Preferences and the effectiveness of behavior-change interventions: Evidence from adoption of improved cookstoves in India*

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Abstract

Preference heterogeneity can influence behavior in economically significant ways, thereby influencing the effectiveness of environmental policies or interventions. We test this hypothesis in the context of efficient cooking technology in India. We use stated preference methods to first characterize household tastes for various features of a more efficient cooking technology. We then relate these typically unobserved preferences to households' adoption decisions during an experiment that allowed them to choose between two alternatives with different features. Stated preferences help predict actual adoption: households initially classified as uninterested are less likely to purchase and use any new technology, while relative distaste for pollution is linked to selection of a cleaner technology. Because of this influence on adoption behaviors, preference heterogeneity has important implications for how environmental policies can impact various health and development outcomes.

Keywords: Discrete choice experiment, latent class analysis, field experiment, India
JEL codes: C93, D12, Q41, Q53

1 Introduction

Many policy interventions seek to change private individuals' behaviors for social efficiency or paternalistic reasons. For example, policy-makers often provide incentives or otherwise seek to stimulate adoption of quasi-public goods that improve health, livelihoods, and environmental quality, to overcome private agents' lack of accounting of their external benefits (Foster and Rosenzweig, 2010). Similarly, they may try to help individuals overcome decision-making biases that harm their long-term social welfare (Allcott and Mullainathan, 2010; Ashraf et al., 2006; Madrian and Shea, 2001). Unfortunately, behavior change interventions frequently fall short of desired results, often because targeted beneficiaries are slow to adopt and use new technologies, or to respond to these new policy incentives (Feder et al., 1985).

A potentially significant challenge to implementation of successful behavior change policies, many of which typically prescribe a single mechanism, incentive or technology, arises from deep-rooted (and typically unobserved) demand heterogeneity (Heckman, 2001). Such interventions downplay the potential importance of beneficiary choice. In this paper, we ask a fairly fundamental question about the role and importance of such preferences, namely: Do practical methods exist for measuring preferences that determine beneficiary choice in advance of implementation? To answer this question, we turn to our specific empirical application, which relates household preferences for improved cookstoves (derived from stated preference surveys) to revealed preferences observed when we offer these same households the option of purchasing one or both of two technologies (each with different attributes).

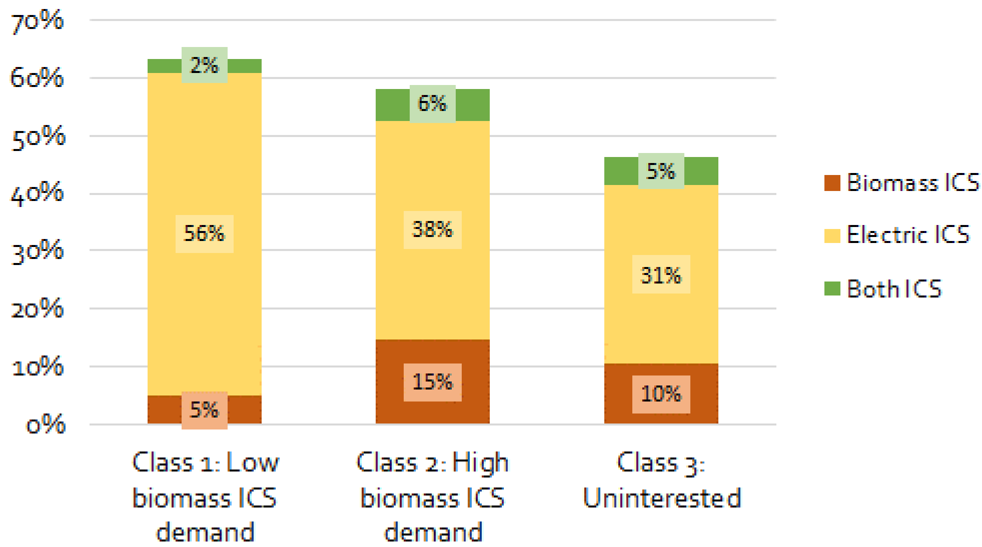
To characterize preferences, we apply generalized multinomial logit methods (Magidson and Vermunt, 2004) to analyze data from a discrete choice experiment (DCE). In this DCE, respondents completed a series of choice tasks in which they considered differences—in price, convenience, smoke emissions, and fuel requirement—between improved cookstoves (ICS) 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 the DCE is to allow consumers to explicitly consider tradeoffs between potential stove alternatives with varying levels of these attributes (Louviere et al., 2000; McFadden and Train, 2000). We use scale-adjusted latent class analysis (LCA) to look for regularities in the choice patterns of different respondents while accounting for uncertainty in the estimated coefficients across groups (Magidson and Vermunt, 2004). We then consider whether classes of households (categorized through the LCA) with specific preferences are more or less likely to purchase a new stove during a randomized technology promotion campaign. A follow-up survey conducted several months after the intervention sheds additional light on the use of these intervention stoves.

We find that about two thirds (67%) of sample households can be categorized as initially 'uninterested' (we apply this label to the class 3 group) in the positive attributes of ICS. At baseline, these households have lower wealth, are older, and are less aware of the health damages caused by smoke inhalation. The other two classes are distinguished by their relative level of interest in an ICS. Class 1 (11%) is a small, price-sensitive group that is primarily interested in smoke emissions reductions, while class 2 (22%) has higher relative demand for the full set of ICS attributes, and particularly for reduced fuel consumption.

Consequently, we observe that class 3 households are much less likely to purchase and use a new stove promoted during a randomized sales campaign (Figure 1). Consistent with predictions from the DCE, class 1 households are relatively more likely to adopt an electric stove that essentially eliminates household emissions. Class 2 households on the other hand are more likely to adopt a biomass-fuel ICS that is slightly more expensive but offers reductions in both fuel needs and emissions. Counterfactual calculations of adoption rates in scenarios in which only one or the other stove would have been offered therefore show substantially lower uptake rates. Importantly, the promotion experiment was designed to address other barriers to adoption of environmental health technologies such as information and liquidity constraints (Bensch et al., 2015), and proved successful in stimulating the acquisition of improved stoves in this population. This perhaps explains why few observable household or community-level covariates other than latent preferences explain stove purchases. Looking beyond stove purchase, we find that differences in adoption rates also translate into differential use, though use rates are mostly similar across groups once we condition on purchase. This latter finding is somewhat limited by statistical power and may stem in part from heterogeneity in treatment effects. These results are robust to a variety of specifications and to dichotomous or continuous probability-based measures of class membership.

We are not the first to argue that latent heterogeneity has important implications for program implementation and policy design (Heckman, 2001; Pinto, 2015). Differences in preferences may arise from variation in beneficiaries subjective expectations about benefits and costs (Manski, 2004; Poe and Bishop, 1999); heterogeneity in risk aversion, time preferences, or trust attitudes (Liu, 2013); differences in tastes and weights related to culture or other factors that beneficiaries place on specific features of a technology (Jeuland et al., 2015a; McFadden and Train, 2000); or from unappreciated complexity in the dynamics that influence technology adoption and the production of benefits (Brown et al., 2017; Jeuland and Pattanayak, 2012). Yet, despite advances in measurement, the role of heterogeneity in influencing outcomes is under-researched (McFadden and Train, 2000; Ravallion, 2012). Indeed, the vast majority of prior work in this vein focuses on attitudes towards risk and time, or trust (Cárdenas et al., 2013; Liu, 2013; Tanaka et al., 2016; Smith and Desvousges, 1986).

Figure 1: Purchase of intervention stoves, by preference class (treated households only)



Most behavior change interventions meanwhile offer only a single alternative to target populations, for a variety of reasons, including political feasibility, ease of implementation, or paternalism. Such an approach assumes that variation in beneficiaries' attitudes towards interventions and technologies, even if it exists, will not be particularly consequential for determining final outcomes. In this respect, a useful question to ask is: How general are the results that we observe, for one particular environmental health technology such as an ICS? After all, a cleaner cooking stove has complex implications for those adopting it: it alters fuel consumption and requirements, cooking time allocation, respiratory health, household cleanliness, and even the taste of food (Jeuland et al., 2015b). And in general, we would caution that the importance of offering choices likely varies across technologies and settings, and may be particularly important in our specific context.

Reflecting more on this point, the absence of choice may not be a serious concern for interventions for which the pathway from cause to effect is relatively simple (e.g., encouraging vaccination against a specific disease). Still, many social welfare-improving interventions feature complex or indirect pathways to improved well-being. For example, marketing of health-improving water and sanitation technology, such as in-house water chlorination, may reduce convenience, or have aesthetic implications that individuals weight differently (Casabonne and Kenny, 2012; Jenkins and Curtis, 2005; Yang et al., 2006), with important consequences for demand and adoption (Jeuland et al., 2016). Preference heterogeneity has also been observed to affect household demand for sanitation (Vasquez and Alicea-Planas, 2018), vaccines (Larson et al., 2014), insecticide-treated bednets (Bonan et al., 2017), and farmers' demand for soil fertility management or other ecosystem service enhancements (Lambrecht et al., 2013; Mulatu et al., 2014). Failure to adequately account for perceptions of costs and benefits, and especially those that relate to taste aspects that are usually unobserved, may therefore lead to systematic errors in projections of the demand for, and outcomes obtained from, behavior change efforts (Orgill et al., 2013; Whittington et al., 2012).[1] And while the results that we present in this paper are clearly specific to cleaner cooking technology, this disconnect may have especially important consequences for efficient adoption of multi-dimensional quasi-public goods, because markets that would better offer choices tend to fail or underprovide (Phaneuf, 2013).

