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Household, community, sub-national and country-level predictors of primary cooking fuel switching in nine countries from the PURE study

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Supplementary material for this article is available [online](#)

Abstract

Introduction. Switching from polluting (e.g. wood, crop waste, coal) to clean (e.g. gas, electricity) cooking fuels can reduce household air pollution exposures and climate-forcing emissions. While studies have evaluated specific interventions and assessed fuel-switching in repeated cross-sectional surveys, the role of different multilevel factors in household fuel switching, outside of interventions and across diverse community settings, is not well understood. **Methods.** We examined longitudinal survey data from 24 172 households in 177 rural communities across nine countries within the Prospective Urban and Rural Epidemiology study. We assessed household-level primary cooking fuel switching during a median of 10 years of follow up (~2005–2015). We used hierarchical logistic regression models to examine the relative importance of household, community, sub-national and national-level factors contributing to primary fuel switching. **Results.** One-half of study households (12 369) reported changing their primary cooking fuels between baseline and follow up surveys. Of these, 61% (7582) switched from polluting (wood, dung, agricultural waste, charcoal, coal, kerosene) to clean (gas, electricity) fuels, 26% (3109) switched between different polluting fuels, 10% (1164) switched from clean to polluting fuels and 3% (522) switched between different clean fuels. Among the 17 830 households

using polluting cooking fuels at baseline, household-level factors (e.g. larger household size, higher wealth, higher education level) were most strongly associated with switching from polluting to clean fuels in India; in all other countries, community-level factors (e.g. larger population density in 2010, larger increase in population density between 2005 and 2015) were the strongest predictors of polluting-to-clean fuel switching. *Conclusions.* The importance of community and sub-national factors relative to household characteristics in determining polluting-to-clean fuel switching varied dramatically across the nine countries examined. This highlights the potential importance of national and other contextual factors in shaping large-scale clean cooking transitions among rural communities in low- and middle-income countries.

Introduction

Cooking with polluting stoves and fuels, such as unprocessed solid fuels (wood, animal dung, agricultural waste, coal, charcoal) and kerosene, is currently practiced by approximately 2.5 billion people (40% of the global population) [1, 2]. The use of polluting cooking fuels presents a serious global health risk due to household air pollution (HAP) exposure. Elevated levels of fine particulate matter of diameter $<2.5 \mu\text{m}$ ($\text{PM}_{2.5}$) due to HAP ($\text{HAP-PM}_{2.5}$) have been linked to respiratory diseases (child pneumonia [3], COPD [4] and lung cancer [5]), adverse pregnancy outcomes [6, 7], cataracts [8], precursors to cardiovascular diseases (CVD), including hypertension [9], and to CVD [10–13]. Exposure to HAP was the second highest environmental risk factor in the Global Burden of Disease 2017 [14], with an estimated 1.64 million attributable deaths [1, 15]. In addition, residential combustion of solid fuels is a major contributor to outdoor air pollution and emissions of climate-forcing agents [16–19], including up to one-third of all global anthropogenic emissions of black carbon [20]. Unsustainable use of wood for cooking may also contribute to local deforestation [21–23]. Deforestation in some areas can increase the travel time needed to collect fuel wood; thus, replacing wood with cleaner sources of energy can potentially offer both fuel and time savings [24, 25].

To reduce $\text{HAP-PM}_{2.5}$ exposures below WHO guidelines [26] and achieve improvements in health outcomes, a complete switch from a polluting cooking fuel/stove to a ‘clean’ cooking fuel/stove (e.g. electricity, liquefied petroleum gas (LPG)) is likely to be necessary [27]. Such a switch may lead to substantial health improvements. For example, a recent cohort study in China identified a reduction in risk of major respiratory diseases when households switched from polluting to clean primary cooking fuels [28].

The complexity of fuel switching

Despite a decline in the global proportion of households using polluting cooking fuels, rapid population growth in low- and middle-income countries (LMICs) has maintained the global number of polluting cooking fuel users relatively constant at ~ 2.5 billion [29].

Progress in the clean cooking sector has been hampered by various social, cultural, economic, political and environmental factors that contribute to the complexity of successfully achieving a complete switch to, and sustained usage of, a clean cooking fuel [25, 30, 31].

Polluting-to-clean fuel switching has historically been approached from an ‘energy ladder’ perspective, such that an improvement in an individual household’s socioeconomic status (SES) will enable movement up the ‘ladder’ and spur a positive energy transition [32–34]. While a positive association between household SES and use of clean cooking fuels has held [32, 33, 35–39], the energy ladder hypothesis has been updated to a ‘multiple fuel’ model [40], encompassing both primary and secondary fuel use and the role of forces outside the household in the clean energy transition [41, 42]. More recently, numerous frameworks have been used to address patterns of household fuel use [43–48] and larger-scale, nation-wide interventions (subsidies, regulations) have been implemented to change household clean energy decisions [41, 49]. Despite the collective effort of various stakeholders, a global lag in uptake of clean cooking fuels suggests that existing policies/interventions may be too narrowly focused to promote clean cooking fuel switching [45, 50, 51].

