DUKE ENVIRONMENTAL AND ENERGY ECONOMICS WORKING PAPER SERIES
organized by the
NICHOLAS INSTITUTE FOR ENVIRONMENTAL POLICY SOLUTIONS
and the
DUKE UNIVERSITY ENERGY INITIATIVE

# Preference Heterogeneity and Adoption of Environmental Health Improvements: Evidence from a Cookstove Promotion Experiment

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Working Paper EE 14-10
September 2014

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**Acknowledgments**
This study was funded by the U.S. Agency for International Development (USAID) under Translating Research into Action, Cooperative Agreement No. GHS-A-00-09-00015-00. This article is made possible by the support of the American people through USAID. Its contents are the sole responsibility of the authors and do not necessarily reflect the views of USAID or the U.S. government. We are grateful to Chirag in Uttarkhand and to The Energy and Resources Institute in Delhi for facilitating our work in the study communities.

# The role of preference heterogeneity in adoption of environmental health improvements: Evidence from a randomized cookstove promotion experiment

**Abstract**

Household preferences should influence adoption of environmental health-improving technologies, but there has been limited empirical research to isolate their importance, perhaps due to challenges of measurement and attribution. This paper explores first the heterogeneity in household preferences for different features of improved cookstoves (ICS). Second, we assess the degree to which these preferences are associated with actual adoption of ICS (electric and biomass-burning) during a randomized stove promotion campaign in northern India. Analyzing data from a discrete choice experiment (DCE) conducted during baseline surveys with 1060 households, we identify three distinct preference types using latent class analysis (LCA). These can be characterized as 1) disinterested (54%); 2) low demand but primarily interested in reduced smoke emissions (27%); and 3) high demand with interest in most features of the ICS (20%). The ICS intervention, which was stratified according to communities' prior history of interactions with the NGO marketing the stoves, was then randomized to 762 of these households. We find that households in the disinterested class are less likely to purchase an ICS; also, preference class is more strongly related to stove purchase than common socio-demographic drivers of technology adoption identified in the literature. Distaste for smoke emissions appears to be a particularly strong driver for adoption of an electric ICS, rather than an improved biomass one. Interestingly, the effect of preference class changes over time, which may indicate that initially recalcitrant households were influenced by the adoption decisions taken by those around them. The effect of preferences on purchase also varies across institutional strata, suggesting in particular that prior interaction with a trusted promoting institution may help to overcome disinterest in unknown technologies such as ICS. Lastly, there is some limited evidence that preference class explains changes in downstream outcomes across households exposed to the intervention.

**Keywords:** Improved cookstoves, discrete choice experiment, latent class analysis, field experiment, India

**JEL Codes**: C93, D12, Q41, Q53

## 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). Such 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).[1]

Yet despite the very significant problems associated with traditional stoves, adoption of cleaner burning stoves has been slow. New biomass-burning technologies have not reached scale, and other alternatives – mainly electric and gas stoves – have been constrained by the lack of a robust distribution system for the energy sources and fuels on which they depend. 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 more efficient biomass stoves sold in each of 2011 and 2012, even though globally sales were in the millions (GACC 2012; Colvin et al. 2013). Beyond well-known problems of high costs and a weak supply chain, researchers and practitioners have claimed, with only limited evidence from rigorous field studies, that the existing range of biomass ICS prototypes are unreliable and 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; Shell Foundation 2013). Meanwhile, more widely accepted ICS technologies such as LPG and electric stoves remain costly for poor households, and the fuels lack a robust and strong supply chain or distribution system in many rural areas (Lewis et al. 2014). Thus, a range of recent studies conducted in South Asia suggest that major challenges remain in the 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).

[1] We use the term improved cook stoves (ICS) in this paper to refer to both of these types of technologies, e.g., more efficient biomass stoves, as well as stoves that use advanced, cleaner-burning fuels such as LPG or electricity.

These recent negative findings raise important questions about ICS promotion and dissemination, but they stand in sharp contrast to those from other field studies, mainly conducted in East and West Africa, that suggest that ICS promotion can in fact succeed, at least in the short-term (Bensch and Peters 2012; Levine and Cotterman 2012). Indeed, 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, 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). To address these challenges of low demand and the diversity of preferences and net benefits of ICS, part of the solution has to lie in learning to engineer and adapt stoves and services to local cooking requirements and conditions, and perhaps in delivering incentives for adoption.

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 of ICS and exposure to existing technologies (especially in terms of understanding their maintenance requirements), peer influences, credit constraints, 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). Given the strong positive externalities associated with adoption of such technologies, outside intervention and subsidy may also be justified (Pattanayak and Pfaff 2009); as such, the effectiveness and nature of the institutions promoting them become critical. Successful promotion strategies for ICS and other environmental health technologies have worked to address some of these barriers, by engaging with institutions that are able to effectively implement social mobilization campaigns (Pattanayak et al. 2009), or by providing financing options and reducing the risk of adoption (Levine et al. 2013).

The purpose of this paper is to shed light on several aspects of this ICS adoption puzzle that have not been previously considered. First, we work to better characterize variation in household preferences for ICS, and the extent to which those preferences relate to uptake and subsequent use of ICS during a randomized ICS promotion campaign. To understand these preferences, we apply generalized multinomial logit methods to analyze discrete choice experiment (DCE) data collected during baseline surveys among all sample households in Uttarakhand, India (Magidson and Vermunt 2004). 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). In particular, we use latent class analysis to look for regularities in the choice patterns of different respondents.

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 purchase an ICS during a randomized ICS promotion campaign. The promotion campaign was stratified along institutional lines; roughly half of households targeted by a stove sales pitch lived in communities in which the ICS-promoting NGO had a history working on a variety of other projects, while the other half were from a set of communities that did not. This stratified design allows us to consider whether the influence of preferences is sensitive to supply-side characteristics of the promotion campaign. A follow-up survey conducted several months after the intervention sheds additional light on longer-term adoption and use of the intervention ICS, as well as downstream outcomes: biomass fuel savings, time spent collecting fuel, and self-reported respiratory illness.

We find that about half (52%) of sample households can be categorized as initially 'uninterested' (we call these class 3) in the positive attributes of ICS. These households have lower wealth, are older, and are less aware of the health damages caused by smoke inhalation at baseline. The other two classes are primarily distinguished by their relative responses to smoke emissions reductions versus reduced fuel requirements and increased convenience, with class 1 (27%) being mainly interested in smoke emissions reductions, and class 2 (~20%) having much higher relative demand for the full set of ICS attributes. Consequently, we observe that class 3 households were significantly less likely to purchase any ICS during the first of three visits by the sales teams implementing the randomized sales campaign (especially in communities without a prior relationship with the sales NGO), an effect that however faded by the end of the sales period. Among the other two groups, class 1 was more likely to adopt an electric, rather than a biomass-burning ICS, suggesting that distaste for smoke may play a particular role in motivating purchase of the 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. Few of the other household or community-level covariates that are commonly associated with demand for environmental health improvements explain stove purchases.

Looking beyond stove purchase, we also find that household use of either ICS, conditional on stove purchase, is not significantly different across preference classes. And though statistical power is limited, ICS use in all three preference classes does appear higher among households living in communities with prior interactions with the promoting NGO. Lastly, there is some limited evidence that preference class explains differential changes in downstream outcomes measured several months after the intervention. Treatment households in class 1, who were most likely to purchase the electric stove, report higher gains in ownership and use of ICS, and are the only group to experience decreases in self-reported respiratory illness. Meanwhile, class 2 households, who were most likely to purchase the biomass-burning stove, do not experience the fuel savings gained by other household types in the treatment group.

Our paper makes several contributions. First, we add to a thin literature on private demand for ICS by being the first to examine how households respond to an ICS sales offer that offers 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 these preference classes relate to the choices revealed in the randomized ICS promotion campaign, and several important outcomes that result from it. Fourth, we generate new evidence on the interaction between preferences and prior exposure to promoting micro-institutions. These contributions serve to elucidate important supply- and demand-side features of the market for ICS, which are critical for product development and market segmentation needed for the successful dissemination and diffusion of these and similar 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, and the 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*;

$\beta_0^{i}$ = 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*;

$\beta^{i}$ = 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

$\varepsilon_{jt}^{i}$ = 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 $\beta_0^{i}$ and $\beta^{i}$ 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 $\beta$ coefficients, and instead estimate two types of generalized multinomial (or random parameters, or mixed) logit models.[2] The first is the mixed logit, which allows for unobserved heterogeneity in tastes across individuals, as specified through inclusion of respondent-specific stochastic components $\eta^{i}$ for each of the estimated

[2] 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.

coefficients $\beta$ in the model. In the mixed logit model, the probability that alternative j will be selected from choice set *t* can be written as:

$$\text{Prob}[C^i = (C^i_{j1}, \dots, C^i_{jT})] = \int \frac{\exp(\beta^{i*}X_{jt} + \beta_0^{i*}p_{jt})}{\sum_{\text{k}=0}^{\text{K}} \exp(\beta^{i*}X_{kt} + \beta_0^{i*}p_{kt})} f(\eta|\Omega)d\eta \,, \qquad (3)$$

where $\beta^* = (\beta + \eta^i)$ and $f(\eta|\Omega)$ denotes the density of the individual disturbance terms $\eta^i$ given the fixed parameters *Ω* of the distribution. The stochastic portion of utility then flexibly accommodates correlations both across alternatives and choice tasks. The coefficients $\beta^*$ 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 according to the predicted probability for each class, and study the correlates of class membership using a multinomial logit model.