Our paper makes two main contributions. First, we add to a thin literature on the private demand for a quasi-public good of importance to economic, environmental, health and energy outcomes—cleaner cooking technologies—by being the first to examine how households respond to a sales offer that allows a choice between two very different technologies. Relatedly, nearly all technology promotion intervention studies in environmental health, and all in the domain of improved cookstoves, focus on the demand for a single pre-selected technology with a specific set of features. Second, we seek to better understand whether and how preference and taste heterogeneity may influence policy outcomes, in terms of both uptake and outcomes among target beneficiaries. The latter contribution speaks to long-standing questions about the reliability of subjective and stated preference data (Bertrand and Mullainathan, 2001; Borghans et al., 2008; Carson et al., 1996). Our findings suggest that stated preference approaches can be used for more than just valuation. That is, stated preferences may serve as a methodological tool for preparing more informative field experiments, and as a policy tool for targetted implementation of programs. These contributions collectively have important implications for policies aiming to promote quasi-public goods and maximize welfare impacts.

The remainder of the paper proceeds as follows: section 2 describes our setting and data; section 3 describes our empirical approach and results concerning preferences; section 4 presents our main findings; and section 5 concludes.

[1] Indeed, we demonstrate the extent to which uptake of a policy can differ as a function of such heterogeneity using an illustrative model presented in Appendix A. Specifically, using numerical simulations, we show that in the presence of across- and within-community differences in preferences over policy attributes, the provision of multiple alternatives greatly increases participation by beneficiaries. In our simple set-up, with policies differentiated only along two attribute dimensions, uptake increases by approximately 40% when two differentiated alternatives are made available.

2 Research context and data

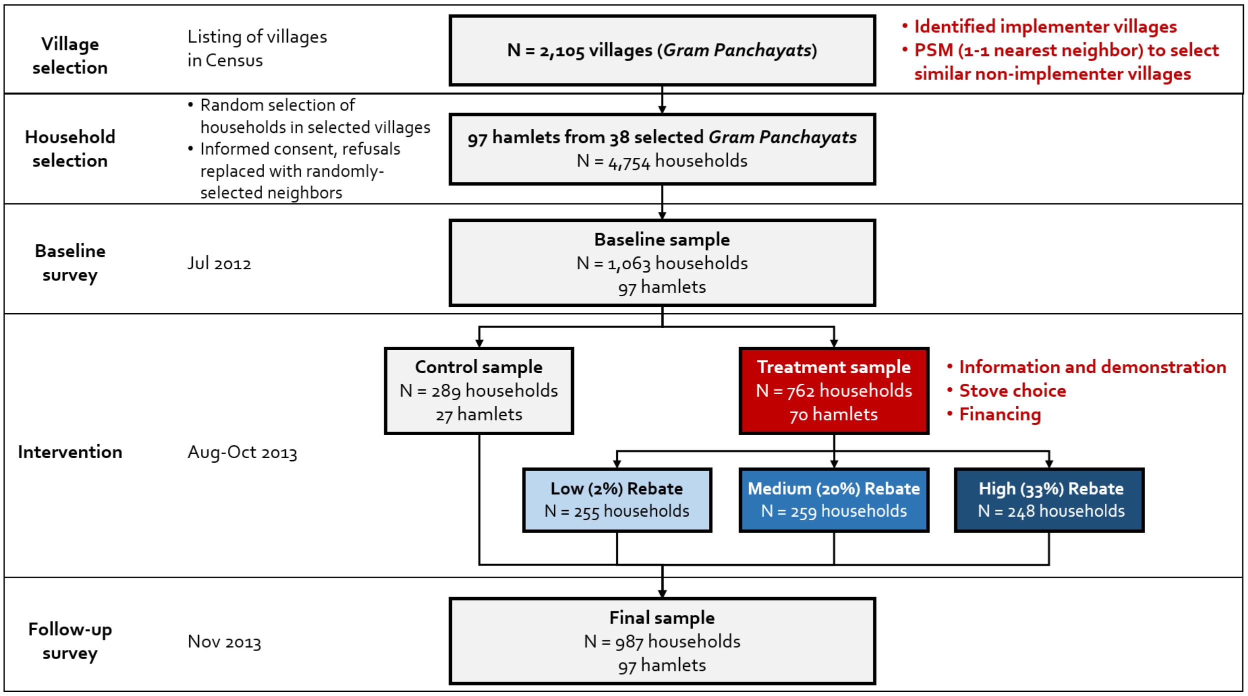
The use of solid biomass or coal fuels for basic household cooking and heating remains widespread throughout the world, and represents approximately 15% of global energy use (Legros et al., 2009; Smith et al., 2000). Such fuels are often burned in inexpensive yet inefficient stoves, which results in damages to health from respiratory illnesses and other conditions (Bruce et al., 2006; Ezzati and Kammen, 2001; Martin et al., 2011), to local environments and development due to unsustainable and time-intensive harvesting of biomass, and to the global climate 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 cook stoves such as gas-, electric-, or cleaner biomass-burning ICS technologies (UN Foundation, 2010).

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 efforts to disseminate more efficient household energy products; *b*) increasing awareness and demand for more efficient cooking technologies, stemming from rising fuel scarcity (resulting from population pressure and concern over deforestation) and the health effects of 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-October 2013, with follow-up surveys occurring shortly thereafter in November and December 2013.

2.1 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 (Figure 2). These 38 GPs were drawn from the prior Census of 2,105 GPs using a propensity score matching approach. Specifically, we aimed to create two sample strata, each with 19 GPs, that were mainly differentiated along institutional lines. The first stratum consisted of GPs where the NGO partner for the study had done prior work unrelated to ICS promotion, while the other included villages selected to be observationally similar to the former using nearest neighbor matching based on Census characteristics. The sample therefore may not be representative of rural Uttarakhand; still, one advantage of this design is that it allows us to argue that the results we obtain are not wholly dependent on prior

Figure 2: Study design



trust in the implementing institution.

Within each of the 38 GPs, we randomly selected households according to the size of the GP, as further detailed elsewhere (Pattanayak et al., 2019). The sampling strategy ensured that surveys were collected throughout the entire extent of the GP and created variation in the number of hamlets sampled from 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, neighbors were randomly selected as replacements.[2] Field supervisors performed household introductions, recorded GPS coordinates and elevation data, and oversaw quality control checks in each village. The final baseline sample consisted of 1,063 households.

[2]In total, 118 households were replaced in this way. Thirty-three households refused to participate, while an additional 85 could not be interviewed because an eligible respondent was not home during the field visit.

2.2 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 were asked to provide specific inputs) answered questions on environmental and stove-related perceptions, household demographic and socio-economic characteristics, stove and fuel use (these questions were supplemented with observations of cooking areas and stoves with clear signs of use, as well as available fuels), and completed the DCE. Follow-up surveys repeated all the aforementioned measurements, except for the DCE. Whenever possible, the primary cook answered questions related to socio-demographics, stove and fuel use, whereas the head of household completed the DCE, socio-economic, and time and risk preference sections. We targeted the head of the household for the latter sections because we judged, based on preparatory focus groups, discussions with our field partners, and prior literature concerning the gendered demand for cooking technology (Krishnapriya and Somanathan, 2019; Miller and Mobarak, 2013), that this individual would ultimately have control over any future decision to adopt an ICS. We also felt that this individual would likely be at least somewhat aware of the preferences of the primary cook as he/she made that purchasing decision. If one of these two was unavailable for the survey (most often the case for male heads of household), the other eligible respondent completed all questionnaire sections. The survey instruments were pre-tested prior to the initiation of fieldwork in approximately 200 households located in nine villages in northern India.

The attributes included in the stove DCE and their levels were selected following a series of eleven focus groups conducted with over 100 respondents in villages similar to sample villages. Attributes retained were fuel requirement, smoke emissions, number of burners, and cost; those 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 the type of fuel allowed. We used SAS software to select efficient combinations of attribute levels for measuring main effects. Important features of the design are summarized in Table 1.

At the start of the stove decision exercise, the ICS technology was described to respondents in detail, and each of the attributes were explained by the enumerator using a specific script accompanied by pictures. After this description, all respondents completed a four-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 three to five years and cost roughly INR 250 per year to maintain, was assured

Table 1: Summary of discrete choice experiment design

Attributes	**Levels**	**Traditional stove level**
Price (INR)	500 1,000 2,500	0
Fuel requirement	1 3 4	3
Smoke emissions	Low High Highest	Highest
Number of cooking surfaces	1 2	1

Notes. USD 1 ≈ INR 52 in 2012.

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.[3] This confirmation was included to decrease the potential for hypothetical bias (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.

