Do stated preferences provide clues into who adopts improved cookstoves?

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Abstract

This paper explores the heterogeneity in household preferences for different features of improved cookstoves (ICS), and the degree to which these are associated with actual adoption behaviors observed during a randomized ICS promotion campaign. The data come from a survey of 1060 households residing in rural communities located in Uttarakhand, India. During baseline surveys, all households participated in a discrete choice experiment (DCE) in which they selected their preferred stove options in a series of stated choice tasks. Analyzing the data from the DCE, we find that households on average have a strong preference for traditional stoves and have greater willingness to pay (WTP) for the smoke emissions reduction feature of ICS than for decreased fuel requirements and increased convenience (number of cooking surfaces), but that this average masks important heterogeneity in preferences. Latent class analysis (LCA) of the choice patterns in the data allows us to identify 3 distinct categories of households, who can be characterized as disinterested in ICS (54%), interested in most features of the ICS (20%), and sensitive primarily to the smoke emissions feature of stoves (27%). We then investigate whether membership in each of these classes helps predict adoption of ICS that were promoted during a randomized promotion experiment with a subset of 770 of these households. In general, we find that the LCA preference classes do relate to stove purchase decisions and responsiveness to randomized rebates. Lastly, as the stove promotion experiment sold both biomass and electric ICS, we find that distaste for smoke emissions (relative to other negative attributes of stoves), as revealed in the LCA, appears to be a particularly strong driver for adoption of the electric ICS.

Keywords: Improved cookstoves, discrete choice experiment, latent class analysis, randomized controlled trial, India

1. Introduction

The use of solid biomass or coal fuels for basic household cooking and heating remains widespread throughout the world, and represents approximately 15% of global energy use (Smith et al. 2000; Legros et al. 2009). These fuels are often burned in inexpensive yet inefficient stoves, which results in damages to health from respiratory illnesses and other conditions (Ezzati and Kammen 2001; Bruce et al. 2006; Martin et al. 2011), to local environments and development due to unsustainable and time-intensive harvesting of biomass, and to the global climate system as a result of emission of black carbon particles and ozone precursor gases (Bond et al. 2004; Ramanathan and Carmichael 2008). These negative effects of traditional stoves have prompted great interest in, and a new push towards development and dissemination of more efficient and cleaner-burning improved cook stoves (ICS) such as gas-, electric-, or cleaner biomass-burning technologies (GACC 2010).

Yet despite the very significant problems associated with traditional stoves, adoption of cleaner burning biomass stoves has been slow, and new technologies have not reached scale. Beyond well-known problems of high costs and a weak supply chain, researchers and practitioners have claimed, without a great deal of systematic evidence from rigorous field studies, that the existing range of biomass ICS prototypes are not sufficiently adapted to local cooking requirements and user preferences (Duflo et al. 2008; GACC 2011; Jeuland and Pattanayak 2012; Lewis and Pattanayak 2012; Singh and Pathy 2012; Foundation 2013). Meanwhile, the most widely accepted ICS technologies such as LPG and electric stoves remain costly for poor households, and lack a robust and strong supply chain in many rural areas. In addition, a range of recent studies conducted in South Asia suggest that major challenges remain in this push to promote ICS, with regards both to private demand for these new technologies (Mobarak et al. 2012), and to the realization of health and other welfare benefits from their use (Hanna et al. 2012).

These recent negative findings raise important questions about ICS promotion and dissemination. Nonetheless, other field studies, mainly conducted in East and West Africa, suggest that ICS promotion can in fact succeed under some conditions, at least in the short-term (Bensch and Peters 2012; Levine and Cotterman 2012). In fact, the range of recent findings on ICS highlights several points that have previously been emphasized in the broader literature on demand for environmental health improvements. First, the demand for such health improvements is often low, and is related to consumers' diverse preferences, circumstances and constraints (Pattanayak and Pfaff 2009). For example, households cannot be expected to adopt a stove that is inconvenient to use or that is insufficient for their specific cooking needs, even if it is highly efficient. Second, this heterogeneity (across communities and individuals) translates into substantial variation in the real costs and benefits of ICS (Jeuland and Pattanayak 2012; Whittington et al. 2012). Third, household decisions about whether or not to adopt and continue to use ICS may not always follow from simple comparisons of economic costs and benefits. Lack of user awareness, peer influences, credit constraints, uncertainties (especially related to servicing and maintaining ICS prototypes), risk aversion and impatience, all influence decisions about whether or not to adopt an unknown technology, with highly uncertain returns (Liu 2011; Tarozzi et al. 2011). Part of the solution has to lie in learning to engineer and adapt stoves and services to local cooking requirements and conditions. Perhaps nowhere is the scale of this challenge greater than in India, the largest potential market for such technologies and one of the world's hot spots for biomass burning in inefficient stoves. Progress in India has been particularly slow with only several tens of thousands of stoves sold in each of 2011 and 2012, even though globally sales were in the millions (GACC 2012; Colvin et al. 2013).

The purpose of this paper is to shed light on some of the challenges of the ICS adoption puzzle, by better characterizing the variation in household preferences for ICS, and then studying the extent to which those preferences relate to uptake of ICS during a randomized ICS promotion campaign. We utilize stated discrete choice experiment (DCE) data collected during baseline surveys in Uttarakhand, India to obtain a better understanding of ICS preferences. In the DCE, respondents completed a series of choice tasks in which they considered differences – in terms of price, number of cooking surfaces, amount of smoke emissions, and fuel requirements – between biomass-burning ICS and traditional stoves. In the context of studying demand for ICS, for which well-developed markets do not currently exist, a particular advantage of DCE preference elicitation is to allow consumers to explicitly consider tradeoffs between hypothetical stove alternatives with varying levels of these types of attributes (Louviere et al. 2000; McFadden and Train 2000). We analyze the DCE data using standard mixed logit models that readily accommodate preference heterogeneity, as well as latent class analyses using more general multinomial logit methods that allow us to look for regularities in choice patterns across different respondents (Magidson and Vermunt 2004). We then consider whether households with specific types of preferences, as categorized through the latent class analysis (LCA) of DCE choices, are more or less likely to adopt an ICS during a real ICS promotion campaign.

We find that households categorized by the latent class analyses as 'uninterested' (roughly 52% of all sample households) in the positive attributes of ICS have lower wealth, are older, and are less aware of the health damages caused by smoked inhalation. Consequently, the ICS promotion campaign revealed this group of households to be significantly less likely to purchase ICS during the campaign. The other two classes were primarily distinguished by their relative responses to smoke emissions reductions versus reduced fuel requirements and increased convenience attributes, with the first class (27%) being mainly interested in smoke emissions reductions, and class two (~20%) having much higher relative demand for the other two attributes. Among these groups, class 1 was more likely to adopt an electric, rather than a more efficient biomass-burning ICS, suggesting that distaste for smoke may play a particular role in motivating purchase of an electric stove. We also find some evidence that class 2 households respond more strongly to randomized rebates when considering the purchase of the cleaner-burning biomass ICS.

