Preference heterogeneity and adoption of environmental health improvements: Evidence from a cookstove promotion experiment

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Abstract

This paper explores how typically unobserved heterogeneity in household preferences influences adoption of environmental health improving technologies. Analyzing data from a discrete choice experiment (DCE) conducted during baseline surveys with 1060 households, we identify three distinct preference types for cleaner cookstoves using latent class analysis (LCA): disinterested (54%); low demand but primarily interested in reduced smoke emissions (27%); and high demand (20%). Using data from a stove promotion intervention that was then randomized to 762 of these households, we find that households in the disinterested class are less likely to purchase a new stove. Preference type is more strongly related to stove purchase than common socio-demographic drivers of technology adoption, and distaste for smoke emissions in particular is related to adoption of an electric stove. The effect of preferences changes over time, perhaps indicating that initially recalcitrant households were influenced by the adoption decisions of those around them. We also find limited evidence that preferences are related to downstream outcomes such as fuel savings and respiratory health. Through its influence on adoption, preference heterogeneity nonetheless has important implications for the effectiveness of health promotion interventions.

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

JEL Codes: C93, D12, Q41, Q53

1. Introduction

Many development projects aim to encourage household adoption and use of new technologies that improve health and socioeconomic outcomes (Besley and Case 1993). Such interventions frequently fall short of desired results, however, often because target beneficiaries are slow to adopt and/or use the technologies. This problem has been observed to apply to solutions in a range of domains – agriculture, water and sanitation, household energy, mosquito bednets, and others – and numerous experiments have been conducted to identify strategies that improve uptake (Giné and Yang 2009, Pattanayak et al. 2009, Ashraf et al. 2010, Cohen and Dupas 2010, Tarozzi et al. 2014). Generally speaking, these experiments attempt to reduce the costs of uptake, either through subsidies, easing of liquidity constraints, or facilitation of knowledge acquisition or learning (Pattanayak and Pfaff 2009). And while these experiments have led to significant progress in identifying effective approaches for boosting demand, the penetration of many beneficial technologies varies, and remains surprisingly limited in many settings.

One potentially significant challenge facing promoters of new technologies, and under-researched in economics (Ravallion 2012), arises from the inherent variability of both demand and outcomes (Whittington et al. 2012). This heterogeneity may arise from the dynamics of local or contextual differences that influence the production of benefits (Jeuland and Pattanayak 2012), or from typically unobserved variation in tastes and preferences of target beneficiaries (McFadden and Train 2000, Jeuland et al. 2013). Indeed, many interventions that seek to increase technology adoption offer a single technology (typically on the basis of their superior expected performance) and neglect the importance of beneficiary choice. Promoters of such interventions thus essentially treat beneficiaries as if they have homogenous preferences, or as if any variation in their preferences is irrelevant. And while this may not be a serious concern for technologies that have relatively simple implications for users (e.g., vaccines or nutritional supplements), many productivity-enhancing and environmental health-improving solutions have varied and complex characteristics. For example, water and sanitation technologies alter the convenience and aesthetic aspects of domestic activities, as well as health and possibly household status (Jenkins and Curtis 2005, Yang et al. 2007, Casabonne and Kenny 2012). Similarly, improved cooking devices may affect a range of factors such as fuel consumption and requirements, cooking time allocation, respiratory health, household cleanliness, and the taste of food (Jeuland et al. 2014). Indeed, failure to adequately account for the variation in perceptions of these varied costs and benefits (and especially typically-unobserved heterogeneity in tastes) may lead to systematic errors in projections of demand for technological improvements, and misrepresentation of the outcomes they produce (Whittington et al. 2012, Orgill et al.

2013). Latent heterogeneity thus has important implications for policy design (Heckman 2001), especially as it pertains to improving adoption of environmental health technologies and other similar quasi-public goods.

This paper aims to shed light on several aspects of the technology adoption puzzle that relate to such typically unobserved preferences. We first apply generalized multinomial logit methods (Magidson and Vermunt 2004) to analyze data from a discrete choice experiment (DCE) that was collected prior to a field experiment implemented in Uttarakhand, India. 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 improved cookstoves (ICS[1]) and traditional stoves. In the context of studying demand for cooking technologies, 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 (LCA) 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 LCA, are more or less likely to purchase a new stove during a randomized promotion campaign. A follow-up survey conducted several months after the intervention sheds additional light on longer-term use of the intervention stoves, 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 biomass 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 a new stove during the first of three visits by the sales teams implementing the randomized sales campaign, an effect that faded somewhat 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 stove, suggesting that distaste for smoke may play a particular role in motivating purchase of the electric option. We also find some evidence that class 2 households respond more strongly to randomized

[1] Consistent with recent terminology in the literature, we use the term improved cookstove (ICS) to refer to more efficient biomass-burning stoves, and do not include stoves that use alternative fuels (such as LPG or electricity) in this category.

rebates when considering the purchase of the cleaner-burning biomass ICS. Importantly, and perhaps because the stove promotion campaign was designed to address commonly-identified barriers to adoption of environmental health technologies such as information and liquidity constraints (Bensch et al. 2014), very few observable household or community-level covariates explain stove purchases.

Looking beyond stove purchase, we also find that household use of either stove, *conditional on stove purchase*, is not significantly different across preference classes. This suggests that there are somewhat different mechanisms governing purchases and usage. Lastly, there is some evidence that preference class explains differential changes in downstream outcomes measured several months after the intervention. In particular, treatment households in class 1, who were most likely to purchase the electric stove, 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, experience lower fuel savings than other household types in the treatment group. All of our results are robust to a variety of specifications and to dichotomous or continuous probability-based measures of class membership.

Our paper makes several contributions. First, we add to a thin literature on the private demand for cleaner cooking technologies by being the first to examine how households respond to a stove sales offer that allows a choice between two very different technologies – an improved biomass-burning stove and an electric coil stove. Existing stove 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 stove options, by conducting latent class analyses of DCE data. Third, after systematically characterizing the choice patterns revealed in these data, we investigate the extent to which preference type is related to the choices revealed in the randomized promotion campaign, which speaks to long-standing questions about the reliability of subjective and stated preference data (Carson et al. 1996, Bertrand and Mullainathan 2001, Borghans et al. 2008). Finally, we generate new evidence on the interaction between preferences and intervention outcomes. These contributions collectively serve to elucidate important supply- and demand-side features of the market for non-traditional stoves. Understanding of these features is critical for developing policies that encourage product development and market segmentation, both of which seems essential for stimulating wider diffusion of these and other similar quasi-public goods.

2. Background and motivation: The case for cleaner cookstoves

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 cook stoves such as gas-, electric-, or cleaner biomass-burning ICS technologies (GACC 2010).

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 cooking 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 cleaner cooking solutions, with regards both to private demand for these new technologies (Mobarak et al. 2012), and to the realization of health and other welfare benefits from their use (Hanna et al. 2012).

