



# Article Rural Energy Transition for Cooking in India—Revisiting the Drivers

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Abstract: The recent analysis from IEA (International Energy Agency) on energy transition in India highlights that cooking continues to be the weakest link in the energy transition process for rural households and that rural energy transition of households to cleaner fuel is nonlinear in nature. Several programs have been designed to plague the voids and address this nonlinearity, but the transition to cleaner alternatives for cooking did not happen in the pace it should ideally have. Therefore, an empirical exercise was carried out at a national level to revisit the disconnect between the income growth and energy transition and identify the drivers of the energy transition process in cooking at the national as well as at the subnational state level for a developing country. The paper adds to the current scholarship on drivers of household energy transition by analyzing the relationship between household energy choices and non-income determinants and proves the nonlinearity in energy consumption of rural households of Bihar. Analyzing unit level record from National Sample Survey, an empirical exercise was carried out by using multinomial logit model to identify the potential determining factors at the individual household and group level. The group effect analysis through fixed and random effect has been conducted purposely to understand if social and cultural norms or community level factors within a village society have any effect on the cooking energy transition of rural households and if that offsets the effect of household income in energy transition for cooking. Furthermore, to statistically examine the perceived non-linearity in the consumption of cooking fuel such as firewood by rural households, Brock-Dechert-Scheinkman (BDS) test was conducted for rural households of 38 districts of Bihar. The analysis helps in inferring that subsidy on modern fuel and/or other cooking alternatives alone may not suffice to drive the transition process, but more targeted intervention rooted in the local cultural context in consonance with social and cultural norms or community level factors could be more effective for sustained rural energy transition.

**Keywords:** cooking energy; energy ladder; energy transition; improved cookstoves; liquefied petroleum gas

# 1. Introduction

# 1.1. Relevance of the Research Topic

Economic development of a nation is interwoven with increase in energy consumption and transition. However, the process of transition from one form of energy to another is quite complex. There is a plethora of factors that underpins this complexity in energy transition. Energy transition is facilitated by the pace at which alternate, cleaner, and greener energy sources such as liquefied petroleum gas (LPG) and renewable energy (RES) and the alternate energy technologies are evolving and disseminated to the intended users. On the other hand, it is also about how the alternate energy sources and new and emerging



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**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). technologies are getting accepted and assimilated in the way of life of household [1]. The acceptance and assimilation of new energy source or a new technology-based appliance depends further on the social and cultural norms and how these norms get influenced by different institutional and administrative arrangements organizational forms, production, and labor processes. In addition, the individual and group behavioral dynamics also play an important role in transition [2]. Hence within the paradigm of the transition literature, the meaning of transition has varied with context and in the last three decades a widely varying differential perspective-based understanding of the transition has gained prominence as it is connected with economic growth and development too, and has cross connections with the growth and development literature.

Beyond this, there is also a need to bring more clarity in understanding the process of energy transition and integrate insights from the physical and social sciences with the process of technology evolution and adoption [4].

#### 1.2. Present State of the Art—Literature Review

The process and pace of energy transition could, however, get impeded by a number of factors. For instance, in the context of cooking energy transition in rural households several studies have identified the prevalence of usage of multiple fuels simultaneously as a deterrent in the transition process to improved cook stoves (ICS) especially in developing countries [5,6]. Despite the challenges that exist, there is a clear imperative to expedite the process of energy transition due to reported health and climate mitigation benefits that arises from reduced energy consumption or shift to cleaner fuels and concomitant reduction in carbon dioxide (CO<sub>2</sub>) emissions.

Transition to cleaner alternatives for cooking purposes continues to be the weakest link in the energy transition process in the developing world. This is evinced by the [7] data which indicate that nearly 2.6 billion people worldwide use traditional polluting fuels and traditional cookstoves primarily in low-income and middle-income countries (LMICs). It is also estimated recently that the use of polluting and highly carbon intensive fuels cause nearly 3.2 million premature deaths every year [8]. Sustainable Development Goal (SDG) 7.1 has a clear focus on universal access to clean cooking as it is deeply intertwined with realization of other SDGs related to health and wellbeing (SDG 3); gender inequality (SDG 5), and climate change (SDG 13). An earlier estimate by [9] indicates that the health and climate mitigation benefits through CO<sub>2</sub> emission across a diverse group of 40 Low Middle-Income Countries (LMICs). The findings indicate that LPG stove adoption by rural households in LMICs will lead to greater reduction in Disability Adjusted Life Years (DALYs) and  $CO_2$  emission reductions. A similar finding emerges from [10] which shows that LPG stoves along with forced draft stoves such as Oorja and Eco-Chula are highly effective in reducing inhouse (indoor) air pollutants as compared to conventional cook stoves. An earlier study by [11] using a metadata-based model showed that the use of improved cooking stoves could lead to a saving of 550 million tons of CO<sub>2</sub> annually and can create significant health benefits.

Improved access coupled with sustained adoption and usage of ICS can additionally help the rural households create avenues for new income generation and services for themselves and for the local economy [12,13]. The energy service generation can improve further if the ICS is integrated with heating and lighting devices especially for ICS that runs on electricity [14]. The improvement in quality-of-life pointers due to transition to cleaner fuels or technologically advanced energy-efficient appliance has been reportedly observed in developing countries such as India [15–18]. Section 2 provides relevant insights and motivation of the proposed study on the drivers of energy transition for cooking in India by drawing from the extant literature.

Present State of the Art—Motivation and Objective from The Literature Review Academic Scoping of Drivers for Cooking Energy Transition: Insights from Extant Literature

The extant literature on energy transition in the context of cooking has not only identified the influence of more conventional factors such as growth, income, education, and asset holdings but the lion's share of the literature gave a huge emphasis on the non-income factors that could potentially drive energy transition for cooking. Some of these factors which are exogenous to the households include market orientation; nature of business models involved in financing a new energy source or appliances; constraints related to operational convenience; awareness about energy saving and environmental impact; product price and attributes; liquidity in the household and/or availability of credit and robustness in the supply chain of a technology. However, the more recent literature on energy transition in cooking underscored that beyond the income of the household, the transition paradigm is largely about day-to-day human interaction and is, therefore, deeply intertwined with the social, cultural, and behavioral practices and village level dynamics. These factors largely determine the choice of cleaner technology or cleaner fuel for cooking. The following paragraphs delve in detail into the extant literature and explores the motivation, objective of the paper which deals with these factors driving the rural energy transition process.