*Modeling the adoption decision*

From the stove promotion campaign and follow-up surveys conducted several months after the promotion campaign, we observe households' ICS purchase and use decisions. We regress these outcomes on latent class membership which was predicted earlier based on responses in the DCE. The most general model we estimate can be written as:

$$Y_{ij} = \beta_0 + \beta_k \cdot C_{kij} + \beta_r \cdot r_{ij} + \beta_n \cdot N_{ij} \cdot C_{kij} + \beta_{li} \cdot X_{lij} + \mu_j + \varepsilon_{ij}. \qquad (3)$$

In this model, $Y_{ij}$ is a dummy variable representing purchase or use of an intervention ICS by household *i* in community *j*. More specifically, we analyze purchase of an ICS during the initial sales visit, purchase during the entire campaign, and use observed at the time of the follow-up survey visits. 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 at the household-level in the communities exposed to the stove offer; $N_{ij}$ is a dummy variable that indicates if a household is in a community *j* with a prior history of interventions implemented by the sales NGO; $X_{lij}$ is a vector of *l* household and community variables that influence the purchasing decision; $\mu_j$ is an error term clustered at the community level; and $\varepsilon_{ij}$ is the usual individual idiosyncratic error term. The coefficients $\beta$ are estimated using OLS regression, and allow us to consider the effects of preferences and price incentives, ($\beta_k$ and $\beta_r$, respectively) on outcomes, and whether these preference effects vary across institutional strata ($\beta_n$).

In the ICS purchase models, we first group the improved biomass and electric stoves into one general category and analyze adoption of any ICS, using a linear probability model. We consider more parsimonious specifications for equation 3 as well as the complete model. We then apply a multinomial logit model that treats the three options as a categorical outcome for each household (no stove, electric, or improved biomass stove). Standard errors in all analyses are clustered at the community or hamlet level as this is the administrative level at which the stove promotion campaign was assigned.

Finally, we also use difference-in-difference (DiD) methods to consider a set of other outcomes (overall ICS ownership, fuel use, fuel collection time, and self-reported respiratory illness) related to adoption and use of ICS. We use DiD analysis for these analyses to adjust for baseline differences across household type and institutional strata given that roughly 30% of sample households already own a clean stove (mostly LPG) at baseline.

## 3. Research site and data

The target region for this study, in the Northern Indian state of Uttarakhand, 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 2013.

*Sampling frame*

The sampling frame for the study consists of 97 geographically distinct communities (or hamlets) located in 38 Gram Panchayats (GPs) in the Bageshwar and Nainital districts of Uttarakhand. The overall sample was stratified along institutional lines – half of the communities in the final sample had prior exposure to the non-governmental organization promoting the stoves, and the other half did not (Figure 1).

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 set of 97 hamlets.

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. The final sample for the household survey consisted of 1,063 households.

*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 2 and Table 1.

Importantly, given the fact that the randomized intervention allowed for a choice between an electric and biomass-burning ICS, the improved options presented in the DCE were biomass-burning stoves. At the start of the stove decision exercise, this ICS stove alternative was 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 were asked to confirm their willingness to pay the price listed on the card: "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?"[3] 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.

[3] 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."

*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; households living in control communities were not (Figure 1). Following careful field piloting of potential ICS promotion techniques (Lewis et al. 2013), 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: an electric coil and biomass-burning ICS.[4] 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 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). Roughly two thirds of purchasing households opted to pay for the ICS in installments.

In addition, households were told that they would receive a randomized rebate to be given at the time of the final payment if they were found to be using the stoves (as observed during unannounced visits). Those paying for stoves upfront were also eligible for the rebate and thus were also revisited roughly one month later. 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% discount). Stoves were sold to households for 960 Rs. (electric coil) or 1380 Rs. (biomass); these prices correspond to the stove-specific prices paid to suppliers. As such, the amount of the high rebate (320 or 460 Rs.) varies somewhat based on the stove that is chosen by a household. Due to concerns over the endogeneity of the high rebate amount, we replace this varying amount with 320 Rs. in our analyses (the rebate for the electric stove); none of our results are sensitive to this approach.[5] Finally, because of this design and the two follow-up visits to intervention communities that it entailed, households that initially declined the ICS

[4] We offered two types of biomass ICS in the initial piloting activities, but it quickly became apparent that demand for these technologies was low. After observing great interest in a similarly-priced electric stove in later pilots, however, we decided to offer it alongside the more affordable of the biomass-burning stoves.

[5] The sensitivity of purchases to the rebate level that we estimate may thus be somewhat overestimated, particularly for the biomass stove.

during the first visit were allowed to purchase a stove during follow-up visits so long as they caught up with the installment payments they had missed.

We opted for this intervention design based on both small-scale piloting experiences in 8 villages and on our analyses of responses in the DCE, which showed great heterogeneity in overall demand, as well as relative weighting that households gave to smoke reductions (greatest with the electric stove) vs. fuel savings (Jeuland et al. 2013; Bhojvaid et al. 2013). This evidence on heterogeneous preferences made us think that artificially constraining the choice set by randomizing specific stoves to different intervention communities might depress demand, though the tradeoff is that it prevents us from clearly differentiating the impacts of stove adoption by ICS type. 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 771 of the 1063 baseline households) were randomly assigned to the treatment group. The remaining 26 hamlets were control hamlets that did not receive any visits from the stove promotion teams (Figure 1).

*Sample balance and descriptive statistics*

This paper reports on data collected at three points in time; at baseline surveys, at the time of the intervention, and post-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. In the post-intervention survey, we collected additional information on whether households owned and used an intervention ICS. Thus, we analyze the DCE data that pertain to the entire sample of households that includes treatment and control communities, but only differentiate the adoption results by class for households in the treatment communities.

Descriptive statistics from the baseline sample of 1063 households are summarized in Table 2. 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 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, and 25% are scheduled caste or 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 used it alongside a biomass stove (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: 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 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%).

The treatment and control households are well balanced across a number of key variables measured in the baseline survey (Table 3). Normalized differences are modest, and only two of variables – female head of household and patience (as measured using hypothetical time preference tradeoffs) – are significantly different at the 10% level when the variable is regressed on treatment status. There are somewhat greater differences between treatment and control households within the NGO stratum, though sample sizes are small and these differences are driven by a few communities with very high baseline ownership of LPG stoves. The most notable differences for treated households in this subgroup are in baseline ICS ownership, spending on fuel, and traditional stove use. If anything, these differences suggest that estimates of impact within this stratum may be biased downward since households already owning an ICS may not experience the same benefits as newly-adopting households (and conversely, estimates of impacts among households living in non-NGO communities may be overestimated), an issue we explore more fully using DiD analysis. We also note that none of our main results change substantively when we drop the few communities with very high LPG ownership at baseline, which largely removes these observed imbalances (results available upon request).

Similarly, the rebate assignment – randomized to all treated households – is generally uncorrelated with baseline household characteristics (Table 4). No normalized differences across groups exceed 0.15 and 10 out of 87 coefficients are significant at the 10% level, which is similar to the proportion that would be expected due to chance. The most notable differences detected are that households in the lowest rebate group are less likely to have taken loans or saved money in the past year, and have slightly more hours of electricity per day than the other groups, while those in the middle rebate group are less likely to have a female head of household. Finally, households in the highest rebate category are slightly more likely to be in the NGO stratum and more likely to have taken a loan in the past year.

## 4. Results

*Analysis of preferences: Mixed logit analyses*

Using the data available from the DCE, we first consider the variation in preferences for ICS attributes. We estimate 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 fixed (Columns 1 and 2) or log-normal (Columns 3 and 4). By restricting the distribution of the price coefficient in these ways, we ensure that price will be negatively related to the adoption decision. The coefficients for these attributes 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 were more likely to be selected (all other attributes being equal). 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 ICS attributes may not vary greatly (Columns 2 and 4), although Column 4 shows that the standard deviation on price is significant. 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; this implies that many respondents would need to see large reductions in these levels to consider adopting an ICS.

*The determinants of preferences for ICS*

Given the heterogeneity in responses to price and traditional stoves as detected by the random parameters model, we next use LCA to look for 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.[6] Of these two classes, the first is considerably more price sensitive but is relatively more responsive to smoke emissions reductions (the implied part-wise utility associated with a 1-unit smoke emissions reduction is still lower than that for class 2, however), whereas the second is less price sensitive and places greater relative weight on the fuel reduction and convenience attributes. In addition, as shown by the alternative-specific constant, class 1 strongly prefers traditional stoves to improved biomass stoves, while class 2 does not, emphasizing that class 2 appears to be the higher demand group, at least for a biomass ICS. In contrast, we consider class 3 (~52%) to be an 'uninterested' group since none of the stove attributes coefficients for this group are significant. We expect that members of this class will perhaps be least likely to adopt an ICS, at least of the biomass-burning type that was shown in the DCE. Considering that class 3 constitutes more than half of the sample, it is important to note the possibility that such respondents simply may not have understood or paid attention to the DCE exercise, although their pattern of responses suggests that they tended to favor the traditional alternative, no matter the attributes of the ICS alternatives, and therefore were not answering questions in random fashion.[7]

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

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

[7] We determined that many of these households were serial non-responders, in the sense that they always chose the traditional stove (see Appendix Table A1).