These recent negative findings raise important questions about stove promotion and dissemination efforts, but they stand in sharp contrast to those from other field studies, mainly conducted in East and West Africa, that suggest that biomass ICS promotion can in fact succeed, at least in the short-term (Levine and Cotterman 2012, Bensch and Peters 2014). Indeed, the range of recent findings from stove promotion studies highlights several points that have previously been emphasized in the broader literature on demand for environmental health improvements. First, there is substantial variation in the real costs and benefits of these technologies across settings and households (Jeuland and Pattanayak 2012). Second, micro-level decisions about whether or not to adopt and continue to use a non-traditional stove may not always follow from simple comparisons of economic costs and benefits. Lack of user awareness and exposure to alternative options (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). Successful promotion strategies for cleaner stoves 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).

Yet the demand for health improvements is also related to consumers' diverse and hard to observe preferences and constraints (Pattanayak and Pfaff 2009). For example, time-constrained households cannot be expected to adopt a stove that is inconvenient to use due to increased fuel processing requirements, even if it is highly efficient. In addition, if adoption of preventive behavior enters directly into a households' utility function (e.g., by making cooking of certain foods that are particularly desirable for a household impossible), then the benefits of adoption will be reduced (Jeuland et al. 2014). The role of such deeply-ingrained preferences warrants greater study, but is challenging to observe and measure.

This challenge perhaps helps to explain the sparsity of the literature on this topic. Indeed, the most direct way to elicit measures of heterogeneity is through the use of survey-based (and stated preference) methods, but these evoke considerable skepticism among economists. Critiques about hypothetical and other biases have consistently been levied against stated preference methods aimed at eliciting demand (Hausman 2012). Bertrand and Mullainathan (2001) offer a more general critique in arguing that subjective data are especially unsuitable as dependent variables because of correlated measurement errors. Nonetheless, there is a consistently increasing body of research suggesting that valuable information can be obtained from simple questions about subjective preferences (Manski 2004, McFadden 2013). A wide range of studies also demonstrate that stated measures of different types correlate well with real behaviors (Griffin et al. 1995, Scarpa et al. 2003, Cárdenas et al. 2013, Johansson-Stenman et al. 2013, Liu and Huang 2013).

3. Modeling

Following Pattanayak and Pfaff (2009), we consider that a household's adoption of an environmental health improvement depends on its contribution to utility given a range of relevant constraints, specifically on its time and budget resources, and on the nature of the production function for health. The decision to adopt is made based on a comparison of the private marginal benefits and costs of investment:

$$\frac{u^i{}_a + u^i{}_s \cdot s_a}{\mu^i} = p \cdot a + p_k \cdot a_k, \qquad (1)$$

where the expression on the left hand side corresponds to the marginal benefit of adopting the preventive health improvement a for a household of type *i*. Accordingly, adoption of the technology provides intrinsic utility through the term $u^i{}_a$, as well as health benefits (*s*) through the term $u^i{}_s \cdot s_a$, which describes the contribution of health to utility as affected by the improvement a. These are benefits are monetized through normalization of these changes in utility by the marginal utility of income μ^i. The right hand side then represents the marginal cost of adoption of a. For a discrete good, these costs are comprised of the purchase and operating price (p) of a and the cost of obtaining knowledge (p_k) about a. In practice, most existing studies attempt to trigger adoption by exogenously reducing the price of a technology via price subsidies, easing of maintenance costs, or information provision, i.e., by making changes to the RHS of equation (1). Parameters on the LHS however cannot be so randomized and are thus frequently neglected, or considered to be of secondary importance. Nonetheless, this inherent heterogeneity in the contribution of health or other implications of a technology to household utility can lead to very different adoption decisions and very different outcomes across households and settings (Heckman et al. 1997, Brown et al. 2014). If this heterogeneity can be characterized in a meaningful way, it could help enhance the effectiveness of efforts to promote seemingly beneficial technologies.

Modeling preferences for cooking technologies

As such, we begin by sorting respondents into different preference groups using survey data collected prior to the stove promotion experiment. The framework for analyzing this DCE data is based in random utility theory. We model repeated household choices of 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:

$$U^i_{jt} = V^i\left(p_{jt}, \beta^i_0, X_{jt}, \beta^i, Z^i\right) + \varepsilon^i_{jt}\ , \qquad (2)$$

where:

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

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

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

β^i_0 = a parameter which represents the marginal utility of money for household *i*;

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

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

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

ε^i_{jt} = 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 $U^i_{jt} > U^i_{kt}$ for all *j* in set *K*, where *j* ≠ *k*, such that $V^i_{jt} - V^i_{kt} > \varepsilon^i_{kt} - \varepsilon^i_{jt}$. With a linear specification of utility $U^i_{jt} = \beta^i X_{jt} + \beta^i_0 p_{jt} + \varepsilon^i_{jt}$ and a Type 1 extreme-value error distribution for the disturbance term, the probability that alternative *j* will be selected from choice set *t* corresponds to the standard conditional logit model (McFadden 1981). The conditional logit model is estimated using maximum likelihood; the values of the coefficient values β^i_0 and β^i are selected to maximize the likelihood that one would observe the choices actually observed in a given sample of respondents.

In this paper, we relax the restrictive assumption of the conditional logit that requires a single set of fixed β coefficients, and instead estimate two types of mixed (or random parameters) 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 η^i for each of the estimated coefficients β in the model. In the mixed logit model, the choice probability function is described by the integral of the product of conditional individual probabilities over all choice occasions *t*, where the marginal utilities for different attributes are measured by β^{i*}:

$$\text{Prob}[C^i = (C^i_{j1}, \dots, C^i_{jT})] = \int \prod_t \frac{\exp(\beta^{i*} X_{jt} + \beta^{i*}_0 p_{jt})}{\sum_{k=0}^{K} \exp(\beta^{i*} X_{kt} + \beta^{i*}_0 p_{kt})} f(\eta|\Omega) d\eta \ , \qquad (3)$$

[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.

where $\beta^* = (\beta + \eta^i)$ and $f(\eta|\Omega)$ denotes the density of the individual disturbance terms η^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 β^* are estimated using simulated maximum likelihood (Revelt and Train 1998). The ratios of coefficients derived from the model then yield the marginal utility to individual *i* for an additional unit of a particular attribute, in money terms.

The second is the latent class logit, a discrete version of the mixed logit, which allows us to categorize households into distinct groups based on the similarity of their choice patterns. In these models, maximum likelihood methods are used to identify *S* class types (where *S* is an integer selected by the modeler) with similar weighting of various attributes of the choice alternatives.[3] The probability of observing respondent *i* selecting alternatives *j* over *T* choice tasks is written as a product of the probability the respondent belonging to class *s* and the probability that the sequence of alternatives is chosen:

$$\mathrm{Prob}[C^i = (C^i_{j1}, \dots, C^i_{jT})] = \prod_{t=1}^{T}\left[\sum_{s=1}^{S}\left(\frac{\exp(\alpha_s' Z_i)}{\sum_{s=1}^{S}\exp(\alpha_s' Z_i)}\right)\left(\frac{\exp(\beta_s X_{jt} + \beta_{0,s} p_{jt})}{\sum_{k=0}^{K}\exp(\beta_s X_{kt} + \beta_{0,s} p_{kt})}\right)\right], \quad (4)$$

The first term in equation (4) is the unconditional probability of class membership, while the second term corresponds to the probability of choosing a sequence of alternatives based on their attributes. In most applications of the latent class approach, the vector Z_i in the first term includes characteristics such as age, education level, and income. In this paper, however, we omit these characteristics and replace Z_i with a vector of individual-specific constants because our goal is to use only information revealed by the choices households make in the DCE to predict adoption of clean stoves.[4] This modeling approach is also conservative as it relies on fewer assumptions to estimate stated preferences. In the second term, the taste parameters (β) are subscripted with the class indicator *s*, meaning that every respondent in class *s* has identical tastes for the attributes of the choice alternatives in the DCE.

