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Fuel choices in rural Maharashtra

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ARTICLE INFO

Article history:
Received 13 December 2013
Received in revised form
10 July 2014
Accepted 12 September 2014
Available online 2 October 2014

Keywords:
Household energy
Energy ladder
Income elasticity
Improved stoves
India

ABSTRACT

We report on and analyze the results of an energy use survey in two tribal villages in rural Maharashtra, India. Though there is significant heterogeneity between the effects of the variables in the two villages there are some robust results. We find modest evidence for the 'energy ladder' hypothesis and that use of higher quality energy sources reduces total energy use, *ceteris paribus*. Income elasticities of fuel use are small. Additionally, we demonstrate that household size, stove ownership, and season influence energy choices. However, the effects of improved stoves are small and not consistent across the villages.

1. Introduction

An increasingly large share of global energy use and carbon emissions are accounted for by developing countries, yet the unique features of energy use in the developing world are often not accounted for adequately in international analyses [1,2]. This is particularly true of the use of traditional biomass, which many global models and studies simply ignore. Globally, 2.7 billion people still rely on traditional biomass as their main source of energy for cooking and heating and 1.3 billion people do not have access to electricity. The majority of these people live in sub-Saharan Africa and South Asia [3]. Where electricity is available in rural areas, supply is often intermittent and/or unreliable. The absence of efficient energy options limits the development scope of households [1] and has implications for the local and global environment, as well as the health of those who prepare meals due to indoor air pollution [4–7].

In India, much of the country's modern energy infrastructure is focused on urban centers, which dominate energy use [8]. Rural energy choices are constrained not only by low incomes, but also by thin markets for commercial fuels and equipment. Often, local availability constrains energy use more than either household budget limitations or energy prices [9]. Moreover, cooking accounts for the majority of rural residential energy consumption [10]. With limited resources and access to alternatives, households effectively rely on biomass to supply their most important energy service.

Effective public policy in developing countries also requires analysis of the factors that affect energy demand in the developing world [9]. Though data is now more available than in the past [10], there is still a need to better understand the factors determining energy use in the rural context. In this

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http://dx.doi.org/10.1016/j.biombioe.2014.09.005

paper, we examine the factors affecting fuel choices and total energy use of households in two villages in Maharashtra state using a primary data set collected by the first author.

Economic theory suggests that "households consume more of the same goods and shift towards higher quality goods as household income increases" [11] and this applies to energy services too. Higher quality fuels are those that provide more economic value per joule of energy content by being converted more efficiently, being more flexible or convenient to use, and by producing less pollution [12]. We would expect that lower income households would be more willing to tolerate the inconvenience and pollution caused by using lower quality fuels to produce energy services. So as household income increases, we would expect households to gradually ascend an "energy ladder" by consuming higher quality fuels and more total energy [9]. Many studies [13–17] have concluded that such an energy ladder exists. However, many more recent studies often find a more ambiguous picture where multiple fuels are used simultaneously with "fuel-stacking" as modern fuels are added to the use of traditional fuels [18–20] or that there is reluctance to move up the ladder [21]. Gupta and Köhlin [22] test the energy ladder hypothesis in India by estimating regressions for the individual demands for fuelwood, coal, kerosene, and liquid petroleum gas (LPG) in Kolkata. They determine that wood, coal, and kerosene act as inferior fuels, while LPG is normal. This implies that as incomes rise, households in Kolkata switch from less efficient fuels to more efficient ones. Reddy [23] researched energy choices for households in Bangalore employing a series of binomial logit models to evaluate the choice between energy pairs. His results suggest that households ascend an energy ladder and that income and some socio-demographic variables are important determinants of energy demand. More recently, Farsi et al. [9] applied an ordered probit model to cooking fuel choices in urban households. Their results indicated that a lack of sufficient income is one of the main factors constraining households. Additionally, several social and demographic factors, including the education and gender of the head of the household, were also found to be important. Other relevant studies for India include Gundimeda and Köhlin [24], discussed below, Heltberg et al. [25] who study total energy consumption, consisting of wood, dung and crop residues in four Rajasthani villages, Köhlin and Amacher [26] who model fuelwood collection in Orissa, World Bank [27] who employ a multinomial logit model to represent household fuel choice for both rural and urban households, Khandker et al. [10] who analyze a large national survey for both rural and urban households, and Pandey and Chaubal [28] who analyze rural households from another national survey. Together, these studies tepidly support the 'energy ladder' hypothesis for India.

Nevertheless, it is interesting to note that many estimated income elasticities of low quality fuels are actually insignificant or even positive [29–32]. This suggests that for many rural households, wood, crop residues, and dung may actually represent normal goods. Hosier and Dowd [13] concede that the energy ladder may not be applicable to all households. In fact, cultural and social preferences may be equally as important as economic ones [9]. Khandker et al. [10] find that even total energy use is not responsive to increased income in the lower half of the income distribution in a large sample of households in rural India.

Obviously, prices are a major determinant of energy use, though as is well known, energy demand is very inelastic [33] and many studies find that prices have a limited effect on fuel choice (e.g. Ref. [34]). Substitution between fuels due to changes in relative prices may also not be so easy in the short run [33,35]. However, Gundimeda and Köhlin [24] found Marshallian (uncompensated) own price elasticities ranging from -0.59 to -1.05 for various fuels in rural India, which is more elastic than is typical for fuels, and (compensated) cross-price elasticities as high as 0.843 for the effect of a rise in the price of LPG on demand for fuelwood in low income rural households. In common with some other rural Indian studies (e.g. Ref. [25]), we did not obtain price data from our field study and energy use was dominated by self-collected firewood. In any case, with data collected from two neighboring villages over the course of a year, price variation was probably limited.