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, which may also explain the lower price sensitivity of such households (due to an income effect) and their 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 are most meaningful to class 2 respondents, which may further contribute to the lower price sensitivity of these respondents. On the other hand, class 1 is more aware of clean stoves and uses traditional stoves for less time each day; these households are more likely to already own LPG stoves and thus perhaps see greater value in reducing use of biomass fuels. Importantly, class type appears unrelated to the prior relationship with the sales NGO.

*Analyzing the ICS adoption and usage decision*

These analyses of preferences 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 five questions on the relationship between the stated preferences and actual ICS purchases and use. 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 binary predicted class variables to explain purchase. We then add the randomized rebate (discount) amounts, followed by interaction terms between preference classes and the institutional stratum, and finally including all of these plus a vector of community and socioeconomic characteristics, many of which constitute common drivers of clean stove ownership considered in the literature (Pattanayak and Lewis 2012). In the ensuing discussion, we report results from all the estimated models but our preferred specification is the full model.

*Question 1: Is preference class related to purchase of ICS during the sales intervention?*

This question arises from the observation that the three preference classes responded very differently to the ICS' positive attributes in the DCE exercise. In particular, we consider two separate purchase variables: at first contact with the sales team (considering that later purchasers declined during the initial visit), and then over the course of the entire sales campaign (with the revised outcome among these lagged purchasers).

Using a linear probability model, the results show that compared to class 1, class 3 households are about 9-11 percentage points less likely on average (or a roughly 20% lower purchasing rate) to purchase an improved ICS during the first sales visit (Table 8, columns 1-4). Controlling for the rebate amount decreases the estimates slightly (columns 2-4) since class 3 households by chance received slightly lower rebates than class 1 and 2 households. Counter to our expectations given their different price sensitivities in the DCE, we do not detect any differences between class 1 and class 2 households with respect to this 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% (Figure 2). Of the other covariates, electricity supply reliability is positively associated with purchase; this is not surprising since one of the two offered stoves, purchased by three quarters of adopting households, was electric. No other controls – these are listed in the notes below Table 8 – are significantly related to ICS purchase, perhaps because the promotion campaign involved intensive information provision and explanation of the costs and benefits of ICS to all households, and relaxed liquidity constraints by allowing 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. This also lends credence to the idea that the inherent technological preferences expressed in the DCE provide information that is not contained in ordinary more typically observed predictors of clean stove demand.

When we include purchases made during subsequent visits to recover the second and third installments (during which 36 additional households chose to buy stoves, out of the 408 who did not originally buy a stove), however, we find that the lower purchase rates among class 3 households fade somewhat (columns 5-8). Purchase rates are 7-10% lower on average in this analysis; this is because these later adopters are more likely to be in class 3. In considering purchases over a period of multiple visits during which neighboring households were exposed to new stoves, inherent individual preferences may become less important given the influence of peers and the potential for learning. The other explanatory variables are similar in magnitude and significance to the previous model.

We further note, based on the results for the interactions of preference class and institutional stratum, that the lower purchase rates among class 3 households are entirely concentrated in communities not having a prior relationship with the promoting institution (Table 9 Columns 3 and 4). This provides additional evidence on the importance of influences that may moderate the effects of preferences, particularly among initially disinterested or cautious households.

*Question 2: Are there differences in the responses to rebates across classes?*

This question emerges from observations 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 households in 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 was also interacted with the rebate amount (Table 9)[8]. The results suggest that classes 1 and 2 are similarly more responsive to the rebate amount than class 3, although differences in responsiveness to the rebate are not significant 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 and class 3 households purchasing stoves by 0.17% on average, compared with a marginal impact of 0.13% for class 3. These marginal effects imply that an increase in the rebate level up to the full amount increases purchase by about 58 percentage points for class 2, compared to 54 and 43 percentage points for classes 1 and 3, respectively. Thus, the rebates may have a slightly larger effect on purchases by classes 1 and 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 from question 1, we expect that class 1 and 2 households should prefer 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 addition, the improved biomass stoves that were offered to the households are somewhat more expensive, suggesting that the more price sensitive class 1 households may prefer the electric ICS. Both accommodate a single pot, but they differ in terms of fuel costs (the electric stove is more expensive to operate).

[8] We only report results for the first purchase sample. Results from the sample with lagged purchases do not changes substantively and are reported in Appendix Table A2.

The results are shown in Table 10.[9] Our first observation is that class 1 households are indeed most likely to purchase the electric ICS (Columns 2 and 4); when including all controls, class 1 households are 6% and 14% more likely to purchase this stove than classes 2 and 3, respectively.[10] In contrast, class 2 households appear more likely to purchase the biomass-burning ICS on average (Columns 1 and 3); specifically, they are 8% and 6% more likely to purchase a biomass ICS than classes 1 and 3, respectively. The model in column 4 also shows that electricity availability is positive and significant only in explaining purchase of the electric ICS, as would be expected. These results indicate that class 2 households prefer biomass-burning ICS' over classes 1 and 3, while class 1 households prefer the electric ICS, which is consistent with the DCE results. As with overall purchase, very few other covariates explain the differences in purchase rates across technologies.

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 most responsive to the rebate amount for the biomass stove; the differences between Rc2 and the other two interacted rebate coefficients are statistically significant. We also note in Column 6 that class 3 households are least responsive to the rebate for the electric ICS, and class 1 households (the omitted category) are most responsive. Taken together, these results suggest that relative distaste for smoke emissions and greater price sensitivity of class 1 households may play a stronger role in motivating the purchase of electric stoves than the biomass ICS.

*Question 4: Are specific preference types more likely to use the ICS?*

Up to this point, our attention has been focused on ICS purchase decisions, but the benefits of ICS only come with sustained use (McCracken et al. 2007; Hanna et al. 2012). We explore the short-term sustainability of ICS usage by using self-reported daily usage of households' ICS during the follow-up survey conducted several months after the sales campaign. Conditional on purchasing ICS, preferences from the DCE are not significantly correlated with use, which is not surprising since the DCE was designed to predict purchase rather than use among purchasers (Table 11). The analysis of use also confirms findings in the literature that highlight that ICS ownership often does not necessarily equate to use. In column 1, for example, we see that only about 56% of purchasers in the omitted class (class 1) use the ICS on a daily basis. The full model in column 4 also shows that the randomized rebate amount is positively associated with use, which suggests that the conditional rebate

[9] We again only report results for the first purchase sample. Results from the sample with lagged purchases do not differ by much and are reported in Appendix Table A3.
[10] These marginal effects are evaluated at the mean value of other covariates.

promised to users at the time of the third sales visit may perhaps have helped to incentivize longer-term use.[11] This effect translates into a roughly 23 percentage point increase in the probability of daily usage. We also see from the class-NGO interactions that prior NGO history in the village contributes to higher daily use across all three preference groups, by about 16 percentage points, though this effect is not statistically significant in all cases (Columns 3 and 4). This suggests that a lack of follow-up support may be an important contributor in reduced long-term success of environmental-health improving technologies. Among the other covariates, electricity supply is somewhat negatively related to use, while time spent collecting fuel and cooking on traditional stoves (at baseline) are positively related to use (results not shown). No other covariates are statistically significant.

We also separately analyzed electric and biomass ICS to consider variation in use by stove type. The results are shown in Columns 5 and 6; several aspects of this conditional analysis are noteworthy. First, daily use is far from universal for either stove (the weighted average across purchasers is 30% for the electric stove and 47% for the biomass stove). Second, for the electric stove, the only significant correlate with use is the time spent collecting fuel at baseline. Finally, for the biomass ICS (column 6), prior NGO history is related to a 25% and 29% greater probability of daily use for classes 2 and 3 (both p-values are very close to 0.1). In fact, the overall result in columns 3 and 4 are mainly driven by the biomass ICS as electric stove use is only about 8% higher overall in the NGO stratum. Households in these NGO villages may be more motivated to use the biomass ICS because they have become more attuned to the NGO's concerns about environmental preservation.

*Question 5: Is NGO history linked to higher use of improved stoves and other stove-related outcomes following the ICS promotion?*

The results presented thus far suggest a) that preference class influences purchase of ICS, and b) that prior NGO history in a community enhances use of the biomass ICS and, to a lesser extent, purchase among initially disinterested households. Yet the initial imbalance in clean stove ownership in the NGO stratum (higher in the treatment group) raises the possibility that these estimates could be biased downwards, if owners of clean stoves were less likely to adopt, use, and benefit from a new one. Alternatively, they could be biased upwards if LPG-owning households were naturally predisposed to try a new and different cooking technology. To better understand the net changes in clean stove ownership, use and other outcomes, we conclude our analysis by applying a difference-in-difference approach that adjusts for baseline differences across our sample groups. For

[11] Other explanations are also possible, for example the presence of income effects, but our experiment was not designed to differentiate among such possibilities.

each of these analyses, we first present DiD results stratified by class, and then further stratify these results by institutional stratum, in the latter analysis also controlling for rebate level.[12] The downstream outcomes we consider are changes in firewood use over time (in kilograms and in minutes of collection time per day), and in self-reported respiratory illness.