Rather than assuming a specific number of classes, 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 the particular class for which its probability of membership is greatest, and study the correlates of class membership using a multinomial logit model.

[3] See Appendix C for a more detailed explanation of latent class logit models.

[4] If socioeconomic characteristics were also included in the estimation of class membership probabilities, these predicted probabilities would then partially reflect these observable factors. In turn, this would conflate our investigation of latent preference heterogeneity which are driven by both observed and unobserved characteristics.

Modeling the adoption decision

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

$$Y_{ij} = \beta_0 + \beta_k \cdot C_{kij} + \beta_r \cdot r_{ij} + \beta_{li} \cdot X_{lij} + \mu_j + \varepsilon_{ij}. \tag{5}$$

In this model, Y_{ij} is a dummy variable representing purchase or use of an intervention stove by household *i* in community *j*. More specifically, we analyze purchase 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)[5]; r_{ij} represents a rebate amount randomized at the household-level in the communities exposed to the stove offer; X_{lij} is a vector of *l* household and community variables that influence the purchasing decision; μ_j is an error term clustered at the community level; and ε_{ij} is the usual individual idiosyncratic error term. The coefficients β are estimated using OLS regression, and allow us to consider the effects of preferences and price incentives, (β_k and β_r, respectively) on outcomes.

In the purchase models, we first group the improved biomass and electric stoves into one general category and analyze adoption of any promotion stove, 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 use difference-in-difference (DiD) methods to consider a set of other outcomes (ownership of any non-traditional stove, fuel use, fuel collection time, and self-reported respiratory illness) related to adoption and use of the experimentally-promoted technologies. We use DiD analysis for these analyses to adjust for baseline differences across household types given that roughly 30% of sample households already own a clean stove option (mostly LPG) at baseline.

[5] To test for sensitivity of our results to the definitions of class membership, we also estimated the same models using the continuous probabilities of class membership generated by the latent class logit procedure. These results are qualitatively identical to those presented in the paper, and are available in the supplementary materials (Appendix D) submitted with the article. We choose to present the dichotomous class indicators only because the interpretation of coefficients is more straightforward.

4. 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 non-traditional stoves, 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 combined with nearby hamlets for the purpose of the stove 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.[6] 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 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 (fuel savings were deemed easier to understand by respondents), 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 stove, the improved options presented in the DCE were biomass-burning ICS. 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

[6]In total, 118 households were replaced in this way. Thirty-three households refused to participate, while an additional 85 could not be interviewed because they were not present during the day of the fieldwork.

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?"[7] This confirmation was included to decrease the potential for hypothetical bias in the stated preference responses (Murphy et al. 2005). Following each choice task, debriefing questions were asked to probe the decision-making process and assess the certainty of respondent answers.

The intervention

The stove 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 promotion techniques (Lewis et al. 2014), trained 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 the stove features for the two available options (an electric coil stove and a biomass-burning ICS), even as they performed a live tea-making demonstration.[8] The information sheet (see Appendix B) 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 payment plan to households. Specifically, all households were given the choice of paying for the stoves upfront or in three equal installments (including a modest financing fee of 60 or 80 Rs., depending on the stove) that would be collected over a period of 4 weeks

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[7] Prior to this question, all respondents were reminded to consider their household budget carefully when choosing their preferred option. 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."

[8] 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, we decided to offer it alongside the more affordable of the biomass-burning stoves.

(i.e., in 3 installments collected 2 weeks apart). Roughly two thirds of purchasing households opted to pay for their chosen stove 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 a stove, 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). The electric stoves were sold to households for 900 Rs. (or 960 Rs. for those paying in installments); biomass stoves were 1300 Rs. (or 1380 Rs. with installments); these prices corresponded to the stove-specific prices paid to suppliers. As such, the amount of the high rebate (320 or 460 Rs.) varied somewhat based on the stove that was 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.[9] Finally, because of this design and the two follow-up visits to intervention communities that it entailed, households that declined a stove during the first visit were allowed to purchase one 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. 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.[10] 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

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

[10] Nine of these 771 treatment households could not be re-located during the stove promotion campaign, and therefore do not appear in any of the results.

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 one 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 stove. Thus, we analyze the DCE data that pertain to the entire sample of households that includes treatment and control communities, but only differentiate 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 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. 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.

5. 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 the 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 the random parameters for the traditional stove type and for price are significant, suggesting some preference heterogeneity (Columns 2 and 4). In terms of magnitude of effects, comparison of the part-wise utilities for a single unit change in the levels of the various attributes suggests that the value of a one-unit (33%) reduction in smoke emissions and additional cooking surface are similar on average, followed by a one-unit (33%) decrease in fuel requirement. The large coefficient on the traditional stove type indicates an average preference for traditional stoves that outweighs the value of a 1-unit reduction in smoke emissions plus fuel consumption several times over; this implies that many respondents would need to see large reductions in these levels to consider adopting a biomass ICS.

The determinants of preferences for biomass ICS

Given the heterogeneity in responses detected by the random parameters model, we next use LCA to look for consistent patterns in the choices made by different respondents, and to test 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 cleaner cooking technologies are supposed to reduce emissions and fuel requirements, we might expect these two classes to be more likely to adopt them.[11] 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 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 alternative stove. 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

[11] Some alternative stoves also have multiple cooking surfaces, though the ones we promoted during this study did not.

the ICS alternatives, and therefore were not answering questions in random fashion.[12] This is further shown by the large relative size of the price coefficient, and the large positive coefficient on the alternative-specific constant (ASC) for the traditional stove.

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.[13] We then regressed predicted class type on a variety of demographic and socio-economic variables using a multinomial logit model, where all reported coefficients are relative to omitted class 3 (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 adoption of clean stoves (Lewis & Pattanayak, 2012), and may help explain why class 3 households 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. Class 2 respondents are also 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 therefore may be more inclined to use commercial fuels (e.g., electric or gas).