Our paper makes several contributions to the literature. First, we make a significant addition to the thin literature on private demand for ICS by being the first to examine how households respond to an ICS sales offer that presents them with a choice between two very different technologies – an improved biomass-burning stove, and an electric coil stove. Existing ICS intervention studies largely ignore user preferences and focus on the demand for a single pre-selected technology with a specific set of features, or seek to isolate differences in demand by varying technologies across the arms of an experiment rather than allowing users to choose the technologies they prefer from several options (Mobarak et al. 2012). Second, we seek to better understand the variation in preferences and tastes for different ICS options, by conducting latent class analyses of stated DCE data. Third, after systematically characterizing the choice patterns revealed in the DCE data, we investigate the extent to which implied weights for specific ICS attributes (i.e. part-wise utilities) relate to the choices revealed in the randomized ICS promotion campaign. These contributions serve to elucidate important demand-side features of the market for ICS, which are critical for product development and market segmentation needed for the dissemination and diffusion of ICS technologies.

2. Modeling

Modeling preferences for ICS

The framework for analyzing the DCE data used in this study is based in random utility theory. We model the repeated household choices from among different combinations of stove alternatives that vary according to well-defined levels of 4 attributes: price, fuel requirement, smoke emissions, number of cooking surfaces. The random utility model we apply assumes that the indirect utility associated with a particular alternative can be written as a function of its attributes, and household characteristics:

$$U_{jt}^{i} = V^{i}\left(p_{jt}, \beta_0^{i}, X_{jt}, \beta^{i}, Z^{i}\right) + \varepsilon_{jt}^{i} , \qquad (1)$$

where:

U_{jt}^{i} = the utility of household *i* associated with cooking alternative *j* in a choice set, where *t* indexes the number of choice tasks completed (4 per household);

$V^{i}(\cdot)$ = the non-stochastic portion of the utility function for household *i*;

p_{jt} = the price of cooking alternative *j* in task *t*;

β_0^{i} = a parameter which represents the marginal utility of money for household *i*;

X_{jt} = a vector of non-price attribute levels for cooking alternative *j* in task *t*;

β^{i} = a vector of parameters which represent the marginal utility for household *i* associated with the different non-price attributes of the alternatives;

Z^{i} = a vector of characteristics for household *i*; and

ε_{jt}^{i} = a stochastic disturbance term.

Assuming that households maximize utility within a given choice task, they will select alternative *j* from among the set of *K* alternatives presented to them if and only if alternative *j* provides a higher overall level of utility than all the other alternatives, i.e. if $U_{jt}^{i} > U_{kt}^{i}$ for all *j* in set *K*, where $j \neq k$, such that $V_{jt}^{i} - V_{kt}^{i} > \varepsilon_{kt}^{i} - \varepsilon_{jt}^{i}$. Assuming a linear specification of utility $U_{jt}^{i} = \beta^{i} X_{jt} + \beta_0^{i} p_{jt} + \varepsilon_{jt}^{i}$ and a Type 1 extreme-value error distribution for the disturbance term, the probability that alternative *j* will be selected from choice set *t* corresponds to the standard conditional logit model (McFadden 1981). The conditional logit model is estimated using maximum likelihood; the values of the coefficient values β_0^i and β^i are selected to maximize the likelihood that one would observe the choices actually observed in a given sample of respondents.

In this paper, we relax the restrictive assumption of the conditional logit that requires a single set of fixed β coefficients, and instead estimate two types of generalized multinomial (or random parameters, or mixed) logit models.[1] The first is the mixed logit, which allows for unobserved heterogeneity in tastes across individuals, as specified through inclusion of respondent-specific stochastic components η^i for each of the estimated coefficients β in the model. The probability that alternative *j* will be selected from choice set *t* can be written:

$$\mathrm{Prob}[C^i = (C_{j1}^i, \dots, C_{jT}^i)] = \prod_{t=1}^{T} \frac{\exp\left[V_{jt}^i(\beta^*)\right]}{\sum_{\mathrm{k=0}}^{\mathrm{K}}\left[V_{kt}^i(\beta^*)\right]}, \tag{2}$$

where $\beta^* = (\beta + \eta^i)$. The stochastic portion of utility includes an individual-specific η^i term, which flexibly accommodates correlations both across alternatives and choice tasks. The coefficients β^* are estimated using simulated maximum likelihood (Revelt and Train 1998). The ratios of coefficients derived from the model then yield the marginal utility to individual *i* for an additional unit of a particular attribute, in money terms.

The second is the latent class multinomial logit, a less restrictive version of the generalized multinomial logit model, which allows us to more thoroughly explore a variety of household- and community-level characteristics that are related to various types of preferences. In this specification, each class identified by the estimation procedure has its own relative weighting of attributes. We rely on the Bayesian Information Criterion (BIC) to select the best-fitting model with up to 10 different classes (Roeder et al. 1999). We then assign a household to a particular class if its predicted probability of membership in that class exceeds 2/3. We then study the determinants of class membership using a multinomial logit model.

[1] There are several problems with the conditional logit, including violation of the independence of irrelevant alternatives (IIA) assumption, the inability to account for correlation across a respondent's choices, and the lack of consideration of differences in individual tastes other than those related to the specified attributes of alternatives.

Modeling the adoption decision

From the stove promotion campaign, we observe households' ICS purchase decision. We regress this purchase decision on latent class membership which was predicted earlier based on responses in the DCE. The general model can be written as:

$$Y_{ij} = \beta_0 + \beta_k \cdot C_{kij} + \beta_r \cdot r_{ij} + \beta_{li} \cdot X_{lij} + \mu_{ij}. \tag{3}$$

In this model, Y_{ij} is a dummy variable that is equal to 1 if household *i* in community *j* purchases an ICS, and 0 otherwise. The variable C_{kij} is a dummy variable that is equal to 1 if the household *i* has preferences of type *k* and 0 otherwise (as revealed by the LCA); r_{ij} represents a rebate amount randomized to all households in the communities exposed to the stove offer; X_{lij} is a vector of *l* household and community variables that influence the purchasing decision; and μ_{ij} is an error term clustered at the community level j. The coefficients β are estimated using regression methods.

In most cases, we treat the improved biomass and electric stoves jointly as ICS and thus the decision for each household is reduced to a single binary variable of purchase/non-purchase. In these cases, we use the linear probability model. However, in other analyses, we treat the stoves as distinct and thus households are faced with three choices. As such, we use the multinomial logit model. Standard errors in all analyses are clustered at the hamlet level as this is the administrative level at which the stove promotion campaign was assigned.

3. Research site and data

The target region for this study in Northern India is a particularly relevant location for a study of the demand for ICS, due to the confluence of several factors: a) growing national and local-level interest and activity in the dissemination of more efficient household energy products; b) increasing awareness and demand for more efficient cooking technologies, due to the rising costs of fuels (as a result of growing scarcity of firewood and concerns over the environmental impacts of deforestation) and greater concern over the health effects of indoor air pollution; and c) location in a region (the Hindu Kush-Himalaya) that is particularly vulnerable to the impacts of climate change. Baseline surveys were conducted in August – October 2012; the promotion intervention occurred from August – November 2013, with follow-up surveys occurring shortly thereafter in November and December.