The first two analyses show that ownership and use of ICS at follow-up are not significantly different across preference classes, though class 1 households (who were most likely to purchase an electric stove) have modestly higher ownership and use levels than the others (Table 12). The rebate is also positively related to each of these outcomes, but its effect is smaller than in the prior analyses. We can therefore conclude that some of the additional purchase and use of intervention stoves was made by households who already owned and used improved stoves at baseline. Turning to changes in firewood and fuel collection, we observe that firewood use decreases among class 1 and class 3 households in the treatment group, by 1.3-2.5 kg/day (Columns 5 and 6) relative to untreated households. Class 1 households also appear to save time on fuel collection, though these time savings are not statistically significant. Class 2 households in the treatment group, who were most inclined to adopt the improved biomass stove, do not experience any fuel savings. The strong positive trend in firewood consumption (an increase of 5.5 kg/day) represents a seasonal effect as follow-up surveys were conducted during the winter season when fuel use increases for heating purposes. In addition, class 1 households in the treatment group report somewhat lower respiratory illness at follow-up, which may reflect their greater propensity to adopt electric stoves which do not generate household emissions. Class 3 households, who are least likely to purchase an ICS, report no gains in respiratory health. Finally, for each of these outcomes, there are no significant differences across institutional strata, though fuel collection time savings and use are somewhat higher overall in the NGO villages.

## 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

[12] DiD analysis with ownership of intervention stoves would yield identical results to those previously shown, since no households in the sample owned the two intervention stoves at the time of the baseline survey.

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, this is the first study to explore the mapping of preferences for any technology elicited through a DCE, to revealed preferences. In addition, our stratified sample design allows us to consider the role of prior institutional history (a proxy for trust in the promoting organization) in encouraging adoption of new and unknown environmental health technologies.

Our sample for this comparison consists of roughly 1,050 households living in rural communities in two districts of Uttarakhand, India, three quarters of whom were randomly assigned to receive stove sales visits where two ICS options were offered to them for purchase. From the DCE, we first find that treated 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 (rather than the ICS options), all other attributes being equal. Yet these average results mask important heterogeneity in households' preferences, which we further explore using latent class analysis of these household choices. 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 classes, class 1 appears to place much greater relative weight on smoke emissions reductions than on the other attributes, whereas class 2 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-SES 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 investigate the link between preference class and the a) likelihood of immediate and lagged ICS purchase, b) responsiveness to price incentives, c) the choice of more efficient biomass versus electric ICS stoves, and finally d) daily usage after purchase. We obtain several results. First, we see that the 'uninterested' class is 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. The silver lining in these results, however, is that class membership becomes less predictive once lagged purchases are included, which suggests that class 3 households (and primarily those in villages that initially did not know the stove promoter) became more likely to adopt an ICS during later visits from the sales team. And while our sample was not developed to allow determination of the precise mechanism behind these changes in decisions, this result provides hope that such 'uninterested' households, though initially more resistant to the ICS, can be convinced to purchase stoves. Second, we find that households in different classes respond somewhat differently to price incentives. In particular, class 2 households appear most (though not significantly so in the statistical sense) responsive to these incentives; these households 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 a change in other ICS attributes, and who had lower WTP for the improved biomass stoves offered in the DCE, are most likely to adopt an electric ICS, which is a wholly different technology that also offers the possibility of eliminating household emissions from cooking. The predictive power of the preference class is retained even when controlling for a large set of household baseline covariates that have been found in previous literature to be related to clean stove and fuel use.

In addition, we find that class membership is not predictive of ICS use conditional on stove purchase, but that households in communities with a prior relationship with the sales NGO are more likely to use the ICS daily, particularly the improved biomass stove. Households in such villages are also slightly more likely to purchase stoves (particularly those in the uninterested class 3). This differential impact suggests the potential value of promoting ICS with institutional partners that communities know and trust. Finally, DiD analyses that control for baseline differences across preference classes and institutional strata, confirm that class 1 households in the treatment group had modestly higher clean stove ownership and use levels (including that related to non-intervention stoves) than the other groups at follow-up, though differences across classes are not statistically significant. The increases do not fully match purchase rates for the intervention stoves, which suggests that some of the purchase and use of intervention stoves was made by households who already owned and used improved stoves (mainly LPG) at baseline. Firewood use among treated class 1 and class 3 households meanwhile decreases by 1.3-2.5 kg/day relative to untreated households in the same classes, and class 1 households appear to save time on fuel collection. Meanwhile, class 2 households in the treatment group, who were most inclined to adopt the improved biomass stove, do not experience any fuel savings. Finally, class 1 households in the treatment group report somewhat lower respiratory illness at follow-up, which may reflect their greater propensity to adopt electric stoves which do not generate household emissions.

In conclusion, these findings offer considerable new information and insights that could be incorporated into planning of future ICS promotion efforts. In particular, demand-responsive planning of interventions that accounts for the heterogeneity of preferences among households suggests that different types of ICS should perhaps be offered to households rather than a single favored technology that may not align with user needs. Non-biomass burning technologies such as the electric ICS, which enable greater fuel savings and appear linked to lower self-reported respiratory illness, should receive serious consideration in such promotion efforts, though the availability of reliable electricity supplies remains a significant challenge in many rural locations in the developing world. Finally, partnerships with local NGOs or other promoters who are trusted may help overcome initial resistance to ICS technologies, and may also encourage households to use their 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<br>1000<br>2500 | 0 |
| Fuel requirement | 1<br>3<br>4 | 3 |
| Smoke emissions | Low<br>High<br>Highest | Highest |
| Number of cooking surfaces | 1<br>2 | 1 |

[1] $US ≈ 52 Rs.

Table 2: Baseline descriptive statistics

| Variable | Mean (s.d.) | St. dev. | N |
|---|---|---|---|
| Below poverty line | 57% | | 1049 |
| Perception of relative wealth: 6 step scale | 2.1 | 0.82 | 1063 |
| # Rooms | 4.6 | 2.4 | 1060 |
| Toilet use/ownership | 0.85 | | 1063 |
| Head of household | | | |
| Is Female | 0.27 | | 1055 |
| Age (years) | 53 | 14 | 1048 |
| Education (years) | 5.8 | 4.6 | 1055 |
| Is main survey respondent | 0.53 | | 1063 |
| Primary cook | | | |
| Education (years) | 4.7 | 4.5 | 1060 |
| Is main survey respondent | 0.77 | | 1063 |
| Caste type | | | |
| General | 0.72 | | 1063 |
| Scheduled caste / tribe | 0.25 | | |
| Hindu | 1.0 | | 1063 |
| Household size | 4.8 | 2.1 | 1063 |
| # Children under 5 | 0.47 | 0.81 | |
| % of all household members with respiratory disease in past 2 wks | 0.073 | 0.18 | 1063 |
| Most patient households | 0.48 | | 1041 |
| Most risk-taking households | 0.42 | | 1046 |
| Electricity | | | |
| Constant | 0.25 | | 1030 |
| Intermittent | 0.70 | | 1030 |
| If intermittent, hours/day supply | 16.0 | 5.8 | 720 |
| Took a loan in past year | 0.15 | | 1063 |
| Stove ownership | | | |
| Traditional stove[1] | 0.97 | | 1063 |
| Any improved stove (mostly LPG) | 0.30 | | |
| Daily use among owners (hrs/day) | | | |
| Traditional stove[1] | 4.8 | 2.4 | 1063 |
| Improved stove | 2.4 | 1.9 | 324 |
| Fuel use | | | |
| Firewood | 0.97 | | |
| Kerosene | 0.082 | | |
| LPG | 0.28 | | 1063 |
| Electricity | 0.01 | | |
| Biogas | 0.01 | | |
| Fuel prices | | | |
| Price LPG cylinder (1,000 rupees) | 0.45 | 0.06 | 824 |
| Price of fuelwood (Rs./100 kg) | 0.63 | 0.64 | 834 |
| Time spent collecting solid fuels (hrs/day) | 1.8 | 1.6 | 1063 |
| Belief in benefits of improved stoves – health or environment | 0.30 | | |
| Health | 0.11 | | |
| Local forests/environment | 0.25 | | 1063 |
| Air quality/climate change | 0.06 | | |
| Awareness of clean stoves | 0.25 | | 1063 |
| Awareness of clean fuels | 0.31 | | 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 3. Balance tests, for treatment vs. control hamlets