Analyzing the stove adoption and use decision

These analyses of preferences serve to motivate several questions related to the likelihood of adoption of a new stove during the randomized sales intervention. In particular, we attempt to answer five questions on the relationship between the stated preferences and actual purchases and use. The covariates of interest in much of the discussion that follows are the binary variables for membership in each of the three latent classes.[14] In the most basic model, we only include the binary predicted class variables to explain purchase. We then add the randomized rebate (discount) amounts (which has a very large effect on purchasing rates, as shown in Figure 3),

[12] 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).
[13] Appendix C shows how this probability is obtained.
[14] Results based on the probabilities of class membership rather than discrete class assignments are included in Appendix C. They are fully consistent with the results presented here.

followed by a set of basic demographic and socio-economic controls, and finally including all of these plus a more complete set of community and socioeconomic characteristics, including those used in Table 7 to predict class membership. In the ensuing discussion, we report results from all the estimated models but our preferred specification is the full model. This is because inclusion of other controls allows us to better isolate the effects of unobserved preferences from the more commonly observed drivers of clean stove ownership in the literature (Pattanayak and Lewis 2012), even if we cannot determine the original source of these perceptions, and even though we lose roughly 5% of our sample (which shrinks from 1,049 to 996) due to missing data on one or more of these included covariates.

Question 1: Is preference class related to purchase of a new stove during the sales intervention?

This question arises from the observation that the three preference classes responded very differently to the stove attributes in the DCE exercise. 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 8-11 percentage points less likely on average (or a roughly 20% lower purchasing rate) to purchase a new stove during the first sales visit (Table 8, columns 1-4). Controlling for the rebate amount decreases the estimates slightly (columns 2-4) mostly because 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 stove cost) to the high rebate (33% of stove cost) level increases purchase from 28% to about 72% (Figure 2). No other controls – the basic ones included in columns 3 and 4, and the larger set listed in the notes below Table 8 – are significantly related to purchase. This and the stability of the coefficients on class membership suggest that the technological preferences expressed in the DCE contain information that is not reflected in these observables. The lack of correlation between common predictors of adoption and uptake is perhaps surprising. However, the combination of features of the intensive promotion strategy – information provision, relaxing of liquidity constraints, and subsidies – may have successfully allowed less educated and lower wealth households to better understand and finance the purchase of a new stove.

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), we find that the lower purchase rates among class 3 households fade somewhat (columns 5-8). Purchase rates are 6-10% lower on average in this analysis; this is because late 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, increasing trust in the stove promotion intervention, or the potential for learning. The other explanatory variables are similar in magnitude and significance to the previous model.

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

This question emerges from observations that the part-wise utilities (see Table 6) implied by the LCA coefficients for classes 1 and 2 imply very different willingness to pay for stove attributes, and that households in different classes have varying preferences for traditional stoves (classes 1 and 3 favor them while class 2 favors a biomass ICS). To evaluate this question, class membership was also interacted with the rebate amount (Table 9)[15]. 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?

In considering this question, we are interested in whether class 1 or class 2 households are more likely to adopt electric vs. biomass-burning stoves. On the one hand, class 2 households dislike traditional stoves and have a greater willingness to pay for all stove attributes, as discussed above. Yet class 1 households place greater weight on smoke emissions relative to other 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 option. Both

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

accommodate a single pot, but they differ in terms of fuel costs (the electric stove is more expensive to operate).

To address the question, we consider purchase of the different stove types using a multinomial logit model. The results are shown in Table 10.[16] Our first observation is that class 1 households are most likely to purchase the electric stove (Columns 2 and 4); when including all controls, class 1 households are 7% and 13% more likely to purchase this stove than classes 2 and 3, respectively.[17] 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. These results indicate that class 2 households prefer biomass-burning ICS' over classes 1 and 3, while class 1 households prefer the electric option, which is consistent with the DCE results. As with overall purchase, very few other covariates explain the differences in purchase rates across technologies. Households in the general caste category are somewhat more likely to select a biomass-burning stove, while those who spend more time cooking with traditional stoves are more likely to purchase an electric one.

We also added the interacted rebate variables to the full model to test if the classes have different sensitivity to 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 stove, 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 a new stove?

Up to this point, our attention has been focused on stove purchases, but the benefits of these technologies only come with sustained use (McCracken et al. 2007, Hanna et al. 2012). We explore the short-term sustainability of use of these new stoves by using self-reported daily use as measured in the follow-up survey conducted several months after the sales campaign. In interpreting the results that follow, however, it should be noted that 74 of the original 1063 households (7.0%) were lost from the sample at follow-up (Figure 2). Although attrition is not

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

significantly correlated with treatment status, a slightly smaller percentage of households receiving the high rebate (4.0% vs. 7.8% in the low rebate group) during the intervention were lost to follow-up. In addition, attrition may affect the generalizability of our results. Households lost to follow-up were smaller, more likely to be female-headed, and tended to be less reliant on traditional stoves, as measured by time spent cooking, fuel consumption, and time spent collecting fuel at baseline (results available upon request).

Unconditional regressions show that class 3 is about 7 percentage points less likely to use one of the new stoves on a daily basis. Yet this lower use is purely due to their lower purchase rates: conditional on purchasing a new stove, preference type is not significantly correlated with use (Table 11). This is perhaps not surprising since the DCE was designed to predict purchase rather than use. The results are also consistent with findings in the literature that highlight that ownership of clean stoves often does not necessarily equate to use. In column 1, for example, we see that only about 58% of purchasers in the omitted class (class 1) use the new stove on a daily basis. The full model in column 3 also shows that the randomized rebate amount is positively associated with use, which suggests that the conditional rebate promised to users at the time of the third sales visit may perhaps have helped to incentivize longer-term use.[18] The effect of the full rebate is to increase the likelihood of daily use by roughly 23 percentage points. Among the other covariates, time spent cooking on traditional stoves at baseline and residence in a village with previous interactions with the promoting NGO are positively related to use, while female headed households are less likely to use a purchased stove (results not shown). No other covariates are statistically significant.

We also separately analyzed the electric and biomass stoves to consider variation in use by stove type. The results are shown in Columns 4 and 5; 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 correlates with use is the time spent collecting fuel at baseline, and the hours of electricity supply. Finally, conditional on purchasing it, female-headed households are much less likely to use the biomass ICS (column 6), while prior NGO history in the village is related to a 25% higher probability of daily use. We cannot say definitively why households in these NGO villages were more motivated to use the biomass ICS, but it may stem from greater concern with environmental preservation, or more effective follow-up by the promoter.

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

Question 5: Is class type linked to other stove-related outcomes following the promotion campaign?
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 (subject to the same caveats about generalizability as those presented above). For each of these analyses, we first present DiD results stratified by class, and then also control for the rebate level and institutional stratum.[19] The downstream outcomes we consider are changes in firewood use over time, measured in kilograms and in minutes of collection time per day, and in self-reported respiratory illness.