Sampling frame

The sampling frame for this study consists of 97 geographically distinct communities (or hamlets) located in 38 Gram Panchayats (GPs) in two districts of Uttarakhand, India. Within each of the 38 GPs, we randomly selected households according to the size of the GP. In small GPs, a minimum of 20 surveys were collected; in medium ones 30; and in large ones 40. If a GP was divided by distinct landmarks (e.g., half the village was to the north of the main road, half the village was to the south), the target number of surveys was split equally among these groups. Upon arrival in the village, the population of the GP was divided by the target number of surveys and every n^{th} household (no more than every 8^{th} house) was surveyed until the target number of surveys was reached. This strategy ensured that surveys were collected throughout the entire extent of the GP and created variation in the number of hamlets sampled in each GP. The "official" number of distinct hamlets sampled in this way was 106; some of the smallest of these were later re-combined for the purpose of the ICS promotion intervention to yield the final sample of 97 hamlets. Based on the sizes of the survey GPs, the final sample for the household survey then consisted of 1,063 households.

Efforts were made to interview each sampled household. If a randomly-selected household was unavailable during the entire day of baseline fieldwork in a particular hamlet, or if it did not have an eligible respondent (i.e., the primary cook and/or head of the household were unavailable) or refused to participate, neighboring houses were randomly selected as replacements. Field supervisors performed household introductions, recorded GPS coordinates and elevation data, and oversaw quality control checks in each village.

Baseline surveys and the DCE

The questionnaires used in the baseline surveys included both household and community instruments (completed by a village leader or key informant). Respondents (both the male and female head of household or primary cook) answered questions on environmental and stove-related perceptions, household socio-demographics, stove and fuel use, socio-economic characteristics, risk and time preferences, and completed the ICS DCE. Whenever possible, women answered questions related to socio-demographics, stove and fuel use, whereas men completed the DCE, socio-economic, and time and risk preference sections. Environmental and stove-related perceptions questions were randomized ahead of time to the male or female head of the household / primary cook, subject to his/her availability (which was recorded on the survey form). If one of these two was unavailable for the survey (most often the male), the other eligible respondent completed all questionnaire sections. In addition, a sub-sample of households participated in a 24-hour biomass fuel weighing exercise for monitoring of fuel consumption. The survey instruments were pre-tested prior to the initiation of fieldwork in approximately 200 households located in 9 villages in northern India.

The attributes included in the stove decision exercise, described above, and their levels, were selected following a series of eleven focus groups conducted with over 100 respondents in villages similar to sample villages. Attributes eliminated due to lack of clarity or salience to respondents included time savings, operation and maintenance requirement, fuel loading approach, lifespan of the stove, and type of fuel allowed. We used SAS software to select efficient combinations of attribute levels for measuring main effects. An example of a choice task, and important features of the design, are summarized in Figures 1 and Table 1.

At the start of the stove decision exercise, the different stove alternatives – all biomass-burning types – were described to respondents in detail, and each of the attributes was explained by the enumerator using a specific script accompanied by pictures. At the end of this description, all respondents completed a 4 question comprehension test. If a respondent answered any questions incorrectly, the relevant description was repeated and the enumerator again verified comprehension before proceeding. Next the respondent was reminded of his/her budget constraint, was told that the ICS options would last 3 to 5 years and cost roughly 250 Rs. per year to maintain, was assured that there were no right and wrong answers, and was reminded that the exercise was purely hypothetical. In each of four choice tasks completed during the survey, respondents were asked to select their preferred option from a set of two ICS alternatives or their existing stove (i.e. neither of the presented ICS). If they selected one of the ICS alternatives, respondents further had to answer affirmatively to the question: “If you had the possibility to purchase this stove at the price stated, would you be willing to make that purchase, if the payment was required at the time of purchase?"[2] This confirmation was included to decrease the potential for hypothetical bias in the stated preference responses (Murphy et al. 2005). Following each choice task, debriefing questions were asked to probe the decision-making process and assess the certainty of respondent answers.

The intervention

The ICS promotion intervention was implemented (and therefore randomized) at the hamlet level; all sample households living in treatment communities were visited by sales teams working for a local NGO, whereas households living in control communities were not. Trained ICS sales people, working in teams of 2, visited treatment households and conducted intensive promotion activities with them. First, these teams presented treatment households with an information sheet and explanation of ICS features, even as they performed a live tea-making demonstration comparing the two different stoves being offered: electric coil and biomass-burning ICS. The information sheet and demonstration were designed to inform households about the benefits (reduced smoke, firewood savings, time savings) and costs (price, electricity cost and risk of electric shocks) of these stoves. Then, once the demonstration was complete, the sales people explained the ICS payment plan options to households. Specifically, all households were given the choice of paying for the stoves upfront or in three equal interest-free installments that would be collected over a period of 4 weeks (i.e., in 3 installments collected 2 weeks apart).

In addition, households were told that at the time of the final payment, they would receive a randomized rebate that would count against that final payment if they were found to be using the stoves. Those paying for stoves upfront were also eligible for the rebate and thus were revisited roughly one month later as well. Prior to the households indicating whether they would purchase the ICS, this randomized rebate was revealed by drawing a chit out of a bag. The bag contained equal numbers of chits corresponding to the three potential rebate levels, low - 25 Rs. (a 2.5% discount), medium - 200 Rs (a 20% discount), and high - equivalent to a full installment (a 33%

[2] Prior to this question, all respondents were reminded to consider their household budget carefully when choosing their preferred options. The specific text in the questionnaire was: "There are no wrong or right answers to these questions. When you make your choice, keep in mind your household budget and your other financial constraints. You should consider carefully whether the benefits of an improved stove would be worth paying for their cost, in terms of stove cost and maintenance requirement. Remember that the improved stoves last 3 to 5 years and cost about 250 Rs. per year to maintain."

discount). Stoves were sold to households for 960 Rs. (electric coil) or 1080 Rs. (Greenway); these prices correspond to the stove-specific prices paid to the supplier of stoves for the intervention. As such, the amount of the full installment rebate varies based on the stove that is chosen by a household. For simplicity, in our analyses, we replace this slightly varying amount with 340 Rs. (the midpoint of the two rebate amounts), though we note that none of our results are sensitive to this approach.

We opted for this intervention design after noting, based on analysis of the responses in the DCE, the heterogeneity in the relative weighting that households gave to smoke reductions (greatest with the electric stove) vs. fuel savings (greatest for the Greenway given the high cost of electricity) (Jeuland et al. 2013; Bhojvaid et al. 2013). This baseline evidence, as well as other findings from stove demand studies in the literature (Mobarak et al. 2012), suggested that artificially constraining the choice set in order to detect differential impacts by stove type might depress demand. On the basis of power calculations and our estimation of the differential treatment effects expected from the alternative rebate levels, 71 of the baseline hamlets (corresponding to 770 of the 1063 baseline households) were randomly assigned to the treatment group. The remaining 26 hamlets were control hamlets that did not receive visits from the stove promotion teams.