| Variable | Mean<br>Control | Mean<br>Treatment | Normalized Difference<br>Overall | Normalized Difference<br>NGO stratum only |
|---|---|---|---|---|
| Village has paved road | 0.26 | 0.31 | 0.080 | 0.315 |
| Distance to doctor (km) | 9.14 | 9.48 | 0.031 | -0.091 |
| Bank facility in village | 0.32 | 0.33 | 0.007 | 0.299 |
| Presence of NGO | 0.43 | 0.53 | 0.134 | n.a. |
| Household size | 4.98 | 4.77 | -0.070 | -0.135 |
| Education- head of household (yrs) | 5.59 | 5.88 | 0.044 | 0.096 |
| Education- primary cook (yrs) | 4.63 | 4.70 | 0.011 | 0.085 |
| Female head of household | 0.32 | 0.25 | -0.107** | -0.133* |
| Below poverty line household | 0.60 | 0.56 | -0.060 | -0.101 |
| Scheduled Caste/Scheduled Tribe | 0.24 | 0.26 | 0.034 | -0.045 |
| % household cold/cough in past 2 wks | 0.06 | 0.08 | 0.059 | -0.008 |
| Relative wealth (1-low to 6-high) | 2.12 | 2.13 | 0.007 | 0.060 |
| Household has taken loan in past yr | 0.12 | 0.16 | 0.088 | 0.046 |
| Household saved money in past year | 0.24 | 0.26 | 0.021 | -0.033 |
| Hours of electricity per day | 17.9 | 17.0 | -0.084 | -0.001 |
| Log of total expenditure (Rs./month) | 8.38 | 8.42 | 0.036 | 0.019 |
| Number of cell phones owned | 1.3 | 1.3 | 0.014 | 0.146* |
| Total rooms in house | 4.43 | 4.70 | 0.082 | 0.147* |
| Presence of toilet | 0.88 | 0.84 | -0.071 | 0.004 |
| Owns/leases agricultural land | 0.94 | 0.98 | 0.153 | 0.188 |
| Most patient respondent | 0.43 | 0.50 | 0.098* | 0.163* |
| Most risk-taking respondent | 0.41 | 0.43 | 0.036 | 0.133 |
| Household believes ICS/clean fuels are beneficial | 0.30 | 0.05 | 0.046 | -0.037 |
| Believe smoke is unsafe | 0 | 1 | 0.054 | -0.098 |
| Traditional stove ownership | 1 | 1 | 0.077 | -0.055 |
| Improved stove ownership | 0.30 | 0.32 | 0.034 | 0.326*** |
| Minutes traditional stove use (min/day) | 307 | 285 | -0.110 | -0.217** |
| Amount of solid fuel used (kg/day) | 6.7 | 6.9 | 0.026 | 0.044 |
| Total fuel expenditure (Rs./month) | 257 | 272 | 0.016 | 0.172* |
| Sample size: Households | 770 | 293 | | |
| Sample size: Hamlets | 71 | 26 | | |

Notes: Balance was also assessed by regressing each variable in the left-hand column on treatment status using OLS, clustering standard errors at the hamlet level. Significance of the coefficient for treatment status from these regressions is indicated in the two rightmost columns as follows: *** p-value < 0.01; ** p<0.05; * p<0.1. There are 532 total observations in the NGO stratum (126 controls and 406 treated).

Table 4. Balance tests across rebate levels (treatment group only)

| Variable | Mean<br>Low Rebate<br>N=255 | Mean<br>Med Rebate<br>N=259 | Mean<br>High Rebate<br>N= 248 | Normalized differences (R1 vs. others) | Normalized differences (R2 vs. others) | Normalized differences (R3 vs. others) |
|---|---|---|---|---|---|---|
| Village has paved road | 0.31 | 0.33 | 0.29 | 0.002 | 0.038 | -0.043 |
| Distance to doctor (km) | 8.8 | 9.4 | 9.7 | -0.084* | -0.004 | 0.027 |
| Bank facility in village | 0.33 | 0.31 | 0.31 | 0.015 | -0.032 | -0.027 |
| Presence of NGO | 0.49 | 0.52 | 0.56 | -0.068 | -0.011 | 0.071* |
| Household size | 4.9 | 4.7 | 4.8 | 0.055 | -0.059 | 0.011 |
| Education- head of household (yrs) | 5.9 | 6.2 | 5.7 | 0.009 | 0.064 | -0.051 |
| Education- primary cook (yrs) | 4.5 | 5.0 | 4.6 | -0.044 | 0.067 | -0.028 |
| Female head of household | 0.28 | 0.20 | 0.26 | 0.071 | -0.128** | 0.020 |
| Below poverty line household | 0.55 | 0.57 | 0.54 | -0.005 | 0.031 | -0.023 |
| Scheduled Caste/Scheduled Tribe | 0.22 | 0.29 | 0.27 | -0.091* | 0.070* | 0.022 |
| % household cold/cough in past 2 wks | 0.06 | 0.08 | 0.09 | -0.077 | 0.003 | 0.078 |
| Relative wealth (1-low to 6-high) | 2.1 | 2.1 | 2.2 | -0.051 | -0.012 | 0.079 |
| Household has taken loan in past yr | 0.12 | 0.16 | 0.21 | -0.124*** | 0.008 | 0.127* |
| Household saved money in past year | 0.22 | 0.27 | 0.27 | -0.089* | 0.044 | 0.026 |
| Hours of electricity per day | 17.7 | 16.5 | 17.0 | 0.098* | -0.080 | -0.004 |
| Log of total expenditure Rs./month) | 8.4 | 8.4 | 8.4 | -0.031 | 0.029 | 0.020 |
| Number of cell phones owned | 1.3 | 1.3 | 1.3 | -0.002 | 0.037 | -0.039 |
| Total rooms in house | 4.7 | 4.7 | 4.7 | -0.009 | 0.009 | -0.001 |
| Presence of toilet | 0.84 | 0.85 | 0.83 | 0.004 | 0.022 | -0.020 |
| Owns/leases agricultural land | 0.98 | 0.98 | 0.98 | -0.002 | 0.003 | -0.005 |
| Most patient respondent | 0.50 | 0.49 | 0.50 | -0.003 | -0.015 | 0.006 |
| Most risk-taking respondent | 0.42 | 0.47 | 0.40 | -0.016 | 0.088 | -0.075 |
| Household believes ICS/clean fuels are beneficial | 0.29 | 0.31 | 0.33 | -0.0397 | 0.012 | 0.052 |
| Believe smoke is unsafe | 0.51 | 0.47 | 0.52 | 0.014 | -0.068 | 0.027 |
| Traditional stove ownership | 0.98 | 0.98 | 0.96 | 0.047 | 0.050 | -0.093* |
| Improved stove ownership | 0.30 | 0.32 | 0.33 | -0.039 | 0.012 | 0.036 |
| Minutes traditional stove use (min/day) | 288 | 283 | 280 | 0.029 | -0.011 | -0.034 |
| Amount of solid fuel used (kg/day) | 7.2 | 6.6 | 7.0 | 0.044 | -0.043 | 0.013 |
| Total fuel expenditure (Rs./month) | 308 | 251 | 262 | 0.051 | -0.032 | -0.016 |

Notes: Balance was also assessed by regressing each variable in the left-hand column on treatment status using OLS, clustering standard errors at the hamlet level. Significance of the coefficient for treatment status from these regressions is indicated in the three rightmost columns as follows: *** p-value < 0.01; ** p<0.05; * p<0.1. Rebate was assigned prior to the intervention; the means and comparisons above include only households that ended up receiving a sales offer (results among all households by rebate level are available upon request).

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

| Variables | Fixed price | | Lognormal price | |
|---|---|---|---|---|
| | (1) Mean | (2) SD | (3) Mean | (4) SD |
| Price (Rs)[2] | -0.239*** | | -1.03*** | 2.53*** |
| | (0.000) | | (0.000) | (0.000) |
| Fuel requirement | -0.143*** | -0.043 | -0.158*** | 0.147*** |
| | (0.000) | (0.836) | (0.000) | (0.321) |
| Smoke emissions | -0.350*** | -0.046 | -0.368*** | 0.071 |
| | (0.000) | (0.865) | (0.000) | (0.680) |
| Number of pots | 0.358*** | 0.099 | 0.389*** | 0.260 |
| | (0.000) | (0.828) | (0.000) | (0.357) |
| Traditional stove[3] | 2.76*** | 5.08*** | 1.32*** | 4.19*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Partwise utility associated with 1-unit decrease ($US)[4] | | | | |
| Fuel requirement | $5.8 | | $4.3 | |
| Smoke emissions | $14.1 | | $9.9 | |
| Number of pots | -$14.4 | | -$10.5 | |
| Observed choices | 9162 | | 9162 | |
| Likelihood ratio ($\chi^2$) | 1278.0 | | 1336.6 | |

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.), and -500 in the logged version.

[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)<br>Class 1 | (2)<br>Class 2 | (3)<br>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) |
| ASC – Traditional stove[2] | 0.588** | -2.509** | 0.828 |
| | (0.034) | (0.016) | (0.804) |
| Fraction of households in class (based on predicted probability from LCA) | 0.27 | 0.20 | 0.52 |
| 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] This is the alternative-specific constant: Traditional stove type = 1 if it was the traditional stove, 0 if improved.