While enablers of the adoption of improved cookstoves have been described in systematic reviews based mainly on cross-sectional surveys [41, 52, 53], the present study leverages information from a longitudinal study of $>20\,000$ households from 177 rural communities in 25 sub-national ‘regions’ in nine LMICs. The large number of households from multiple locations with longitudinal measurement of primary fuels also provides sufficient power to examine factors related to less common forms of primary fuel switching, such as clean-to-polluting and polluting-to-polluting. Polluting-to-polluting fuel switching can be either a (1) decrease in emissions [54]/upward movement on the ‘energy ladder’ (e.g. wood to charcoal) (2) increase or decrease in emissions/horizontal (e.g. shrubs/grass to agricultural waste) or (3) increase in emissions/downward on the energy ladder (e.g. wood to agricultural waste) [34, 55].

This study uniquely evaluated the within-household fuel switching across diverse household and community settings in a longitudinal analysis. Understanding fuel switching longitudinally among the same households may suggest new approaches to accelerate clean fuel transitions.

Methods

A multinational, prospective cohort study, the Prospective Urban and Rural Epidemiological (PURE) study was designed to examine how development and urbanization influence lifestyle and, subsequently, chronic disease [56]. PURE encompasses 25 countries, with households clustered in urban and rural ‘communities’ defined by a geographical area (e.g. postal codes, catchment area of health service/clinics, neighborhoods). Rural communities in PURE were defined as small villages at a distance >50 km from urban centers or that lacked easy access to commuter transportation at the time of study commencement, yet were also within a 45 min drive of a laboratory in order to process biological samples [56].

While rural PURE communities were selected on the basis of convenience, household recruitment within communities was randomly conducted to be age/sex representative of adults aged 35–70 in each community [57]. Only rural PURE communities with >10% prevalence of polluting fuel use for cooking at baseline were included in the final analytic sample (figure 2 in Arku *et al* 2018) [58]. Rural communities in nine countries met the inclusion criterion: two upper-middle-income countries (Chile, South Africa), two lower-middle income countries (China, Colombia) and five low-income countries (Bangladesh, India, Pakistan, Tanzania, Zimbabwe); these classifications were based on World Bank data at study commencement [56].

Rapid growth and improvements in transportation during the decade of follow up (~2005–2015) may have altered the urban/rural classification of rural PURE communities. As such, a measure of the fastest travel time to nearest ‘densely populated area’ in 2015 [59] was used as an alternative metric of the degree of remoteness of rural PURE communities (figure S2 in supplemental information (SI), available online at stacks.iop.org/ERL/14/085006/mmedia). As the densely populated areas are defined differently than the study specific ‘urban centers’ it is possible for ‘densely populated areas’ to be <50 km from ‘rural’ PURE communities.

Study variables

All PURE households completed a Household Questionnaire at baseline (~2005) and follow up (~2015); years of baseline and follow up differed between countries due to rolling recruitment (table S2). The PURE Household Questionnaire included the same

question posed to the head of the household at baseline and follow up: ‘Primary fuel used for cooking? (check one only).’ The options included kerosene, charcoal, coal, gas, wood, agriculture/crop, gobar gas, electricity, animal dung, shrub/grass and ‘other’. If the respondent selected ‘other’, they had the option to fill in the fuel type used. Gobar gas is a specific type of biogas produced by anaerobic digestion of animal dung. Biogas could be reported as one of the ‘other’ fuels. For this analysis, fuels were categorized as ‘polluting’ (wood, dung, agricultural waste, charcoal, coal, kerosene) or ‘clean’ (gas—including gobar gas and biogas, electricity).

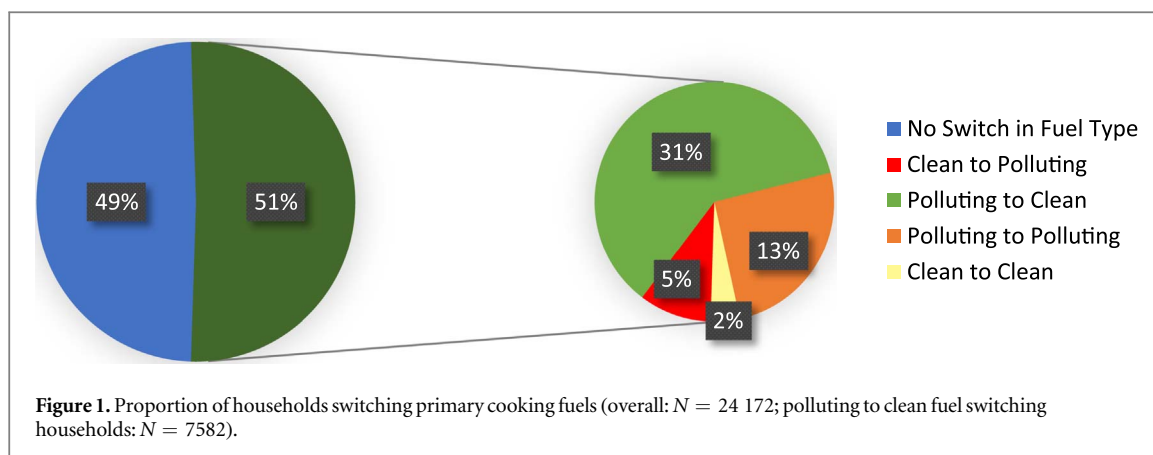
Variables considered for analysis were based on two criteria: (1) *a priori* hypothesized relationship with household cooking fuel use and (2) <2% missing values. All individual-level variables were aggregated at a household-level. Continuous variables were all grouped into three equally sized ‘tertiles’ to standardize comparisons (table S2).