More efficient energy conversion technologies, such as improved stoves and electricity, can reduce energy use [33,36]. There is mixed evidence, however, as to whether technological change actually reduces demand [25,29,37–39]. There are many factors that may reduce or even eliminate any efficiency gained through better technology. For example, stoves may be in disrepair, operated improperly, used sparingly, designed with features other than efficiency in mind, or cause households to consume more energy through the rebound effect [39–41]. Jeuland and Pattanayak [42] carry out a Monte Carlo simulation cost-benefit model that shows that the private net benefits of improved cooking stoves will sometimes be negative, and in many instances highly so. Hanna et al. [41] found that a large share of the 2600 households that received free improved stoves in a randomized control trial failed to maintain them properly so that usage declined significantly after the first year of the trial. Andrianzen [40] found that the iron frames in half the stoves distributed in a region of the Peruvian Andes had failed within five years of distribution, which was among the reasons why many households had stopped using the improved stoves.

Besides the traditional energy choice determinants of price, income, and substitutes, the importance of contextual factors is well documented in the literature [29,32,43]. Household characteristics, including number of members, gender composition, and education, are all associated with 'fuel switching' [21]. Similarly, cultural characteristics, such as religion or caste, can have a pronounced influence on energy use [18]. Fuel characteristics other than price may also play a role in household decision-making, including: ease of use, availability, and pollution generation [18]. Finally, spatial and temporal characteristics, such as geographic location and season, affect household practices.

The model we develop in this paper tests the importance of the various factors described above on energy use and fuel choice in two tribal villages in Maharashtra State, India. The remainder of the paper is organized as follows. First we describe the location in India where our data were collected followed by the design of the survey in section three, the statistical model in section four, and results and analysis in section five. The final section of the paper presents a discussion and conclusions.

2. Location

The survey described below was carried out in two tribal villages in Maharashtra State northeast of Mumbai: Kohane and Purushwadi. Fig. 1 shows the locations of the two villages. Kohane is located at 19° 25′ 09″ N, 73° 51′ 47″ E at 900 m above sea level a few kilometers to the southeast of Purushwadi, which is at 19° 27′ 51″ N, 73° 50′ 08″ E at close to 800 m above sea level. Both Kohane and Purushwadi are dominated by the Hindu Mahadev-Koli tribe constituting 95% of those surveyed. The Indian Constitution classifies this group as a 'scheduled tribe' [44]. This tribal group is concentrated in the Maharashtran Districts of Pune, Ahmednagar, and Nasik, near the Mahadev Hills. Their principal occupation is agriculture but they also engage in wage labor, cattle breeding, and dairy and poultry farming.

The majority of households in both Kohane and Purushwadi are situated in a centralized village, surrounded by agricultural fields. At the time of our survey, all families relied on a chulla – a biomass fueled cooking device with a 'U'-shaped enclosure situated on the floor and made of brick, mud or concrete – for their primary cooking needs. Most families also owned additional cooking devices, typically used as secondary appliances for activities requiring minimal supervision or a localized flame, such as making chai, cooking rice, or warming food.

Since chullas were the primary cooking devices, families relied heavily on biomass. The villagers' preferred fuel was wood, which was occasionally supplemented by dung. Also, many households used a small amount of kerosene as a fire starter. Plant residues were not used for cooking purposes; instead they were stored and used for soil enrichment prior to the planting season. Depending on household size, wood was collected about two times per week in approximately 25 kg headloads. It was obtained from private stocks grown between fields or from the surrounding hills. Dung, on the other hand, was collected daily from the household livestock.

The overwhelming majority of households in both villages prepared and ate two meals per day. The first was close to midday, while the second occurred in the evening. At the start of each day, a fire was used to prepare morning chai and to heat water for bathing purposes. The same fire was kept going throughout the morning and was eventually used to prepare the midday meal after which it was extinguished. It was reignited in the evening for both meal preparation and heating purposes. Thus, there were two lengthy fuel-burning events per day.

Fig. 1 – Locations of Purushwadi and Kohane within western Maharashtra, India.

Both Kohane and Purushwadi are connected to the electricity grid. Most houses near the central areas of the villages had a connection, legal or otherwise, with 47% of households surveyed having some form of connection. Electricity was used exclusively for lighting and electronic devices, which were very rare. The region's electricity schedule was eight days of power followed by eight nights of power. Thus for long periods electrical lighting was unavailable. Because the use of electricity was very low, we did not collect data on electricity consumption, but we do control for an electricity connection in our regression analysis. Kerosene was a ubiquitous substitute for electric lighting, which in India is subsidized and distributed through the Public Distribution System, though black market supplies also exist [45]. Households in this area reported to us that they were permitted a quota of 5 L of kerosene per month. Since this quantity is insufficient for cooking needs, it was almost exclusively used for lighting as is usual in rural areas in India [45]. The current allocation in rural areas of Maharashtra for households not using a gas ration are 2 L per capita up to a maximum of 15 L [46]. All households owned at least one kerosene lamp, with many using two or three. Kerosene markets were absent in the surrounding region and it could not be purchased in either village. Although limited black market sales occurred, most kerosene purchases were made in the nearest towns, around 3 h traveling time by share jeep.

3. Survey design and data collection

The survey was designed and implemented by Gregory in 2009–10 for Watershed Organisation Trust (WOTR), an Indian NGO based in Pune, Maharashtra. Their mission is "to provide committed development support that motivates, energizes and empowers individuals, groups, communities and other organizations and to undertake integrated ecosystems development for enhancement of well being on a sustainable basis" [47]. The NGO's activities focus on halting land degradation and reducing water scarcity by developing social cohesion and human capital in rural villages. It works with communities to ameliorate both economic and environmental outcomes. The data for this study was originally requisitioned for the quantification of rural greenhouse gas emissions as part of a larger environmental accounting process throughout the WOTR's region of operation.

Following the Indian census, we defined a household as a group of people who regularly use common cooking devices [48]. In total, there were 257 households in the two villages. Villagers assigned households to wealth ranks: very poor, poor, average, and better off. The village people themselves agreed on the criteria for the rankings, and thus, they reflect the socio-economic circumstances of a specific village. We randomly selected 110 households so that the distribution of wealth ranks in the sample roughly matched those in the population (see Table 1). This ensured that we would have a sample of at least 100 households after eliminating erroneous surveys. However, out of a survey sample of 100, only 13 households were either 'very poor' or 'better off'.