Table 7. Correlates of latent class membership

| Variables | (1)<br>Class 1 | (2)<br>Class 2 |
|---|---|---|
| Relative wealth | 0.066 | 0.34*** |
| | (0.11) | (0.12) |
| Took loan in past year | 0.28 | 0.37 |
| | (0.25) | (0.25) |
| Age of household head | -0.014** | -0.016*** |
| | (0.007) | (0.006) |
| Education of household head | -0.011 | 0.004 |
| | (0.026) | (0.024) |
| Female household head | 0.25 | 0.28 |
| | (0.24) | (0.24) |
| Scheduled caste or tribe | 0.21 | 0.25 |
| | (0.28) | (0.26) |
| Household size | -0.064 | 0.042 |
| | (0.046) | (0.060) |
| HH has child <5 yrs old | 0.15 | 0.022 |
| | (0.12) | (0.12) |
| Respondent is primary cook | -0.16 | -0.19 |
| | (0.18) | (0.21) |
| % of household sick with cough/cold in past 2 wks | -0.16 | 0.059 |
| | (0.47) | (0.67) |
| Believe traditional stoves have negative health impacts | 0.46** | 0.67*** |
| | (0.22) | (0.25) |
| Aware of clean stoves | 0.65*** | -0.22 |
| | (0.20) | (0.30) |
| Traditional stove use (hrs/day) | -0.075** | 0.001 |
| | (0.038) | (0.040) |
| Sales NGO presence | 0.17 | 0.26 |
| | (0.23) | (0.25) |
| Most patient[1] | -0.048 | 0.83*** |
| | (0.23) | (0.25) |
| Most risk-seeking[1] | 0.19 | -0.059 |
| | (0.22) | (0.19) |
| Constant | -0.083 | -2.2*** |
| | (0.59) | (0.62) |
| Observations | 1002 | 1002 |

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 and most risk-seeking as determined by responses to 3 hypothetical time and risk preference questions.

Table 8. ICS purchase by latent class

| VARIABLES | (1)<br>Basic<br>Visit 1 purchase | (2)<br>+Rebate<br>Visit 1 purchase | (3)<br>+Basic controls<br>Visit 1 purchase | (4)<br>+All controls<br>Visit 1 purchase | (5)<br>Basic<br>With later purchases | (6)<br>+Rebate<br>With later purchases | (7)<br>+Basic controls<br>With later purchases | (8)<br>+All controls<br>With later purchases |
|---|---|---|---|---|---|---|---|---|
| Treatment group (exposed to sales) | 0.52*** | 0.24*** | 0.24*** | 0.26*** | 0.56*** | 0.28*** | 0.24*** | 0.28*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Treatment*Rebate amount (Rs.) | | 0.0015*** | 0.0015*** | 0.0015*** | | 0.0015*** | 0.0015*** | 0.0015*** |
| | | (0.000) | (0.000) | (0.000) | | (0.000) | (0.000) | (0.000) |
| Electricity supply (hr/day) | | | 0.006*** | 0.006*** | | | 0.005*** | 0.006*** |
| | | | (0.001) | (0.001) | | | (0.005) | (0.0023) |
| General caste | | | 0.019 | 0.024 | | | 0.027 | 0.033 |
| | | | (0.53) | (0.43) | | | (0.38) | (0.27) |
| Age of household head | | | -0.00 | -0.00 | | | -0.00 | -0.000 |
| | | | (0.82) | (0.75) | | | (0.66) | (0.54) |
| Education of household head | | | 0.0013 | -0.0014 | | | 0.003 | 0.000 |
| | | | (0.69) | (0.70) | | | (0.45) | (0.090) |
| Relative wealth | | | 0.0073 | 0.0048 | | | 0.002 | -0.000 |
| | | | (0.67) | (0.78) | | | (0.92) | (0.99) |
| Treatment*Class 2[1] | 0.018 | 0.010 | 0.012 | 0.008 | 0.015 | 0.007 | 0.009 | 0.000 |
| | (0.75) | (0.85) | (0.82) | (0.88) | (0.77) | (0.89) | (0.85) | (0.99) |
| Treatment*Class 3[1] | -0.11*** | -0.087** | -0.088** | -0.10** | -0.095** | -0.067 | -0.067 | -0.076* |
| | (0.007) | (0.044) | (0.035) | (0.016) | (0.031) | (0.13) | (0.12) | (0.078) |
| Constant | -0.00*** | -0.00*** | -0.13* | -0.20* | 0.00*** | 0.00*** | -0.12 | -0.17* |
| | (0.004) | (0.000) | (0.099) | (0.030) | (0.000) | (0.000) | (0.13) | (0.076) |
| Other controls[2] | No | No | No | Yes | No | No | No | Yes |
| Observations | 1,049 | 1,049 | 1,031 | 996 | 1,049 | 1,049 | 1,031 | 996 |
| R-squared | 0.204 | 0.309 | 0.325 | 0.330 | 0.228 | 0.332 | 0.344 | 0.354 |

Notes: Linear probability model; *** p<0.01, ** p<0.05, * p<0.1; p-value in parentheses. Standard errors clustered at the hamlet level.
[1] 'Class 2' and 'Class 3' are indicator variables denoting assignment to a latent classes 2 and 3, respectively. Class 1 is the omitted class.
[2] The other controls include all but the respondent gender and NGO presence covariates shown in Table 7 plus toilet ownership, solid fuel collection time and price of firewood. None of these were found to be significantly related to purchase; as shown they did not alter the sign or significance of the main results shown here. Observations with missing values for these additional covariates are omitted from these regressions (Columns 4 and 8).

Table 9. Differential responses to rebate amount and prior institutional presence (first sales visit only), by preference class

| VARIABLES | (1)<br>Visit 1<br>purchase | (2)<br>Visit 1<br>purchase | (3)<br>Visit 1<br>purchase | (4)<br>Visit 1<br>purchase |
|---|---|---|---|---|
| Treatment group (exposed to sales) | 0.19***<br>(0.002) | 0.22***<br>(0.000) | 0.24***<br>(0.000) | 0.24***<br>(0.002) |
| Treatment*Rebate amount (Rs.) | | | 0.0015***<br>(0.000) | |
| Electricity supply (hr/day) | | 0.0064***<br>(0.002) | | 0.0059***<br>(0.004) |
| Treatment*Class 2[1] | 0.013<br>(0.89) | -0.010<br>(0.92) | -0.015<br>(0.87) | -0.034<br>(0.78) |
| Treatment*Class 3[1] | -0.012<br>(0.87) | -0.041<br>(0.57) | -0.16***<br>(0.013) | -0.11<br>(0.20) |
| Treatment*Rebate*Class 1 | 0.0017***<br>(0.000) | 0.0017***<br>(0.000) | | 0.0017***<br>(0.000) |
| Treatment*Rebate*Class 2 | 0.0017***<br>(0.000) | 0.0018***<br>(0.000) | | 0.0017***<br>(0.000) |
| Treatment*Rebate*Class 3 | 0.0013***<br>(0.000) | 0.0013***<br>(0.000) | | 0.0013***<br>(0.000) |
| Treatment*NGO*Class 1 | | | -0.009<br>(0.91) | -0.036<br>(0.63) |
| Treatment*NGO*Class 2 | | | 0.032<br>(0.75) | 0.019<br>(0.85) |
| Treatment*NGO*Class 3 | | | 0.14**<br>(0.040) | 0.11*<br>(0.10) |
| Constant | -0.00***<br>(0.000) | -0.20**<br>(0.034) | -0.00<br>(0.32) | -0.19*<br>(0.055) |
| Other controls[2] | No | Yes | No | Yes |
| Observations | 1,049 | 996 | 1,049 | 996 |
| R-squared | 0.31 | 0.33 | 0.32 | 0.34 |

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

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

[2] The other controls include all of those from the complete model in Table 8 (e.g., the basic controls from Table 8 Column 3 plus those indicated in the notes below Table 8). Very few of these were found to be significantly related to purchase; as shown they did not alter the sign or significance of the main results shown here. Observations with missing values for these additional covariates are omitted from these regressions (Columns 2 and 4).

Table 10. ICS choice among households exposed to sales intervention, by latent class (marginal effects)

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | Basic | | +Rebate & Controls | | +Rebate-class interactions | |
| VARIABLES | Biomass ICS | Electric ICS | Biomass ICS | Electric ICS | Biomass ICS | Electric ICS |
| Rebate amount (Rs.) | | | 0.00070*** | 0.0010*** | 0.00057*** | 0.0015*** |
| | | | (0.000) | (0.000) | (0.002) | (0.000) |
| Electricity supply | | | 0.0010 | 0.010*** | 0.0010 | 0.010*** |
| (hr/day) | | | (0.54) | (0.001) | (0.57) | (0.001) |
| Class 2[1] | 0.083** | -0.062 | 0.079** | -0.082 | | |
| | (0.011) | (0.18) | (0.022) | (0.11) | | |
| Class 3[1] | 0.028 | -0.14*** | 0.021 | -0.15*** | | |
| | (0.34) | (0.000) | (0.40) | (0.001) | | |
| Rebate*Class 2 | | | | | 0.00034** | -0.00035 |
| | | | | | (0.014) | (0.18) |
| Rebate*Class 3 | | | | | 0.00012 | -0.00075*** |
| | | | | | (0.24) | (0.001) |
| Other controls[2] | No | | Yes | | Yes | |
| Observations | 761 | | 721 | | 721 | |
| | 0.012 | | 0.13 | | 0.13 | |

Notes: Multinomial logit model using initial purchase decision only; we report marginal effects at the mean of the sample covariates; *** p<0.01, ** p<0.05, * p<0.1; p-values in parentheses. Standard errors are clustered at the hamlet level.