Analyses

Data analysis was conducted in RStudio, version 1.1.423 [60]. The relative importance of specific drivers of fuel switching were examined separately for changes from baseline to follow-up of: (1) a polluting fuel at baseline to a clean fuel at follow-up (2) a clean fuel at baseline to a polluting fuel at follow-up and (3) a polluting fuel at baseline to a different type of polluting fuel at follow-up. For each, the odds of fuel switching were calculated for all potential explanatory variables using hierarchical logistic regression, controlling for study design factors (years between baseline/follow up survey administration, clustered sampling design).

For examining polluting-to-clean fuel switching, multinational (nine countries, seven countries excluding China and India) and country-specific (China, India) hierarchical logistic regression models (households nested within communities nested within sub-national regions) were used to account for the likelihood that household fuel decisions were more similar within communities than between communities, and within sub-national regions than between these regions.

The intra-class correlation coefficient (ICC), obtained from the *sjstats* package [61], was calculated for community and sub-national random effects to compare the proportion of variation in polluting-to-clean primary fuel switching at each geographic level [62]. Household and community-level fixed effects were added separately to evaluate their impact on altering the explained variance [63]. The marginal pseudo- R^2 (referred to as R^2 from this point forward), obtained from the *piecewiseSEM* package [64], was used to quantify the total variance explained by fixed effects.



Results

Fuel switching percentages

Due to varying periods of recruitment in different countries in the PURE study, baseline and follow up years varied between countries (median:10 years, IQR:8–11, range:3–13) (table S1). Self-reported primary cooking fuel data was available for 27 804 rural households at baseline. Approximately 0.3% and 0.1% of the analytic sample had paraffin and biogas written in as ‘other’ primary fuels, respectively; ‘paraffin’ was combined with ‘kerosene’, and ‘gas’, ‘biogas’ and ‘gobar gas’ were condensed into ‘gas’ fuel type. Households that reported ‘other’ fuels besides paraffin or biogas (0.1%) were excluded.

Approximately 13% of rural households had missing primary cooking fuel data during follow up and were excluded, leaving a final study sample of 24 172 households. A sensitivity analysis comparing the final sample to the entire 27 786 households showed no significant differences in baseline fuel types and SES characteristics (table S3).

The final study sample had the largest number of households recruited in China ($N = 11\,411$ households, 65 communities, 11 sub-national regions) and India ($N = 7206$ households, 50 communities, 6 sub-national regions), with households in the seven other LMICs ($N = 5555$) recruited from 69 communities. There was an average of 108 (range: 1–482) households amongst the included PURE rural communities.

Overall, 51% (12 369) of the 24 172 households reported different primary cooking fuels between baseline and follow up (31% switching from polluting to clean fuels, 13% switching from polluting to different polluting fuels, 5% switching from clean to different clean fuels and 2% switching from clean to polluting fuels) (figure 1). There were large country-level differences in proportions of the categories of primary fuel switching (table 1).

The proportion of each fuel type used at baseline and follow up among PURE households in each country, and within sub-national regions in China, India and South Africa, are shown in figures 2(a) and (b),

respectively. The largest increases in clean fuel use among PURE households using polluting fuels at baseline occurred in India, China and South Africa (all ~35%), followed by Chile (~25%) and Colombia (~20%). Bangladesh, Pakistan, Tanzania and Zimbabwe had rates $\leq 10\%$. Large differences in rates of polluting-to-clean fuel switching occurred among PURE sample households, particularly in China, with eastern regions (Beijing, Jiangsu, Jiangxi, Shandong) having $>40\%$ switching to clean fuels, compared to western China (Inner Mongolia, Liaoning, Qinghai, Xinjiang) where rates were $<15\%$. Numerical proportions of cooking fuel types by country and sub-national region are provided in SI (tables S4, S5, respectively).

In China, three western regions had $>50\%$ of households switch between polluting fuels: Xinjiang (73%); Qinghai (61%) and Inner Mongolia (57%). In Tanzania, polluting-to-polluting fuel switching was primarily ‘upward’, with one-third of households transitioning from kerosene (13%) or wood (20%) to charcoal. In Bangladesh and western China, polluting-to-polluting fuel switching was largely ‘horizontal’ or ‘downward’; for example, 32% and 17% of polluting-fuel-switching households transitioning from wood to agricultural waste, respectively (tables S4, S5).