Sample balance and descriptive statistics

This paper reports on data collected during the baseline surveys – detailed further below – and at the time of the intervention. The intervention data include only basic information on whether a household purchased a stove, which ICS it chose, the randomly-assigned rebate level, and the specific payment made during each visit from the sales team. Thus, we analyze the DCE data that pertain to the entire sample of households that includes treatment and control communities, but only relate those results to the adoption results observed in the treatment communities. Table 2 shows the sample balance across these two groups of communities for key variables. Judging by the normalized differences across groups, the treatment and control communities appear well balanced on average, though control communities are somewhat more likely to have a paved road, and improved stove ownership and fuel use are also somewhat higher in the control communities. None of the variable differences are statistically significant at the 10% level, however.

Similarly, Table 3 shows the sample balance across household rebates within the treatment communities. The rebate assignment is generally uncorrelated with baseline household characteristics. No normalized differences among groups exceed 0.15 and 10 of 74 pairwise t-tests are significant at the 10% level, which is roughly the proportion that would be expected due to chance. Households in the middle rebate group were slightly more educated than those in the other groups: the household heads in this group were more educated than those in the high rebate group ($p<0.05$), and its primary cooks had more years of education than those in the low rebate group ($p<0.1$). Households in the high rebate group were more likely to have taken a loan in the past year than those in the low rebate group ($p<0.01$), while the latter were less likely to have saved money than those in the middle group ($p<0.05$). In responding to hypothetical questions, the middle group also expressed greater willingness to take risks than those in the other two groups. Electricity supply was somewhat greater in the low rebate group (compared to the middle group, $p<0.05$). Finally, the middle rebate group had higher improved stove ownership at baseline that the high rebate group ($p<0.1$).

Descriptive statistics from the baseline sample of 1063 households are summarized in Table 4. In 73% of surveys, the respondent for all questions was a woman (primary cook and/or female head of household). Interviews with the remaining 27% generally included both a male head of the household and the primary cook, according to the assignments described above. The average household size at the time of the survey was 4.8 people. Overall, 73% of households are in the open/general caste category, 24% are scheduled caste, and 1% are scheduled tribe. Sample households are generally rural, poor, and primarily agricultural. Over half of the survey population reported being below the poverty line, and access to credit was low (with just 15% of households availing of credit in the prior year). Almost all have electricity, but only 24% report having electricity all the time. Just over 7% of household members were reported to have experienced a cough or a cold in the two weeks prior to the survey.

At the time of the interviews, nearly all households had a traditional mud stove (40%) or traditional 3-stone stove (49%). Other commonly-found stoves were LPG (29%), or a traditional metal sagarh stove (21%). Very few households had kerosene pump stoves (1.2%) or biogas stoves (1%). The average number of stoves owned by each household was 1.4. Nearly all (93-98%) households owning LPG and traditional stoves reported using these in the week prior to the survey, and almost all LPG-owning households were stackers (only 7% of these did not also use their traditional stoves on a daily basis). Households reported total stove use time to be 5.7 hours/day, and identified that the three best aspects of traditional stoves were (ranked in order): the taste of the food (90%), the cost of the stove (55%), and the ability to cook all foods (7%). The four worst features identified were the smoke that is produced (63%), the cleaning requirements (45%), and the amount of fuel required and the heat given off by the stove (22%). The most commonly used fuels by households, many of whom regularly used multiple types, were firewood (97%), LPG (28) and kerosene (8%), the latter primarily as a lighter fluid. Nearly all users of firewood had fuel in their house at the time of the interview (99%), whereas 85% and 80% of households using LPG and kerosene had some on hand, respectively. The main respondent in each household was asked whether he/she had heard or knew about each of three negative impacts of traditional stoves and biomass fuels, on health, on local forests, and on air quality and/or climate. Awareness of the negative health effects was highest (62%), followed by local environment and forests (58%), with only 39% recognizing outdoor air pollution and/or climate change. Women or primary cooks reported greater awareness of these three types of impacts. Knowledge of ways to mitigate impacts was more limited. Only 25% of respondents said they had heard of stoves that produce less smoke than others at the time of the interview, and only 31% believed that some fuels produce less smoke than others when burned. Thirty-three percent of respondents believed their actions could have medium or large effects for mitigating either health (11%), local forest (25%), or global climate impacts (6%).

4. Results

Analysis of preferences: Mixed logit analyses

Using the data available from the baseline household survey, we first consider the extent of variation in preferences for the four ICS attributes (using the mixed logit analysis of the DCE data). We estimated two mixed logit models with random parameters (Table 5). The difference between these two models is in the assumed distribution of the random coefficient for price, either normal (Columns 1 and 2) or log-normal (Columns 3 and 4). By restricting the distribution of the price coefficient to be log-normal, we ensure that price will be negatively related to the adoption decision. The coefficients for the ICS attributes in the DCE all have the expected signs: alternatives with higher prices, emissions and fuel requirements were less likely to be selected by respondents, whereas alternatives with a greater number of cooking surfaces or of traditional type (e.g., the decision to choose neither of the ICS alternatives, all other attributes being equal) were more likely to be selected. In this sample, the standard deviations for most of the random parameters, except for traditional stove type and price, are not significant, suggesting that preferences for the other attributes may not vary greatly (Table 5, columns 2 and 4). In terms of magnitude of effects, comparison of the part-wise utilities for a single unit change in the levels of the various attributes suggests that the value of a one-unit (33%) reduction in smoke emissions and additional cooking surface are similar on average, followed by a one-unit (33%) decrease in fuel requirement. The large coefficient on the traditional stove type indicates an average preference for traditional stoves that outweighs the value of a 1-unit reduction in smoke emissions plus fuel consumption several times over; the implication is that many respondents would likely need to see large reductions in these levels or otherwise be strongly lobbied to see value in adopting an improved stove.

The determinants of preferences for ICS

Given the heterogeneity detected by the random parameters model, we next used LCA in an effort to uncover consistent patterns in the choices made by different sample sub-groups. This approach allows us to better characterize and understand the preferences of these groups, and the extent to which they are associated with observable household and respondent characteristics. In the 3-class model with the best fit according to the BIC, classes 1 (~27% of respondents) and 2 (~20%) both react negatively to increased fuel usage, smoke emissions, and react positively to increased cooking capacity (Table 6). Given that typical ICS' are supposed to reduce emissions and fuel requirements, we might expect these two classes to be more likely to adopt them.[3] Of these two classes, the first places is more price sensitive and responsive to smoke emissions reductions (though the implied part-wise utility associated with a 1-unit smoke emissions

[3] Some ICS models also have multiple cooking surfaces, though the ones we promoted during this study do not.

reduction is still lower than that for class 2), whereas the second is less price sensitive and places greater relative weight on the fuel reduction and convenience attributes. In addition, class 1 strongly prefers traditional stoves while class 2 does not. In contrast, we consider class 3 (~52%) to be an 'uninterested' group since none of the coefficients for the stove attributes are significant for them. We expect that members of this class will perhaps be less likely to adopt ICS, especially if it is a biomass-fuel burning ICS. Considering that class 3 constitutes more than half of the sample, it is critical to more fully investigate whether such respondents simply did not understand the DCE exercise, or whether their pattern of responses reveal a true aversion to the ICS alternatives.