Data collection was performed in person using a structured survey. The head male or female of each household was the preferred respondent, although all family members were encouraged to participate. The survey was primarily composed of questions relating to fuel usage, specifically regarding cooking and lighting; although it also covered some basic socio-economic indicators, such as family size, market income, and caste. We field-tested the survey in May 2009, in the village of Sattichewadi, Maharashtra. Data was collected in three survey rounds in June 2009, January 2010, and October 2010 corresponding to the summer, winter, and monsoon seasons, respectively. We completed our on-site work for each survey round over a single week.

Table 1 – Kohane and Purushwadi household population and sample by wealth ranking.

Wealth ranking	Total households	Sample	Qualified sample
Very Poor	21	9	8
Poor	115	49	45
Average	107	46	42
Better off	14	6	5
Total	257	110	100

We instructed the survey respondents to provide us with a physical sample of their daily fuel use. Interviewers measured the sample using a 25 kg hanging scale, a 2–5 kg basket scale or a 200 mL graduated cylinder. Where measurements of this type could not be made, participants' educated guesses were accepted. We converted all mass and volume data to energy units so that the different fuels could be compared on a common basis. Energy conversion factors for wood, dung, and kerosene are taken from Ref. [49], while density values are provided by Ref. [50]. These factors are not species specific, but do take into account the moisture content of samples.

We found that the primary cooking-related fuel source was wood with a mean overall household consumption of 11.2 ± 0.5 kg per day and 100% utilization amongst the surveyed households. The types of wood used from greatest to least overall mean mass were dry branches, thick wood, and sticks. Dung was used less frequently than wood, and accounted for 2.3 ± 0.3 kg per day.

As wood was clearly the most prominent fuel source, we also collected data on the species of trees used (Table 2). We asked the respondents to list all types of trees used and then rank their frequency of use. Thus, the responses have been compared based on two criteria: the frequency of entries and the frequency of first ranks. With these in mind, the evergreen spindle tree is the most important, as it has more first ranks than the three next most cited species combined despite being mentioned by fewer households.

As the original purpose of the survey was to provide an estimate of greenhouse gas emission patterns in tribal villages, we did not collect any data on prices. Opportunity cost variables, such as collection time and alternative wage rates can be used in place of market prices where fuels are largely produced through subsistence activity but we did not collect such data either. Ekholm et al. [51] do provide average rural fuel prices in 2000, including biomass and kerosene. But this national average data is not useful for explaining the variation in behavior across households and seasons.

Table 2 – Wood species used for cooking/boiling.

Common name	Species name	Frequency of entries	Frequency of first ranks
		#	#
Evergreen spindle tree	*Strobilanthes callosus*	46	39
Lantana	*Lantana camera*	52	22
Karonda	*Carissa carandus*	57	9
Indian laurel	*Terminalia tomentosa*	66	7
Mango tree	*Mangifera indica*	41	6
Black myrobalan	*Terminalia chebula*	44	3
Crape myrtle	*Lagerstroemia parviflora*	33	2
Jamun	*Syzygium cumini*	28	1
Indian tulip	*Thespesia populnea*	11	1
Myna	*Vangueria spinosa*	26	0
Cluster fig tree	*Ficus racemosa*	12	0
–	Other	61	6
Total		477	96

From conception of the survey to data collection there were three main interfaces: between the survey developers and the translators, the translators and the interviewers, and the interviewers and the respondents. Each additional step was an opportunity for the intention of the survey, which was originally prepared in English and then translated into Marathi, to be confused. We worked closely with a small team of translators to ensure the essence of the questions remained unaffected. Furthermore, the field test assisted in highlighting inconsistencies that we were able to correct prior to commencing the actual data collection. We facilitated the interviewers' understanding through a training program, which instructed them on the objectives and methods of the survey so that they could link questions to the desired information. We also engaged them in a number of mock interviews, which provided an opportunity to teach through practice.

Even with careful field-testing and well-prepared interviewers, it is impossible to guarantee the reliability of respondents' answers. We encouraged interviewers to be creative and persistent in searching for the necessary information. We found the best way to develop such skills was to share experiences on a regular basis. After each day, a group debriefing session was held. The meetings reinforced our objectives and the proper interview techniques. Unfortunately, the same team leaders did not carry out the three seasonal surveys. Therefore, many of the on-site practices may not have followed the exact methods outlined above. Moreover, even though the same households were interviewed each time, it was impossible to identify specific households through time.

4. Statistical model

We estimate regressions for total energy use and the quantity shares of the various fuels in total energy use. Lacking price data, we assume that energy use is a function of income per capita, household size, the quantity shares of the various fuels, and other control variables. The first two variables are uncontroversial. Household size is included separately from income per capita to allow us to test for economies of scale in household size and income effects separately. The quantity shares of the fuels are included because we hypothesize that a household with a higher quality energy mix, will, *ceteris paribus*, consume less energy. Following Gupta and Köhlin [22] we estimate a double log specification for total energy use:

$$\ln(E_i) = \alpha_0 + \alpha_1 \ln(y_i) + \alpha_2 \ln(h_i) + \sum_{j=1}^{2} \alpha_{j+2} s_{ji} + \sum_{k=1}^{K} \alpha_{k+4} x_{ki} + \varepsilon_i \tag{1}$$

where E_i is the total energy used for cooking and lighting per household i, y is income per household, h is the number of household members, and the s_j are the quantity shares of wood and kerosene in energy use. As the shares sum to unity we omit the share of dung from the equation. The x_k represent the K other exogenous determinants, the α_i are the regression coefficients, and ε is a random error term.