Household asset index, highest level of education and household size were generally higher among households using clean primary cooking fuels at baseline, compared to households using polluting primary fuels at baseline, (table S7). Community-level factors (e.g. % polluting fuels in community at baseline, population density) were markedly lower among households transitioning from polluting to clean cooking fuels, compared to switching between types of polluting fuels.

Factors predictive of polluting-to-clean fuel switching at different geographical levels

To model factors predictive of polluting-to-clean fuel switching, 17 830 (74% of study sample) households that reported using polluting fuels at baseline were included. A subset of these households (3226) that did

Table 1. Number of households in each fuel switching category by country (%).

Country	All households	No switch	Polluting to clean	Polluting to polluting	Clean to polluting	Clean to clean
Bangladesh	870	413 (47%)	19 (2%)	401 (46%)	36 (4%)	1 (0%)
Chile	357	238 (67%)	97 (27%)	4 (1%)	18 (5%)	0 (0%)
China	11 411	4285 (38%)	4071 (36%)	2013 (18%)	691 (6%)	351 (3%)
Colombia	1927	1345 (70%)	366 (19%)	73 (4%)	93 (5%)	50 (3%)
India	7201	3950 (55%)	2618 (36%)	362 (5%)	218 (3%)	53 (1%)
Pakistan	414	363 (88%)	1 (0%)	41 (10%)	9 (2%)	0 (0%)
South Africa	1042	475 (46%)	352 (34%)	64 (6%)	84 (8%)	67 (6%)
Tanzania	495	336 (68%)	23 (5%)	134 (27%)	2 (0%)	0 (0%)
Zimbabwe	455	390 (86%)	35 (8%)	17 (4%)	13 (3%)	0 (0%)
Total	24 172	11 795 (49%)	7582 (31%)	3109 (13%)	1164 (5%)	522 (2%)

not switch to a clean fuel during follow were evaluated in polluting-to-polluting fuel models. For modeling clean-to-polluting fuel switching, 6342 (26%) households in the study sample that reported using a clean primary cooking fuel at baseline were included.

Among all nine countries, 4% of variability in polluting-to-clean fuel switching was explained by household SES factors; this increased to 13% when adding community-level factors to the model and to 28% when adding in a country-level indicator (table 2). In India, household level factors explained 17% of the variability in polluting-to-clean fuel switching, compared to only 4% in China. In India and China, there was greater variability in fuel switching between regions within the country than within sub-national regions (India: $ICC_{\text{sub-national}} = 0.60$, China: $ICC_{\text{sub-national}} = 0.56$). After controlling for community and household characteristics, the variability in fuel switching between rural communities within the same sub-national region in China ($ICC_{\text{community}} = 0.18$) was greater than that in India ($ICC_{\text{community}} = 0.02$) and the seven other countries combined ($ICC_{\text{community}} = 0.05$), where almost all variability occurred within communities (table 2).

Association of specific factors with polluting-to-clean fuel switching

Across all countries, participants living in communities with the lowest percent of polluting fuel use at baseline, living in larger households, living in communities with the highest 2010 population density and the highest population density increase between 2005 and 2015, and participants with a higher education level and higher amount of household assets had the highest odds of polluting-to-clean fuel switching (figure 3(a)). For example, households in communities in the highest category of 2010 population density (>800 people km^{-2}) had 1.08 times the odds (95% CI:1.03–1.13) of polluting-to-clean fuel switching, compared with those in the lowest category of population density (1–300 people km^{-2}), after adjustment for years between survey administration.

In China (figure 3(b)), the strength of the association of community-level factors with clean-to-polluting fuel switching was higher than the nine-country average

(figure 3(a)). For example, rural Chinese households in communities in the highest tertile of population density increase between 2005 and 2015 (>100 people km^{-2}) had 1.29 times the odds (95% CI:1.11–1.50) of polluting-to-clean primary fuel switching, compared with those in the lowest tertile (<30 people km^{-2}), after adjustment for years between survey administration. However, in India, three of the four factors most strongly associated with polluting-to-clean fuel switching (higher education level, higher household asset index and larger household) were at the household level (figure 3(c)). In the seven other countries (excluding India and China), community-level factors were more strongly associated with polluting-to-clean fuel switching than household-level factors; population density was a slightly stronger independent predictor of polluting-to-clean fuel switching than education level or household assets (figure 3(d)).

Association of specific factors with clean-to-polluting fuel switching

Higher household-level SES was generally more strongly negatively associated with clean-to-polluting switching compared to community-level factors (figure 4). One exception was that households in communities with the largest increase in population density had the highest odds of clean-to-polluting fuel switching. Older PURE participants (aged 55–70) were significantly less likely to switch from polluting to clean fuels and significantly more likely to switch from clean to polluting fuels, compared to participants aged 35–45.