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

[2] The other controls include all of those from the complete model in Table 8 (e.g., the basic controls from Table 8 Column 3 plus those indicated in the notes below Table 8). Very few of these were found to be significantly related to purchase; as shown they did not alter the sign or significance of the main results shown here. Observations with missing values for these additional covariates are omitted from these regressions (Columns 2 and 4).

Table 11. ICS use conditional on purchase, by latent class

| VARIABLES | (1)<br>Basic<br>Daily use | (2)<br>+Rebate<br>Daily use | (3)<br>+NGO interact<br>Daily use | (4)<br>+SES<br>Daily use | (5)<br>Electric ICS<br>Daily use | (6)<br>Biomass ICS<br>Daily use |
|---|---|---|---|---|---|---|
| Rebate amount (Rs.) | | 0.001*** | 0.001*** | 0.001*** | 0.0004 | 0.0006 |
| | | (0.005) | (0.008) | (0.002) | (0.12) | (0.19) |
| Electricity supply (hr/day) | | | | -0.010** | -0.007 | -0.002 |
| | | | | (0.014) | (0.19) | (0.68) |
| Class 2 | -0.073 | -0.080 | -0.088 | -0.097 | -0.080 | -0.009 |
| | (0.39) | (0.33) | (0.46) | (0.41) | (0.61) | (0.97) |
| Class 3 | -0.033 | -0.013 | -0.0025 | -0.022 | -0.036 | -0.26 |
| | (0.55) | (0.82) | (0.98) | (0.80) | (0.74) | (0.16) |
| Class 1*NGO | | | 0.16 | 0.17* | 0.088 | 0.024 |
| | | | (0.14) | (0.09) | (0.35) | (0.91) |
| Class 2*NGO | | | 0.15 | 0.16 | 0.022 | 0.29 |
| | | | (0.23) | (0.16) | (0.87) | (0.11) |
| Class 3*NGO | | | 0.14* | 0.17*** | 0.10 | 0.25* |
| | | | (0.050) | (0.009) | (0.23) | (0.099) |
| Constant | 0.56*** | 0.38*** | 0.30*** | 0.46** | 0.39* | 0.62* |
| | (0.000) | (0.000) | (0.0081) | (0.001) | (0.067) | (0.063) |
| Other controls[2] | No | No | No | Yes | Yes | Yes |
| Observations | 386 | 386 | 386 | 369 | 303 | 116 |
| R-squared | 0.003 | 0.027 | 0.048 | 0.15 | 0.10 | 0.36 |

Notes: Linear probability model using all households that purchased ICS; *** p<0.01, ** p<0.05, * p<0.1; p-values in parentheses. Standard errors are clustered at the hamlet level.

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

[2] The other controls include all of those from the complete model in Table 8 (e.g., the basic controls from Table 8 Column 3 plus those indicated in the notes below Table 8). Very few of these were found to be significantly related to purchase; as shown they did not alter the sign or significance of the main results shown here. Observations with missing values for these additional covariates are omitted from these regressions (Columns 2 and 4).

Table 12: Difference-in-difference analysis of the effect of NGO history on improved stove ownership, use, and fuel collection outcomes

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Basic DiD[1] | …+Rebate +NGO int[2] | Basic DiD[1] | …+Rebate +NGO int[2] | Basic DiD[1] | …+Rebate +NGO int[2] | Basic DiD[1] | …+Rebate +NGO int[2] | Basic DiD[1] | …+Rebate +NGO int[2] |
| VARIABLES | Own improved stove | Own improved stove | Use improved stove daily | Use improved stove daily | Firewood (kg/day) | Firewood (kg/day) | Fuel collection time (min/day) | Fuel collection time (min/day) | % in hh w/cough or cold – past 2 wks | % in hh w/cough or cold – past 2 wks |
| Post | -0.017 | -0.017 | -0.028 | -0.028 | 5.57*** | 5.57*** | 14.9 | 14.9 | 0.094 | 0.094 |
| | (0.65) | (0.65) | (0.46) | (0.46) | (0.000) | (0.000) | (0.43) | (0.43) | (0.11) | (0.11) |
| Post*Treatment | 0.34*** | 0.25*** | 0.28*** | 0.20** | -1.37 | -2.14** | -36.9 | -30.1 | -0.13* | -0.14 |
| | (0.000) | (0.002) | (0.000) | (0.014) | (0.11) | (0.030) | (0.11) | (0.32) | (0.083) | (0.17) |
| Post*Treatment* Rebate | | 0.0008*** | | 0.0006*** | | 0.0006 | | 0.017 | | 0.0001 |
| | | (0.000) | | (0.001) | | (0.75) | | (0.60) | | (0.32) |
| Post*Treatment* Class 2 | -0.025 | -0.072 | -0.044 | -0.12 | 2.82*** | 2.63** | -1.9 | -5.0 | 0.075 | 0.060 |
| | (0.68) | (0.37) | (0.48) | (0.17) | (0.002) | (0.047) | (0.90) | (0.83) | (0.33) | (0.62) |
| Post*Treatment* Class 3 | -0.032 | -0.081 | -0.002 | -0.049 | -1.29* | -0.35 | 6.3 | 26.8 | 0.16*** | 0.13 |
| | (0.47) | (0.20) | (0.96) | (0.46) | (0.085) | (0.69) | (0.67) | (0.17) | (0.006) | (0.14) |
| Post*Treatment* NGO*Class 1 | | -0.10 | | -0.062 | | 1.22 | | -18.8 | | -0.037 |
| | | (0.28) | | (0.48) | | (0.31) | | (0.48) | | (0.71) |
| Post*Treatment* NGO*Class 2 | | -0.017 | | 0.068 | | 1.31 | | -11.0 | | -0.007 |
| | | (0.89) | | (0.54) | | (0.40) | | (0.72) | | (0.96) |
| Post*Treatment* NGO*Class 3 | | 0.019 | | 0.052 | | -0.59 | | -11.4 | | 0.015 |
| | | (0.78) | | (0.35) | | (0.48) | | (0.40) | | (0.87) |
| Constant | 0.29*** | 0.29*** | 0.28*** | 0.28*** | 6.18*** | 6.18*** | 96.9*** | 96.9*** | 0.20*** | 0.20*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 2,098 | 2,098 | 2,098 | 2,098 | 2,097 | 2,097 | 2,098 | 2,098 | 2,098 | 2,098 |
| R-squared | 0.10 | 0.13 | 0.073 | 0.098 | 0.12 | 0.12 | 0.010 | 0.027 | 0.012 | 0.014 |

Notes: Linear probability models using all treatment and control group households; *** p<0.01, ** p<0.05, * p<0.1; p-values in parentheses. Standard errors are clustered at the hamlet level.

[1] The basic DiD also includes controls for baseline differences across preference classes among those exposed to the intervention (e.g. treatment, Treat*class2, and Treat*class3; treated class 1 households are the omitted group).

[2] The fully-interacted DiD also includes controls for baseline differences across preference classes and preference class interactions (e.g. treatment, Treat*class2, Treat*class3, Treat*NGO*class1, Treat*NGO*class2, and Treat*NGO*class3; treated non-NGO stratum class 1 households are the omitted group).