2.3 The intervention

Approximately one year after the baseline surveys, the stove promotion intervention was implemented and randomized at the hamlet level; all sample households living in these treatment hamlets were visited by sales teams working for a local NGO; households living in control communities were not (Figure 2). Following careful field piloting of potential

[3]Specifically, they were asked: "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?" 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 three to five years and cost about INR 250 per year to maintain."

promotion techniques (Lewis et al., 2015), trained sales people working in teams of two visited treatment households and conducted intensive promotion activities with them. First, these teams presented treatment households with an information sheet and explanation of the features of the two available stoves (an electric coil stove and a biomass-burning ICS), even as they performed a live tea-making demonstration.[4] The information sheet (see Appendix B) and demonstration were designed to inform households about the stoves' benefits (reduced smoke, firewood savings, time savings) and costs (price, electricity cost and risk of electric shocks). Then, once the demonstration was complete, the sales people explained the payment and warranty plan. Specifically, all households were given the choice of paying for the stoves upfront or in three equal installments (including a modest financing fee of INR 60 or 80, depending on the stove) that would be collected over a period of four weeks (i.e., in three installments collected two weeks apart). The stoves were protected by a one-year warranty, that households could access by contacting the NGO if they had problems. 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 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 at that time. Prior to 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—INR 25 (roughly 2.5%), medium—INR 200 (roughly 20%), and high—equivalent to a full installment (a 33% discount). The electric stoves were sold to households for INR 900 (or INR 960 for those paying in installments); biomass stoves were INR 1,300 (or INR 1,380 with installments). These prices corresponded to the stove-specific prices paid to suppliers. As such, the amount of the high rebate (INR 320 or 460) 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 INR 320 in our analyses (the rebate for the electric stove); none of our results are sensitive to this approach.[5] Finally, because of this design and the two follow-up visits to intervention communities that it entailed, households that 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

[4]We offered two types of biomass ICS in initial piloting activities, but it quickly became apparent that demand for one of 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.

[5]The sensitivity of purchases to the rebate level that we estimate may thus be somewhat overestimated, particularly for the biomass stove, but the difference in values is qualitatively small.

eight villages and on initial analyses of the DCE responses. The latter revealed substantial heterogeneity in overall demand, as well as relative weighting that households gave to smoke reductions, which were greatest with the electric stove, versus fuel savings, for which the biomass ICS was better given the cost of electricity (Bhojvaid et al., 2014; Jeuland et al., 2015a). This evidence on heterogeneous preferences gave us reason to believe that artificially constraining the choice set by offering one stove prescriptively in all intervention communities might depress demand.

It might seem strange that a household would opt for a seemingly more rudimentary biomass ICS when offered a modern electric stove that was itself slightly cheaper, but there are a number of reasons why the latter may not strictly dominate in this context. First, the relative cost of electricity—or at least its perceived relative cost—may be considerably higher for some, particularly those households consuming in higher blocks of the increasing block tariff for electricity pricing, those with a lower shadow value of fuel collection time, or those for whom time costs are less salient than pecuniary costs. The fact sheet emphasized that households should expect that their bill would increase by at least INR 260 per month if they used the stove for one hour each day. Pushing in the opposite direction, some households did not have working meters or had irregular electricity connections; these consumers would know that they essentially face zero marginal cost for additional electricity consumption. Second, electricity reliability varies across time and space in Uttarakhand, and different households may have varying tolerance for outages. Third, the perceived durability of the stoves might be a source of heterogeneity; in this respect, we did not have data on durability prior to the intervention but did find the electric stove to be more prone to breakage (e.g., regulator knobs falling off, wires becoming loose). This was also manifest in a risk of electric shocks, which were mentioned in the fact sheet. Fourth, the portability of the electric stove was limited due to the required proximity of a power outlet. And finally, qualitative work showed that households believed that biomass stoves provided better-tasting food, especially for bread (Bhojvaid et al., 2014). This list of issues is also reflective of observations made about divergent preferences for different ICS in other contexts (Hollada et al., 2017).

On the basis of power calculations and our estimation of the differential treatment effects expected from the alternative rebate levels, 70 of the baseline hamlets (corresponding to 762 of the 1,063 baseline households) were randomly assigned to the treatment group.[6] The remaining 27 hamlets were control hamlets that only received survey visits, at baseline and follow-up (Figure 2).

[6]Two of these 762 treatment households could not be re-located during the stove promotion campaign, and therefore do not appear in any results

2.4 Sample balance and descriptive statistics

The analyses in this paper use data collected at three points in time: at baseline (all study households), at the time of the intervention (treatment households only), and three months after the intervention (all study households who could be relocated). 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 with all households, as discussed in Section 2.2, we again collected detailed information on outcomes such as households' stove ownership, and use of stoves and fuels. Thus, we analyze the DCE data that pertain to the entire sample of households that includes treatment and control communities to characterize preference patterns, then analyze purchase of stoves for the entire sample to account for any adoption of the biomass and electric ICS that might have occurred independently of our intervention (we find none), but only differentiate use results by class for households in the treatment communities, given the lack of adoption of intervention stoves among controls.

Descriptive statistics from the baseline sample of 1,063 households (overall and disaggregated by treatment group) are summarized in Table 2. In 73% of surveys, the main 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. 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 had electricity, but only 25% reported having continuous power, and the average hours of supply per day were about 17.

At the time of the baseline interviews, nearly all households had a traditional mud stove (40%) or three-stone stove (49%). Other commonly-found stoves were LPG (28%), or a traditional metal *sagarh* stove (21%). 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 daily). Households reported total stove use time to be 5.7 hours per day, and solid fuel collection time was also substantial at 1.8 hours per day. Respondents 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% each).

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. 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 air pollution and/or climate change. Women or primary cooks reported greater awareness of these impacts, but knowledge of ways to mitigate them was 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.

The treatment and control households were well balanced across a number of key variables measured at baseline, as shown in column (4) of Table 2. Normalized differences are modest, and only three out of more than 50 variables—female head of household, reported price of LPG, and a belief that ICS can deliver environmental benefits—are significantly different at the 10% level when the variable is regressed on treatment status.[7]

3 Empirical analysis of preferences

3.1 Modeling

We begin our analysis by sorting respondents into preference groups using the baseline stated preference data collected prior to our stove promotion experiment. The framework for analyzing this DCE data is based in random utility theory. We model repeated household choices across the combinations of stove alternatives that vary according to well-defined levels of four specific 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:

$$U^i_{jt} = V^i \left(p_{jt}, \beta^i_0, X_{jt}, \beta^i, Z^i\right) + \epsilon^i_{jt} \tag{1}$$

[7] In the appendix, we also show that the rebate level—randomized across all treated households—is generally uncorrelated with baseline household characteristics (Appendix Table C1). No normalized differences across these groups exceed 0.2 and 8 out of 87 analyzed coefficients are significant at the 10% level, similar to the proportion that would be expected due to chance.

Table 2: Baseline descriptive statistics and balance tests, by treatment group

Variable	**(1) Mean (Overall)**	**(2) Mean (Control)**	**(3) Mean (Treatment)**	**(4) Normalized difference (Treatment − Control)**
Village has paved road	0.30	0.26	0.31	0.106
Distance to doctor (km)	9.28	9.16	9.33	0.021
Bank facility in village	0.32	0.33	0.32	-0.011
Presence of implementing NGO	0.50	0.43	0.53	0.190
Household size	4.83	4.98	4.77	-0.101
Number of children under five	0.47	0.54	0.44	-0.118
Age: Head of household (years)	54.0	53.9	54.0	0.011
Education of household head (years)	6.21	6.17	6.23	0.014
Education of primary cook (years)	4.76	4.74	4.76	0.006
Female head of household	0.27	0.32	0.25	-0.150*
Main respondent: Head of household	0.53	0.58	0.51	-0.157
Main respondent: Primary cook	0.77	0.75	0.78	0.060
Hindu	1.0	1.0	1.0	0.00
General caste	0.72	0.71	0.73	0.042
Scheduled caste or tribe	0.25	0.24	0.26	0.047
Household members cold/cough in past two weeks	0.073	0.063	0.077	0.079
Below poverty line household	0.57	0.60	0.56	-0.089
Perception of relative wealth (1: Low to 6: High)	2.13	2.12	2.13	0.010
Household took loan in past year	0.15	0.12	0.16	0.121
Household can save money	0.25	0.24	0.26	0.028
Constant electricity supply	0.25	0.27	0.24	-0.067
Intermittent electricity supply	0.72	0.70	0.72	0.042
Hours of electricity per day	17.3	17.9	17.0	-0.116
Log of total expenditure (INR/month)	8.41	8.37	8.42	0.065
Number of cell phones	1.30	1.29	1.30	0.010
Total rooms in house	4.63	4.43	4.70	0.113
Household has private toilet	0.85	0.89	0.84	-0.123
Household owns/leases agricultural land	0.97	0.94	0.98	0.253
Respondent is most patient	0.48	0.44	0.50	0.125
Respondent is most risk-taking	0.43	0.41	0.43	0.042
Respondent aware of clean stoves	0.25	0.24	0.26	0.036
Respondent aware of clean fuels	0.31	0.29	0.32	0.051
Respondent believes clean stoves/fuels can reduce negative impacts	0.30	0.27	0.31	0.081
Respondent believes ICS deliver health benefits	0.11	0.10	0.11	0.044
Respondent believes ICS deliver benefits for local forests/environment	0.26	0.25	0.26	0.032
Respondent believes ICS deliver air quality/climate benefits	0.063	0.024	0.077	0.219***
Respondent believes smoke is unsafe	0.50	0.47	0.51	0.076
Household owns traditional stove	0.97	0.96	0.98	0.138
Household owns improved stove	0.31	0.29	0.31	0.047
Traditional stove use (minutes/day)	289	306	282	-0.165
Improved stove use (minutes/day)	44.9	40.0	46.8	0.073
Use firewood	0.97	0.96	0.98	0.098
Use kerosene	0.081	0.066	0.087	0.077
Use LPG	0.28	0.26	0.29	0.062
Use electricity	0.01	0.003	0.007	0.041
Use biogas	0.01	0.010	0.009	-0.012
Amount of firewood used (kg/day)	7.68	8.09	7.52	-0.104
Time spent collecting solid fuels (hours/day)	1.84	1.62	1.93	0.189
Price LPG cylinder (INR 1,000)	451	443	455	0.191*
Price of fuelwood (INR/100 kg)	626	603	635	0.049
Total fuel expenditure (INR/month)	247	247	247	0.001
Preference class 1 - Low demand	0.11	0.12	0.11	-0.043
Preference class 2 - High demand	0.22	0.25	0.21	-0.088
Preference class 3 - Uninterested	0.67	0.63	0.68	0.106
Sample size: Households	1063	771	292	
Sample size: Hamlets	97	70	27	