The first two analyses show that the stove promotion effort increased both ownership and use of cleaner cooking options, but these changes are not significantly different across preference classes (Table 12). The rebate amount is also positively related to each of these outcomes. We can therefore conclude that some of the additional purchase and use of intervention stoves was among households who already owned and used cleaner cooking options (mostly LPG) at baseline, and who were also most likely to be in class 1. Turning to the changes in firewood and fuel collection, we observe a strong positive trend in firewood consumption (an increase of about 6 kg/day), which represents a seasonal effect as follow-up surveys were conducted during the winter season when fuel use increases for heating purposes (Columns 5 and 6). Firewood use was relatively lower amount treatment households in classes 1 (who were more likely to adopt electric stoves) and 3, but not among the class 2 households (who were most likely to adopt the biomass ICS). Consistent with these fuel savings, most households in the treatment group also appear to save time on fuel collection, though these estimates are not precise. Turning to respiratory outcomes, there is again a positive seasonal trend. Class 1 households in the treatment group report somewhat lower cough and cold at follow-up, which may reflect their greater propensity to adopt electric stoves that do not generate household emissions. Class 3 households, who are least likely to purchase any promotion stove, report no gains in respiratory health.

6. Discussion

Implementers of development and health interventions are often perplexed when households choose to forego technologies that have the potential to improve their health and economic outcomes. This problem of low demand has been observed across a wide variety of sectors, and numerous solutions for boosting it have been

[19] 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.

proposed, ranging from subsidies and free provision, to information provision and social marketing. Even with all of these efforts, progress often continues to be slow, and the search for effective and scalable solutions to the technology adoption problem continues.

A particularly stark example of this problem concerns the use of the traditional, inefficient and highly polluting cooking technologies used by billions of the world's poorest people (Smith et al. 2000, Legros et al. 2009). Such technologies are responsible for 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). And nowhere does the adoption puzzle appear more challenging than in India, where progress has been slow despite several decades of highly subsidized promotion interventions and the largest potential market for cleaner cooking technologies in the world.

In light of these realities, this study investigated the role that latent preferences may play in affecting adoption of non-traditional cooking technologies. To the best of our knowledge, ours is the first study to explore the mapping of preferences for any technology elicited through a DCE, to experimentally-observed adoption decisions. Our sample consists of rural households from two districts of Uttarakhand, India. Three quarters of the 1050 households in the experiment were randomly assigned to receive stove sales visits during which two very different stoves were offered to them for purchase. The analysis shows that household preferences for non-traditional stoves are highly varied. Latent class analysis identifies two classes of households, comprising 27% and 20% of the sample, respectively, who appear differentially 'interested' in the features of cleaner cooking technologies, 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 smoke reductions, fuel savings and cooking convenience. Closer examination of the make-up of each class shows that the 'uninterested' class mainly consists of lower-SES households who lack knowledge of clean cooking options and of 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 delayed purchase of promoted stoves, b) responsiveness to price incentives, c) the choice of more efficient biomass versus electric stoves, and finally d) daily use following purchase. Our first important result is that the 'uninterested' class is less likely to purchase a new stove despite the fact that the promotion effort 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. The silver lining in these results, however, is that class membership becomes less predictive once delayed purchases are included, which suggests that these class 3 households become more likely to adopt a new stove 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 'disinterested' households can with time 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 incentives; these households were also deemed in the LCA to have the greatest demand for biomass ICS. 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 stove, which is both cheaper and offers the possibility of eliminating household emissions from cooking. The predictive power of 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 stove use conditional on purchase. This is perhaps unsurprising given that different considerations and mechanisms may govern the adoption and use decisions. Related work on decisions made at the intensive and extensive margins has considered such issues, e.g., in the context of recreational (Phaneuf 2013), transportation (Bhat 2005), and land use decisions (Hardie et al. 2004). The extensive decision in this case concerns purchase of a new stove, while the intensive decision governs the amount of cooking done with it. Numerous approaches can then be used to solve for the optimal solution of adoption and usage. Towards this end, an interesting and useful extension of this study would be to examine in-depth the different conditions governing adoption and use of cleaner cooking technologies.

Finally, DiD analyses reveal few differences in ownership and use of clean stoves across preferences classes. This 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 decreases by about 1.5 kg/day relative to untreated households in the same classes, while class 2 households in the treatment group, who were most inclined to adopt the improved biomass stove, do not experience 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 stove (and other technology) promotion efforts, as well as for other similar quasi-public goods. An oft-neglected feature of the challenge of environmental health goods provision in low-income settings is that the government, or socially-minded micro-institutions, must frequently act as the primary suppliers to local beneficiaries, which typically results in limited (or no) options for consumers. Private markets naturally meet heterogeneous demand through market segmentation and product differentiation, but the competitive forces that drive such innovations may be lacking when markets – such as those for alternative cookstoves – are thin. In addition, NGOs and governments are often tempted to pick specific solutions based on sound technical criteria (e.g., an emissions profile), a model that has failed over and over in multiple sectors (Pritchett and Woolcock 2004). By clearly demonstrating the implications that latent (and typically unobserved) preferences have for purchases of new stoves, our work points to the need for offering beneficiary households choices rather than prescribing specific solutions that may not align with their needs. Non-biomass burning technologies such as electric stoves, which promise greater savings of solid fuel and lower household emissions, should receive serious consideration in such promotion efforts.

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Tables and Figures

Table 1. Summary of discrete choice experiment design

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

[1] $US ≈ 52 Rs.

Table 2: 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 Control	Mean Treatment	Normalized Difference Overall
Village has paved road	0.26	0.31	0.080
Distance to doctor (km)	9.14	9.48	0.031
Bank facility in village	0.32	0.33	0.007
Presence of NGO	0.43	0.53	0.134
Household size	4.98	4.77	-0.070
Education- head of household (yrs)	5.59	5.88	0.044
Education- primary cook (yrs)	4.63	4.70	0.011
Female head of household	0.32	0.25	-0.107**
Below poverty line household	0.60	0.56	-0.060
Scheduled Caste/Scheduled Tribe	0.24	0.26	0.034
% household cold/cough in past 2 wks	0.06	0.08	0.059
Relative wealth (1-low to 6-high)	2.12	2.13	0.007
Household has taken loan in past yr	0.12	0.16	0.088
Household saved money in past year	0.24	0.26	0.021
Hours of electricity per day	17.9	17.0	-0.084
Log of total expenditure (Rs./month)	8.38	8.42	0.036
Number of cell phones owned	1.3	1.3	0.014
Total rooms in house	4.43	4.70	0.082
Presence of toilet	0.88	0.84	-0.071
Owns/leases agricultural land	0.94	0.98	0.153
Most patient respondent	0.43	0.50	0.098*
Most risk-taking respondent	0.41	0.43	0.036
Household believes ICS/clean fuels are beneficial	0.30	0.05	0.046
Believe smoke is unsafe	0	1	0.054
Traditional stove ownership	1	1	0.077
Improved stove ownership	0.30	0.32	0.034
Minutes traditional stove use (min/day)	307	285	-0.110
Amount of solid fuel used (kg/day)	6.7	6.9	0.026
Total fuel expenditure (Rs./month)	257	272	0.016
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 rightmost columns as follows: *** p-value < 0.01; ** p<0.05; * p<0.1.