Various approaches have been taken to estimating fuel choice equations depending on the data available. With complete price and quantity information fully flexible demand systems such as AIDS can be estimated (e.g. Ref. [24]). With more restricted information various logit and multinomial logit (e.g. Refs. [13,52]) or probit (e.g. Ref. [22]) specifications are typically used. Given that in our sample most households use some of all the fuels we chose a simpler specification for fuel choice equations, assuming that the quantity shares, s_j, are linear functions of the logs of income, household size, and the control variables:

$$s_{ji} = \frac{e_{ji}}{E_i} = \beta_{j0} + \beta_{j1} \ln(y_i) + \beta_{j2} \ln(h_i) + \sum_{k=1}^{K} \beta_{jk+2} x_{ki} + \nu_{ji} \tag{2}$$

where j is the index for the fuels – wood, dung, and kerosene, e_j represents the fuel used per household, and ν_j represents a random error term, while all other variables are defined as in (1). We also estimated energy use regressions for each individual fuel. The results were reasonably consistent with those for the shares. A variety of alternative models exist for compositional data of this type but the most common approach of log ratios of the shares cannot be estimated where some shares are zero [53], which is the case here for dung in some households. Fry et al. [53] recommend replacing

Table 3 – Summary statistics.

Variable	Units	Mean	Std. dev.	Min	Max
Monthly income p.c.	$ per capita	11.37	9.81	1.45	81.10
HH size	Persons	6.0	2.6	1	18
Share females		0.49	0.15	0	1
Share children		0.24	0.20	0	0.80
Household daily energy use	MJ	221	107	31	875
Wood share		0.86	0.09	0.36	0.99
Dung share		0.11	0.08	0	0.57
Kerosene share		0.04	0.04	0	0.35
Kerosene stove	Dummy	0.18	0.38	0	1
Other stove	Dummy	0.04	0.19	0	1
Electricity	Dummy	0.47	0.50	0	1

the zeros with a small number but Aitchison and Egozcue [54] argue that this is not appropriate where the true value really is zero. The income elasticities of individual fuels are given by:

$$\frac{\partial \ln(e_j)}{\partial \ln(y)} = \frac{\partial \ln(E)}{\partial \ln(y)} + \frac{\beta_{j1}}{s_j} \tag{3}$$

which states that each elasticity is equal to the sum of the income elasticity of total energy use and the ratio of the income effect from (2) to its quantity share. Evidently, as a household uses greater quantities of a given fuel relative to other fuels, the second term shrinks and its income elasticity gets closer to that of total energy use. The income elasticity of total energy use is:

$$\frac{\partial \ln(E)}{\partial \ln(y)} = \alpha_1 + \sum_{j=1}^{2} \alpha_{2+j}\beta_{j1} \tag{4}$$

Similar expressions can be derived for the elasticities with respect to the other exogenous variables.

Equations (1) and (2) form a recursive system, which we estimate using the seemingly unrelated regression estimator. The sample has large observed variations in both household size and income, which could be a source of heteroskedasticity. Therefore, we use heteroskedasticity robust standard errors.

5. Results and analysis

5.1. *Summary statistics and correlations*

Table 3 provides an overview of the variables we use in our statistical analysis. The first four are household socio-economic observations. We convert income data to U.S. Dollars at the exchange rate of 1 January 2010 of 46.29 INR per U.S. Dollar. The average monthly income per capita was $11.37, while the average household size is approximately 6 people. This income level is only around 1/10 of Indian GDP per capita but consists of market income only and does not include the value of subsistence production. It would be good to have a broader measure of income, but unfortunately we did not collect such data. As noted in the previous section, both values have a high variance. The shares of females and of children less than or equal to 14 years-of-age are important variables because these groups typically eat less food and might use less energy than an average adult male.

The following four variables represent the energy data. We combined wood, dung, and kerosene measurements into a common unit. On average, households in Kohane and Purushwadi consume 221 MJ per day (not including any use of electricity), though consumption varies over a wide range. Of the energy consumed, most is derived from wood, followed by dung, and then kerosene. Over 90% of daily energy needs result from cooking, which is primarily satisfied by wood or dung. Kerosene is primarily reserved for lighting purposes, which requires much less energy input. Only 19% of the kerosene consumed was used for cooking purposes. Average per capita household energy use in rural India is 24 MJ per day and, excluding electricity, 90% is derived from biomass. But only 64% of traditional energy is provided by fuelwood [10].

Fig. 2 illustrates the range and relationship of the income and energy use per capita variables. There is a very large variation in per capita energy use at any given level of per capita income and a wide range of incomes. There is a weak positive linear relationship between the two variables and there are no obvious outliers when logarithmic axes are used.

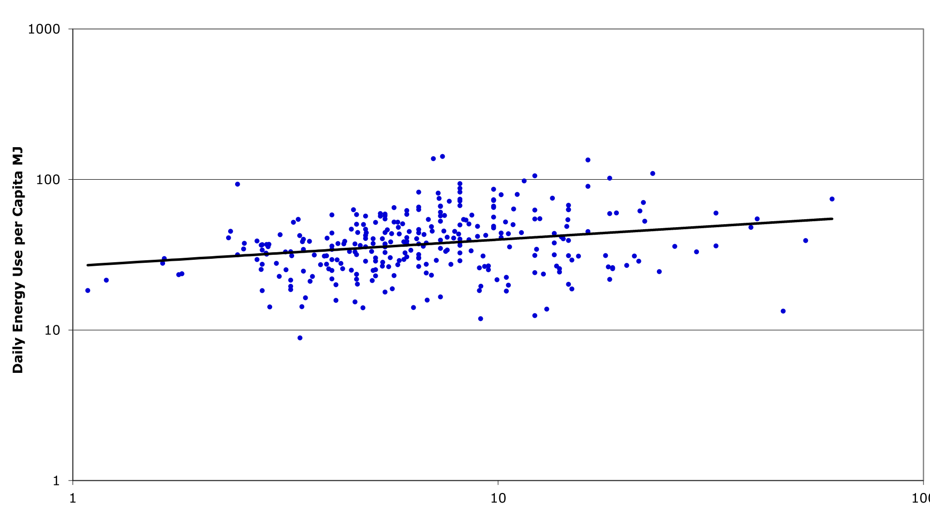

Fig. 2 – Energy use and income.

