apartment		0.836***	0.855***	0.827***	0.842***
	Semi-detached house		ref.	ref.	ref.	ref.
	Compound		0.429***	0.454***	0.458***	0.480***
	Huts/buildings		0.372***	0.420***	0.434***	0.426***
	Makeshift dwelling		0.701*	0.705*	0.746*	0.732*
	Other		0.0516	0.0601	0.0632	0.0728
	No response		−0.419***	−0.483***	−0.484***	−0.466***
	<30,000 INR		0.00231	0.00104	−0.0139	−0.0181
	30–40,000 INR		ref.	ref.	ref.	ref.
	>40,000 INR		−0.00601	−0.0169	−0.0213	−0.00626
Bank account			0.0760	0.0153	0.0140	0.00416
Log skills				−0.0596	−0.0647*	0.0263
Education	No response				0.206**	0.390
	Below primary				ref.	ref.
	Primary				0.0886	0.206
	Secondary				0.0720	1.061***
	Tertiary				0.301***	1.167***
Education × log skills	No response					−0.0488
	Below primary					ref.
	Primary					−0.0365
	Secondary					−0.284***
	Upp. Sec. & Tertiary					−0.253**
Constant		11.09***	10.73***	11.01***	10.96***	10.69***
Observations		1,167	1,166	1,096	1,096	1,096
R-squared		0.078	0.168	0.177	0.186	0.197
Postcode		Ö	Ö	Ö	Ö	Ö
Adj. r-squared		0.0765	0.158	0.167	0.172	0.181

***p<0.01, **p<0.05, *p<0.1

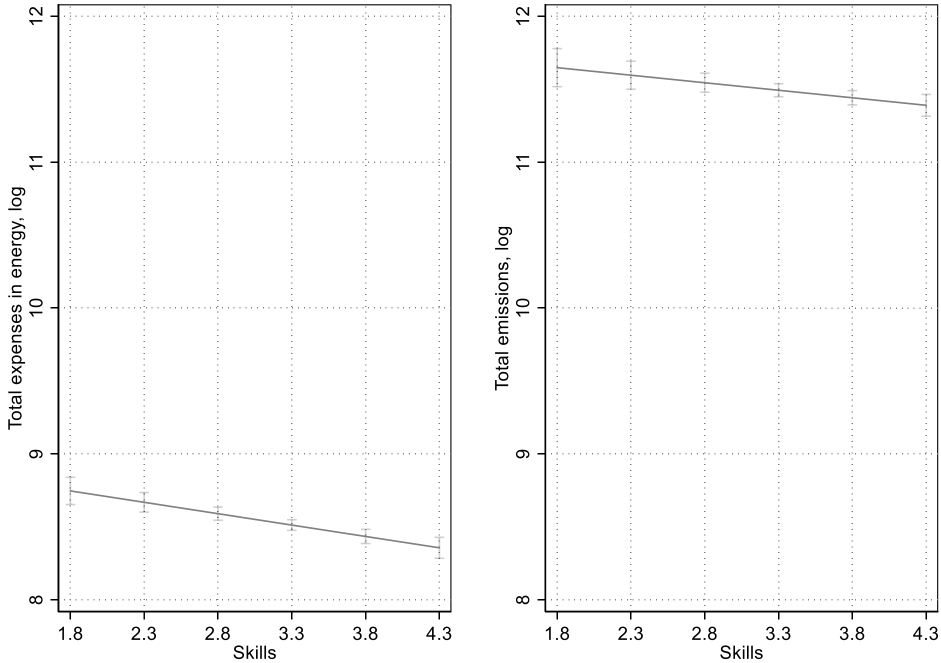

Figure 2. Marginal effects for expenditures (left) and emissions (right) by skills.

include terms for household location, which will capture variation in energy access between different areas.

In Table 6 below, we repeat the cross-sectional modelling exercise, this time using the natural logarithm of GHG emissions as the dependent variable. Qualitatively, the results are similar as for expenditures in that emissions are increasing with household size and dwelling type. However, we do not observe statistically significant effects for income category and having a bank account (proxy for engagement with formal economic sector). Overall, skills have a weakly statistically significant effect on emissions (−6%) in Model 4. However, when we look at the results for interaction models, skills have a negative impact on emissions for those holding secondary and upper-secondary/tertiary education.

The association between skills and expenditures and emissions are plotted in Figure 2. Overall, we see a negative association between skills and both expenditures and emissions. However, the downward slope is steeper for expenditures than emissions.

These associations are disaggregated in Figure 3. For energy expenditures, skills have a negative impact for all education categories except primary.