To further investigate the characteristics of these classes, we assigned each respondent household to the class to which it had the highest predicted probability of membership, as obtained from the LCA. We then regress predicted class type on a variety of demographic and socio-economic variables using the multinomial logit model, where all reported coefficients are relative to the omitted class 3 respondents (Table 7). We observe that, in comparison to class 3, classes 1 and 2 are generally wealthier, have younger heads of household, and are more aware of the negative impacts of smoke inhalation. This is consistent with earlier research that finds similar factors to be positively associated with ICS stove adoption (Lewis & Pattanayak, 2012), and may help explain why class 3 appear less interested in ICS attributes. Comparing between classes 1 and 2, we observe that class 2 is wealthier and typically has larger households, which may also explain the lower price sensitivity of such households (due to an income effect) and their much higher willingness to pay for all three ICS attributes. We also see that class 2 respondents are the most patient (as judged by responses to hypothetical time preference questions). This may imply that the future health benefits of using improved stoves is most meaningful to class 2 respondents, which may further contribute to the lower price sensitivity of these respondents.

Analyzing the ICS adoption decision

These analyses of preferences based on responses to the DCE serve to motivate several questions related to the likelihood of ICS adoption during the randomized sales intervention. In particular, based on the results of the LCA, we attempt to answer three questions on the relationship between these stated preferences and the actual ICS purchase data. The covariates of interest are the binary variables for membership in each of the three classes. In the most basic model, we only include the predicted class binary variables to explain purchase. We then add the randomized rebate (discount) amounts, followed by an indicator variable that controls for the prior presence of the sales NGO in the village, and finally a vector of socioeconomic characteristics. In the ensuing discussion, we report results from all the estimated models but our preferred specification is the full model.

Question 1: Are class 3 households less likely to purchase ICS than the other classes?
This question arises from the observation that class 3 did not appear responsive to any of the ICS' positive attributes in the DCE exercise. Using a linear probability model, the results show that relative to a class 1 household, a class 3 household is about 9% less likely on average to purchase an improved ICS (Table 8, columns 1-4). Controlling for the rebate amount is important (columns 2-4) since class 3 households by chance received slightly lower rebates than class 1 and 2 households. Conversely, we do not detect any differences between class 1 and class 2 households with respect to the purchase decision. The rebate amount itself has a strong positive effect on stove purchase: an increase from the low rebate of 25 Rs. (about 2% of the ICS cost) to the high rebate (worth 33% of the ICS cost) level increases purchase from 28% to about 72%. Of the other covariates, electricity supply reliability is positively associated with purchase; this is not surprising since one of the two offered stoves was electric. ICS purchases are also 6-8% higher in villages where the NGO conducting the sales campaign has previously worked. Contrary to expectations, other demographic and socio-economic characteristics are not significantly related to ICS purchase. One possible explanation for this is that the promotion campaign involved intensive information provision and explanation of the costs and benefits of ICS, as well as the opportunity for all targeted households to pay for the stoves in installments. These features of the promotion campaign may have allowed lower educated and less wealthy households to better understand the ICS as well as facilitating their ability to finance the stoves.

Question 2: Are there clear differences in the responses to rebates across classes?
This question emerges from the fact that the part-wise utilities implied by the LCA coefficients for classes 1 and 2 imply very different willingness to pay for ICS attributes, and that class 3 appears uninterested by improvements in these features. In addition, households in the different

classes have very different preferences for traditional stoves (classes 1 and 3 favor them while class 2 favors the ICS). To evaluate this question, class membership is interacted with the rebate amount (these interactions are denoted as RCX in Table 9). The results suggest that class 2 may be somewhat more responsive to the rebate amount, although the parsimonious model specifications yield similar coefficients and no differences are significantly different across specifications (based on the results of a Wald test). In the full model (Column 3), one additional rupee of rebate increases the probability of class 2 households purchasing stoves by 0.17% on average, compared with a marginal impact of 0.15% for class 1, and 0.13% for class 3. These marginal effects imply that an increase in the rebate level up to the full amount increases purchase by 51% for class 1, 58% for class 2, and 44% for class 3. Thus, the rebates may have a greater effect on purchase by class 2.

Question 3: Do specific preference types favor the electric stove relative to the biomass-burning ICS?

To address this question, we consider purchase of the different ICS types, using a multinomial logit model. Based on the results obtained regarding question 1, we expect that class 1 and 2 households should prefer both types of ICS over class 3 households. It is less clear, however, if class 1 or class 2 households would be more likely to adopt electric vs. biomass-burning stoves, an issue that is further complicated by the fact that the DCE did not include electric options. On the one hand, class 2 households dislike traditional stoves and have a greater willingness to pay for ICS attributes, as discussed above. Yet class 1 households place greater weight on smoke emissions relative to other ICS attributes, and these are reduced to zero inside the house by the electric stoves. In fact, the electric and improved biomass stoves that were offered to the households are similar in terms of the price and convenience attributes, since they only accommodate a single pot, but they differ in terms of fuel costs (electric stove is more expensive to operate) and smoke emissions (biomass ICS has higher emissions).

The results are shown in Table 10. Our first observation is that class 1 households are significantly more likely to purchase the electric ICS than classes 2 and 3 (Columns 2 and 4). When controlling for the rebate amount and other control variables (Column 4), these class 1 households are 10% and 13% more likely to purchase an electric stove than classes 2 and 3, respectively. In contrast, class 2 households appear more likely to purchase the biomass-burning ICS on average (Columns 1 and 3), though the differences with other the classes' purchase of this stove are not statistically significant. The model in column 4 also shows that electricity availability is positive and significant in explaining purchase of the electric ICS, as would be expected. These results together would seem to indicate that class 2 households prefer biomass-burning ICS' over classes 1 and 3, while class 1 households prefer the electric ICS. The lack of statistically significant differences in biomass ICS purchase across classes may be due to the loss of power that results from crowding out of purchases of the biomass ICS by the electric stove.

In addition, we also added the interacted rebate variables to the full model to test if the classes have different sensitivity towards the rebate amount for these different types of stoves. In Column 5, we see that class 2 is much more responsive to the rebate amount than classes 1 and 3; the differences between Rc2 and the other two interacted rebate-class coefficients Rc1 and Rc3 are statistically significant. We also note in Column 6 that class 2 and 3 households would not be significantly less likely to buy the electric ICS if the rebate level were zero (the coefficients for the indicator variables for class membership are negative, but much smaller and not significant in this case), but that these do not respond as strongly to the rebate as the class 1 households. The fact that these differences (both in the class membership coefficients and the interaction terms with the rebate amount) are not statistically distinguishable from one another is likely due to lack of statistical power. Taken together, these results suggest that relative distaste for smoke emissions of class 1 households may play a stronger role in motivating the purchase of electric stoves than the biomass ICS.

5. Discussion

Despite the very significant problems associated with use of traditional stoves, adoption of cleaner burning improved stoves has been slow, and many new technologies have not reached scale. Nowhere does the adoption puzzle appear more challenging than in India, where progress has been slow despite several decades of promotion interventions and the largest potential market for ICS in the world. This study attempted to shed light on this puzzle by considering how user preferences for different stove features, as revealed through responded stated choices in a discrete choice experiment, may relate to actual revealed purchases of distinct types of ICS. To the best of our knowledge, ours is the first study to explore the mapping of preferences for any technology elicited through a DCE, to revealed preferences.