Discussion

This analysis of a diverse population from 177 rural communities across nine LMICs reveals that half (51%) of the study population switched primary cooking fuels in a ~ 10 year period. The most common form of primary cooking fuel switching was polluting-to-clean switching (31%). A decrease in the proportion of households using polluting fuels was

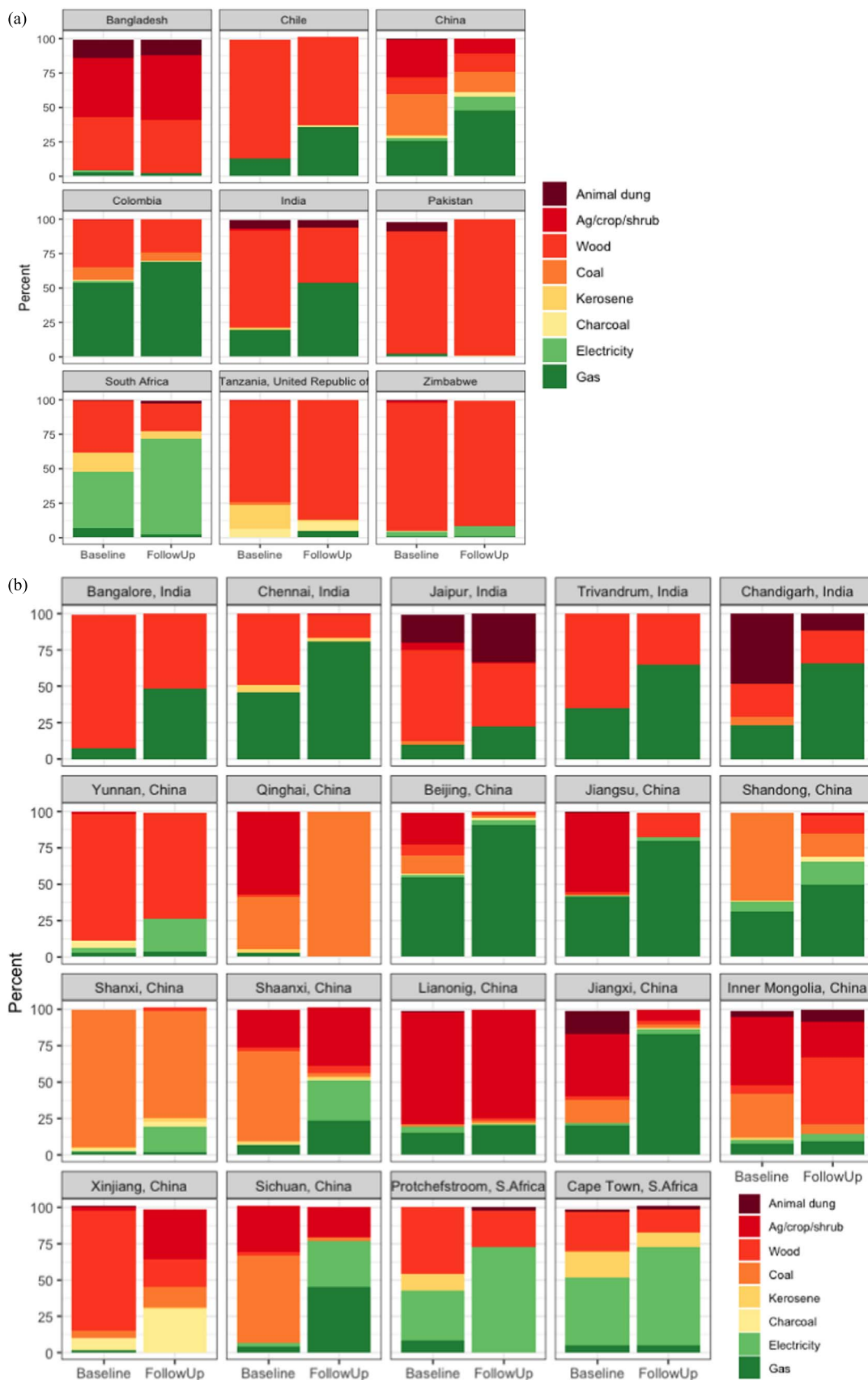


Figure 2. (a) Self-reported proportions of PURE baseline and follow up primary cooking fuels by PURE households within each country. Notes: Percentages are from the PURE sample and not nationally representative. Country percentages <100% indicate that ‘other’ fuel types were excluded. ‘Clean’ fuels are in green color. (b) Self-reported proportions of PURE baseline and follow up primary cooking fuels for PURE countries with multiple sub-national regions (China, India and South Africa). Notes: Percentages are from the PURE sample and not necessary representative of the full population in each community.

Table 2. Intra-class correlation coefficient (ICC) and R^2 for polluting to clean fuel switching models including household, community, sub-national and (for multinational models) country-level factors.