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

Variable	Mean Low Rebate N=255	Mean Med Rebate N=259	Mean High Rebate 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 (χ^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) Class 1	(2) Class 2	(3) Class 3
Price[1]	-0.338***	-0.137***	-1.135
	(0.000)	(0.0020)	(0.614)
Fuel requirement	-0.114**	-0.211***	0.0778
	(0.048)	(0.0016)	(0.804)
Smoke emissions	-0.507***	-0.326*	1.586
	(0.0004)	(0.060)	(0.376)
Number of pots	0.244*	0.647***	-1.493
	(0.099)	(0.000)	(0.461)
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)	0.28	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) Class 1	(2) 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. Stove purchase by latent class

VARIABLES	(1) Basic Visit 1 purchase	(2) +Rebate Visit 1 purchase	(3) +Basic controls Visit 1 purchase	(4) +All controls Visit 1 purchase	(5) Basic With later purchases	(6) +Rebate With later purchases	(7) +Basic controls With later purchases	(8) +All controls With later purchases
Treatment group (exposed to sales)	0.52***	0.24***	0.23***	0.25***	0.56***	0.27***	0.26***	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)			-0.001	-0.001			-0.001	-0.002
			(0.79)	(0.68)			(0.61)	(0.49)
General caste			0.024	0.027			0.029	0.035
			(0.44)	(0.40)			(0.36)	(0.26)
Age of household head			-0.000	-0.000			-0.0003	-0.0004
			(0.96)	(0.95)			(0.78)	(0.72)
Education of household head			0.003	0.001			0.004	0.002
			(0.39)	(0.86)			(0.24)	(0.56)
Relative wealth			0.055	0.038			0.059	0.040
			(0.16)	(0.32)			(0.13)	(0.30)
Treatment*Class 2[1]	0.018	0.010	0.012	0.015	0.015	0.007	0.014	0.007
	(0.75)	(0.85)	(0.81)	(0.78)	(0.77)	(0.89)	(0.77)	(0.89)
Treatment*Class 3[1]	-0.11***	-0.087**	-0.082*	-0.092**	-0.095**	-0.067	-0.063	-0.069
	(0.007)	(0.044)	(0.054)	(0.033)	(0.031)	(0.13)	(0.14)	(0.12)
Constant	-0.00***	-0.00***	-0.07	-0.13	0.00***	0.00***	-0.03	-0.08
	(0.004)	(0.000)	(0.43)	(0.22)	(0.000)	(0.000)	(0.13)	(0.48)
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	0.318	0.325	0.228	0.332	0.342	0.350

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 covariate 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 (first sales visit only), by preference class

VARIABLES	(1) Visit 1 purchase	(2) Visit 1 purchase
Treatment group (exposed to sales)	0.19***	0.22***
	(0.002)	(0.001)
Treatment*Rebate amount (Rs.)		
Treatment*Class 2[1]	0.013	0.002
	(0.89)	(0.98)
Treatment*Class 3[1]	-0.012	-0.033
	(0.87)	(0.64)
Treatment*Rebate*Class 1	0.0017***	0.0016***
	(0.000)	(0.000)
Treatment*Rebate*Class 2	0.0017***	0.0017***
	(0.000)	(0.000)
Treatment*Rebate*Class 3	0.0013***	0.0013***
	(0.000)	(0.000)
Constant	-0.00***	-0.13
	(0.000)	(0.23)
Other controls[2]	No	Yes
Observations	1,049	996
R-squared	0.311	0.326

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). 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 2 and 4).

Table 10. Stove 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	Biomass ICS	Electric	Biomass ICS	Electric
Rebate amount (Rs.)			0.00068***	0.00093***	0.00054***	0.0014***
			(0.000)	(0.000)	(0.002)	(0.000)
Class 2[1]	0.083**	-0.062	0.079**	-0.078		
	(0.011)	(0.18)	(0.025)	(0.13)		
Class 3[1]	0.028	-0.14***	0.022	-0.13***		
	(0.34)	(0.000)	(0.39)	(0.002)		
Rebate*Class 2					0.00034**	-0.00034
					(0.015)	(0.17)
Rebate*Class 3					0.00013	-0.00068***
					(0.23)	(0.002)
Other controls[2]	No		Yes		Yes	
Observations	761		721		721	
Pseudo-R^2	0.012		0.119		0.123	

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). 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. Stove use conditional on purchase, by latent class

VARIABLES	(1) Basic Daily use	(2) +Rebate Daily use	(4) +SES Daily use	(5) Electric stove Daily use	(6) Biomass ICS Daily use
Rebate amount (Rs.)		0.001***	0.001***	0.0004	0.0007
		(0.005)	(0.006)	(0.16)	(0.14)
Electricity supply (hr/day)			0.005	0.012**	0.007
			(0.50)	(0.039)	(0.59)
Class 2	-0.079	-0.085	-0.10	-0.11	0.021
	(0.36)	(0.30)	(0.21)	(0.20)	(0.93)
Class 3	-0.033	-0.014	-0.045	-0.021	-0.23
	(0.55)	(0.81)	(0.42)	(0.73)	(0.23)
Constant	0.58***	0.41***	0.30	0.13	0.51
	(0.000)	(0.000)	(0.21)	(0.54)	(0.13)
Other controls[2]	No	No	Yes	Yes	Yes
Observations	373	373	357	285	111
R-squared	0.003	0.0263	0.131	0.106	0.362

Notes: Linear probability model using all households that purchased a stove; *** 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). Inclusion of controls does not alter the sign or significance of the main results shown here, though households in communities with prior relationships with the sales NGO are much more likely to use a stove (and particularly the biomass one) on a daily basis. 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 class membership on improved stove ownership, use, and fuel collection outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Basic DiD[1]	…+Rebate +NGO controls[2]	Basic DiD[1]	…+Rebate + NGO controls [2]	Basic DiD[1]	…+Rebate + NGO controls [2]	Basic DiD[1]	…+Rebate + NGO controls [2]	Basic DiD[1]	…+Rebate + NGO controls [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	0.007	-0.016	-0.007	-0.044	6.26***	5.95***	20.2	26.6	0.12**	0.12*
	(0.84)	(0.69)	(0.83)	(0.23)	(0.000)	(0.000)	(0.30)	(0.18)	(0.048)	(0.069)
Post*Treatment	0.35***	0.22***	0.29***	0.19***	-1.68**	-1.55	-37.6	-46.2	-0.14*	-0.15
	(0.000)	(0.0004)	(0.000)	(0.001)	(0.046)	(0.10)	(0.12)	(0.10)	(0.068)	(0.11)
Post*Treatment*		0.001***		0.001***		-0.001		0.053		0.000
Rebate		(0.001)		(0.003)		(0.68)		(0.20)		(0.94)
Post*Treatment*	-0.0025	-0.014	-0.024	-0.037	3.03***	2.97***	-3.54	-2.48	0.064	0.065
Class 2[3]	(0.97)	(0.81)	(0.71)	(0.55)	(0.001)	(0.001)	(0.83)	(0.88)	(0.42)	(0.42)
Post*Treatment*	-0.017	-0.0067	0.013	0.023	-1.09	-1.08	6.48	6.59	0.16***	0.16***
Class 3[3]	(0.71)	(0.89)	(0.77)	(0.63)	(0.13)	(0.14)	(0.67)	(0.66)	(0.009)	(0.009)
Constant	0.29***	0.28***	0.28***	0.28***	6.28***	6.15***	99.0***	86.2***	0.20***	0.18***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,974	1,974	1,974	1,974	1,973	1,973	1,974	1,974	1,974	1,974
R-squared	0.125	0.140	0.091	0.104	0.146	0.149	0.010	0.025	0.015	0.017

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 extended specification also includes controls for baseline differences across rebate levels and NGO strata.