There appears to be a significant difference in the relationship between income and energy use in the two villages, which will be explored in the econometric analysis. Fig. 3 shows per capita energy use in each village arranged by per capita income quintile. There is little variation in energy use by income quintile in Kohane with the middle quintile having the highest energy use. In Purushwadi per capita consumption of both wood and kerosene increase strongly with income. Neither pattern is typical for rural India as a whole, where biomass consumption seems to be constant with income while the use of modern fuels increase with income [10].

The final three variables in Table 3 relate to technological advances. We have included two types of stoves – kerosene and other – along with access to electricity. Kerosene stoves were of two types, pressure and wick, while the other stoves included both improved biomass stoves and LPG stoves. These more technological advanced appliances should reduce household energy use, *ceteris paribus*. The default is, therefore, an unimproved traditional stove.

In addition to the variables listed in Table 3, we also defined dummy variables to indicate location and season. The Kohane dummy is equal to 1 for Kohane and 0 for Purushwadi so that the default results are for Purushwadi. We use two seasonal dummies as markers for the summer and monsoon seasons. Their regression coefficients represent the difference in energy usage between energy use in the summer and monsoon seasons and the winter season, *ceteris paribus*. The default results are, therefore, for the winter season.

Table 4 presents the correlation coefficients between the dependent variables, income, and household size and all the other variables. As we expected, total energy use is negatively correlated with the share of kerosene and positively correlated with the share of wood. Higher total income and larger household size are positively associated with total energy use but higher per capita income is in fact negatively correlated with total energy use. This is probably because income per capita is negatively correlated with household size and there are economies of scale in energy use. Income per capita is positively correlated with energy use per capita. The various improved types of stoves are only slightly negatively correlated with total or per capita energy use. Electricity connection is associated with higher energy use, likely because it is positively correlated with household size and income. A larger share of children is associated with lower per capita energy consumption as expected. Residents of Kohane have higher income and larger households and use less wood and more kerosene and dung but total energy use is lower in Kohane. Energy use is lower in summer and the monsoon season relative to winter as might be expected. Total income does have the expected relationship with the four wealth rankings but per capita income does not. It seems that villagers assessed households by total resources rather than per capita resources when assigning them to wealth rankings or it is possible that market income substitutes for wealth in the form of land.

5.2. *Regression results for the base model*

Estimates of the base model are presented in Table 5. The effect of income is small in each equation and is not very statistically significant. The income elasticity of energy use is just 0.05. There are several likely explanations for this. First, income only includes market income, so, if subsistence income and market income are substitutes, then total income and market income may not be very correlated. As discussed above, there is a low correlation between the wealth rankings and income. Second, this may be the result of thin markets and environmental constraints. The kerosene market is restricted through monthly household consumption limits, and while wood is clearly the most abundant fuel available, there may be limits to the amount that can be collected. Third, there may be a ceiling at which point basic cooking and

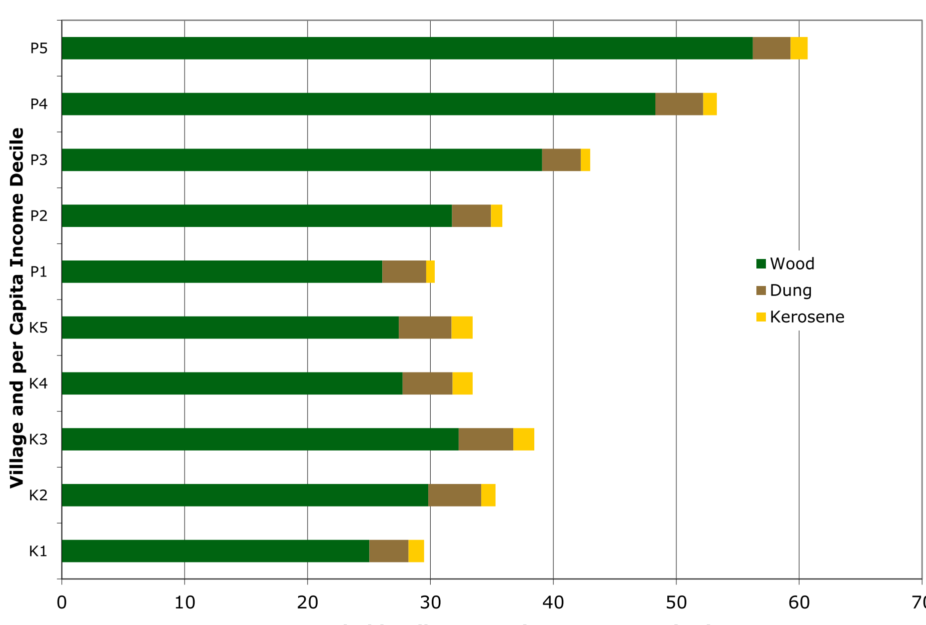

Fig. 3 – Per capita energy use by village and per capita income quintile.

Table 4 – Correlation coefficients.

