Energy Economics 107 (2022) 105796

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Speaking from experience: Preferences for cooking with biogas in rural India

Marta Talevi [a,*], Subhrendu K. Pattanayak [b], Ipsita Das [b], Jessica J. Lewis [c], Ashok K. Singha [d]

[a] London School of Economics and Political Science (LSE), London, UK
[b] Sanford School of Public Policy, Duke University, United States
[c] Nicholas School of the Environment, Duke University, United States
[d] CTRAN Consulting, Bhubaneswar, India

ARTICLE INFO

JEL classification:
I3
Q2
Q4

Keywords:
Energy poverty
Biogas
Improved cookstoves
Air pollution
Firewood
Discrete choice experiment
Odisha

ABSTRACT

Biogas has the potential to satisfy the clean energy needs of millions of households in under-served and energy-poor rural areas, while reducing both private and social costs linked to (i) fuels for household cooking, (ii) fertilizers, (iii) pressure on forests, and (iv) emissions (e.g., $PM_{2.5}$ and methane) that damage both household health and global climate. While the literature has focused on identifying these costs, less attention has been paid to household preferences for biogas systems — specifically what attributes are popular with which types of households. We conduct a discrete choice experiment with 503 households in rural Odisha, India, to better characterize preferences for different attributes (smoke reduction, fuel efficiency, and maintenance) and for different cooking technologies (biogas and an improved biomass cookstove). We find that on average households value smoke reduction and fuel efficiency. Willingness to pay (WTP) a premium for the improved biomass cookstove is low, while willingness to pay a premium for biogas is high. Nonetheless, WTP varies by the type of previous experience with biogas (e.g., good or bad experience) and with time and risk preferences of households. While risk-averse and impatient respondents have lower WTP for the improved cookstoves, previous experience with biogas attenuates this gap. These findings suggest that biogas uptake and diffusion could be improved by complementing existing subsidies with technology trials, good quality products, maintenance, and customer services to reduce uncertainty.

1. Introduction

Burning polluting fuels in inefficient stoves with poor ventilation is still a common practice, especially among rural households in low- and middle-income countries (LMICs). While reducing energy poverty and increasing primary reliance on clean technologies is a key target of the UN Sustainable Development Goal (SDG) 7, it is estimated that 2.8 billion people still lack access to clean cooking fuels and technologies as of 2018 (IEA et al., 2020).[1] This persistent trend has detrimental consequences for millions of households, from respiratory and cardiovascular health risks (Gordon et al., 2014; Jeuland et al., 2015b; Lewis et al., 2016; Rao et al., 2021) and expense of scarce time to find fuel (Tinker, 1987; Krishnapriya et al., 2021) to broader externalities such as forest degradation (Bensch and Peters, 2013), local pollution, and climate change (Jeuland and Pattanayak, 2012; Pant et al., 2014). Several of these burdens fall disproportionately on women and children (World Health Organization, 2016; Krishnapriya et al., 2021). Part of the reason these problems persist is because energy poverty makes it difficult for people to escape socio-economic poverty, given the channels discussed above (World Health Organization, 2016; Krishnapriya et al., 2021; Churchill et al., 2020; Thomson et al., 2017). In turn, the poor face barriers to adopting and using clean energy. This in-built negative reinforcement makes energy poverty an especially pernicious problem (Sovacool, 2012; Herington et al., 2017). While the energy poverty literature in high-income countries tends to focus on electrification, heating, and cooling, cooking remains an essential component of energy demand by the poor in LMICs (Daioglou et al., 2012). If we can better characterize demand for clean cooking technologies by the rural poor – as this paper attempts – we could better support policies to end energy poverty (Sovacool, 2014; Paudel, 2021; Nussbaumer et al., 2013).

Our study was conducted in India, a global hotspot for pollution-laden cooking practices and energy poverty. Millions of Indians are poor and not surprisingly almost one-third of the population still cooks primarily with dirty fuels and technologies. This situation is even worse

* Corresponding author.
E-mail address: m.talevi1@lse.ac.uk (M. Talevi).