Level name	Variables	Global model		7 Country model ^a		India model		China model	
		ICC ^b	Fixed effect ^c R^2	ICC	Fixed effect R^2	ICC	Fixed effect R^2	ICC	Fixed effect R^2
Base level	<i>Random effects:</i> community, sub-national	C: 0.05	1%	C: 0.13	0%	C: 0.12	4%	C: 0.17	3%
	<i>Fixed effects:</i> study design variable ^d	S: 0.54		S: 0.51		S: 0.13		S: 0.62	
Household level	<i>Random effects:</i> community, sub-national	C: 0.14	4%	C: 0.13	5%	C: 0.11	17%	C: 0.18	4%
	<i>Fixed effects:</i> household variables ^e	S: 0.55		S: 0.51		S: 0.21		S: 0.61	
Community level	<i>Random effects:</i> community, sub-national	C: 0.14	13%	C: 0.05	14%	C: 0.02	31%	C: 0.18	27%
	<i>Fixed effects:</i> household and community variables ^f	S: 0.48		S: 0.54		S: 0.60		S: 0.56	
Country level	<i>Random effects:</i> community, sub-national	C: 0.17	28%	C: 0.06					
	<i>Fixed effects:</i> household, community variables ^f and country ^g	S: 0.36		S: 0.48	24%	N/A	N/A	N/A	N/A

^a **7 Country Model** includes Bangladesh, Chile, Colombia, Pakistan, South Africa, Tanzania and Zimbabwe.

^b **ICC** represents intra-class correlation at (C) community and (S) sub-national-level. ICC(C) represents the variability between communities relative to the total variance between and within communities. ICC(S) represents the variability between sub-national regions relative to the total variance between and within sub-national regions.

^c **Fixed effects R^2** represents marginal R^2 (percent variability explained by fixed effects in the model).

^d **Study design variable:** years between baseline and follow up survey.

^e **Household variables:** household asset index, highest level of education, % income on food, age, family size, # of members earning income, # of rooms, roof material.

^f **Community variables:** 2010 population, 2005–2015 change in population density, % of households using polluting fuels in community at baseline, travel time to densely populated area.

^g **Country:** In 7 Country Model, country effect only includes binary indicator for South Africa as the six other countries only have one sub-national region from which PURE households were recruited.