	ln energy	Share kerosene	Share wood	Share dung	ln income	ln HH	ln energy/HH	ln income/HH
ln energy	1.00	−0.35	0.18	−0.04	0.19	0.52	0.42	−0.22
Share kerosene	−0.35	1.00	−0.44	0.05	0.07	−0.06	−0.28	0.11
Share wood	0.18	−0.44	1.00	−0.92	0.04	0.06	0.11	−0.01
Share dung	−0.04	0.05	−0.92	1.00	−0.07	−0.04	0.00	−0.04
ln income	0.19	0.07	0.04	−0.07	1.00	0.35	−0.18	0.70
ln household size (HH)	0.52	−0.06	0.06	−0.04	0.35	1.00	−0.55	−0.43
ln energy/HH	0.42	−0.28	0.11	0.00	−0.18	−0.55	1.00	0.24
ln income/HH	−0.22	0.11	−0.01	−0.04	0.70	−0.43	0.24	1.00
Kerosene stove	−0.03	0.33	−0.25	0.13	0.02	0.06	−0.09	−0.02
Other stove	−0.03	−0.06	0.10	−0.08	0.05	−0.03	0.00	0.07
Electricity	0.16	−0.05	0.06	−0.04	0.10	0.12	0.03	0.01
Share female	0.02	0.02	−0.01	0.00	−0.02	0.02	0.00	−0.04
Share children	0.18	−0.06	0.04	−0.02	0.12	0.43	−0.27	−0.21
Kohane	−0.19	0.32	−0.30	0.19	0.15	0.05	−0.24	0.11
Summer	−0.09	0.06	−0.17	0.17	−0.17	0.01	−0.11	−0.18
Monsoon	−0.16	−0.12	0.00	0.05	0.12	−0.05	−0.10	0.16
Very poor	−0.12	0.01	0.10	−0.12	−0.12	−0.22	0.12	0.05
Poor	0.07	−0.10	0.05	−0.01	−0.08	−0.01	0.08	−0.07
Average	−0.04	0.14	−0.14	0.09	0.08	0.16	−0.21	−0.05
Better off	0.07	−0.11	0.07	−0.03	0.15	−0.06	0.14	0.20

lighting needs are met, causing households to shift consumption towards other goods especially as electricity use is not included in our measure of energy use. Khandker et al. [10] find that increased income has no effect on total energy use in the lower half of the income distribution of a large sample of households. Therefore, our result is not so surprising.

Increased income has very small positive effects on the shares of kerosene and wood and, therefore, a negative effect on the share of dung, as the coefficients of each variable sum to zero across the three quantity share equations. The signs on the income variables are consistent with expectations. Corresponding to the energy ladder, greater incomes encourage more energy use as well as a shift towards higher-quality fuels, in this case, kerosene and wood. Nonetheless, any general conclusions should not be overstated, as the coefficients are close to zero and not very statistically significant. If we had collected data on electricity consumption and included it in the model, it is possible that these income effects would be larger, though electricity consumption was very low even in the highest income households.

Unsurprisingly, household size is a highly statistically significant driver of energy use. There are, however, economies of scale such that the coefficient of the log of household size in the energy use equation is only 0.46. Household size appears to have little impact on the fuel shares. The share of wood is possibly larger in larger households, which could be connected to having more labor available to collect it and constraints on the quantities of the other fuels available. The share of kerosene is lower in larger households.

The shares of wood and kerosene have a negative effect on energy use. The relationship between the kerosene share and energy use is statistically significant at the 1% level, which should be expected as it is a much more efficient fuel than either wood or dung. Wood also appears to be a higher

Table 5 – Energy use and fuel shares: regression results.

Regressors	Energy use (ln)		Kerosene share		Wood share		Dung share	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Constant	4.877	13.22	0.007	0.22	0.843	12.73	0.150	2.48
Income (ln)	0.050	1.55	0.005	1.23	0.005	0.54	−0.009	−1.26
HH size (ln)	0.459	10.48	−0.007	−1.89	0.011	0.93	−0.004	−0.35
Kerosene share	−4.472	−3.86						
Wood share	−0.419	−1.29						
Kerosene stove	0.064	1.147	0.024	3.20	−0.043	−2.61	0.018	1.25
Other stove	0.002	0.025	−0.014	−1.80	0.057	2.43	−0.044	−1.84
Electricity	0.038	0.93	−0.007	−2.13	0.010	1.05	−0.003	−0.29
Female share of HH	0.137	1.05	−0.003	−0.30	0.024	0.90	−0.020	−0.77
Children share of HH	−0.168	−1.60	−0.007	−0.88	0.002	0.08	0.005	0.17
Kohane	−0.150	−3.24	0.019	6.32	−0.052	−5.22	0.034	3.44
Summer	−0.214	−4.34	−0.001	−0.19	−0.040	−3.29	0.041	3.53
Monsoon	−0.278	−6.34	−0.008	−1.68	−0.027	−2.58	0.035	3.68
DF	287		289		289		289	
R^2	0.475		0.205		0.187		0.117	

quality fuel in our context but the effect is smaller and less significant.

The following three regressors in the table are dummy variables for the various advanced technologies. None of these are significant at conventional significance levels in the energy use equation. As Nepal et al. [38] also found, improved biomass stoves do not, therefore, help in reducing energy use. These dummy variables do, however, have statistically significant effects on the fuel share equations. Kerosene stoves are associated with increased kerosene and reduced wood shares and other stoves are associated with increased wood and reduced dung shares. We hypothesize that reduced smoke from improved stoves could result in more use of these stoves and hence higher wood consumption. However, research shows that possession of a stove does not mean that it is necessarily used [41] and most households in our study area still retained traditional stoves in addition to the improved varieties. Electricity appears to substitute for kerosene, as we would expect.

Household demographic features have effects on total energy use, though they are not very statistically significant. A larger female share is associated with greater energy use and a larger share of children with less energy use, *ceteris paribus*. Presumably, more female household members means more cooking activity, while children need less food than adults.

The Kohane dummy variable is statistically significant at the 1% level across all equations, indicating that geographical location is important. Kohane uses less energy on average, while consuming more kerosene and dung and less wood than Purushwadi. As Kohane has less woody biomass available, alternatives were more prevalent. The seasonal variables were also statistically significant. Less energy is consumed on average in the warmer periods – summer and monsoon – compared to winter. It is also interesting to note that the share of kerosene and wood decrease in the warmer periods, while dung increases. There are two likely explanations for this trend. First, dung may be used for different purposes during the warm and cold periods of the year. Traditionally, the dry or winter periods are when households make repairs to their dwellings, which consist primarily of a mud-dung mixture. As such, there would be less available for cooking purposes. Alternatively, it may be a result of less energy use during the warmer periods. Households could cut back on costly fuels, and increase the share of cheap, easily accessible alternatives.

We analyzed our full energy use specification for outliers. We identified these by calculating studentized residuals [55] and applying a Bonferroni *t*-test [56]. We calculated leverage and influence – based on Cook's distance [55] – for each value; however, none were determined to significantly alter our conclusions.