A recent study published in the journal *Nature Energy* [19] predicted that universal access to cooking energy might be difficult to attain even in 2050. The prediction is primarily driven by the bout of prolonged recession that ensued post-pandemic. The study inferred that the recession could make clean cooking services inaccessible and unaffordable for 470 million additional people in 2030 relative to a reference scenario, and the people in the region of sub-Saharan Africa and Asia are going to face the worst consequences.

Going by the more conventional factors that influence energy choices of households, a recent study by [20] reveals that the determinants of household energy choice include education, household dwelling type, household size, employment, and income group. The study also observed that 'whereas education, modern housing, paid employment, and higher income increase the adoption of cleaner energy, a higher dependency ratio and employment in the informal sector increase the likelihood of using unclean energy'.

Furthermore, to allow for internalization for market and behavioral obstacles, the tools of spatial mapping could be used as it offers a "more nuanced understanding of the costs needed to deliver cleaner cooking transitions than was previously possible" [21]. This would clearly provide an apt armor in the hand of policymakers in improving the effectiveness of the targeted interventions.

Murshed (2022) [22] inferred in the context of a study carried out in sub-Saharan Africa that the major drivers of clean cooking fuel transition are economic growth, environmental pollution, financial globalization, financial development, and women's empowerment. However, the study observed that the impacts of these macroeconomic variables tend to be higher for the nations within sub-Saharan Africa that are less dependent on unclean fuels for cooking.

Considering the role of institutional and structural factors that potentially influences energy transition for cooking, a classic study by [23] identified that market-oriented approaches can make the energy market accessible and attractive to local investors, communities, and consumers facilitating in improved access to devices such as ICS for cooking for rural poor. The public knowledge and awareness of the importance of the type of fuel and technology in the stove; operational convenience; environmental protection and energy-saving can also influence ICS adoption rates considerably [24,25]. Other potential drivers that have been identified in the extant literature include: product price [26]; product attributes and market segmentation [27]; regional coverage and policies; nature of business models associated with a new technology for cooking such as design, customers targeted, financing, marketing, channel strategy, and organizational characteristics [28]. Constraints related to availability of credit for households coupled with dearth of liquidity of households to pay back a loan could also affect the adoption and usage of new technology such as improved cookstove by rural households [29].

Considering the behavioral, social, and cultural factors and their role in sustainable energy transition, role of social networks behind rural energy transition for cooking has been emphasized by some studies [30]. Often, if a rural household belong to certain social institutions and networks such as self-help groups that can also determine the nature, extent, and degree of information that is transmitted to rural households about new technologies/modern fuel [31]. This most recent study carried out in an Indian context [32] further reaffirmed why it is not just the income but the enabling role of institutional confidence and social capital that plays a more critical role in household energy transitions in India This has been reaffirmed by [30] which also shows that education of female members of the household and membership in networks that are led by females plays a critical role in driving clean fuel adoption.

In India, 87 percent of the rural households and 26 percent of the urban households still depend on biomass for cooking [33]. In 2014, a program to promote ICS based on traditional biomass, known in Indian national vernacular as Unnat Chula Abhiyan, was launched to initiate the energy transition for cooking by using ICS. However, the sustained adoption of ICS does not seem to have happened. Reasons for low adoption include: mismatch between design and user expectations; low willingness to pay because of low awareness and dearth of knowledge on perceived benefits [34]. Another recent study [35] indicates that the chance of switching to cleaner options of cooking gets enhanced by relaxing the income and liquidity constraints in rural households. This could be made possible by enabling a market and financing environment [36].

For LPG the Government of India launched Prime Minister Ujjwala Yojana (PMUY)scheme in 2016 which is aimed at providing access to LPG to ten crore rural households having no access to clean cooking [37]. However, this program has also not been able to promote sustained adoption and usage of LPG for cooking within the rural households of India. This could largely be attributed to supply side constraints arising from marketing and distribution issues; delay in after sales services; and personal and cultural preferences of rural households. The basic fact that the consumption of cleaner fuels such as LPG is limited in rural areas, and the use of traditional biomass continues to be predominant among rural households is largely in consonance with findings from earlier empirical research [38–40].

The data from [41] further indicate that within India, there is only a reduction of 10 percentage points in the share of population relying on biomass and kerosene between 2010 and 2015 for cooking. Most of the 10 percentage points drop in the share could be attributed due to rural households switching to LPG for cooking. Since 2015, an additional 80 million free LPG connections have been provided to poor households under PMUY to facilitate their transition from firewood for cooking to LPG for cooking purposes. However, there is no clear-cut evidence on whether this additional provision has eventually led to increased adoption and usage of LPG in rural households. Even though the income of rural households has progressively gone up, the constraints with respect to access to LPG, as mentioned above, have led rural households to continue with the practice of stacking fuelwood. The weakness in the link between income and energy transition in the context of adopting modern fuel such as LPG has also been emphasized in a recent study by [42]. Another study by [43] based on LPG sales data reinforces the continued dependence on solid fuel/firewood by the household and indicates very low off take of LPG cylinders per month. In a follow-up study/paper by [44] additionally reaffirms that one-time capital subsidy on LPG may not be adequate to provide a big push to LPG and make the households shift from solid fuel/firewood. Masera et al., 2000 [45], in an earlier study carried out in the context of Mexico, demonstrated that very rarely the fuelwood got replaced completely, even in households that have been using LPG for years. Fuelwood was still considered essential for tortilla making in Mexico-both for technical and cultural

reasons. What was striking in the study was that they observed that multiple fuel users were even willing to pay a "premium" for continuing to use fuelwood.