Notes. "Traditional" stoves include: *mitti ka chulha* (mud stove), *anjeti*, three-stone fire, and *sagarh* (coal stove). At the time of the baseline survey in 2012, USD 1 ≈ INR 52. 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 column (4) as follows: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

where U_{jt}^{i} represents household i's utility from cooking alternative j in a choice set, and t indexes the number of choice tasks completed (four per household); $V^{i}(\cdot)$ is the non-stochastic portion of the utility function for household i; p_{jt} is the price of cooking alternative j in task t; β_{0}^{i} is a parameter that represents household i's marginal utility of money; X_{jt} is a vector of non-price attribute levels for cooking alternative j in task t; β^{i} is a vector of parameters that represent the marginal utility for household i associated with the different non-price attributes of the alternatives; Z^{i} is a vector of characteristics for household i; and ϵ_{jt}^{i} is 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 that alternative provides a higher overall level of utility than all others, that is, if $U_{jt}^{i} > U_{kt}^{i}$ for all $j \in K$, where $j \neq k$, such that $V_{jt}^{i} - V_{kt}^{i} > \epsilon_{kt}^{i} - \epsilon_{jt}^{i}$. With a linear specification of utility $U_{jt}^{i} = \beta^{i} X_{jt} + \beta_{0}^{i} p_{jt} + \epsilon_{jt}^{i}$ and a Type 1 extreme-value error distribution for the disturbance term, the probability that alternative j will be selected from choice set t corresponds to the standard conditional logit (McFadden, 1981), which is estimated using maximum likelihood.

We relax the restrictive assumption of the conditional logit that requires a single set of fixed β coefficients, and estimate two types of mixed (or random parameters) logit models.[8] 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*}:

$$\mathbb{P}\left[C^{i} = \left(C_{j1}^{i}, \ldots, C_{jT}^{i}\right)\right] = \int \prod_{t} \frac{\exp\left(\beta^{i*} X_{jt} + \beta_{0}^{i*} p_{jt}\right)}{\sum_{k=0}^{K} \exp\left(\beta^{i*} X_{kt} + \beta_{0}^{i*} p_{kt}\right)} f\left(\eta \mid \Omega\right) \mathrm{d}\eta, \tag{2}$$

where $\beta^{*} = (\beta + \eta^{i})$ and $f(\eta \mid \Omega)$ denotes the density of the individual disturbance term η^{i} given the fixed parameters Ω of the distribution. The stochastic portion of utility flexibly accommodates correlations 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 monetized marginal utility to household i for an additional unit of a given attribute. This mixed logit model is useful for understanding the overall heterogeneity in preferences for different attributes within our sample.

[8] 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.

The second model we estimate is the scale-adjusted latent class logit, a discrete version of the mixed logit that allows us to examine the extent to which respondents can be grouped into distinct sub-populations with similar preferences. This model allows for two sources of heterogeneity (Magidson and Vermunt, 2004; Thiene et al., 2014). First, households with similar choice patterns and weighting of attributes are categorized into preference classes. Second, households within each preference class are further classified into scale groups, which indicate the level of uncertainty of their classification within a preference class.[9]

In these models, maximum likelihood methods are used to identify C preference class types and S scale groups (where C and S are integers selected by the modeler).[10] The probability of observing respondent i selecting alternatives j over T choice tasks is written as a product of the probability of the respondent belonging to preference class c and scale group s:

$$\mathbb{P}\left[C^i = \left(C^i_{j1}, \ldots, C^i_{jT}\right)\right] = \prod_{t=1}^{T}\left[\sum_{s=1}^{S}\sum_{c=1}^{C}\left(\frac{\exp\left(\alpha_c Z_i\right)}{\sum_{c=1}^{C}\exp\left(\alpha_c Z_i\right)}\right)\left(\frac{\exp\left(\gamma_s Z_i\right)}{\sum_{s=1}^{S}\exp\left(\gamma_s Z_i\right)}\right)\left(\frac{\exp\left(\lambda_s\beta_c X_{jt} + \lambda_s\beta_{0,c}pjt\right)}{\sum_{k=0}^{K}\exp\left(\lambda_s\beta_c X_{kt} + \lambda_s\beta_{0,c}p_{kt}\right)}\right)\right]. \tag{3}$$

The first two terms on the right hand side of equation (3) are the unconditional probabilities of membership in preference class c and scale group s, respectively, while the third term corresponds to the probability of choosing a sequence of alternatives based on their attributes (e.g., β_c is a vector of coefficients for the attributes of the alternatives and λ_s is the scale parameter for scale group s). In most latent class applications, the vector Z_i in the first and second term includes characteristics such as age, education level, and income. Here, we omit these characteristics and replace Z_i with a vector of class and scale-specific constants α_c and γ_s because our goal is to use only information revealed by the choices households make in the DCE to predict adoption of cleaner stoves.[11] This modeling approach thus requires very few assumptions about the structure of stated preferences. In the last term, the taste parameters (β) are subscripted with the class indicator c, meaning that every respondent in class c has identical tastes for the attributes of the choice alternatives in the DCE.

Rather than assuming a specific number of classes and scales, we rely on the Bayesian

[9]The role of the scale parameter in estimating logit models was first highlighted by Swait and Louviere (1993). Magidson and Vermunt (2007) later extended this work to the LCA framework, showing that different scale parameters can confound interpretation of the part-wise utilities across latent classes.

[10]See Appendix D for a more detailed explanation of latent class logit models, and a technical description of the scale-adjusted model.

[11]If socioeconomic characteristics were also included in the estimation of class membership probabilities, these predicted probabilities would then partially reflect these observable factors. This would conflate our investigation of the role of latent preference heterogeneity in technology adoption.

Information Criterion (BIC) to select the best-fitting model with up to six different classes and three scales (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.

3.2 Simple mixed logit analysis without preference classes

We first analyze the heterogeneity in preferences for ICS attributes. We estimate two mixed logit models (Table 3), which are differentiated by the assumed distribution of the random coefficient for price: either fixed (Columns 1 and 2) or log-normal (Columns 3 and 4).[12] 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 those with a greater number of cooking surfaces or of traditional type were more likely to be selected (all other attributes being equal). The standard deviations of the random parameters for the traditional stove type and for price are significant (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 one-unit reduction in smoke emissions plus fuel consumption several times over; this implies that respondents on average would need to see large reductions in these levels to consider adopting an ICS.

3.3 The preference classes and their determinants

Given the heterogeneity in responses identified by the random parameters model, we next use LCA to look for consistent patterns in the choices made by different groups of respondents, and to test the extent to which they are associated with observable household and respondent characteristics. In the 3-class and 2-scale model with the best fit according to the BIC, classes 1 ($\sim$12% of respondents) and 2 ($\sim$23%) react negatively to increased fuel usage and smoke emissions, and react positively to increased cooking capacity (Table 4). Given that cleaner cooking technologies are supposed to reduce emissions and fuel requirements, we might expect these two classes to be more likely to adopt them.[13] In contrast, class 3 ($\sim$65%) is an 'uninterested' group; none of the stove attribute coefficients for this group are significant,

[12] By restricting the distribution of the price coefficient in these ways, we ensure that price will be negatively related to the adoption decision.

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

Table 3: Mixed logit analysis of DCE choices

Variables	**Fixed price**		**Lognormal price**	
	(1) Mean	**(2) SD**	**(3) Mean**	**(4) SD**
Price (INR)†	-0.239***		-1.03***	2.53***
	(0.026)		(0.196)	(0.264)
Fuel requirement	-0.143***	-0.043	-0.158***	0.147***
	(0.036)	(0.209)	(0.039)	(0.148)
Smoke emissions	-0.350***	-0.046	-0.368***	0.071
	(0.087)	(0.269)	(0.091)	(0.172)
Number of pots	0.358***	0.099	0.389***	0.260
	(0.084)	(0.455)	(0.090)	(0.282)
Traditional stove‡	2.76***	4.52***	1.32***	4.19***
	(0.276)	(0.295)	(0.322)	(0.326)
Part-wise utility associated with one-unit decrease (USD)§				
Fuel requirement	\$5.8		\$4.3	
Smoke emissions	\$14.1		\$9.9	
Number of pots	-\$14.4		-\$10.5	
Observed choices	9,162		9,162	
Likelihood ratio (χ^2)	1,278.0		1,336.6	

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard errors in parentheses. Model excludes respondents who answered any one of four comprehension questions incorrectly prior to the first choice task. †Price is in INR divided by 500 (USD 1 $\approx$ INR 52 in 2012), and -500 in the logged version. ‡Traditional stove type = 1 if it was the traditional stove, 0 if improved. §One unit in the DCE represents 33% of traditional stove smoke emissions and fuel consumption, and a single cooking surface.

except for its clear preference for traditional stoves. Comparing classes 1 and 2, class 1 is considerably more price sensitive, but is relatively more responsive to smoke emissions reductions (the implied part-wise utility associated with a one-unit smoke emissions reduction is still lower than that for class 2, however), whereas class 2 places greater relative weight on fuel reduction and convenience. All else being equal, both of these classes also prefer improved biomass stoves to traditional stoves, as shown by the alternative-specific constant (ASC). Based on these households' choice patterns, we can consider class 2 to be a high demand group, class 1 to be low demand, and class 3 to be much less interested by the ICS.