5.3. *Alternative specifications and data groupings*

The results in the previous section show that income only has small and not very statistically significant effects on total energy use and the fuel shares. In this section we investigate how robust these findings are by testing some alternative model specifications and estimating separate regressions for the two villages.

It is possible that some of the explanatory variables – specifically, the various stove technologies and electricity connections – are not exogenous but are instead affected by income. Controlling for these variables will reduce the measured effect of income on energy use. However, in Table 4 the correlations between these technology dummies and income are low. We tested excluding these variables from all equations. However, the coefficients and standard errors of the remaining variables were hardly changed.

Gundimeda and Köhlin [24] demonstrate that the level of expenditure influences income elasticities for fuelwood. They found that the elasticities were above unity until expenditures reached 750 Rs ($17.29 at the exchange rate of 30 June 1999) per month. Our first test of this hypothesis was to add the square of the logarithm of income to each equation. In the total energy use equation the coefficient of the log of income is 0.706 ($p = 0.13$) and that of its square -0.042 ($p = 0.16$). This suggests that the income elasticity is higher at lower incomes though the joint significance of the two income terms is only $p = 0.15$. Other results were essentially unchanged. Looking at Fig. 2 there is little sign of non-linearity in the relationship between income and energy use per capita. We also tested adding the wealth rankings to the regressions but their coefficients were all statistically insignificant.

Next, we looked at whether the relationship between energy use and income per capita varies by season, wealth rank, and village. Table 6 gives the correlations between these variables in the subsamples of the data. As shown in Table 4 the correlation between these two variables in the full sample is 0.24. However, the correlations in the two villages are very different: 0.12 and 0.53. There appear to be higher correlations between income and energy use in the better-off wealth rank and winter. But it turns out that better-off households only occur in Purushwadi and the correlation in winter in Kohane is only 0.17, while in Purushwadi it is 0.50. Across the various possible groupings the correlations are consistently higher in Purushwadi. We do not know the reason for this.

Adding an interaction between income and the Kohane dummy to the regression resulted in an income elasticity of 0.20 in Purushwadi ($p = 0.0004$) and a negative but insignificant elasticity in Kohane. However, we decided to present separate estimates for the two villages in Tables 7 and 8. As expected, the results are quite different for the two villages. The coefficient of income in the energy use equation is 0.144 in Purushwadi but insignificantly different from zero in Kohane. Energy ladder effects are more mixed than in the pooled model. Seasonal effects also have a somewhat larger effect in

Table 6 – Correlations between income and energy use per capita by group.

	Total	Kohane	Purushwadi
Total	0.24	0.12	0.53
Very poor	0.18	0.11	0.49
Poor	0.20	0.07	0.48
Average	0.19	0.15	0.60
Better off	0.58		0.58
Summer	0.23	0.13	0.40
Monsoon	0.19	0.19	0.49
Winter	0.35	0.17	0.50

Table 7 – Regression results: Purushwadi.

Regressors	Energy use (ln)		Kerosene share		Wood share		Dung share	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Constant	4.553	6.74	0.037	1.69	0.810	9.79	0.153	1.92
Income (ln)	0.144	2.27	−0.001	−0.33	0.018	1.73	−0.017	−1.69
HH size (ln)	0.421	6.79	−0.003	−1.00	−0.011	−0.79	0.014	1.06
Kerosene share	−8.467	−5.50						
Wood share	−0.604	−1.20						
Kerosene stove	−0.105	−1.30	−0.002	−0.35	−0.008	−0.23	0.010	0.29
stove other	−0.255	−1.67	−0.01	−1.58	−0.124	−5.16	0.133	5.73
Electricity	−0.024	−0.42	−0.000	−0.02	−0.003	−0.22	0.003	0.24
Female share of HH	0.143	0.71	−0.002	−0.24	0.028	0.62	−0.025	−0.62
Children share of HH	0.052	0.30	−0.001	−0.10	−0.001	−0.03	0.002	0.06
Summer	−0.423	−4.92	0.003	0.62	−0.070	−4.66	0.067	4.94
Monsoon	−0.320	−3.93	0.003	0.95	−0.084	−6.28	0.081	6.22
DF	104		105		105		105	
R^2	0.619		0.028		0.344		0.361	

Purushwadi. Both villages have similar energy quality effects on total energy use, though they are stronger in Purushwadi.

Improved stoves have a negative effect on energy use in Purushwadi and a significantly negative effect on the share of wood in Purushwadi and a positive one in Kohane. Electricity connections have a positive effect on total energy use in Kohane. Several other significant effects have opposite signs in the two villages. Kerosene stoves increased the share of kerosene in Kohane but had no effect on shares in Purushwadi. Other stoves reduced the kerosene and wood shares in Purushwadi but increased the wood share in Kohane.

5.4. *Elasticities*

Table 9 presents estimates of income elasticities for total energy and the individual fuels. The elasticities for the fuels are computed using (3) with the effects of income on the shares of kerosene and wood factored into the total effect of income on energy use. First the models were re-estimated using de-meaned explanatory variables so that the constants in the share equation are then the predicted sample mean shares [57]. Equation (3) can then be computed for the sample mean as a function of regression parameters alone and standard errors computed using the delta method (via the SUMMARIZE command in RATS).

Because of the positive effects of income on the shares of wood and kerosene in the sample as a whole and the negative effects the shares of these fuels have on total energy use the income elasticities of total energy use are less positive than the coefficients of income in the energy use equation. Income elasticities for kerosene are positive but small and not very statistically significant. The income elasticity of wood is positive in Purushwadi and negative in Kohane. Dung has a negative but insignificant income elasticity in each sample. These findings provide some support for the existence of an energy ladder in these villages.