What one could essentially infer from the literature is that the rural households do not seem to give up on the usage of fuel wood/biomass for cooking even if their income rises. This is not only due to the dearth of a reliable cooking alternative but due to interplay of a plethora of institutional, regional, social, cultural, and behavioral factors. A disconnect thus clearly exists between the income growth and energy transition to modern sources of energy for cooking for rural households. Thus, there is a clear imperative to revisit the energy ladder hypothesis and examine the disconnect that exists between income and sustainable energy transition. Hence, the paper identifies this gap and attempts to identify the driving factors behind the rural energy transition in cooking followed by analyzing the nature of rural energy transition process at the state level for an energy poor state such as Bihar. The paper succinctly through an empirical analysis of an econometric model establishes the statistical significance of local factors determining the chance of switch over to a clean fuel from firewood and further by means of a nonlinear dynamic model establishes the nonlinear pattern of firewood consumption in rural households of Bihar through the application of the Census Data of Bihar.

#### 1.3. Research Gap and Innovative Contribution of the Paper

Considering the stark fact that a population of more than 2 billion continues to rely on solid fuels for cooking or heating, there is a dire need to increase the pace of access to cleaner alternatives (technology and fuel) given the negative spillovers on health, environment, and climate. However, despite piles of evidence on how to go about implementation on the ground, the outcome continues to be disappointing because the translation of the body of evidence into practice remained abysmally low [46]. Several programs have been designed to plague the voids, but the transition to cleaner alternatives for cooking did not happen in the pace it should ideally have. The study of the extant literature reaffirms that even though there has been significant effort towards improving the access and/or adoption in cleaner technology or fuels for cooking, those alternatives could not be made a part of the life permanently for the energy poor people in the developing world.

One of the shortcomings that could be found in the design of the program in a developing country context is the belief that income continues to be the key driver of the sustainable energy transition process. The literature survey clearly acknowledges that income is a critical driver in adoption of cleaner alternatives for cooking, but the growing body of literature enables us to categorically contest the 'energy ladder' hypothesis [47]. This set of literature clearly emphasizes that it is not just income but institutional, structural, behavioral, social, and cultural factors and their unique interplay that often turns out to be decisive in influencing the cooking energy transition process. This set of literature also indicates that energy transitions do not necessarily occur in a series of 'simple, linear or even discreet steps' as advocated by the 'energy ladder' hypothesis. Instead, use of a portfolio of fuel options is more common, a phenomenon known as 'fuel stacking' [31,38,48]. Studies by Herington and Malakar (2016) [49] and Malakar et al. (2018) [50] carried out in other developing country contexts further contended that households adopt risk coping strategies purposefully in situations of energy insecurity and may resist shifting away from traditional fuels and reverse a transition to retain traditional energy forms as backup. The COVID-19 pandemic only added to the challenges in the transition process to cleaner alternatives for cooking by worsening the condition of energy insecurity for the energy poor people [19].

Understanding the dynamics of energy access and adoption is crucial for designing and putting into practice the policies that would expand energy access and sustain rural energy transition of rural households in India. Recognizing the limitations of the current policies and taking cue from the extant literature on the drivers of energy transition in cooking, an attempt has been made in this paper to revisit the disconnect between the income growth and energy transition and analyze more deeply the drivers of the energy transition process in cooking at the national as well as the state level in the context of a developing country namely India. The paper in a way also adds to the current scholarship on drivers of household energy transition by also analyzing the relationship between household energy choices and non-income determinants. The most innovative contribution of the paper is that it attempts to statistically direct towards the possible driving factors behind the rural energy transition process in cooking for rural households of Bihar. Further, it scientifically through a nonlinear, dynamic analysis establishes the nonlinearity in the firewood consumption of rural household of Bihar.

The next section describes the statistical, econometric, nonlinear dynamic system methodology that has been adopted in the paper for analyzing rural energy transition at the national and sub-national level.

## 2. Research Methodology

The methodology section of the paper has been divided into two broad strands of analysis—(a) one based on the analysis at the national and the other based on, (b) sub-national level on rural energy transition in cooking. The examination of the national level data essentially involves construction of econometric model and examining the variables/drivers that potentially influences the probability of a switchover from firewood to the basket of modern fuel options. At the state level, the state of Bihar has been singled out for the case study. Bihar, despite being on the economic growth path more recently, has largely remained an energy poor state, particularly when it comes to energy choices for cooking. For the households level analysis, households have been selected from 38 districts of Bihar.

An empirical exercise using multinomial logit model has been carried out to examine the transition process in cooking energy and fuel options for rural households. The data used for the modeling are at the household level and are extracted from the 66th Round of National Sample Survey Organisation (NSSO) The dependent variable in the model is the primary cooking fuel used by rural households. It is assumed that for the primary cooking fuel, the household can select either firewood or a basket of alternative clean fuel options. In the alternative basket, as per the NSSO energy related rounds, different fuel choices such as kerosene and biogas have been considered for the three identified income classes. Hence, even though in the rural energy transition literature, the transition is envisaged from firewood to Liquified Petroleum Gas (LPG) via improved cookstoves. In the intermediary stages, kerosene, biogas is also seen as clean cooking fuel options for rural households depending solely on firewood for cooking. The NSSO data clearly reflect on that.

Taking cue from the extant literature, various explanatory variables have been identified as potential drivers that could influence the chance or probability of shifting from one fuel (firewood as primary cooking fuel) to the other clean fuel options such as LPG, kerosene, and biogas. Amongst the list of independent variables, access to the internet has been chosen here consciously as an all-encompassing proxy for access to modern information that subsumes all other technological access under it. Access to information through the internet is also expected to empower households with information that potentially influences better realization of their quality of life and livelihood. Table 1 provides a brief description of the variables, their measure along with the rationale of inclusion in the models.