[1] The SDGs are a United Nations initiative that delineate development targets for 2030; SDG7 relates to “ensuring access to affordable, reliable, sustainable, and modern energy for all”.

https://doi.org/10.1016/j.eneco.2021.105796
Received 5 February 2021; Received in revised form 7 December 2021; Accepted 19 December 2021
Available online 6 January 2022

in rural India where approximately half of the population is reliant on dirty fuels (World Health Organization, 2021). In some cases, the use of cleaner cookstoves has even declined over time, often because of insufficient maintenance or repair or supply constraints on the fuel (Hanna et al., 2016; Pattanayak et al., 2019). Naturally, this situation has led to several waves of policies, programs, and projects to promote improved cookstoves (ICS) and clean(er) fuels. National ICS programs in India have been around since the 1980s, including the National Project on Biogas Development (which started in 1981–1982) and the National Program on Improved Chulhas (1985–2002). This was followed by the National Biomass Cookstove Initiative in late 2009 and more recently by the *Pradhan Mantri Ujjwala Yojana* (PMUY) program in 2015 (Bond and Templeton, 2011; Mani et al., 2020).

Yet, many of these improved cookstove policies and programs have been criticized for attempting to supply solutions in a top-down remote engineering way, without understanding local demand for different technologies and services, which in some cases could simply be low (Mobarak et al., 2012; Pattanayak et al., 2018). By subsidizing the upfront costs for the poorest segments of the population, the recent PMUY scheme has dramatically increased the number of households with liquefied petroleum gas (LPG) connections in India. Nonetheless, this achievement has not yet translated into sustained use of cleaner fuels because LPG refills remain unaffordable for a substantial share of the population, LPG supply networks are limited, and solid fuels (such as firewood, agricultural residues, and dung cakes) are more readily available (Mani et al., 2020; Gould et al., 2020; Kar et al., 2019; Sharma et al., 2019; Gould and Urpelainen, 2018; Swain and Mishra, 2020). Many barriers to eradicating energy poverty in cooking continue to exist.

There is a relatively small but growing applied micro-economics literature on household energy demand and energy poverty in LMICs (Takama et al., 2012; Van der Kroon et al., 2014; Jeuland et al., 2015b, 2019; Berkouwer and Dean, 2019; Jagger et al., 2019, among others). This literature has focused on low uptake and low willingness to pay (WTP) for ICS. This literature suggests that the barriers to adoption and sustained use include affordability, liquidity and credit constraints, lack of awareness of the negative impacts, supply chain bottlenecks, and intra-household bargaining and gender-related issues (Beltramo et al., 2015; Bensch et al., 2015; Miller and Mobarak, 2015; Mohapatra and Simon, 2017). Yet, we still do not have a full picture of which types of households demand which types of technologies and services, acknowledging that any technology is a complex bundle of attributes. Some of the new technologies are simply not appropriate for the context in which they are introduced, for example in terms of households' needs, size, cultural background, and type of food cooked. An economics interpretation of this mismatch is that households have heterogeneous preferences for cooking and cookstoves, even within seemingly homogeneous villages (Pattanayak et al., 2018). One-size-fits-all solutions are unlikely to exist and care must be used to understand the specific needs, tastes, and constraints on the ground (Van der Kroon et al., 2014; Pant et al., 2014; Rehfuess et al., 2014; Pattanayak et al., 2019).