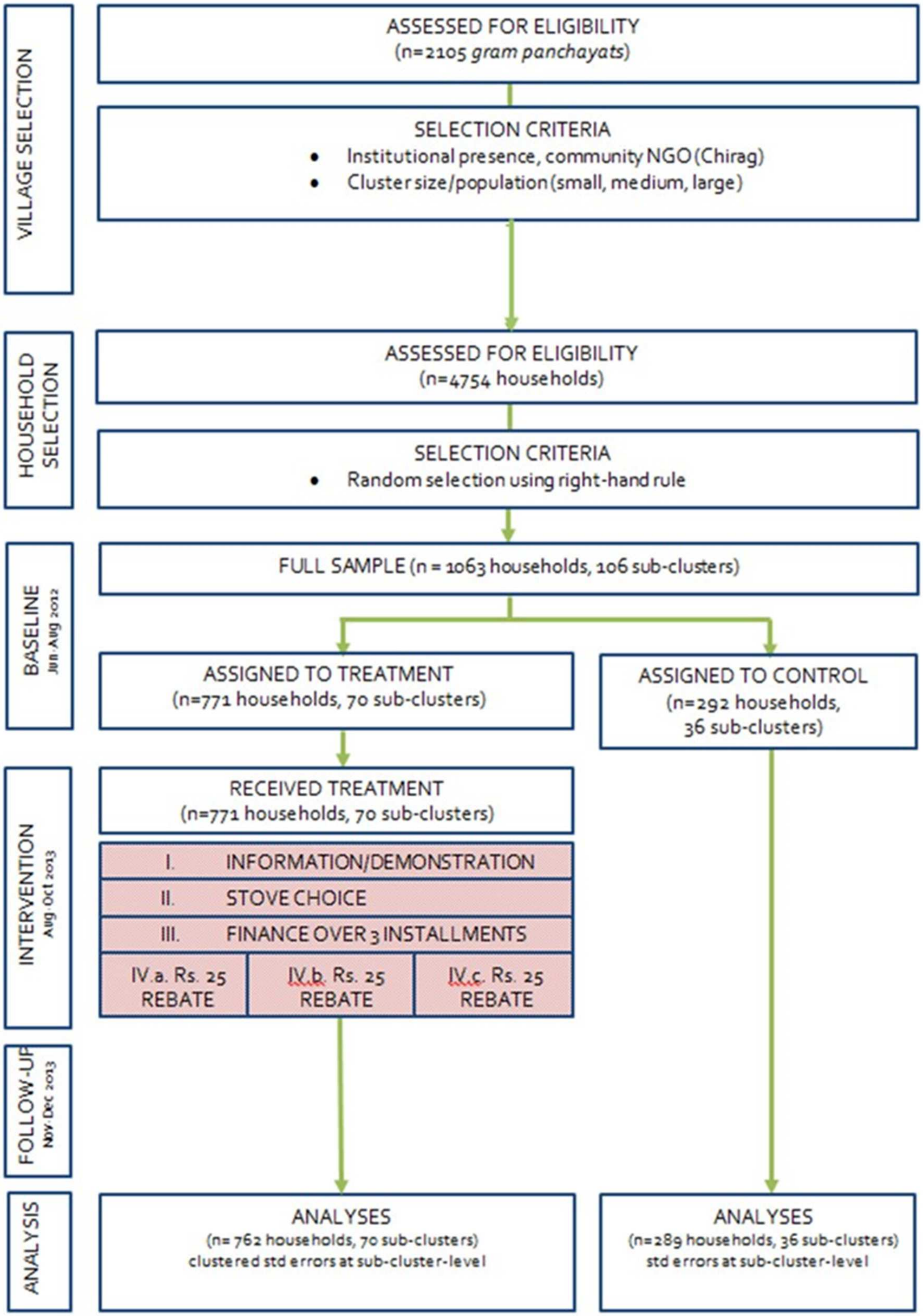



**Figure 1.** Study design

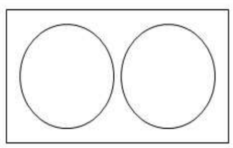
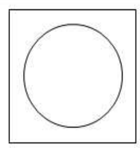
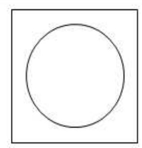
| | ICS 1 | ICS 2 | Traditional stove |
|---|---|---|---|
| Attribute चूल्हे | उन्नत चूल्हा 1 | उन्नत चूल्हा 2 | मिट्टी का चूल्हा |
| Price दाम | 1000 रुपए  | 1000 रुपए  | 0 रुपए |
| Smoke Emissions धुआं |  |  |  |
| Fuel ईंधन की जरूरत |  |  |  |
| # of Surfaces चूल्हे के मुंह की गिनती |  |  |  |

**Figure 2.** An example choice task in the stove decision exercise

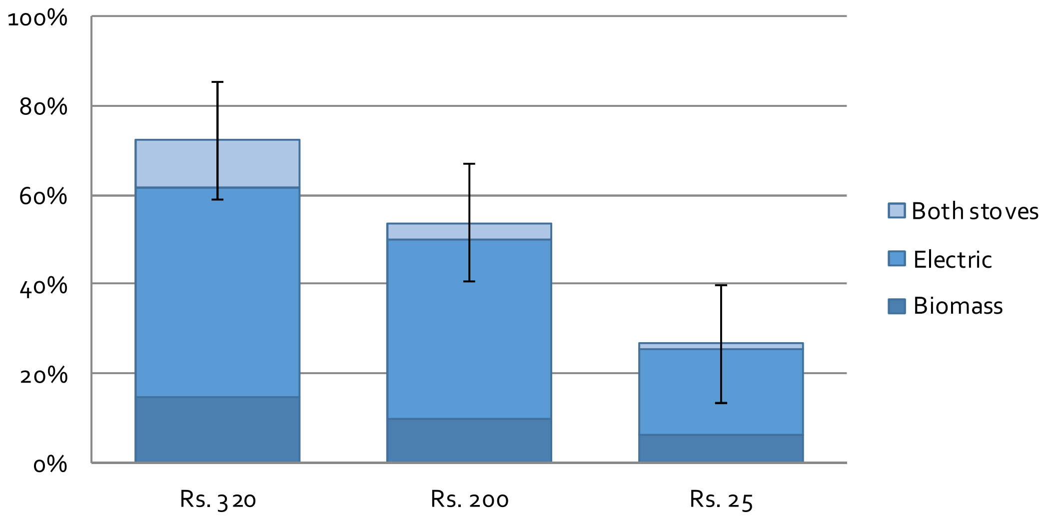



**Figure 3.** Purchase of intervention stoves, by rebate group

**Appendix: Additional Tables**

**Table A1**. Analysis of serial non-response and class 3 membership

| VARIABLE | Serial non-respondent | Other respondent | N |
|---|---|---|---|
| Household in class 3 | 332 | 245 | 577 |
| Household not in class 3 | 0 | 486 | 486 |
| N | 332 | 731 | 1063 |

Notes: Serial non-respondents are households who selected the traditional stove alternative in the DCE in all 4 choice tasks, no matter the attributes of the ICS options.

Table A2. Differential responses to rebate amount and prior institutional presence (all sales visits), by preference class

| VARIABLES | (1)<br>All purchases | (2)<br>All purchases | (3)<br>All purchases | (4)<br>All purchases |
|---|---|---|---|---|
| Treatment group (exposed to sales) | 0.19***<br>(0.002) | 0.22***<br>(0.001) | 0.25***<br>(0.000) | 0.22***<br>(0.004) |
| Treatment*Rebate amount (Rs.) | | | 0.0015***<br>(0.000) | |
| Electricity supply (hr/day) | | 0.0062***<br>(0.002) | | 0.0058***<br>(0.004) |
| Treatment*Class 2[1] | -0.003<br>(0.98) | -0.031<br>(0.76) | -0.005<br>(0.96) | -0.049<br>(0.68) |
| Treatment*Class 3[1] | 0.069<br>(0.40) | 0.049<br>(0.54) | -0.11<br>(0.11) | 0.004<br>(0.97) |
| Treatment*Rebate*Class 1 | 0.0019***<br>(0.000) | 0.0019***<br>(0.000) | | 0.0019***<br>(0.000) |
| Treatment*Rebate*Class 2 | 0.0020***<br>(0.000) | 0.0020***<br>(0.000) | | 0.0020***<br>(0.000) |
| Treatment*Rebate*Class 3 | 0.0012***<br>(0.000) | 0.0012***<br>(0.000) | | 0.0012***<br>(0.000) |
| Treatment*NGO*Class 1 | | | 0.035<br>(0.62) | |
| Treatment*NGO*Class 2 | | | 0.048<br>(0.63) | |
| Treatment*NGO*Class 3 | | | 0.12<br>(0.10) | |
| Constant | -0.00***<br>(0.000) | -0.17*<br>(0.088) | -0.00<br>(0.32) | -0.15<br>(0.12) |
| Other controls[2] | No | Yes | No | Yes |
| Observations | 1,049 | 996 | 1,049 | 996 |
| R-squared | 0.34 | 0.36 | 0.324 | 0.36 |

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

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

[2] The other controls include all of those from the complete model in Table 8 (e.g., the basic controls from Table 8 Column 3 plus those indicated in the notes below Table 8). Very few of these were found to be significantly related to purchase; as shown they did not alter the sign or significance of the main results shown here. Observations with missing values for these additional covariates are omitted from these regressions (Columns 2 and 4).

Table A3. ICS choice among households exposed to sales intervention, by latent class (marginal effects), including all sales

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | Basic | | +Rebate & Controls | | +Rebate-class interactions | |
| VARIABLES | Biomass ICS | Electric ICS | Biomass ICS | Electric ICS | Biomass ICS | Electric ICS |
| Rebate amount (Rs.) | | | 0.00036*** | 0.0012*** | 0.00020 | 0.0018*** |
| | | | (0.003) | (0.000) | (0.24) | (0.000) |
| Electricity supply | | | -0.0002 | 0.012*** | 0.0025 | 0.012*** |
| (hr/day) | | | (0.90) | (0.000) | (0.89) | (0.000) |
| Class 2[1] | 0.084** | -0.079* | 0.064* | -0.098* | | |
| | (0.012) | (0.09) | (0.064) | (0.051) | | |
| Class 3[1] | 0.053* | -0.16*** | 0.040 | -0.15*** | | |
| | (0.10) | (0.000) | (0.20) | (0.001) | | |
| Rebate*Class 2 | | | | | 0.00033** | -0.00041 |
| | | | | | (0.037) | (0.13) |
| Rebate*Class 3 | | | | | 0.00015 | -0.00086*** |
| | | | | | (0.25) | (0.000) |
| Other controls[2] | No | | Yes | | Yes | |
| Observations | 761 | | 721 | | 721 | |
| | 0.014 | | 0.12 | | 0.13 | |

Notes: Multinomial logit model using initial purchase decision only; we report marginal effects at the mean of the sample covariates; *** p<0.01, ** p<0.05, * p<0.1; p-values in parentheses. Standard errors are clustered at the hamlet level.

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

[2] The other controls include all of those from the complete model in Table 8 (e.g., the basic controls from Table 8 Column 3 plus those indicated in the notes below Table 8). Very few of these were found to be significantly related to purchase; as shown they did not alter the sign or significance of the main results shown here. Observations with missing values for these additional covariates are omitted from these regressions (Columns 2 and 4).