The multinomial logit model uses the cumulative distribution function, specified as below:

$$F(l) = P(L \le l) = 1/1 + e - l = (e^l/1 + e^l)$$
(1)

Logit  $(p) = \log (p/(1-p)) = \log (e^l/1 + e^l/1 - \{e^l/1 + e^l\}) = \log(e^l) = \log (e^{\alpha} + \beta 1 (mpce) + \beta 2 (district) + \beta 3 (internet) + \beta 4 + \beta 4 (regsal) + \beta 5 (hh) + \beta 6 (cv) + \beta 7 (stat reg) + \beta 8 (rel) + \beta 9 (socgrp)$ Hence the equation specification of the model comes out to be as

Predicted Logit (lfp = 1, 0) (choice of primary cooking fuel) =  $\alpha$  +  $\beta$ 1 (mpce) +  $\beta$ 2 (district) +  $\beta$ 3 (internet) +  $\beta$ 4 (regsal) +  $\beta$ 5 (hh) +  $\beta$ 6 (cv) +  $\beta$ 7 (stat reg) +  $\beta$ 8 (rel) +  $\beta$ 9 (socgrp) (2)

Predicted Logit (lfp = 1, 0) (choice of primary cooking fuel) =  $\alpha + \beta 1$  (cv) +  $\beta 2$  (stat reg) +  $\beta 3$  (rel) + (socgrp) (3)

In comparison to Equation (2), Equation (3) does not consider the impact of liquidity and household size on the probability of switching to a cleaner fuel by dropping the two independent variables owing to a possibility of a multicollinearity which can lead to an overestimation or underestimation of the elasticity.

Four models have been tested with a logit model and the four models can be explained in the Table 2.

**Table 1.** List of Variables Considered in the Limited Dependent Variables Models and/or in GroupEffects (Fixed and/or Random Effects).

Variable Name	Description and Measurement
Dependent Variable Y: Choice of the primary cooking fuel	Refers to the choice between firewood or clean fuel used as primary cooking fuel for cooking. If a household uses firewood, then the data entry is one and for other fuel usage it is given a different value.
Mpce: monthly per capita expenditure used as a proxy for liquidity	Refers to monthly expenditure per household on a basket of goods. (Measured at nominal value in Indian Rupees)
mpce_mrp: Monthly per capita expenditure for marginal rural population	Refers to the monthly expenditure per household of rural population whose daily energy consumption is 629 kcal or below. Measured at nominal value in Indian Rupees.
District: type of district	Refers to the type of district in terms of provision of basic infrastructure in the form of roads, transportation, health, schools, banks, and sanitation. The variable is a time-cumulative dummy.
Internet: internet availability	Refers to access to information using the internet with the aid of mobile telephony, broadband, and spectrum-based technological advent. If the household is using all of the above technological forms, then a value of one is imposed otherwise a value of zero is imposed.
Regsal: liquidity	Refers to liquidity, indicating the number of times households make a purchase in a month and is measured as a nominal value.
Hh_size: household size	Refers to the size of a household measured in nominal value.
Hh_type: Household characteristics	Refers to the classification of households into low, medium, and high as per the NSSO data and their agroeconomic nature.
Calorific value (cv): Quality of fuel	Refers to fuel quality in terms of the calorific value which determines fuel efficiency.
Stat reg: presence of social groups (stat reg)	Refers to the presence of social groups such as SC, ST, and others in a region which may influence the transition to cleaner fuels. It is measured by the number of social groups around the area of the households and is measured in nominal value.
Rel: belonging to a particular community	Refers to community (NSSO classification) of which a household is a part.
Socgrp: presence of social/institutional groups (socgrp)	Refers to the existence of social or institutional groups such as SHGs.

The variables have been listed in the NSSO Round and the input values of the variables have emerged from NSSO Round.

Within the dependent variable, clustered samples are created. Within these clustered samples, fixed effects of the explanatory variables on the dependent variable are checked. For every sample, a maximum likelihood estimator convergence test is carried out. The estimators are finalized only after the maximum likelihood test-based estimators are observed as complying with the reliability range as per the multinomial logit model simulation for the clustered samples of the different rural households. A group effect analysis has been conducted purposely to understand and contextualize the impact of social and cultural norms of a village society on rural cooking for energy transition in India. As evident from the extant literature, culture, identity, group lineages can influence the improved cookstove adoption behavior of rural households. Hence, analysis of group effects as a part of the econometric model is critical in the context of this research.

**Table 2.** Summary of the Four Models.

Cooking Code (Base Outcome—Firewood)	Model 1 (Household Level Model)	Model 2 (District Level Model)	Model 3 (District Level Model)	Model 4 (Household Level)	P > {z} (Model 1)	P > {z} (Model 2)	P > {z} (Model 3)	P > {z} (Model 4)
Calorific Value of Cooking Fuel	Elasticity Estimated	Elasticity Estimated	Elasticity Estimated	Elasticity Estimated	Significant	Significant	Sig Nificant	Sig Nificant
Household Type (explained through an index of household asset holdings, land, consumer durables, etc.)	Elasticity Estimated	Not Tested	Not Tested		Significant			Significant
Marginal Per Capita Expenditure (High Income Class)	Elasticity Estimated	Not Tested	Not Tested	Not Tested	Significant			
Marginal Per Capita Expenditure (Low Income Class, mpce)	Elasticity Estimated	Not Tested	Not Tested	Not Tested	Significant			
Belonging to a social group particular to the remoteness of a district	Not Tested	Elasticity Estimated	Not Tested	Not Tested		Significant		
District Index	Not Tested	Elasticity Estimated	Elasticity Estimated	Not Tested		Significant	Significant	
Household Size from the district level data	Not Tested	Not Tested	Elasticity Estimated	Not Tested			Significant	
Belonging to a particular religion	Not Tested	Not Tested	Elasticity Estimated	Not Tested			Significant	
Belonging to a particular social group according to population type of a district	Not Tested	Not Tested	Elasticity Estimated	Not Tested			0.000	
Constant	Estimated	Estimated	Estimated					

Source: Model Description by Authors.