Similar expressions to Equation (3) can be derived for the other variables in the model. Of particular interest are the technology variables. The positive effect of kerosene stoves in Kohane on kerosene use dominates due to the larger sample from that village. Kerosene stoves have negative effects on wood use and positive effects on dung use though none of these elasticities are significant. Other stoves have larger effects. They reduce kerosene use in all samples. They reduce

Table 8 – Regression results: Kohane

Regressors	Energy use (ln)		Kerosene share		Wood share		Dung share	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Constant	5.306	11.64	−0.001	−0.02	0.837	9.19	0.164	2.03
Income (ln)	−0.029	−0.73	0.010	1.55	−0.009	−0.71	−0.001	−0.14
HH size (ln)	0.479	7.58	−0.014	−2.12	0.040	2.05	−0.026	−1.35
Kerosene share	−3.900	−3.33						
Wood share	−0.521	−1.29						
Kerosene stove	0.041	0.66	0.028	3.42	−0.044	−2.54	0.016	0.99
Other stove	0.006	0.07	−0.011	−1.21	0.071	3.55	−0.060	−3.31
Electricity	0.091	1.77	−0.011	−2.29	0.014	1.08	−0.002	−0.20
Female share of HH	0.096	0.59	0.002	0.11	0.000	0.01	−0.002	−0.06
Children share of HH	−0.227	−1.75	−0.005	−0.42	−0.002	−0.07	0.007	0.19
Summer	−0.058	−0.99	−0.006	−0.79	−0.017	−0.98	0.023	1.37
Monsoon	−0.211	−3.55	−0.019	−2.09	0.018	1.23	0.001	−0.11
DF	175		176		176		176	
R^2	0.435		0.163		0.142		0.072	

Table 9 – Elasticities at the sample mean.

Dependent variable	Sample	Income	Kerosene stove	Other stove	Electricity
Total Energy	Pooled	0.026	−0.028	0.039	0.066
		(0.72)	(−0.48)	(0.44)	(1.56)
	Purushwadi	0.141	−0.086	−0.099	−0.021
		(2.04)	(−1.09)	(−0.74)	(−0.34)
	Kohane	−0.064	−0.047	0.014	0.128
		(−1.50)	(−0.74)	(0.15)	(2.47)
Kerosene	Pooled	0.154	0.593	−0.31	−0.118
		(1.62)	(3.52)	(−1.60)	(−1.46)
	Purushwadi	0.100	−0.153	−0.488	−0.024
		(0.84)	(−0.83)	(−1.94)	(−0.20)
	Kohane	0.150	0.550	−0.225	−0.112
		(1.17)	(3.68)	(−1.19)	(−1.14)
Wood	Pooled	0.031	−0.077	0.106	0.078
		(0.84)	(−1.26)	(1.24)	(1.73)
	Purushwadi	0.162	−0.095	−0.238	−0.025
		(2.34)	(−0.98)	(−1.75)	(−0.37)
	Kohane	−0.074	−0.100	0.099	0.145
		(−1.66)	(−1.49)	(1.05)	(2.66)
Dung	Pooled	−0.069	0.145	−0.381	0.041
		(−0.78)	(0.93)	(−1.42)	(0.43)
	Purushwadi	−0.064	0.034	1.475	0.013
		(-0.44)	(0.09)	(4.32)	(0.08)
	Kohane	−0.076	0.087	−0.496	0.107
		(-0.74)	(0.55)	(-2.52)	(0.86)

t statistics in parentheses.

wood use and increase dung use in Purushwadi and the opposite in Kohane. Electricity connections have small and insignificant effects in Purushwadi and increase the use of wood in Kohane.

6. Discussion and conclusions

We found considerable heterogeneity across the two villages in our study and many estimated effects are subject to considerable imprecision. This heterogeneity raises the interesting question of whether such variation is common across India or what variables might explain it. In any case, it warns against generalizing the conclusions of such studies too extensively. Still some robust results can be derived from our research. These robust findings are:

- Use of higher quality energy sources reduces total energy use, *ceteris paribus*. In our study, dung is the lowest quality energy source and kerosene is the highest, with wood in between.
- Income elasticities and effects are small and are at most 0.15 for the energy-income elasticities. These results are similar to those of the majority of comparable studies such as Nepal et al. [38] who find a small and insignificant income elasticity (0.014) for villages in Nepal. By contrast, using a large sample of more than 100,000 households from across rural and urban India, Gundimeda and Köhlin [24] found income elasticities of 0.76–1.01 for fuelwood and 0.56–0.67 for kerosene in rural areas. The authors note that these estimates are high compared to previous studies but do not elaborate on the reasons for this.
- The data support the energy ladder hypothesis that households use more of higher quality energy sources as their income rises.
- There are economies of scale in household size with a household size elasticity of around 0.45. Nepal et al. [38] also estimate a low household size elasticity of approximately 0.2.
- Improved stoves do not have large or consistent effects on energy use. In one village they reduced the share of wood and in the other increased it.
- Electricity substitutes for kerosene.
- Energy use is higher in winter and lower in the summer and monsoon seasons.

In summary, our findings conform to the majority of similar small-scale studies that we reviewed that find small income elasticities for energy, low effectiveness of efficient stoves in reducing energy use, and indications of an energy ladder with increasing income in poor rural areas of India and Nepal. This suggests that we should expect traditional energy use in such areas to be little changed by increasing incomes and improved biomass burning technologies. We also showed that a shift to higher quality energy sources saves energy, *ceteris paribus*. Modern energy carriers are, however, in limited supply in the region and incomes might be more strongly correlated with energy use when these constraints are released.

Acknowledgments

We thank Paul Burke, Anne Patching, and Michael Ward for helpful comments on the manuscript. We also thank the entire team from the Watershed Organisation Trust for all their support throughout Jack Gregory's time in India. In particular, we thank Dr Marcella D'Souza and Mr Sushil Bajpai for help with the development of the survey; Mr Kishor Telang and Mr Sudhire Sahare for their help and hospitality in the field; and Mr Joseph Shinde for his translation to and from Marathi. We also thank the rural chroniclers, including: Navnath, Vijay, Shivram, Kailas, Savita, Sindhu, and Seema as well as Mrs Veena Panse and Mrs Chhaya Nikrad for collecting and entering the data.

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