[3] 'Class 2' and 'Class 3' are dummy variables indicating membership in latent classes 2 and 3, respectively. Class 1 is the omitted class.

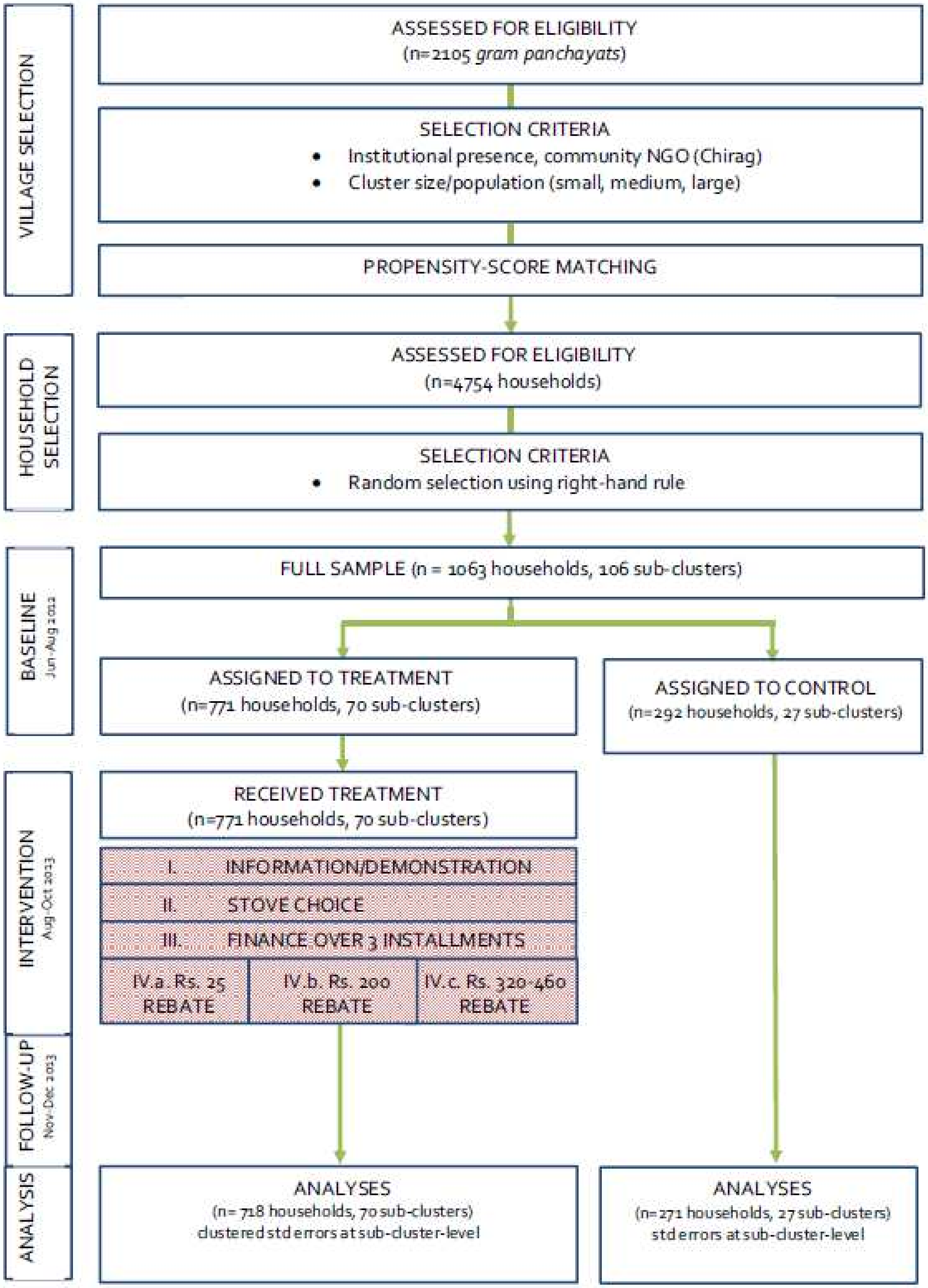

Figure 1. Study design

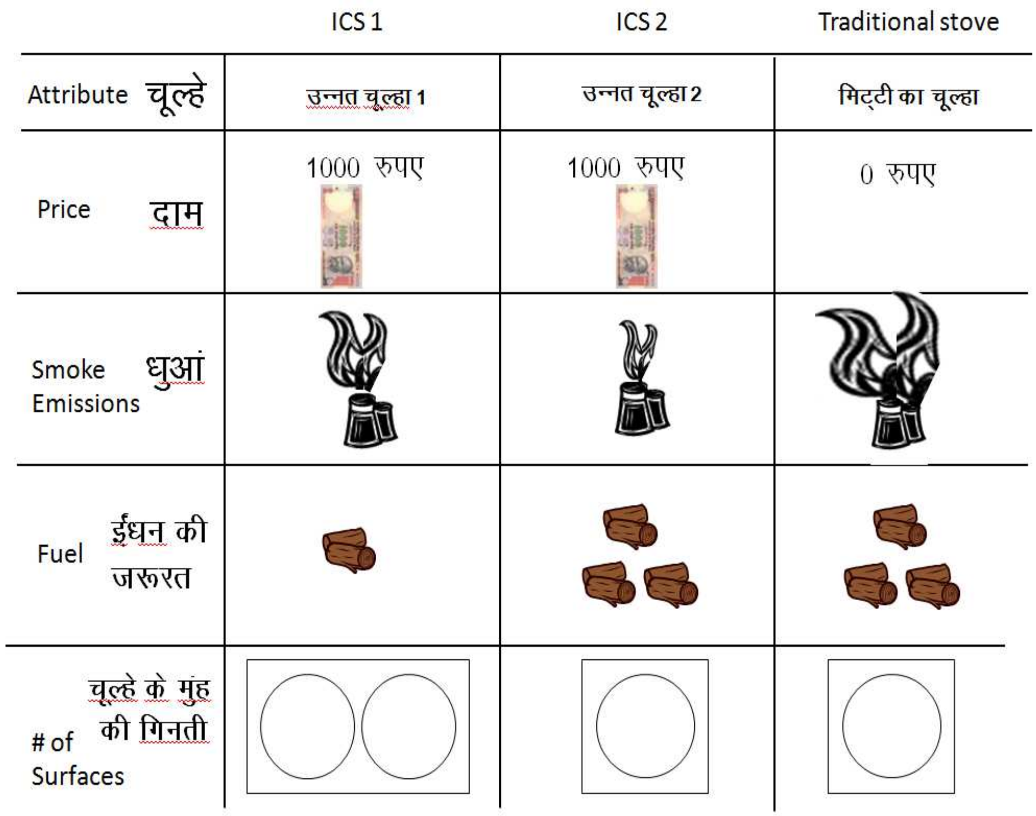

Figure 2. An example choice task in the stove decision exercise

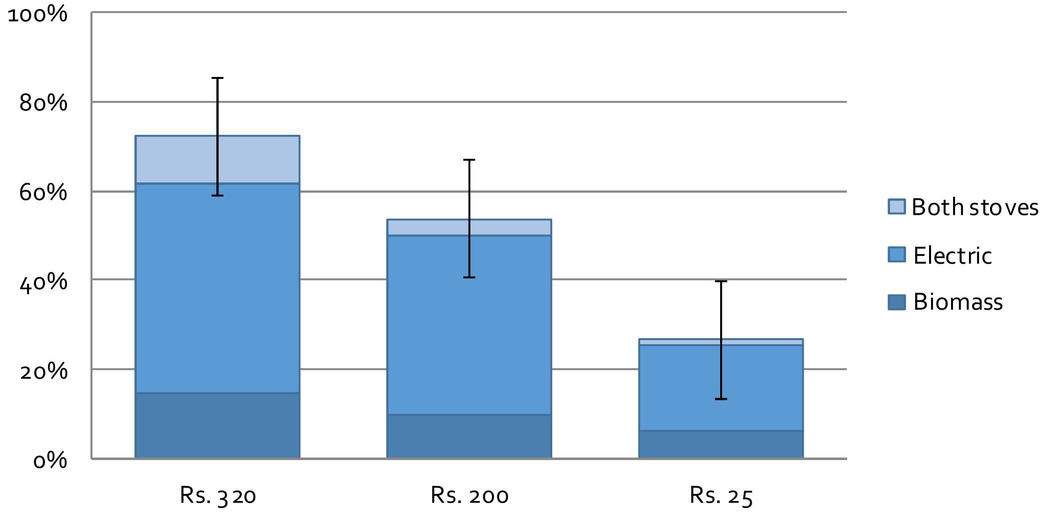

Figure 3. Purchase of intervention stoves, by rebate group

Appendix A: Additional tables of results

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) All purchases	(2) All purchases
Treatment group (exposed to sales)	0.19***	0.22***
	(0.002)	(0.001)
Electricity supply (hr/day)		0.0062***
		(0.002)
Treatment*Class 2[1]	-0.003	-0.031
	(0.98)	(0.76)
Treatment*Class 3[1]	0.069	0.049
	(0.40)	(0.54)
Treatment*Rebate*Class 1	0.0019***	0.0019***
	(0.000)	(0.000)
Treatment*Rebate*Class 2	0.0020***	0.0020***
	(0.000)	(0.000)
Treatment*Rebate*Class 3	0.0012***	0.0012***
	(0.000)	(0.000)
Constant	-0.00***	-0.17*
	(0.000)	(0.088)
Other controls[2]	No	Yes
Observations	1,049	996
R-squared	0.34	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. Stove 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	Biomass ICS	Electric	Biomass ICS	Electric
Rebate amount (Rs.)			0.00036***	0.0012***	0.00020	0.0018***
			(0.003)	(0.000)	(0.24)	(0.000)
Electricity supply (hr/day)			-0.0002	0.012***	0.0025	0.012***
			(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).

Appendix B: Stove Fact Sheet (with translation)

Appendix C: Latent class logit

The conditional choice probability of respondent *i* choosing alternative *j* in choice task *t*, given that she belongs to class *s* is:

$$\text{Prob}\left[C_t^i = j \middle| class\ s\right] = \frac{\exp(\beta_s X_{jt} + \beta_{0,s} p_{jt})}{\sum_{\mathrm{k=0}}^{\mathrm{K}} \exp(\beta_s X_{kt} + \beta_{0,s} p_{kt})}, \tag{C1}$$

where β_s is a vector of coefficients for the attributes of the alternatives.

Next, the unconditional probability that respondent *i* belongs to class *s* is:

$$\text{Prob}[respondent\ i\ is\ class\ s] = \left(\frac{\exp(\alpha_s' Z_i)}{\sum_{\mathrm{s=1}}^{S} \exp(\alpha_s' Z_i)}\right). \tag{C2}$$