Since class 3 constitutes about two thirds of the sample, it is important to note the possibility that such respondents may not have understood or paid attention to the DCE. Yet the pattern of this group's responses suggests that they were not answering questions haphazardly; rather, they simply tended to prefer the traditional alternative, no matter the

Table 4: Latent class analysis of DCE data for improved biomass cookstove

Variables	**(1) Class 1 Low demand**	**(2) Class 2 High demand**	**(3) Class 3 Uninterested**
Price (INR)†	-1.95***	-0.13***	-0.50
	(0.50)	(0.048)	(0.36)
Fuel requirement	-0.39**	-0.26***	0.060
	(0.17)	(0.071)	(0.24)
Smoke emissions	-0.93**	-0.46**	0.22
	(0.39)	(0.18)	(0.66)
Number of pots	1.01**	0.67***	-0.65
	(0.41)	(0.16)	(0.73)
ASC – Traditional stove‡	-1.60**	-2.44**	3.49**
	(0.75)	(0.96)	(1.46)
Fraction of households in class (based on predicted probability from LCA)	0.11	0.22	0.67
Fraction of class in scale group 1§ (based on predicted probability from LCA)	0.91	0.85	0.82
Observations	9,162	9,162	9,162

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors in parentheses. †Price is in INR divided by 500 (USD 1 $\approx$ INR 52 in 2012). ‡This is the alternative-specific constant: Traditional stove type = 1 if it was the traditional stove, 0 if improved. §The two scale parameters are 1 (class 1) and 0.16 (class 2).

attributes of the ICS alternatives.[14] This is further shown by the large relative size of the price coefficient, and the large positive coefficient on the ASC for the traditional stove.

We also note that the estimation identifies two scale classes that are defined by their respective scale parameters of 1 (following normalization) and 0.16. These parameters can be interpreted as indicating greater uncertainty in the responses for those in the second scale class (scale parameter=0.16). The overall proportion of respondents in scale class 1—as obtained from the predicted probability derived from the posterior distribution estimated in the model—is 83.7%, with the remaining 16.3% belonging to scale class 2.

To further investigate the characteristics of these classes, we assigned each respondent household to the class for which it had the highest predicted probability of membership, as obtained from the LCA. We then regressed this predicted class 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 5). We observe that, in comparison to class 3, classes 1 and 2 are generally wealthier, have better educated household heads (especially class 2), and better able to save, and for class 1, have younger heads of household. This is consistent

[14] We determined that many of these households were serial non-responders, in the sense that they always chose the traditional stove (see Appendix Table C2).

with earlier research that finds similar factors to be positively associated with adoption of clean stoves (Lewis and Pattanayak, 2012). Both classes are also more aware of clean stoves, especially class 1; the latter furthermore report high firewood prices and use traditional stoves somewhat less (though the latter difference is not statistically distinguishable from zero). Comparing between classes 1 and 2, we observe that class 2 is wealthier, which may also explain the lower price sensitivity of such households 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). If future health benefits of using improved stoves are most meaningful to these respondents, this may further contribute to their lower price sensitivity.

4 Empirical analysis of stove adoption and use

4.1 Modeling

From the stove promotion campaign and follow-up surveys conducted several months later, 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:

$$Y_{ij} = \beta_0 + \beta_1 \cdot T_{ij} + \beta_k \cdot C_{kij} + \beta_r \cdot r_{ij} + \beta_{kr} \cdot C_{kij} \cdot r_{ij} + \beta_c \cdot X_{mij} + \mu_j + \epsilon_{ij}. \quad (4)$$

In this model, Y_{ij} is an indicator 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 and at the end of the campaign, and use observed at the time of the follow-up survey visit. The variable T_{ij} is an indicator variable that equals 1 if the household i is in the treatment group and 0 otherwise, and C_{kij} is equal to 1 if the household i has preferences of type k and 0 otherwise (as revealed by the LCA)[15]; r_{ij} represents a rebate amount randomized at the household-level in the communities exposed to the stove offer; X_{mij} is a vector of m household and community variables that influence the purchasing decision (the same set of variables used in the multinomial logit described above); μ_j is an error term clustered at the

[15]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. We choose to present the dichotomous class indicators only because the interpretation of coefficients is more straightforward. The results with continuous probabilities are qualitatively identical to those presented in the paper, and are available in Appendix E. We also estimated models that controlled for the scale grouping; this covariate was never statistically significant, and likewise did not change any of the results (results available upon request).

Table 5: Correlates of latent class membership

Variables	**(1) Class 1**	**(2) Class 2**
Presence of implementing NGO	0.32	0.083
	(0.26)	(0.24)
Household size	-0.032	0.022
	(0.073)	(0.055)
Household has child under five	-0.017	0.27
	(0.30)	(0.21)
Age of household head	-0.030***	0.003
	(0.010)	(0.006)
Education of household head	0.029	0.058**
	(0.028)	(0.023)
Education of primary cook	-0.006	0.003
	(0.026)	(0.019)
Female household head	0.39	0.19
	(0.30)	(0.26)
Respondent is primary cook	-0.22	-0.26
	(0.28)	(0.21)
General caste	-0.44	-0.27
	(0.30)	(0.25)
Proportion of household sick with cough/cold	0.068	-0.42
in past two weeks	(0.53)	(0.69)
Perception of relative wealth	0.092	0.46***
	(0.17)	(0.11)
Household took loan in past year	0.079	0.26
	(0.29)	(0.21)
Household can save money	0.76***	0.74***
	(0.25)	(0.22)
Household has private toilet	-0.024	-0.61*
	(0.30)	(0.24)
Respondent is most patient†	-0.36	0.59***
	(0.31)	(0.23)
Respondent is most risk-seeking†	0.40	-0.12
	(0.37)	(0.21)
Respondent aware of clean stoves	1.0***	0.34
	(0.38)	(0.42)
Respondent believes clean stoves/fuels can	0.29	-0.52
reduce negative impacts	(0.35)	(0.38)
Respondent believes smoke is unsafe	-0.10	-0.33*
	(0.24)	(0.17)
Household owns improved stove	-0.22	-0.27
	(0.31)	(0.26)
Traditional stove use (hours/day)	-0.075	0.030
	(0.065)	(0.044)
Log of time spent collecting solid fuels	0.014	0.057
	(0.045)	(0.043)
Respondent reports high price of firewood	0.62**	-0.80***
	(0.25)	(0.20)
Constant	-0.79	-2.2***
	(0.80)	(0.57)
Observations	987	987
Pseudo-R^2	0.125	

Notes. Multinomial logit specification, class 3 is the omitted class. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors in parentheses. †Most patient and most risk-seeking as determined by responses to three hypothetical time and risk preference questions.

community level; and ϵ_{ij} is the usual individual idiosyncratic error term. The coefficients β are estimated using OLS, and allow us to consider the effects of preferences and price incentives (β_k and β_r, respectively) on outcomes.

In the purchase models (which shed light on the general patterns shown in Figure 1), 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 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). We consider more parsimonious specifications for equation 3 as well as the complete model. In the most basic model, we include only the binary predicted class variables to explain purchase. We then add the randomized rebate amounts, which have a very large effect on purchasing rates (Figure 3), followed by a comprehensive set of community and socioeconomic characteristics, including those used in Table 6 to predict class membership. To better interpret whether class membership adds meaningful explanatory power to the model, we compare the fit (using an F-statistic) for the specification that includes class indicators and the full set of controls to that with the full set of covariates alone.[16] In addition to the regression analyses, we derive choice probabilities from the DCE for each stove-preference class combination using their relative attribute levels, in order to make counterfactual predictions of the adoption levels that would have been observed in the absence of stove choice.