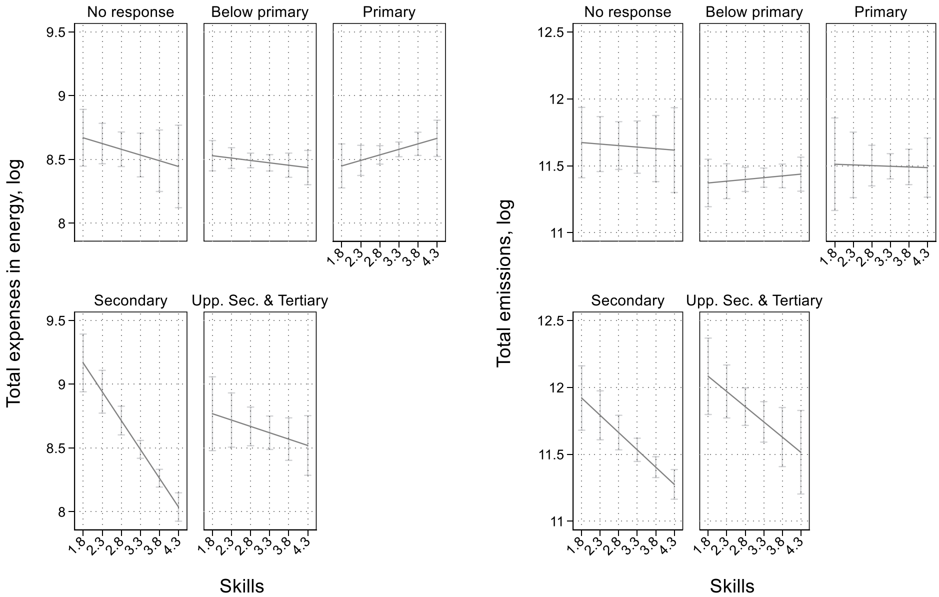

Figure 3. Marginal effects for expenditures (left) and emissions (right) by skills and attainment group.

5 Discussion: ex ante could skills development reduce household expenditures on energy and GHG emissions?

As Pavlova and Askerud (2023) point out, greening of the economy is seen to require the formation of relevant skills in the population. Imagine, if we could improve skills, such as through a civic education programme, what sort of impact do the statistical results imply could be achieved in principle? Taking the statistical results at face value, we observe a substantial and statistically significant negative relationship between skills and energy expenditures for the whole sample. This implies that a 1 standard deviation increase in skills, reduces energy us by as much as having 1 fewer household members.

This relationship does not carry over to emissions – nor should it necessarily as energy expenditures only correlate imperfectly with emissions due to compositional differences in energy use. Examining these relationships separately by attainment group reveals a bifurcation among respondents, where skills have a negative association with both energy expenditures and emissions for those with higher qualifications. For the attainment groups where there is a relationship between skills and emissions, the results indicate up to 28% reduction in emissions per unit of log skills or approximately 20% per standard deviation improvement in skills. This is a large potential effect, equivalent to a reduction of household size by 2.5 members but one that only applies to just under 40% of the respondents.

A crucial question, therefore, is what is hindering the remaining respondents in using their skills to reduce expenditures on energy and emissions? Due to data limitations, our modelling is circumscribed in its ability to control for confounding factors such as income and occupation. Therefore, it stands to reason that the highest qualification attained is picking up more than just the stripped effect of formal education, in particular socioeconomic position. Interpreted from this vantage point, the results are consistent with the environmental Kuznets curve, which implies that critical level of affluence is required before environmental impacts start lessening.

Is it possible that results are simply driven by compositional effects, where skills are associated with less-energy intensive and less emission-intensive livelihoods? This possibility cannot be excluded, but equally requires some strong assumptions to hold. The statistical analyses control for location, so any potential location-specific effect in livelihoods can be discounted. Similarly, there are some controls for nature of household (i.e. dwelling, income bracket and possession of bank account), which whilst not directly capturing nature of livelihoods are likely to capture some of the variation in domestic economic activity. Therefore, for effects to be driven by nature of livelihoods, these need to be strongly correlated with skills, independent of income bracket, possession of bank account, dwelling or location. Naturally, it would be a much preferable situation to be able to give a comprehensive account of each household's economic activities, but this would have required a much longer survey, which other things being equal, could only have been administered to a much smaller sample or would have required much more extensive fieldwork.

Recall that the skills use indicator was derived from a survey of general tasks as way of indirectly assessing relative skill levels of respondents and therefore represents an average of a broad range of skills, some of which may be helpful for environmental behaviours and others not. If a survey instrument could be devised to capture more precisely the particular skills affecting pro-environmental behaviours, then it is plausible that a stronger relationship between particular skills and the environment could be identified in future research. Attempts to disaggregate results by skills domain did not prove successful due to multicollinearity problems. That is to say, different types of skills are strongly correlated and therefore it is difficult to discern statistically, which skills in particular are driving the results. A further task for future research is obtaining a more nuanced account of how different skills affect environmental impacts. This is important as a priori it is not clear how structural issues affect the relationship between skills and emissions. A possible mechanism suggested by the findings of Owusu-Agyeman & Aryeh-Adjei (2023) is that the formation of green skills interacts with opportunities, which is consistent with only finding a skills-emissions gradient for more highly qualified respondents.