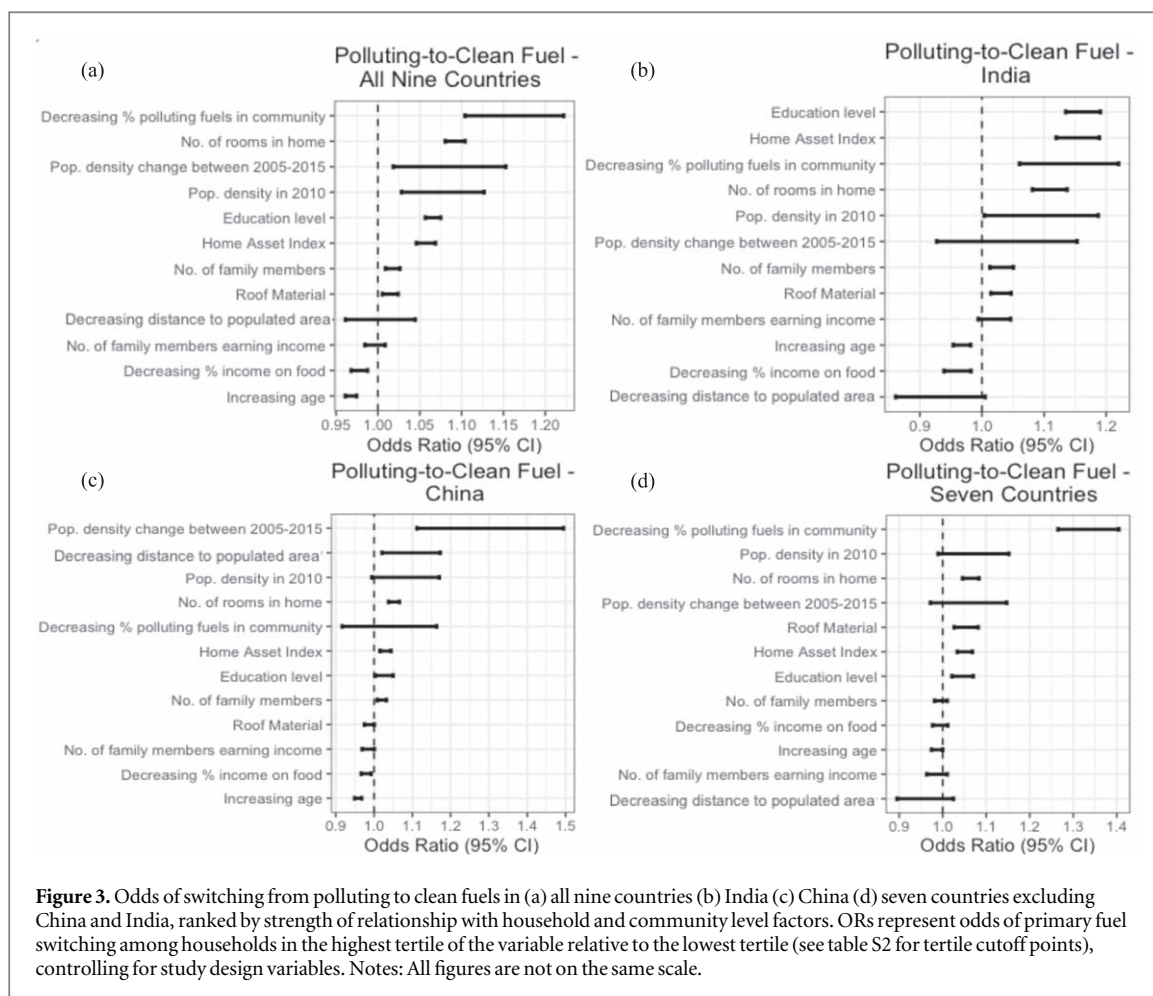


Figure 3. Odds of switching from polluting to clean fuels in (a) all nine countries (b) India (c) China (d) seven countries excluding China and India, ranked by strength of relationship with household and community level factors. ORs represent odds of primary fuel switching among households in the highest tertile of the variable relative to the lowest tertile (see table S2 for tertile cutoff points), controlling for study design variables. Notes: All figures are not on the same scale.

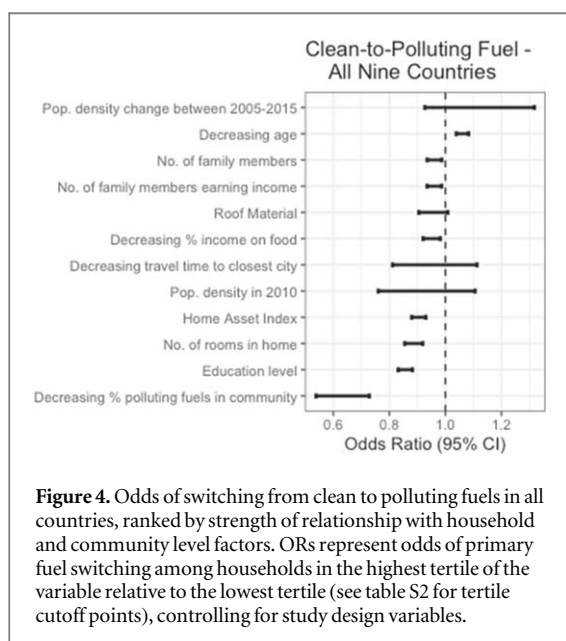


Figure 4. Odds of switching from clean to polluting fuels in all countries, ranked by strength of relationship with household and community level factors. ORs represent odds of primary fuel switching among households in the highest tertile of the variable relative to the lowest tertile (see table S2 for tertile cutoff points), controlling for study design variables.

observed in India, China, Chile, Colombia, and South Africa, while no overall improvements were observed in Bangladesh, Pakistan or Tanzania, and only minor improvements in Zimbabwe. Notably, this switching occurred without any targeted interventions at the household or community level. Sub-national and

community-level factors were strongly positively associated with polluting-to-clean primary fuel switching in all countries, with the degree of association of household SES factors varying by country (highest in India and lowest in China) (table 2).

Community, sub-national and national factors

The community-level enablers of polluting-to-clean switching found in this study (higher population density (2010), change in population density between 2005 and 2015 and lower percent of households using polluting fuels in the community at baseline) are consistent with results of a recent global ecological analysis [65], which found factors such as the political environment, economic development, population size and type of local fuel production to be associated with the proportion of clean cooking fuels used at a country-level. A systematic review of barriers and enablers to clean fuel adoption and sustained use in rural areas identified several macro-level factors that can influence a household’s cooking fuel decision, including financial, tax/subsidy forces, market development and program/policy mechanisms [41].

Although data were not available to explicitly assess the impact of national programs focused on household energy, there were notable country-level differences in the rate of polluting-to-clean fuel

switching. For example, the net increase in clean fuel-using PURE households in Bangladesh and Pakistan (0%–5%) contrasted dramatically with large improvements in the five regions in India (35%) and 11 regions in China (30%). In multinational analysis, ‘country level’ models explained a higher percentage of variability (R^2) in polluting-to-clean fuel switching (table 2), suggesting that national-level factors were important determinants of fuel switching.

In India, the Pratyaksha Hastaantarit Laabh national program, implemented in 2012, altered the mechanism of subsidized LPG by delivering the subsidy directly to consumers’ bank accounts; 140 million Indian consumers have been enrolled in the cash transfer program [66]. In 2016, the Pradhan Mantri Ujjwala Yojana program was launched to provide free household LPG connections to 50 million consumers by 2019 [66]. In India, very low between-community ($ICC_{\text{community}} = 0.02$) variation in fuel switching (table 2) may be due to national LPG programs that target all households in poor rural communities. Such programs may have minimized community-level differences in clean fuel access within the same region. Evaluation studies are needed to further examine the effect of national programs on LPG use in India.

In China, the proportion of coal use among rural PURE communities was cut in half (30%–15%) between baseline and follow up (figure 2(a)). A rapid increase in the number of stove factories, new policies and increasing coal prices have shifted many regions off of coal (figure 2(b)) [42, 67]. In 2013, the Chinese government launched a National Action Plan on Air Pollution Prevention and Control, consisting of province-specific limits on $PM_{2.5}$ emissions and coal consumption; a 50% reduction in coal consumption between 2013 and 2017 was targeted in the Beijing-Tianjin-Hebei area [68]. The province-specific limits on coal consumption could potentially explain the high between-region variability in the China model ($ICC_{\text{region}} = 0.56$). These and other policies in China focused on outdoor air pollution may have led to increases in household use of clean fuels [69], an approach that may also yield dividends in India where emissions related to residential sources are also major contributors to ambient air pollution [17].