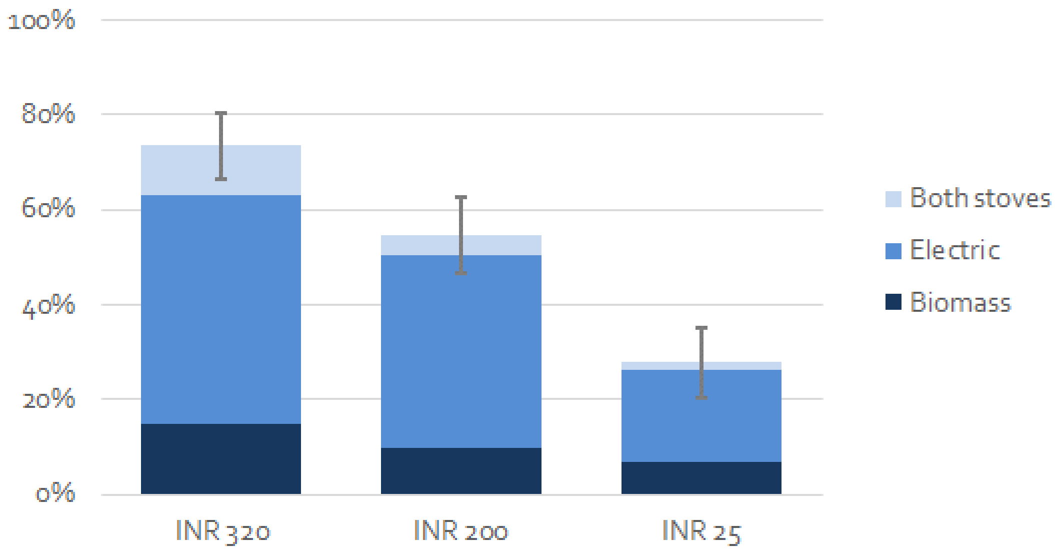
Standard errors in all analyses are clustered at the community or hamlet level as this is the administrative level at which the stove promotion campaign was assigned.

4.2 Analysis of stove adoption and use

Below we consider two main questions on the relationship between stated preferences and adoption. The primary variables of interest in much of the discussion that follows are the binary variables for membership in each of the three latent classes. In the ensuing discussion, we report results from all 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 documented in the literature (Lewis and Pattanayak, 2012).

[16] We also explore whether information on these more easily observable variables might facilitate systematic targeting of households more likely to adopt an ICS. To do so, we use a two-stage least squares model that generates predictions of preference class as a function of the observed covariates among the treated, and relate those predicted classes to actual purchases.

Figure 3: Purchase of intervention stoves, by rebate group (treated households only)



Question 1: Is preference class related to adoption of a new stove?

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, and then over the course of the entire sales campaign, with a revised purchasing outcome that includes lagging purchasers.

The results show that compared to class 1, class 3 households were about 18-20 percentage points less likely on average (or a roughly 33% lower purchasing rate) to purchase a new stove during the first sales visit (Table 6, columns 1-3). Counter to our initial expectations given their different price sensitivities in the DCE, we do not detect statistically meaningful differences between class 1 and class 2 households with respect to this purchase decision, though the coefficient for class 1 is substantially larger.[17] The rebate amount itself had a strong positive effect on stove purchase: an increase from the low rebate of INR 25 (about 2% of stove cost) to the high rebate (33% of stove cost) increased purchase from 28% to about 72% (Figure 3). No other controls are significantly related to purchase, including those for relative firewood cost and average hours of electricity supply. The F-statistic comparing the model fit for the model with a) classes plus controls versus b) controls only is highly

[17] p-values for significance on differences in these coefficients range between 0.24 and 0.44. The lack of difference may be because class 1 purchased relatively more electric stoves as rebate level increased, while class 2 purchased relatively more biomass ICS. We also interacted the rebate level with the class membership to test for differential sensitivity to price; those results suggest that classes 1 and 2 were more responsive to price discounts than class 3, although differences based on a Wald test are not significant across specifications (see Appendix Table C3). One additional rupee of rebate increases the probability of class 1 and 2 households purchasing stoves by 0.16-0.20% on average, compared with a marginal impact of 0.14% for class 3.

significant ($F = 9.54; p < 0.001$), while that comparing the fit with *a*) classes plus controls versus *b*) classes only is not ($F = 1.04; p = 0.41$). These comparisons of model fit 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 more readily observable characteristics. And while the lack of correlation between common predictors of adoption and uptake is perhaps surprising, the intensiveness of the promotion strategy—with information provision, financing, and subsidies—seems to have allowed less educated and lower wealth households to better understand and finance a new stove purchase.

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 4-5). Purchase rates were 16-17% lower than class 1 on average in this analysis (and 8-12% lower than class 2); this is because late adopters were more likely to be in class 3 (and less likely to be in class 2).[18] In considering purchases over a period of multiple visits during which neighboring households were exposed to new stoves, inherent preferences or preference uncertainty may become less important given the influence of peers, increased trust in a promotion intervention, or the potential for learning. The effect of the other controls is unchanged from the first analysis.

The effects of class on the daily use of an intervention stove 3 months after promotion are also somewhat reduced compared to purchase, but class 3 remains 9-12% less likely to be using a stove than class 1 (columns 6-7), and 3-5% less likely than class 2. In addition, perhaps unsurprisingly considering that the DCE was principally designed to shed light on the demand for stove acquisition, the preference classes do not explain use of stoves in the subsample of households who acquired a stove, except for the biomass ICS. Thus, in this setting and with this technology, the influence of preferences appears to work principally through its influence on the purchasing decision (as shown in Appendix Table C5). In interpreting these use results, we note that 76 of the original 1,063 households (7%) were lost from the sample at follow-up (Figure 2). Although attrition is not significantly correlated with treatment status, it may affect the generalizability of our results. Households lost to follow-up were smaller, more likely to be female-headed, and were less reliant on traditional stoves, as measured by time spent cooking, fuel consumption, and time spent collecting fuel at baseline.

[18]Specifically, of the 36 households who adopted a stove during these later visits, 29 were in class 3. We estimated probit and OLS regressions to explore the determinants of later purchases, using the same covariates as those in the class determinants analysis; the power of this analysis is limited due to the small number of such households, and we find only weak correlations with greater patience and lower perception of health risk from smoke exposure. Only class 3 membership is consistently and strongly related to lagging purchases.

Table 6: Stove purchase by latent class

Variables	**(1) Basic** Visit 1 purchase	**(2) + Rebate** Visit 1 purchase	**(3) + All controls** Visit 1 purchase	**(4) Basic** With later purchases	**(5) + All controls** With later purchases	**(6) Basic** Stove use at follow-up§	**(7) + All controls** Stove use at follow-up§
Treatment group (exposed to sales)	0.43***	0.16***	0.16***	0.48***	0.21***	n.a.	n.a.
	(0.034)	(0.039)	(0.040)	(0.036)	(0.042)		
Treatment × Rebate amount (INR)		0.0015***	0.0015***		0.0015***		0.0011***
		(0.0002)	(0.0002)		(0.0002)		(0.0001)
Age of household head			-0.0004		-0.0007		-0.0009
			(0.001)		(0.001)		(0.001)
Female household head			-0.022		-0.021		-0.073
			(0.032)		(0.033)		(0.047)
Education of household head			-0.0009		-0.0001		0.0005
			(0.004)		(0.004)		(0.005)
Perception of relative wealth			0.009		0.008		-0.023
			(0.017)		(0.017)		(0.023)
Hours of electricity supply per day			-0.003		-0.003		0.003
			(0.003)		(0.003)		(0.004)
Respondent reports high price of firewood			-0.030		-0.055*		-0.032
			(0.030)		(0.028)		(0.036)
Treatment × Class 1†	0.20***	0.18***	0.19***	0.17***	0.16***	0.090	0.12**
	(0.063)	(0.058)	(0.057)	(0.062)	(0.057)	(0.058)	(0.056)
Treatment × Class 2†	0.14**	0.12**	0.11*	0.12**	0.076	0.045	0.025
	(0.056)	(0.054)	(0.055)	(0.055)	(0.053)	(0.045)	(0.043)
Constant	0.00***	-0.00***	-0.13	0.00***	-0.088	0.27***	-0.021
	(0.00)	(0.00)	(0.11)	(0.00)	(0.11)	(0.027)	(0.13)
Other controls‡	No	No	Yes	No	Yes	No	Yes
Observations	987	987	987	987	987	716	716
R^2	0.220	0.326	0.341	0.243	0.365	0.005	0.127

Notes. Linear probability model. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses; standard errors clustered at the hamlet level. The analytical sample is the final sample, after sample attrition (results are qualitatively identical for the full sample with sales intervention data, however). †'Class 1' and 'Class 2' are indicator variables denoting assignment to a latent classes 1 and 2, respectively. Class 3 is the omitted class. ‡The other controls that are not displayed include all but the covariate "respondent is primary cook" shown in Table 5, which was omitted because the ultimate purchasing behavior should not depend on who participated in the DCE during the baseline survey. None of these controls were found to be significantly related to purchase; as shown they did not alter the sign or significance of the main results (Columns 3, 5 and 7). Observations with missing values for these additional covariates are retained in these regressions by filling in median hamlet-level values; results are not sensitive to this procedure. §The use outcome is only analyzed for households who were in the intervention group; hence the smaller sample size.

Using two-stage least squares and informed by the results in Table 6, we attempted to predict class membership as a function of the predictors included in those regressions, to test whether predictions of class membership using observables would be informative about ICS purchases. These analyses offer suggestive evidence that households less likely to purchase an ICS (in class 3) could be pre-identified, though standard errors are large. The point estimates indicate that households predicted to be in class 3 are 7-15% less likely to purchase an ICS, consistent with the results presented above (Table 7, columns 1-2). The estimates are unstable, however, and vary greatly with the choice of first stage variables. Similar to the nested F-tests, this tells us that the latent classes convey information beyond easily observed attributes that is highly relevant to household choices.