Our sample for this comparison consists of 770 households living in rural communities in two districts of Uttarakhand, India. From the DCE, we first find that households, on average, respond as expected to the attributes of ICS, favoring those with reduced fuel requirements, smoke emissions and greater convenience (though the latter two attributes receive more weight relative to the fuel requirement). On average, they also appear to favor the traditional stoves they know (rather than the ICS options) if all other attributes are the same. Yet these average results mask important heterogeneity in households' preferences, as shown by the significant standard deviations of the mixed logit coefficients for price and stove type, and as further revealed in the LCA of household choices. In particular, the LCA identifies two classes of households, comprising 27% and 20% of the sample, respectively, who appear differentially 'interested' in the features of ICS, whereas a third class of respondents is generally 'uninterested' by these attributes (52% of households). Within the first two interested classes, the first appears to place much greater relative weight on smoke emissions reductions than on the other attributes, whereas the second is less price sensitive and values positive changes in all three ICS attributes. Closer examination of the make-up of each class shows that the 'uninterested' class mainly consists of lower-income households who lack knowledge on ICS in general and on the harmful effects of smoke inhalation.

We then consider whether the analyses of stated preferences based on responses in the DCE map to actual purchase decisions during a randomized stove promotion intervention. Specifically, our analyses consider whether class membership (as obtained from the LCA) is related to a) likelihood of ICS purchase, b) responsiveness to price incentives, and finally c) the choice of more efficient biomass versus electric ICS .stoves. We note several important results. First, we see that the 'uninterested' class does remain less likely to purchase ICS on average despite the fact that the stove promotion included intensive information provision and household-level stove demonstrations. This suggests that significant barriers exist in getting such households, who comprise a majority of our sample, to adopt a new unknown technology such as an ICS. Second, we find that households in different classes respond differently to price incentives. In particular, class 2 households appear most responsive to these incentives; these were also deemed most likely to adopt ICS based on the results of the LCA. Third, we note that the class 1 households who placed the greatest relative weight on reduced smoke emissions relative to change in other ICS attributes are actually most likely to adopt an electric ICS, which is a wholly different technology that also offers the possibility of eliminating indoor air pollution associated with cooking. Purchase of the electric ICS is also related to the availability of electricity supply, though, which is unreliable in many rural locations in the developing world.

In conclusion, these findings offer considerable new information and insights that should be incorporated into planning of future ICS promotion efforts. In particular, the heterogeneity of preferences among households suggests that such campaigns should seriously consider offering different types of ICS to households as opposed to a single technology that may not align with all users' preferences. Such demand responsiveness would also seem critical to ensuring long term use of ICS.

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Tables and Figures

Table 1. Summary of discrete choice experiment design

Attributes	Levels	Traditional stove level
Price (Rs.)[1]	500 1000 2500	0
Fuel requirement	1 3 4	3
Smoke emissions	Low High Highest	Highest
Number of cooking surfaces	1 2	1

[1] $US ≈ 52 Rs.

Table 2. Balance tests, for treatment vs. control hamlets

Variable	Mean: Treatment	Mean: Control	Difference: Normalized
Village has paved road	0.26	0.42	0.24
Distance to doctor (km)	9.43	9.41	0.00
Bank facility in village	0.34	0.27	-0.09
Prior NGO intervention in hamlet	0.49	0.53	0.06
Household size	4.80	4.91	0.03
Education- head of household (yrs)	5.84	5.58	-0.04
Education – primary cook (yrs)	4.56	4.75	0.03
Female head of household	0.26	0.30	0.07
Below poverty line household	0.56	0.59	0.05
Scheduled Caste/Scheduled Tribe	0.23	0.32	0.15
% household cold/cough in past 2 wks	0.07	0.08	0.02
Households owning improved stoves	0.28	0.41	0.20
Fuel wood used per day (kg)	6.92	6.58	-0.04
Relative wealth (1-low to 6-high)	2.08	2.26	0.15
Household has taken loan in past year	0.13	0.19	0.11
Household saved money in past year	0.10	0.11	0.00
Hours of electricity per day	17.2	17.2	-0.01
Log of total expenditure	8.40	8.43	0.03
Number of cellphones per household	1.27	1.40	0.10
Household believes ICS/clean fuels are beneficial	0.29	0.30	0.01
Household believes smoke is unsafe	0.50	0.48	-0.04
Traditional stove ownership	0.98	0.96	-0.07
% households using improved fuel	0.34	0.48	0.21
Minutes traditional stove use	297	286	-0.05
Log of total fuel expenditure	5.61	5.82	0.14
Sample size: Households	770	293	
Sample size: Hamlets	71	26	

Notes. No pairwise t-tests were found to be significant at the 10% level.

Table 3. Balance tests across rebate levels

Variable	Mean: Low Rebate	Mean: Med Rebate	Mean: High Rebate	Significant differences (p<0.1)
Village has paved road	0.30	0.32	0.30	
Distance to doctor (km)	9.12	9.36	10.1	
Bank facility in village	0.34	0.31	0.31	
Presence of Chirag (NGO)	0.50	0.52	0.56	
Household size	4.86	4.67	4.78	
Education- head of household (yrs)	5.93	6.20	5.38	R2 vs. R3**
Education- primary cook (yrs)	4.28	5.02	4.60	R1 vs. R2*
Female head of household	0.27	0.22	0.28	
Below poverty line household	0.56	0.55	0.57	
Scheduled Caste/Scheduled Tribe	0.22	0.26	0.29	R1 vs. R3**
% household cold/cough in past 2 wks	0.22	0.20	0.24	
Relative wealth (1-low to 6-high)	2.12	2.12	2.13	
Household has taken loan in past year	0.12	0.16	0.21	R1 vs. R3***
Household saved money in past year	0.08	0.14	0.11	R1 vs. R2**
Hours of electricity per day	17.8	16.4	16.7	R1 vs. R2**
Log of total expenditure	8.44	8.45	8.36	
Total rooms in house	4.61	4.88	4.60	
Presence of toilet	0.85	0.85	0.83	
Owns/leases agricultural land	0.99	0.98	0.98	
Most risk-taking respondent	0.40	0.49	0.41	R1 vs. R3**; R2 vs. R3*
Most patient respondent	0.48	0.51	0.51	
Household believes ICS/clean fuels are beneficial	0.33	0.29	0.30	
Traditional stove ownership	0.99	0.98	0.96	R1 vs. R3**
Improved stove ownership	0.31	0.36	0.29	R2 vs. R3*
Minutes spent cooking, total	331	339	341	
Minutes traditional stove use	292	284	286	
Minutes improved stove use	39.6	51.7	48.3	
Log of total fuel expenditure	5.62	5.70	5.75	

Notes. No normalized differences for comparisons between groups exceeded 0.15. Significance of t-tests for 74 pairwise comparisons is denoted by: *p<0.1; **p<0.05; ***p<0.01.