Depending on the researcher's objective, Z_i can be a vector of observable characteristics such as education and income or just a vector of constants. If Z_i contains individual characteristics, this probability expression is expressed as a multinomial form where the coefficient for the excluded class is normalized to zero. As such, α_s' should be interpreted relative to the excluded class.

Combining these expressions, the probability that respondent *i* chooses alternative *j* in task *t* is:

$$\text{Prob}[C_t^i = j] = \sum_{s=1}^{S} \left(\frac{\exp(\alpha_s' Z_i)}{\sum_{\mathrm{s=1}}^{S} \exp(\alpha_s' Z_i)}\right) \left(\frac{\exp(\beta_s X_{jt} + \beta_{0,s} p_{jt})}{\sum_{\mathrm{k=0}}^{\mathrm{K}} \exp(\beta_s X_{kt} + \beta_{0,s} p_{kt})}\right). \tag{C3}$$

If we multiply this expression by the probabilities from the other choice tasks, we recover the probability for choosing a particular sequence of alternatives:

$$\text{Prob}[C^i = (C_{j1}^i, \dots, C_{jT}^i)] = \prod_{t=1}^{T} \left[\sum_{s=1}^{S} \left(\frac{\exp(\alpha_s' Z_i)}{\sum_{\mathrm{s=1}}^{S} \exp(\alpha_s' Z_i)}\right) \left(\frac{\exp(\beta_s X_{jt} + \beta_{0,s} p_{jt})}{\sum_{\mathrm{k=0}}^{\mathrm{K}} \exp(\beta_s X_{kt} + \beta_{0,s} p_{kt})}\right)\right]. \tag{C4}$$

This expression is then summed over the entire sample to arrive at the log likelihood:

$$\ln L = \sum_{i=1}^{N} \ln\left\{Prob[C^i = (C_{j1}^i, \dots, C_{jT}^i)]\right\}. \tag{C5}$$

The preference parameters β_s and *S* – 1 class parameters α_s can be recovered from this log likelihood function either by maximum likelihood estimation or through application of the EM algorithm (Green & Hensher, 2003; Train, 2008; Bhat, 1997).

Using Bayes theorem and the parameters from the likelihood function, we then estimate the conditional probability that a respondent belongs to each class *s* given her selection of alternative *j*:

$$\begin{aligned}&\text{Prob}\left[respondent\ i\ is\ class\ s \middle| C_t^i = j\right] \\ &\quad = \frac{\text{Prob}[respondent\ i\ is\ class\ s] * Prob[C_t^i = j | respondent\ i\ is\ class\ s]^{dijt}}{\text{Prob}\left[C_t^i = j\right]}.\end{aligned} \tag{C6}$$