The use of polluting fuels in China is highly correlated with local fuel availability [67]. As regions in western China (e.g. Liaoning) have substantial forest areas, a payment of any amount for clean cooking fuels is less appealing than gathering free biomass fuels [70–72]. In western China, rural PURE communities are especially remote, with four regions (Inner Mongolia, Shaanxi, Xinjiang, Yunnan), having at least half of communities >50 min travel time from a densely populated area. An unreliable supply of cooking fuels because of transportation time/costs could partially explain the importance of community-level factors in clean-to-polluting fuel switching in western China (figure 3(c)).

Household factors

Despite the overall importance of community, sub-national and national factors, we observed a consistent association between household SES indicators (e.g. higher household asset index, education level, household size—figure 3(a)) with switching to cleaner fuels. This observation was consistent with findings from systematic reviews of enablers to clean fuel adoption [52, 53, 73]. Among all household SES variables included in this analysis, increasing household size (number of rooms) was the strongest independent predictor of polluting-to-clean fuel switching in all countries. Participants in the youngest age group (35–45) also had significantly higher odds of switching than participants in the oldest age group (55–70) (figure 3(a)), in line with results from several studies [53, 74, 75].

While the association between increasing household SES and polluting-to-clean fuel switching was evident in all countries, the degree of association varied by country; household SES factors were more predictive of a positive household energy transition in India than China (figures 3(b) and (c), respectively). It is difficult to ascertain whether country-level differences in the significance of household factors may be due to greater remoteness of rural PURE communities in China than India (figure S2), or political, social and structural differences between the two countries. Nonetheless, country-level differences in the significance of household factors demonstrate that contextual factors can impact the importance of household economic standing in the decision to switch to cleaner primary cooking fuels.

Reverse switching: clean to polluting fuels

Household-level SES characteristics were more strongly associated with reverse (clean-to-polluting) fuel switching than community-level factors (figure 4); for example, education level, household size and the household asset index were more strongly (negatively) associated with reverse fuel switching than were factors such as 2010 population density and travel time to closest densely populated area. The stronger association of household-level compared to community-level factors in reverse fuel switching may explain why the ~1200 rural households switching from clean to polluting primary fuels were not concentrated in a particular region (table 1).

Among the nine countries, South Africa experienced the highest rate of clean-to-polluting fuel switching (8%), with ~60% of households switching from electricity to wood and nearly 20% switching from electricity to kerosene fuel. The move away from electricity may be the result of frequent power outages that have occurred in South Africa since 2008 due to increasing electricity demand exceeding the available supply [76, 77].

Strengths and limitations

This study is one of the largest and most geographically diverse to examine rates of primary fuel switching using within-household longitudinal data. While we have identified country as an important predictor of change, we did not attempt to attach this effect to specific policies that were implemented or even to differentiate between potential impacts of national scale policies related to household energy use and overall socioeconomic development that occurred within each country during the duration of our analysis. However, the clustered sampling used in the PURE study allowed for examination of several household, community, sub-national and national-level determinants of fuel switching.

By only considering primary cooking fuels, this study does not account for proliferation of stove stacking, a common phenomenon in which households utilize a polluting cooking fuel in conjunction with a clean cooking fuel to serve their household energy needs [40, 44, 52, 78]. Thus, PURE households reporting use of a primary clean cooking fuel at follow up may use a secondary polluting fuel, thereby reducing the health benefits of using a clean primary fuel [27]. The PURE-Air HAP study [58] involves data collection on secondary fuels/stoves. As such, future analyses within the PURE-Air HAP study can inform the extent of fuel/stove stacking in the PURE cohort.

Questions about the type of stove in which fuels were combusted (e.g. open fire, improved biomass stove) were not contained in the PURE Household Questionnaire. Misclassification of 'clean' versus 'polluting' fuels/stoves may exist; for example, the findings of polluting to polluting fuel switching in China should be interpreted cautiously as they do not consider potential adoption of improved biomass stoves. While the PURE study was not specifically designed to be nationally representative, these results from a diverse sample of >20 000 households undergoing primary fuel switching are valuable for assessing within and between-country differences in fuel switching between ~2005 and 2015 and establishing potential macro-level pathways to achieve fuel switching.

Impact

As global health policymakers seek to prioritize strategies that most efficiently promote the clean household energy transition, this diverse, multinational analysis identifies broader societal factors associated with urbanization and economic growth as important drivers of the polluting-to-clean cooking fuel transition in rural areas of LMICs. This analysis reinforces calls to consider the community and national context of household energy options [79] and suggests the potential for policies that accelerate ongoing societal trends to transition to gas/electricity to meet household cooking needs.

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