In the econometric modeling exercise conducted at the national level, the base outcome was that households select firewood for cooking (represented as Y = 1). The alternative outcome was selecting other fuel options (represented as Y = 0). Likelihood Ratio (LR) and chi-square tests were used to confirm if improved cook stove (ICS) and clean cooking options were used by households dependent on firewood for cooking.

Coming down to the sub-national level, an exploratory analysis has been carried out to identify if there are any state-level factors that may potentially influence the chance of transition to cleaner cooking options. In order to do so an analysis of the level of income and energy consumption by rural households have been carried out. The data from the 66th NSSO survey in India brought by Central Statistical Organisation (CSO), India were used to analyze the factors influencing the transition to cleaner cooking options by rural households at the state level. The income level was determined by the specific expenditure of different income classes.

Correspondingly, monthly fuel consumption in Kcal was estimated for each income class. Per capita energy consumption of 629 kcal or less per month was used as the yardstick of energy poverty [51]. This standard was used to identify the states with the most energy-deficient rural households. The useful energy consumption was calculated by multiplying the fuel consumed, conversion rate, and fuel efficiency, considering a harmonized conversion factor of around 24% to 30% for every cooking fuel. The state of Bihar, used as a case study for the current research, was found to be the most energy-deficient state and is lagging due to the concentration of low-income population and broad social and cultural diversity. Figure 1 (See Appendix A, Table A1) provides the monthly average consumption of various energy sources for India and Bihar.



**Figure 1.** Monthly Consumption of Energy Sources in India and Bihar as per NSSO 64th and 66th Round. Source: NSSO 64th and 66th Round.

In addition, for the income classes, as already mentioned in the beginning, the pattern of useful energy consumption for cooking across the districts of Bihar has also been analyzed and mapped against the district specific average monthly per capita expenditure.

In order to assess the perceived non-linearity in energy transition for cooking fuels statistically, a district level analysis has also been carried out for Bihar by using the Brock–Dechert–Scheinkman (BDS) test for firewood consumption of energy-poor households selected from 38 districts. The test originally developed by [52] and further expanded in [53,54] is considered as the most popular test for nonlinearity. It was designed to test the null hypothesis of independent and identical distribution (iid) of a series for the purpose of detecting non-random chaotic dynamics.

The BDS test statistic, which has a limiting standard normal distribution is represented as:

$$W_{m,I}(\xi) = \frac{T^{1/2}C_{m,I}(\xi) - C_{I,T}(\xi)^m}{\sigma_{m,I}(\varepsilon)}$$

where  $\sigma_{m,I}(\varepsilon)$  and  $K(\varepsilon)$  is estimated by

$$K(\varepsilon) = 6 \sum h_e(\varepsilon) X_1^m, X_2^m, X_3^m / [(T - m + 1) (T - m) (T - m - 1)]$$

Note: *m* refers to vectors clusters of household units,  $\sigma_{m,I}(\varepsilon)$  is Standard deviation of fireword consumption of I households belongs to m vector clusters.

The threshold statistics value for any set of observations in which BDS is applied is 1.96. If for any set of observation within a nonlinear dynamic system, the BDS value is above 1.96, it implies that the data are nonlinear and nonparametric in nature.

#### 3. Results and Analysis

#### 3.1. Results Pertaining to National Level

Figure 2A–C (See Appendix B, Tables A2–A4) highlight the results of how various context, location-specific variables such as social group, community impacts the probability of transition to clean fuel/cooking options such as biogas and LPG (denoted as Y). Four Model results along with the variable specifications are presented in Table 3.



**Figure 2.** (A–C): Logit Regression Models and Outcomes. Source: Based on Tables A2–A4, Appendix B—Author Estimates. \* Rel: belonging to a particular community.

Outcome—Firewood)Level Model)Level Model)(Household Level)(Model 1)(Model 2)(Model 3)	(Niodel 4)
Calorific Value of cooking fuel $0.0019$ $5.09 \times 10^{-6}$ $0.0145$ $0.007901$ $0.003$ $0.002$ $0.000$	0.000
Household Type (explained through an index of household asset 4.5934 2.81 × 10 <sup>-6</sup> 0.002 holdings, land, consumer durables, etc.)	0.000
Marginal Per CapitaExpenditure (High0.0076Income Class)0.001	
Marginal Per CapitaExpenditure (Low Income 0.305Class, mpce)	
Belonging to a social group particular to the0.0064750.001remoteness of a district0.0064750.001	
District Index 0.020797 0.0152 0.014 0.037	
Household Size from the district level data0.35850.000	
Belonging to a particular religion0.28230.007	
Belonging to a particular         social group according to         population type of         a district	
Constant         -16.714         -7.572         -7.376         -5.22         0.002         0.0001         0.0001	0.000

Table 3. Four Model Results along with Variable Specifications. Statistical Significance of The Four Model Estimators.

Note: Results of the four models explained in the table.

Figure 2A: logit Regression Model 1: Y axis measures the probability of the change in the consumption of the primary fuel, group variable considered—hh\_type, offset variable (considering fixed effect)—hh\_size, level—1 (group variable—hh\_type).

In the outcome Figure 2A: logit Regression Model 1: No. of Observation-5000, No. of groups—4, Integration Points—7, Log likelihood—2635.0129, Wald Chi2—4978.09, Prob > Chi2—0.0000, No. of Observation—5000, No. of groups—4, Integration Points—7, Log likelihood—2635.0129, Wald Chi2—4978.09, Prob > Chi2—0.0000, LR test vs. logistic regression: chibar2(2) = 83.01 Prob  $\geq$  chibar2 = 0.0000. \* specific dummies.

Figure 2B: logit Regression Model 2: Y axis measures the probability of the change in the consumption of the primary fuel, group variable considered—rel, offset variable (considering fixed effect)—none, since rel is a group variable, effect considered is random, level—1 (group variable—rel) \* specific dummy.