Whilst our results are consistent with the Environmental Kuznets-Curve, this concept refers to a frequently observed empirical pattern and does not provide a model of the underlying factors that generate this pattern. Therefore, it is useful to examine our findings more closely in terms of existing theoretical positions on the relationship between skills and economic/environmental behaviour. For skills and energy expenditures, our results imply a simple relationship, consistent with neoclassical thinking about the benefits of human capital as set out by McMahon (2000, Ch. 9). In the neoclassical tradition, human capital is a homogenous quantity, that can increase efficiency by substituting for other inputs in a production function at a given level of outputs. As manifested in our findings, the higher the skills level, the lower energy expenditures, given the size of the household.

Subsequent results are more difficult to explain. The analytical parsimony of human capital excludes context. At the micro level, Becker (1994) focussed on the individual's investment decision and did not explicitly model the host economy. When used to examine overall economic activity at a macro level (Krueger Alan and Lindahl 2001) human capital is an input in aggregate production functions, and the opportunities and constraints facing particular individuals are not observed. Moreover, human capital assumes a continuous pathway, while education is a discrete factor by definition (Marginson 2019) and the pathway from education to out-of-school outcomes is complex and nonlinear as is widely illustrated in the sociology of stratification literature (Ballarino and Bernardi 2016; Breen and Karlson 2014; Bukodi and Goldthorpe 2013; Scandurra and Calero 2019). Volumes have been written highlighting these blind spots and critiquing human-capital inspired policy making (e.g. Colclough 2012; Marginson 2019; Zancajo and Valiente 2019). Whilst more recent economic approaches explicitly identify links between individuals and their host economy, for instance Search Theory (Pissarides 2011) and Task-Based approaches (Acemoglu and Autor 2011), the interplay between an individual's aspirations and opportunities is central to sociological thinking on the relationship between livelihoods, education and skills (Furlong 2009) and the link between space, time and sociality within critical spatial theory (Jessop, Brenner, and Jones 2008; Massey 2005). On balance, our findings for the relationship between skills and emissions do not fit well with the well-behaved continuous predictions of neoclassical framework and align better with the sociological perspective of seeing outcomes as the interplay between individual capacities and opportunity structures. A possible alternative way to think about this would be to differentiate between the availability of skills and their utilisation, as advocated by Anon (2023) in the context of skills policy.

6 Conclusion

Reducing emissions in order to mitigate the worst consequences of climate change represents an existential challenge for humanity in the 21st century. Empirical observation of economic development as captured in the stylised Environmental Kuznets Curve relationship, suggests this aspiration is at odds with the concurrent challenge of improving the material well-being of low-income groups globally, especially in the context of ongoing population growth. In response to this, the abstract logic of neo-classical economics offers a tantalising prospect, that of green growth, where increased human capital acts as a substitute input for natural resources in the production of economic output.

We explore the relevance of skills for reducing environmental impacts by modelling energy expenditures and emission of rural households in India, based on data from a recent field survey of over 1,200 households. Our findings are consistent with previous literature, suggesting that economic activities can decouple from environmental impacts once a certain threshold is reached. Skills clearly moderate energy use and emissions, but only for a sub-population of rural households in India, which in our analysis is defined by educational attainment. This suggests skills play a role in de-coupling economic activity and environmental impacts for those with sufficient educational attainment (secondary education and above) but not for others. A crucial question therefore arises, what is holding back those with lower educational attainment from using their skills to reduce energy expenditures and environmental impacts? Our findings suggest, there are structural features common to the less educated that play a vital role and need to be discovered to untap potential for greener economic development.

The substantial effect-size revealed in our findings demonstrate strong ex ante potential for deploying skills-development policies as a means to reduce energy use and emissions. At minimum, this warrants more detailed examination of how individuals and households draw on skills when it comes to managing household energy use and the resulting emissions.

Notes

1. The IPCC was founded by the United Nations in 1988 and is now in its 6th round of reporting. For an overview of publications in the 6th round see: https://www.ipcc.ch/reports/?rp=ar6
2. For details see: https://unfccc.int/process-and-meetings/the-paris-agreement
3. The United Nations Department of Economic and Social Affairs expect World population to increase by nearly 2 billion persons in the next 30 years, from the current 8 billion to 9.7 billion in 2050 and could peak at nearly 10.4 billion in the mid-2080s (UNDESA– United Nations Department of Economic and Social Affairs, Population Division 2022).

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