Question 2: Do different preference types choose different stoves?

Based on differences in the relative weighting of ICS attributes revealed by the DCE, we expected that households in distinct preference classes might choose to purchase alternative technologies at different rates. In particular, class 2 households dislike traditional stoves and have a greater willingness to pay for all stove attributes, while class 1 households place greater weight on smoke emissions relative to other attributes. Moreover, the improved biomass stoves that were offered to households were more expensive; more price sensitive class 1 households might therefore prefer the electric option. The stoves also differed in terms of their fuel costs (the electric stove is likely more costly for many households, unless they place a high value on time savings).

We consider the purchase of different stove types using a multinomial logit model, and then analyze daily use of each stove with an OLS specification (Table 8).[19] Our first observation is that class 1 households are most likely to purchase and use the electric stove (columns 2, 4, and 6); when including all controls, class 1 households are 17% and 25% more likely to purchase this stove than classes 2 and 3, respectively, and 9 and 10% more likely to use it daily than these two classes.[20] In contrast, class 2 households appear more likely to purchase and use the biomass-burning ICS (columns 1, 3, and 5); specifically, they are 7% and 5% more likely to purchase a biomass ICS than classes 1 and 3, respectively, and 7 and 8% more likely to use it than classes 1 and 3.[21] As with overall purchase, few other covariates explain differences in purchase and use rates, including those for relative firewood cost and average

[19] We again only report results for the first purchase sample. Results from the sample including later purchases are qualitatively identical and are reported in Appendix Table C4.

[20] The marginal effects for purchase are evaluated at the mean value of other covariates.

[21] Even conditioning on purchase, we find that households in class 3 are also less likely to report daily use of the biomass ICS. In these conditional regressions, we also find that the rebate is positively related to use, which suggests that larger rebates promised to users at the time of the third sales visit also helped to incentivize greater use.

Table 7: Two-stage model results for the effect of preference class on purchase

Variables	**(1) Visit 1 purchase**	**(2) All purchases**	**(3) Biomass ICS purchase**	**(4) Electric ICS purchase**
Treatment	0.20***	0.25***	0.043	0.20***
	(0.039)	(0.040)	(0.027))	(0.036)
Treatment × Rebate amount (INR)	0.0015***	0.0015***	0.0006***	0.0012***
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Predicted Class 1†	0.12	0.15	-0.20*	0.24
	(0.16)	(0.15)	(0.12)	(0.15)
Predicted Class 2†	0.071	0.068	-0.12	0.22*
	(0.14)	(0.14)	(0.11)	(0.13)
Constant	-0.032	-0.034	0.052	-0.082**
	(0.045)	(0.041)	(0.034)	(0.041)
Observations	987	987	987	987
R^2	0.321	0.343	0.048	0.234

Notes. Two-stage least squares model. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses; standard errors clustered at the hamlet level. The analytical sample is the final sample, after sample attrition (results are qualitatively identical for the full sample with sales intervention data, however). †The controls used to predict class membership are: Relative wealth, age of head of household, female head of household, general caste, took loan in past year, able to save money, private toilet, aware of clean stoves, and belief that smoke is unsafe for health.

hours of electricity supply. Households in the general caste category were somewhat more likely to purchase a biomass ICS, while those who spend more time cooking with traditional stoves and who own private toilets (perhaps reflecting a higher propensity to engage in health risk-averting behavior) were more likely to purchase an electric one.

In additional analysis, we further observed that classes 2 and 3 were somewhat less responsive to the rebate amount for the electric stove only (Appendix Table C4), consistent with the results presented above. And similarly to the previous two-stage analysis, we find some evidence that the households least likely to purchase an electric ICS (class 3) could perhaps be identified using household characteristics, though class 2 households were not so easily identified (Table 7, columns 3-4). As with the analyses of the dichotomous purchase decision, however, these two-stage estimates are unstable and imprecise.

When describing the intervention in Section 3.3, we noted that households might associate different pros and cons with the technologies that were offered to them, and that this might explain why some would favor the biomass ICS while others would opt for the electric stove. At endline, following exposure to these technologies, we surveyed households concerning their opinions of these pros and cons. Beliefs about traditional stoves were mostly unchanged: The main advantages of this technology were the good taste of food (53%), the ability to cook all foods (36%), and its low cost (31%), while key disadvantages were the smoke produced (78%), the amount of fuel required (27%), and the (slow) speed of cooking (22%). Households in the treatment group meanwhile identified clear differences between the electric and biomass ICS. The principal advantages of the former were identified as the (fast) speed of cooking (28%), the attractiveness of the stove (15%), and its portability and low emissions (11% each), while the former was seen as advantageous for its low fuel requirement (25%), portability (19%), and low emissions (17%). Meanwhile, the electric stove's disadvantages were identified as the risk of shocks (34%), the high cost (32%) and unreliability (17%) of electricity, and the stove cost (13%). The biomass ICS, in contrast, had two main disadvantages: high purchase cost (39%), and need for additional fuel processing (i.e., wood chopping) prior to use (11%).

Question 3: What would ICS adoption have been in the absence of stove choice?

The results presented above collectively indicate that higher demand class 2 households preferred biomass-burning ICS' over classes 1 and 3, while smoke- and price-sensitive class 1 households preferred the electric option. These differences across classes suggest that adoption rates might have been lower in the absence of choice. To test this idea, we conducted a set of counterfactual predictions of what would have happened if only one of the new technologies had been offered, using the preference weighting obtained from the DCE analysis (reported in Table 4) and via the following steps. First, we specified the relative levels of the four

Table 8: Stove adoption among households exposed to sales intervention, by latent class (marginal effects)

Variables	(1) **Basic** Biomass ICS purchase	(2) **Basic** Electric ICS purchase	(3) **+ Rebate and Controls** Biomass ICS purchase	(4) **+ Rebate and Controls** Electric ICS purchase	(5) **+ Rebate and Controls** Biomass ICS use	(6) **+ Rebate and Controls** Electric ICS use
Rebate amount (INR)			0.00066***	0.0011***	0.0004***	0.0005**
			(0.0001)	(0.0002)	(0.0001)	(0.001)
Class 1[†]	-0.042	0.23***	-0.027	0.25***	-0.010	0.087*
	(0.050)	(0.061)	(0.046)	(0.064)	(0.027)	(0.046)
Class 2[†]	0.043	0.099*	0.047	0.075	0.071**	-0.015
	(0.027)	(0.053)	(0.031)	(0.062)	(0.031)	(0.031)
Hours of electricity supply per day			-0.003	-0.0001	0.001	0.004
			(0.004)	(0.006)	(0.002)	(0.003)
Respondent reports high price of firewood			0.019	-0.071	0.014	0.004
			(0.024)	(0.042)	(0.021)	(0.030)
Other controls[‡]	No	No	Yes	Yes	Yes	Yes
Observations	716	716	716	716	716	716
Pseudo-R^2	0.017	0.017	0.130	0.130	0.074	0.074

Notes. Columns 1-4 report results from a multinomial logit model using initial purchase decision only; we report marginal effects at the mean of the sample covariates; columns 5 and 6 are linear probability models for daily use of the biomass and electric intervention stoves, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses; standard errors clustered at the hamlet level. The analytical sample is the final sample, after sample attrition (results are qualitatively identical for the full sample with sales intervention data, except that class 2 households are significantly more likely to adopt the biomass ICS with that larger sample). [†]Class 1 and Class 2 are indicator variables denoting assignment to latent classes 1 and 2, respectively. Class 3 is omitted. [‡]The other controls include all of those from the complete model in Table 6 (e.g., the basic controls from Table 6, column 3 plus those indicated in the notes below Table 6). 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 (columns 3-6). Observations with missing values for these additional covariates are retained in these regressions by filling in median values; results are not sensitive to this procedure.

attributes corresponding to our two ICS alternatives, also incorporating the price variation arising from the three rebate levels. Second, we assumed that if only one of the two stoves had been offered, those already purchasing each of the ICS in our real-world experiment would still have selected it. In other words, removing the alternative not favored by specific households would not have affected their purchasing decision, given that they had been observed to favor that remaining option anyway. Similarly, those who had opted out of stove purchases entirely would not have selected the remaining option that they did not favor when given the choice of two ICS. Thus, this left a group of households whose preferred ICS was assumed to no longer be available in our counterfactual. For this group of households, we derived class-specific probabilities of adoption for the remaining ICS, based on the relative probabilities obtained from that class' preference weighting for it versus the opt-out alternative. We conducted these calculations for the low and high prices in our field experiment (that is, the price of the each ICS was allowed to vary between the lowest and highest rebate amounts, affecting the probability of adoption, as shown in Table 9). We then assigned this sub-group of households from each class to the two remaining alternatives - the single ICS and the opt-out status quo - in direct proportion to these derived relative probabilities.[22]

We present these probabilities as a percentage of all households in a given preference class in Table 9, for the two counterfactual situations: electric ICS only, and biomass ICS only. The predictions of the stove purchases that would have been made in the situation where only one or the other ICS would have been presented following re-assignments based on these choice probabilities then appears in Figure 4.[23] These calculations suggest that purchase rates would have been 5-14 percentage points lower if only the electric ICS had been available, and 13-34 percentage points lower with only the biomass ICS. The high end of this range corresponds to a higher rebate, since purchase rates are increasing in this price discount.