In the outcome Figure 2B: logit Regression Model 2: No. of Observation—5000, No. of Groups—4, Integration Points—7, Log likelihood—2668.9793, Wald Chi2—532.74, Prob > Chi2—0.000, LR test vs. logistic regression: chibar2(01) = 15.16 Prob  $\geq$  chibar2 = 0.0000. \* specific dummy.

Y axis measures the probability of the change in the consumption of the primary fuel, Figure 2C: logit Regression Model 3 group variable considered-socgrp, offset variable (considering fixed effect)—none, since the social group is group variable, the effect considered is random. Level—1 (group variable—socgrp) \* specific dummy.

Outcome Figure 2C: logit Regression Model 3: No. of Observation—5000, No. of Groups-4, Integration Points-7, Log likelihood—2661.4289, Wald Chi2—600.11, Prob > Chi2—0.0000, LR test vs. logistic regression: chibar2(01) = 30.26 Prob  $\geq$  chibar2 = 0.0000.

Figure 2A–C (See Appendix B, Tables A2–A4) clearly shows that keeping other variables as controls, household size, community identity, and monthly per capita expenditure does have an impact on the probability of switching to a cleaner cooking choice. This validates the importance of local level non-income factors in the process of transition to cleaner fuels for cooking. The last four columns of the Table 3. highlights how the four logit models with different variable specifications shows the statistical significance of variables such as calorific value of cooking fuel, household type, household size, marginal per capita expenditure (as a proxy of liquidity), belonging to a particular religion or a social group in deciding the chance of shifting from firewood to other clean cooking fuels by rural households. The results clearly indicate household endogenous factors decided by their liquidity, identity, size, belongingness to a particular network or group does impact their decision to shift from firewood to a clean cooking fuel choice in a rural context. These endogenous variables are household specific and often generic macro- and meso-level energy transition policies fail to address these endogenous factors which are very localized with a strong cultural context.

The finding also substantiates the insights drawn from the extant literature. To further assess the impact of local level factors, variables representing community identity and social group are randomized, whereas other variables, such as monthly per capita expenditure, household size, are kept as controls (as they can be decided by the households themselves).

Figure 3 (See Appendix C, Table A5) further shows that district type, location and belonging to a social group also have a positive and significant impact on the chance of fuel switching. The district dummy is a cumulative dummy and captures the impact of the district across space and time. The figure also shows that the choices of the cooking energy are affected by the calorific value (denoted as cv here) of the fuel used by rural households. It indicates that higher the calorific value of fuelwood smaller will be the chance of switching to alternative fuels as higher calorific value results in more efficient cooking (assuming no variation in the cooking end-use devices or medium).

Here in this figure, Y axis measures the probability of the change in the consumption of the primary fuel. To check for reliability of the model results, likelihood tests of the above estimators were carried out for a total data observation of 63,061 and reported in



Figure 4. The probability and likelihood value indicates that the estimates of the above model are robust and hence can be relied upon.

Figure 3. Impact of Determining Factors on Choice of Cooking Fuels. Source: Author Estimates.



**Figure 4.** Model Reliability Tests. Source: Author Estimates. High likelihood ratio and low probability value of less than 5% and a positive explainability factor statistically indicates the significance and reliability of the model.

All the three variables related to the quality of the fuel resources namely location, type of the district, and whether the household belongs to a particular community/social group and participation in social network may potentially positively influence the chance of switching to cleaner cooking options by the rural households. Statistical significance of the positive impact of these variables on the probability of switching to a clean cookstove is also explained through the tables in Appendices (See, Tables A1–A6). It is clear from Tables A1–A6 that belonging to a particular community, social group under the random effects model positively impacts the probability of the chance of switching to a cleaner fuel. The fixed effect model with households as a fixed effect shows a positive impact of the household size on the probability of the chance of switching to a clean fuel for cooking from firewood.

All these possible relationships in rural household energy transition have been examined and reported in Figure 5.



Figure 5. Impact of Determining Factors on Fuel Choices. Source: Author Estimates.

Figure 5 (See Appendix D, Table A6) clearly indicates that the characteristics of rural households defined by their religious grouping, social group status, household size can impact the chance of switching from firewood to other alternative fuels for cooking. The district dummy is a default control factor for both Figures 5 and 6.

### 3.2. Results Pertaining to Sub-National Level

The graphical illustration in Figure 6 below shows a clear disconnect between income and energy transition and a possible presence of non-linearity in the relationship between firewood consumption and income at the district level in the state of Bihar. The Figure 6 depicts that some of the districts in Bihar with a high average value of monthly per capita expenditure (the blue line) are showing low useful energy consumption. The observation hints towards possible usage of firewood as primary cooking fuel even in the high-income earning district. On the other hand, useful energy consumption has been observed to be higher for low-income districts than that for high-income districts.



**Figure 6.** Pattern of useful energy consumption across income classes within districts of Bihar catering only to cooking. The useful energy consumption was calculated by multiplying the fuel consumed, conversion rate, and fuel efficiency, considering a harmonized conversion factor of around 24% to 30% for every cooking fuel and considering the threshold level of 629 Kcal per kg of fuel consumed. The monthly per capita expenditure (blue curve) is solely based on the primary energy consumption for cooking alone. The green curve (Final energy consumption (Kcal/month)) based on per capita estimates assuming an average household size as 4.

The pattern that has been observed here also points to the fact that even if income happens to be a significant determinant or driver in the energy transition, other nonincome factors could more than offset the income effect while driving the process of energy transition and essentially makes the dynamics of energy transition non-linear.

The Brock–Dechert–Scheinkman (BDS) test that has been carried out on firewood consumption of rural households from the 38 districts of Bihar to statistically validate this perceived non-linearity, shows the test statistic value is exceeding "1.96" for the firewood consumption of rural households of Bihar. As 1.96 is a threshold value beyond which there is an existence of nonlinearity, the paper concludes towards a nonlinearity in firewood consumption behavior of rural households of Bihar. This observation thus reinforces what could be observed from the graphical illustration in Figure 6 and hints towards a chaotic/non-linear pattern in the long-term firewood consumption data of the rural households from the energy poor districts of Bihar. The finding in a way also complements the observations that have been obtained from the results of multinomial regression model on impact of district level factors on choice of cooking based on multinomial logit models at the national level using NSSO data.