Table 4: Baseline descriptive statistics

Variable	Mean (s.d.)	N
Below poverty line	57%	1030
Perception of relative wealth: 6 step scale	2.1 (0.8)	1061
# Rooms	4.6 (2.4)	1060
Toilet use/ownership	85%	1063
Head of household		
Is Female	27%	1050
Age (years)	53 (14)	1047
Education (years)	6 (5)	1043
Respondent		
Household head	53%	1063
Primary cook	77%	1063
Only female respondent	73%	1049
Caste type		
General	73%	1063
Scheduled caste / tribe	25%	
Hindu	100%	1063
Household size	4.8 (2.1)	1063
# Children under 5	0.5 (0.8)	
% of all household members with respiratory disease in past 2 wks	7.3%	1063
Most patient households	48%	1041
Most risk-taking households	42%	1046
Electricity		
Constant	24%	1063
Intermittent	69%	1063
If intermittent, hours/day supply	16.0 (5.9)	720
Took a loan in past year	15%	1063
Stove ownership		
Traditional stove[1]	97.3%	1063
LPG stove	28.5%	
Kerosene	1.2%	
Biogas	1.0%	
Median daily use among owners (hrs/day)		
Traditional stove	5.0	1034
LPG stove	2.6	303
Kerosene	0.8	13
Biogas	1.6	11
Fuel use		
Firewood	97.3%	1060
Crop residue	0.2%	
Dung	0.2%	
Kerosene	8.2%	
LPG	27.8%	
Electricity	0.6%	
Biogas	0.9%	
Fuel prices		
Price LGP cylinder (1,000 rupees)	0.45 (0.06)	1063
Report high price of fuelwood	0.55 (0.50)	
Awareness of impacts of traditional stoves		
Health	61.7%	1063
Local forests/environment	58.4%	
Air quality/climate change	38.7%	
Awareness of clean stoves	25.1%	1063
Awareness of clean fuels	31.0%	1063

[1] Traditional stoves include: mitti ka chulha (mud stove), anjeti, 3-stone fire, and sagarh (coal stove).
[2] At the time of the baseline survey in 2012, US$1 = 52 Rs.

Table 5. Mixed logit analysis of DCE choices[1]

Variables	Normal price		Lognormal price	
	(1) Mean	(2) SD	(3) Mean	(4) SD
Price (Rs)[2]	-0.457***	-0.507***	-1.03***	2.53***
	(0.000)	(0.000)	(0.000)	(0.000)
Fuel requirement	-0.162***	-0.133	-0.158***	0.147***
	(0.000)	(0.301)	(0.000)	(0.321)
Smoke emissions	-0.351***	-0.228	-0.368***	0.071
	(0.000)	(0.267)	(0.000)	(0.680)
Number of pots	0.377***	0.067	0.389***	0.260
	(0.000)	(0.842)	(0.000)	(0.357)
Traditional stove[3]	2.45***	4.55***	1.32***	4.19***
	(0.000)	(0.000)	(0.000)	(0.000)
WTP for 1-unit decrease ($US)[4]				
Fuel requirement	$3.41		$4.26	
Smoke emissions	$7.39		$9.91	
Number of pots	-$7.93		-$10.48	
Observed choices	9162		9162	
Likelihood ratio (χ^2)	1316.1		3567.1	

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; p-values in parentheses

[1] Model excludes respondents who answered any one of four comprehension questions incorrectly prior to the first choice task.

[2] Note that price is in Rupees divided by 500 (2012$US= 52 Rs.)

[3] Traditional stove type = 1 if it was the traditional stove, 0 if improved.

[4] 1 unit in the DCE represents 33% of traditional stove smoke emissions and fuel consumption, and a single cooking surface.

Table 6. Latent class analysis of DCE data

Variables	(1) Class 1	(2) Class 2	(3) Class 3
Price[1]	-0.338***	-0.137***	-1.135
	(0.000)	(0.0020)	(0.614)
Fuel requirement	-0.114**	-0.211***	0.0778
	(0.048)	(0.0016)	(0.804)
Smoke emissions	-0.507***	-0.326*	1.586
	(0.0004)	(0.060)	(0.376)
Number of pots	0.244*	0.647***	-1.493
	(0.099)	(0.000)	(0.461)
Traditional stove[2]	0.588**	-2.509**	0.828
	(0.034)	(0.016)	(0.804)
Observations	9,168	9,168	9,168
Number of groups	3,060	3,060	3,060

Notes: *** p<0.01, ** p<0.05, * p<0.1 ; p-values in parentheses
[1] Note that price is in Rupees divided by 500 (2012$US= 52 Rs.)
[2] Traditional stove type = 1 if it was the traditional stove, 0 if improved.

Table 7: Correlates of latent class membership

Variables	(1) Class 1	(2) Class 2
Relative wealth	0.0415	0.343***
	(0.701)	(0.00308)
Age of hh head	-0.0150**	-0.0143**
	(0.0283)	(0.0115)
Yrs. education of hh head	-0.0243	-0.00845
	(0.354)	(0.731)
General caste	-0.0731	-0.424
	(0.847)	(0.190)
Most patient[1]	0.0835	0.329***
	(0.419)	(0.00146)
Perceptions of smoke safety[2]	-0.127	0.0473
	(0.126)	(0.574)
Aware of clean stoves	0.778***	-0.130
	(0.000631)	(0.711)
Aware of negative health impacts of traditional stoves	0.597**	0.726***
	(0.0134)	(0.00444)
HH Size	-0.0816**	0.0370
	(0.0406)	(0.462)
Respondent is primary cook	-0.204	-0.233
	(0.272)	(0.273)
HH has child <5 yrs old	0.103	-0.0146
	(0.359)	(0.896)
Sales NGO present	-0.195	-0.277
	(0.503)	(0.281)
Constant	0.294	-2.041***
	(0.744)	(0.00379)
Observations	991	991

Notes: Multinomial logit specification, class 3 is the omitted class; *** p<0.01, ** p<0.05, * p<0.1; p-values in parentheses. Standard errors are clustered at the hamlet level.

[1] Most patient as determined by responses to 3 hypothetical time preference questions.

[2] Perceptions of smoke safety measured on a subjective scale where 0 is totally unsafe and 0 is totally safe.

Table 8: ICS purchase by latent class

VARIABLES	(1) StoveBuy	(2) StoveBuy	(3) StoveBuy	(4) StoveBuy
maxlclass2[1]	0.0168	0.00276	-0.00201	-0.0246
	(0.676)	(0.946)	(0.959)	(0.661)
maxlclass3[1]	-0.118***	-0.0868**	-0.0855**	-0.0892**
	(0.00166)	(0.0383)	(0.0434)	(0.0247)
Rebate amount (Rs.)		0.00140***	0.00138***	0.00141***
		(7.91e-07)	(1.08e-06)	(1.13e-06)
Sales NGO present			0.0794*	0.0559
			(0.0587)	(0.210)
Hours of electricity supply				0.00757***
				(0.000317)
Relative wealth				0.0331
				(0.279)
Age of hh head				-2.01e-06
				(0.998)
Yrs. education of hh head				0.00308
				(0.677)
General caste				0.0277
				(0.445)
Constant	0.523***	0.247**	0.210**	-0.0124
	(1.61e-06)	(0.0112)	(0.0262)	(0.901)
Observations	770	770	768	716
R-squared	0.016	0.144	0.150	0.160

Notes: Linear probability model; *** p<0.01, ** p<0.05, * p<0.1; pval in parentheses. Standard errors are clustered at the hamlet level.