5 Discussion

In this study, we considered the hidden nature and latent preferences for new technology, and then assessed whether this source of heterogeneity was related to actual purchasing decisions. To the best of our knowledge, it is the first study mapping preferences for technology to

[22]An alternative setup for this calculation would use the hypothetical DCE data to make predictions under two hypothetical scenarios - one with and one without stove choice. In this approach, we would be putting a great deal of weight on the attributes that were included in the DCE, and especially on the alternative-specific constant for a biomass ICS. We feel that this is less compelling than use of both the revealed preference information and the weights from the DCE.

[23]Clearly then, this calculation assumes that stove selection preferences would not have been affected by the sheer presence of choice, which might occur if households selected a particular stove solely because they could compare it to the other option being offered.

Figure 4: Purchase of ICS stoves, revealed in the experiment, and for "no choice" counterfactual

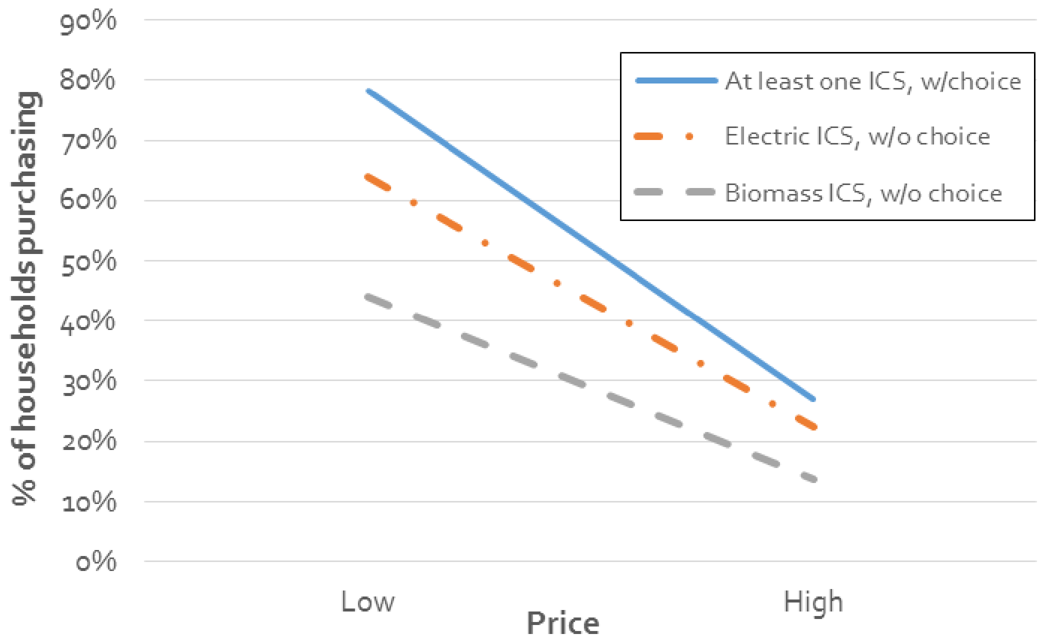


Table 9: Choice probabilities for preference class-ICS combinations, at high and low price levels

Electric stove only	**Low ICS Price (INR 640)**		**High ICS price (INR 935)**	
	Electric ICS	Traditional	Electric ICS	Traditional
Class 1	86%	14%	68%	32%
Class 2	71%	29%	70%	30%
Class 3	21%	79%	17%	83%
Biomass stove only	**Low ICS Price (INR 720)**		**High ICS price (INR 1,055)**	
	Biomass ICS	Traditional	Biomass ICS	Traditional
Class 1	44%	56%	19%	81%
Class 2	57%	43%	56%	44%
Class 3	26%	74%	21%	79%

Notes. Probabilities are for purchase of the stove given only the alternative traditional stove. For smoke, we assume zero smoke emissions for the electric ICS, a 20% reduction for the biomass ICS. We further assume the biomass ICS reduces fuel requirements by 25%, whereas the electric ICS has maximum fuel requirements.

experimentally-induced choices. As such, our work draws on the literature that compares or combines data from stated and revealed preference measures of demand (Adamowicz et al., 1994; Carson et al., 1996; Hensher and Bradley, 1993), but extends it in a new and different way. Specifically, we test the hypothesis that attitudes characterized using stated preference methods can predict technology adoption.

Our specific application considers the challenge of clean energy technology adoption in Uttarakhand, India. The use of traditional, inefficient and highly polluting cooking technologies is ubiquitous in this setting, but more generally affects billions of the world's poorest people (Legros et al., 2009; Smith et al., 2000). These technologies cause illness (Bruce et al., 2006; Ezzati and Kammen, 2001; Martin et al., 2011), unsustainable and time-intensive harvesting of biomass, and environmental damage (Bond et al., 2004; Ramanathan and Carmichael, 2008). Many have proposed that solutions available to households are not sufficiently adapted to local cooking requirements and user preferences (Bishop et al., 2013; Cordes, 2011; Duflo et al., 2008; Jeuland and Pattanayak, 2012; Lewis and Pattanayak, 2012; Singh and Pathy, 2012). In India, for example, penetration and impacts of improved cooking technology have been limited despite decades of subsidized promotion and the largest potential market for cleaner cooking technologies in the world (Hanna et al., 2016).

In this setting, we found that household preferences for non-traditional stoves were highly varied. Latent class analysis identified three broad classes of respondents: two classes, comprising 12% and 23% of the sample, who appeared to be differentially 'interested' in the features of cleaner technology, whereas a large third class (65% of households) was generally 'uninterested' in these attributes. Within the first two classes, class 1 placed greater relative weight on smoke emissions reductions, whereas class 2 was less price sensitive and equally valued emission reductions, fuel savings and greater convenience. Closer examination of the make-up of each class showed that the 'uninterested' class mainly consisted of lower-SES households who were less aware of clean options and the harmful effects of smoke inhalation.

Turning to the relationship between preferences and adoption decisions during a randomized stove promotion intervention, we found that households in the 'uninterested' class were less likely to purchase and use a new stove, despite the fact that the promotion effort intensively provided information and conducted in-house demonstrations. These recalcitrant class 3 households were also least responsive to incentives. The silver lining in these results, however, is that class membership became somewhat less predictive over time, as the initially 'uninterested' households were more likely to adopt a new stove during later sales visits. And while our study was not designed to allow determination of the precise mechanism behind this changing of minds, this result provides hope that these households' decisions can evolve.

We further noted that class 1 households—who placed the greatest relative weight on reduced smoke emissions, and had lower WTP for the improved biomass stoves offered in the DCE—were most likely to adopt an electric ICS, which is both cheaper and offers the possibility of eliminating cooking smoke. Critically, the predictive power of preference class was retained even when controlling for a large set of household baseline covariates (e.g., expenditures, perceived relative wealth, education, age) that are typically associated with adoption. Also importantly, using those covariates to predict class membership yielded point estimates of the effects of predicted class membership on adoption that were not inconsistent with the experimental results, though the estimates were imprecise. Thus, interventions may be able to improve targeting by working to characterize preferences ex ante. Or they may offer alternatives to beneficiaries instead: counterfactual calculations indicate that adoption would have been depressed in the absence of choice.

Our findings thus offer new insights that could improve efforts to promote other beneficial consumer products and quasi-public goods. An oft-neglected feature of the challenge of technology provision in low-income settings is the fact that governments, NGOs or other practitioners must frequently act as the primary suppliers, which typically results in limited (or no) options for consumers. Private markets meet heterogeneous demand through market segmentation and product differentiation, but the competitive forces that drive such innovations are typically lacking when markets—such as those for quasi-public goods, and especially in developing countries—are thin. In addition, implementers and practitioners (whether NGOs or governments) are often tempted to pick specific solutions based on technical criteria (e.g., an emissions profile). These well-meaning implementers may have aims that are not wholly compatible with beneficiaries' desires - for example, the cookstove sector is dominated by rather dogmatic views about appropriate technology, based on strong beliefs about which fuels or which stoves are able to deliver health benefits. Such a top-down supply-driven model has failed over and over in multiple sectors (Pritchett and Woolcock, 2004). In this sense, support for market-based provision of innovations that meet consumer preferences while providing positive spillovers, such as results-based financing, are a potentially promising approach.

It is also expensive for implementers to offer choices, since an entire supply chain—in our case, manufacturers, wholesalers, retailers, financiers, maintenance, and fuel suppliers—must often be repurposed to do so. Such costs must be weighed against the value of choice, which will vary considerably across contexts and technologies. Moreover, political feasibility often dictates delivery of simple interventions. It can also be difficult to craft programs with messages that do not confuse target beneficiaries, especially when programs entail complex tradeoffs and/or lead to unintended negative outcomes. For example, an option that is offered may be popular but ineffective, or an intervention may be designed around a technology that only provides a specific type of benefit (e.g., health, or climate mitigation) at the expense of others. Still, even in contexts where choices appear to not be preferred for political or cost reasons, we must also assess the the downside of limiting choices. Indeed, studies to uncover preference heterogeneity could be used to help policymakers understand how uptake may be affected by constraining options, and what, if any options warrant additional investment and marketing. By clearly demonstrating that latent preferences influence technology adoption, our research points to the need for more seriously considering behaviors and choices rather than prescribing technical fixes that may not align with household needs.

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