### 4. Discussion

Given that transition to cleaner alternatives for cooking will continue to be the weakest link in the energy transition process particularly in the developing world, the paper revisited the problem of energy transition in the context of cooking in rural household in a developing country in Asia. Acknowledging the shortcomings and bias of the design in current policies towards cooking energy transition in developing countries and drawing insights from the extant literature on the drivers of energy transition in cooking, the paper examined the drivers of cooking energy transition at national and subnational level for India. It explores if there is a disconnect between the income growth and energy transition and analyzes more deeply the drivers of the energy transition process in cooking at the national as well as the state level in the context of a developing country namely India. The paper in a way, thus adds to the current scholarship on drivers of household level cooking energy transition in the context of a developing country by reassessing the relationship between household energy choices and non-income determinants at the national as well at the sub-national level for a developing country. Within the domain of the rural energy transition literature from a developing country context, the paper empirically proves that household level endogenous factors do significantly impact the probability of a switchover of a rural household from firewood to a clean fuel for cooking. The paper moreover analyses the nonlinear nature of this transition pattern at a subnational level by showing scientifically that the pattern of firewood consumption of rural household is nonlinear in nature in an energy poor state within the larger system of rural household energy consumption for cooking. This, therefore, lucidly brings forward the need of localized, culturally contextualized, dynamic, and innovative rural energy transition policies for developing countries such as India where every state by itself is a country owing to a large diversity of local level different group identities, social and cultural contexts, and with varying access to liquidity, and the developmental infrastructure in which the rural households are placed.

The insights, therefore, drawn from the findings could easily be used for designing similar studies in other developing countries of Asia and Africa with identical challenges and impediments in rural energy transition.

## 5. Conclusions

The findings from the exercise using multinomial logic models suggest the interplay of non-income drivers in influencing the choice of cooking options and tend to counter the more conventional wisdom rooted in the 'energy ladder' hypothesis in the context of rural energy transition for cooking in India. The findings from BDS test for non-linearity reinforces the disconnect in the relationship between income and energy transition even at the subnational level and in a novel way scientifically proves that the system of firewood consumption of rural households of Bihar is nonlinearly dynamic which has not been proved by other papers in the extant literature on rural energy transition in India. The

lead to a choice of a superior or cleaner alternatives. The results of group effects (fixed and random effects) carried out in this paper also demonstrates statistical significance of both individual household level variables (such as location, district, household size, quality of fuels, and liquidity) and group level variables (such as influence of social group/network, cultural norm, and community identity across different districts) in explaining the choice of fuel consumption.

non-linearity in this context basically implies that increasing income does not essentially

There is no second thought that transition to modern forms of cooking fuel choices from firewood to cleaner fuel such as LPG, or cleaner energy efficient appliances such as ICS or any other options depends to a large extent on the trust levels of community on new technology choices and local factors related to cultural practices and beliefs embedded in cooking. The trust factor, i.e., social capital, also happens to be context, community, and culture-specific, and is determined by the nature, extent, and degree of information that is passed onto the rural household users about a fuel such as LPG or new technology applications such as ICS.

Even if income happens to be a significant determinant, other non-income factors, as illustrated in the paper, could more than offset the income effect while driving the process of energy transition and make the dynamics of rural energy transition for cooking essentially non-linear. Hence it might be difficult to conclusively infer if capital or operational subsidy on LPG or that on an energy efficient modern cooking appliance could really make significant difference in the choice of households unless the non-income drivers are adequately factored in policy discourse and/or deciding on the policy instruments. One way the paper is unique in comparison to earlier papers is that it facilitates policy making to integrate local, social, and cultural factors towards successful energy transition policy making can be through decentralized vocational centers in local village networks at the Panchayat level through self-help groups which can feed on the local information to these vocational centers of policy making. Further, the local vocational centers can pass on the local, social, and cultural information towards subnational policy making at the state level by means of these vocational centers. The states can further scale it up at a national level for a more effective national level clean energy transition policies in cooking.

In time, the mainstream energy policy discourse that is built on a more linear path of energy transition as embedded in the 'energy ladder' hypothesis may not be able to appropriately identify the right kind of instruments or perhaps a mix of instruments that would be necessary to provide a big push to plug this weak link in the rural transition to cleaner energy or technology alternatives. The existing policy discourse needs to draw insights from potential factors causing the non-linearity in the dynamics of energy transition when it comes to cooking and/or internalize the cultural, social and community level fulcrum of household preferences. The extant literature and the results and analysis of the paper clearly indicates that the energy policy discourse and implementation process on rural energy transition for a developing country ought to be cognizant of the complex nexus between social norms, culture, gender, and community level differences in developing countries and design and target policies in a customized and need-based manner for different intended groups so as to make the policies more effective and for more pervasive impact.

It is also well established in the literature that focuses on the interlinkage between energy and development that economic prosperity can come from access to lighting as it helps in enabling access to essential economic services and facilitates in meeting the unmet needs of the rural community. This can in turn potentially enhance quality of life, and may in turn influence a household's decision of switching to clean fuels for cooking, given that significant progress has been already made in electrifying the rural areas in developing countries. It would, therefore, be interesting and worthwhile to carry out an exercise to explore the coupled chain effect-based feedback from electricity used for lighting to that for cooking. In such a framework, specific determining factors related to investments need to be found out to understand how investment related factors facilitate rural energy transition through a feedback model. A simultaneous equation model structure or a systems dynamic model framework could perhaps be more appropriate to capture this coupled effect and could be considered as a future area of research. In that context, it would also be worthwhile to explore if decentralized renewable energy-based cooking appliances could be utilized in the rural area of developing countries to enable smoother transition to cleaner choices.