[1] maxlclass2 and maxlclass3 are indicator variables denoting assignment to a latent classes 2 and 3, respectively. Class 1 is the omitted class.

Table 9: Response to rebate amount, by latent class

VARIABLES	(16) StoveBuy	(17) StoveBuy	(18) StoveBuy
maxlclass2[1]	-0.00513	-0.0120	-0.0660
	(0.957)	(0.826)	(0.325)
maxlclass3[1]	-0.0374	-0.0358	-0.0468
	(0.593)	(0.495)	(0.280)
Rc1	0.00154***	0.00152***	0.00150***
	(1.14e-09)	(9.90e-06)	(1.98e-05)
Rc2	0.00157***	0.00156***	0.00170***
	(3.85e-07)	(0.000323)	(7.14e-05)
Rc3	0.00127***	0.00125***	0.00127***
	(0)	(2.54e-05)	(2.45e-05)
Sales NGO present		0.0802*	0.0567
		(0.0538)	(0.197)
Hours of electricity supply			0.00761***
			(0.000298)
Relative wealth			0.0338
			(0.273)
Age of hh head			1.58e-05
			(0.988)
Yrs. education of hh head			0.00307
			(0.685)
General caste			0.0298
			(0.411)
Constant	0.220***	0.182**	-0.0348
	(0.000181)	(0.0252)	(0.775)
Observations	770	768	716
R-squared	0.145	0.151	0.162

Notes: Linear probability model; *** p<0.01, ** p<0.05, * p<0.1; pval in parentheses. Standard errors are clustered at the hamlet level.

[1] maxlclass2 and maxlclass3 are indicator variables denoting assignment to a latent classes 2 and 3, respectively. Class 1 is the omitted class.

[2] Rc1, Rc2, and Rc3 are interaction terms for the rebate and indicator variables for assignment to specific latent classes.

Table 10: ICS choice, by latent class

VARIABLES	(1) Improved biomass	(2) Electric	(3) Improved biomass	(4) Electric	(5) Improved biomass	(6) Electric
maxlclass2	0.671	-0.189	0.522	-0.347**	-0.816	-0.183
	(0.126)	(0.119)	(0.433)	(0.0349)	(0.226)	(0.603)
maxlclass3	-0.0101	-0.651***	0.0490	-0.584***	-0.505*	-0.121
	(0.971)	(5.82e-06)	(0.874)	(0.00137)	(0.0888)	(0.629)
Rebate amount (Rs.)			0.00839***	0.00557***		
			(0)	(5.06e-09)		
Rc1					0.00625***	0.00686***
					(1.45e-05)	(3.02e-08)
Rc2					0.0115***	0.00626***
					(0)	(0.000103)
Rc3					0.00826***	0.00461***
					(0)	(0.000393)
Sales NGO present			0.306	0.264	0.293	0.269
			(0.310)	(0.318)	(0.340)	(0.298)
Hours of electricity supply			-0.0165	0.225*	0.0200*	0.0451***
			(0.946)	(0.0669)	(0.0927)	(8.50e-07)
Relative wealth			0.00501	-0.00276	-0.00989	0.231*
			(0.479)	(0.519)	(0.968)	(0.0656)
Age of hh head			0.0461	0.00180	0.00529	-0.00300
			(0.268)	(0.952)	(0.456)	(0.477)
Yrs. education of hh head			0.960***	-0.143	0.0452	0.00216
			(0.00429)	(0.522)	(0.298)	(0.943)
General caste			0.0194*	0.0446***	0.989***	-0.134
			(0.0964)	(8.95e-07)	(0.00477)	(0.539)
Constant	-0.776***	-0.336	-4.406***	-2.673***	-4.428***	-2.623***
	(0.000297)	(0.158)	(1.16e-05)	(4.84e-08)	(3.59e-09)	(3.24e-06)
Observations	770	770	716	716	716	716

Notes: Multinomial logit model, with no purchase as the omitted category; *** p<0.01, ** p<0.05, * p<0.1; pval in parentheses. Standard errors are clustered at the hamlet level.

[1] maxlclass2 and maxlclass3 are indicator variables denoting assignment to a latent classes 2 and 3, respectively. Class 1 is omitted.

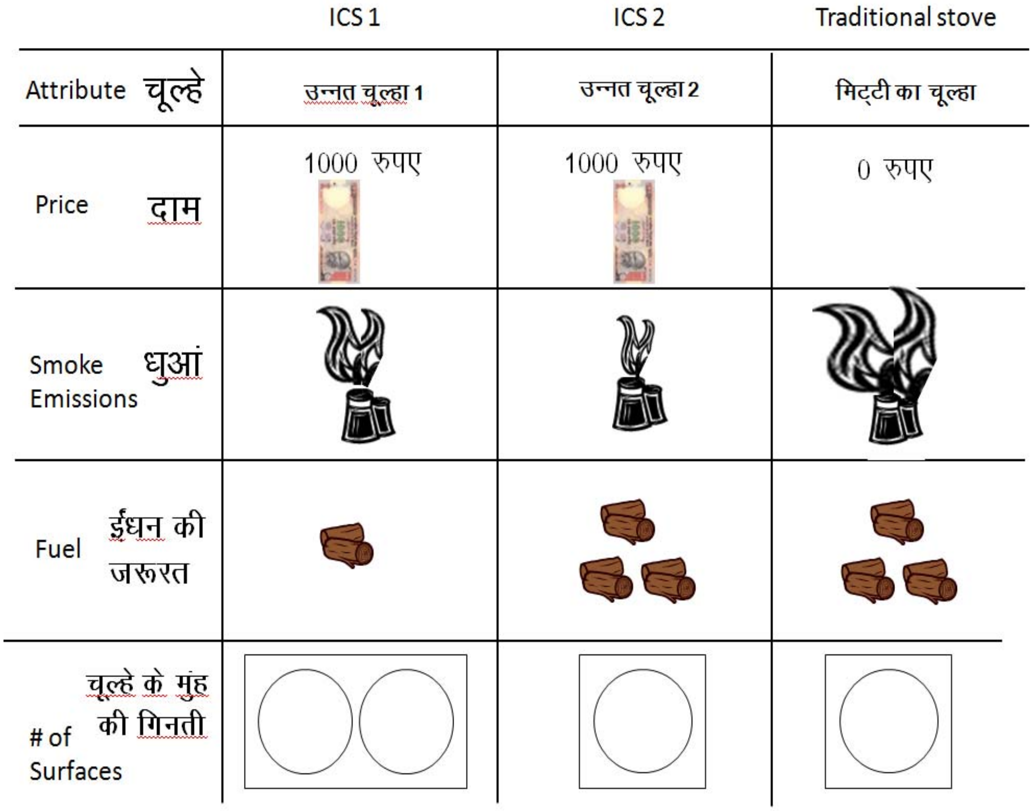

Figure 1. An example choice task in the stove decision exercise