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#### Appendix A

Table A1. Monthly Consumption of Various Energy Sources.

Energy Source	Unit	India	Bihar
Firewood	Kg	42	60
Electricity	KWh	644	120
Kerosene	Liter	0.93	2.53
LPG	Kg	7.7	0.93

Source—NSSO 64th and 66th Round.

## Appendix B

 Table A2. Logit Regression: Model 1.

	Coeff	Standard Error	Z	p > z	95% Confidence Interval	
hh_size	-0.881	0.016	-55.51	0.000	-0.913	-0.850
hh_type	-0.050	0.035	-1.42	0.154	-0.119	0.019
Rel	-0.159	0.057	-2.81	0.005	-0.270	-0.048
Socgrp	-0.000	0.058	0.01	0.994	-0.112	0.113
mpce_mrp	0.000	$7.53 \times 10^{-7}$	20.90	0.000	0.000	0.000
Constant	-1.639	1.860	-8.81	0.000	-2.004	-1.275
hh_size	1	(offset)				

Source: Author Estimates. group variable considered—hh\_typeoffset variable (considering fixed effect)—hh\_sizelevel—1 (group variable-hh\_type).

No. of Observation—5000. No. of groups—4. Integration Points—7. Log likelihood— -2635.0129. Wald Chi2—4978.09. Prob > Chi2—0.0000.

<b>Random-Effects Parameters</b>	Estimate	Standard Error	95% Confidence Interval	
rel *	0.095	0.040	0.041	0.219
socgrp *	0.106	0.045	0.056	0.243

**Outcome Table A2: Logit Regression: Model 1.** 

LR test vs. logistic regression: chibar2(2) = 83.01 Prob  $\geq$  chibar2 = 0.0000. \* specific dummies.

Table A3. Logit Regression: Model 2.

	Coeff	Standard Error	Z	p > z	95% Confidence	Interval
hh_size	0.114	0.016	7.36	0.000	0.084	0.145
hh_type	-0.071	0.015	-4.51	0.00	-0.102	-0.040
rel *	-0.091	0.052	-1.75	0.080	-0.194	0.011
Socgrp	0.010	0.017	0.60	0.548	-0.023	0.043
mpce_mrp	0.000	$7.57 imes10^{-7}$	22.64	0.000	0.000	0.000
Constant	-1.912	0.280	-6.83	0.000	-2.460	-1.363

Source: Author Estimates. group variable considered-reloffset variable (considering fixed effect)—none, since rel is a group variable, effect considered is randomlevel-1 (group variable-rel). \* specific dummy. No. of Observation-5000. No. of Groups—4. Integration Points—7. Log likelihood—-2668.9793. Wald Chi2—532.74. Prob > Chi2—0.0000.

#### **Outcome Table A3: Logit Regression: Model 2.**

<b>Random-Effects Parameters</b>	Estimate	Standard Error	95% Confidence Interval	
rel *	0.281	0.117	0.124 0.638	
	a(04) = 4 = 4 < D = 1	1 11 0 0 0 0 0 0 1		

LR test vs. logistic regression: chibar2(01) = 15.16 Prob  $\geq$  chibar2 = 0.0000. \* specific dummy.

## Table A4. Logit Regression: Model 3.

	Coeff	Standard Error	Z	<i>p</i> > z	95% Confidence	Interval
hh_size	0.133	0.016	8.53	0.000	0.102	0.164
hh_type	-0.071	0.016	-4.47	0.00	-0.101	-0.039
rel *	-0.086	0.026	-3.35	0.001	-0.137	-0.035
Socgrp	-0.025	0.043	-0.59	0.558	-0.111	0.059
mpce_mrp	0.000	$7.74 imes10^{-7}$	24.07	0.000	0.000	0.000
Constant	-1.824	0.261	-7.00	0.000	-2.335	-1.313

Source: Author Estimates. group variable considered—socgrpoffset variable (considering fixed effect)—none, since the social group is group variable, the effect considered is random. level—1 (group variable-socgrp). \* specific dummy.

#### **Outcome Table A4: Logit Regression: Model 3.**

No. of Observation—5000. No. of Groups—4. Integration Points—7. Log likelihood— -2661.4289. Wald Chi2—600.11. Prob > Chi2—0.0000.

<b>Random-Effects Parameters</b>	Estimate	Standard Error	95% Confidence Interv		
Socgrp	0.253	0.102	0.114	0.560	
P test vs. logistic regression: $dihar2(01) = 20.26$ Prob $\geq dihar2 = 0.0000$					

LR test vs. logistic regression:  $chibar2(01) = 30.26 \text{ Prob} \ge chibar2 = 0.0000.$ 

# Appendix C

**Table A5.** Impact of District Profiles, Presence of Social Groups and Fuel.Quality on the Choice of Cooking Fuels.

Total Population	63,061
Likelihood Ratio	13.96
Probability	0.0000009
Log value of the likelihood ratio	-37.053
Explainability Factor	0.16

Source: Author Estimates.

# Appendix D

Table A6. Impact of Social Groups, Communities, Household Size on the Choice of Cooking.

	Coefficient	Standard Error	Z	P >  z
Cv	-0.0145812	0.0015198	-9.59	0.000
District	0.0152199	0.0073121	2.08	0.037
hh_size	0.3585109	0.0337609	10.62	0.000
rel *	0.2823244	0.1038493	2.72	0.007
socgrp **	0.1805408	0.0335194	5.39	0.000
Constant	-7.376072	0.3716588	-19.85	0.000

Source: Author Estimates. population size = 63051. log likelihood Ratio Chi Square Statistics = 16,286.50. Probability of the likelihood = 0.0000. Logarithmic value of likelihood of convergence = -35,886. Ratio of Explainability = 0.1850. \* proxy of belonging to a particular community group/identity (Group identity can often act as a driver in building the element of trust). \*\* proxy of belonging to local institutional frameworks/groups such as self-help groups (SHGs) (Belonging to a particular SHGs can often help in taking a collective decision).

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