In this study, we build on these strands of literature, but avoid duplication by focusing on household preferences for specific attributes and for an understudied cooking technology — biogas digesters (or biogas for short). Specifically, we make three contributions. First, while most of the literature on clean cooking has focused on biomass ICS and LPG, we focus on family-size biogas systems for cooking (i.e., household 'self-produced' biogas) because it has the potential to deliver important co-benefits and positive externalities, especially in rural contexts with a hot and humid climate. Family-size biogas systems are used to transform livestock manure and other agricultural waste into gas for cooking, which can then be used in a similar way to LPG and burned without producing smoke (Bond and Templeton, 2011). Further details on the technology are presented in Section 3.1. An important advantage with respect to LPG is that biogas systems do not use fossil fuels and are therefore (a) not affected by the price of oil nor its supply chain and (b) not a source of climate forcing. Moreover, this technology allows safer waste disposal and provides fertilizer as a byproduct. As summarized in Section 3.1, various national and state government policies have attempted to promote biogas, but the economics research basis for the policy has been weak. The small economics literature on biogas has so far focused on Nepal (Pant et al., 2014; Somanathan and Bluffstone, 2015; Meeks et al., 2019), Indonesia (Bedi et al., 2017), Rwanda (Bedi et al., 2015), and Ethiopia (Kelebe et al., 2017). These studies have typically focused on the benefits and/or adoption of biogas. Our study is different both because we consider the technology as a bundle of attributes – therefore untangling household preferences for smoke emissions, fuel requirements, and maintenance assistance – and because we focus on how their valuation vary by experience and by time and risk preferences.

Second, we rely on a stratified random sample to study how demand is mediated by previous experience (positive, negative, or none) with the biogas technology in our study site. Too many recent studies of demand in rural areas of LMICs assume that the technology is new for everyone, when in reality the landscape is littered with past trials and partial successes. This introduces heterogeneity in demand, for example through learning. Understanding the role of both positive and negative experiences is therefore crucial because technology adoption and diffusion is a dynamic process. As cookstoves start aging and require repair, some benefits are realized and others are not, leading to sustained use or abandonment. Therefore, in our study site, we look at households that have had a *good experience* (i.e., whose system has never broken down), households that have had a *bad experience* (i.e., whose system has malfunctioned, for example because the structure cracked or they have had pipe or inlet/outlet problems), and finally households that have *no experience* with the technology.

Third, we look at how risk and time preferences correlate with technology demand. Learning-by-doing and technology trials can provide information, improve skills, and reduce risk, and have been shown to influence technology adoption. This is particularly true because most beneficiaries are risk-averse and/or impatient (Cameron, 1999; Marra et al., 2003; Foster and Rosenzweig, 2010). For example, Atmadja et al. (2017) show that adoption of environmental health technologies (e.g., cookstoves, toilets, treated bed-nets) depends on whether households are impatient or patient. Likewise, Jeuland et al. (2020) find that ICS use is correlated with risk aversion. Nevertheless, most empirical studies on these aspects of demand in LMICs tend to focus on agriculture rather than energy choices. Thus, following Jeuland et al. (2015a, 2019), we study how demand is mediated by risk aversion and impatience. Specifically we test the hypotheses that risk-averse and impatient households have lower demand for unfamiliar new ICS, but that previous experience with biogas modifies this lower demand. While this interaction has been suggested in other studies, we are not aware of any that test it explicitly.

We followed the design in Jeuland et al. (2015a) and implemented a labeled discrete choice experiment (DCE). Our DCE consisted of a series of choice cards, in which respondents were presented with three alternative options: *gobar gas* (biogas plant), biomass *rocket stove*, and the traditional *chulha* as the outside option. (See Figure 4 in Appendix A).[2] Each alternative technology is presented as a combination of price, maintenance assistance, smoke emissions, and fuel requirements. The DCE was conducted with 503 households in rural Odisha, India. We stratified our sample by households with different types of experience with biogas systems.

[2] *Gobar gas* is a family-size biogas plant for cooking. The biomass *rocket stove* is typically manufactured using metal and burns firewood or other biomass in a combustion chamber to improve the efficiency of the combustion process and reduce smoke emissions. The local traditional *chulha* is a self-built mud structure for burning solid fuels such as firewood, agricultural residues, dung cakes (dry manure), and other biomass.

Section 2 presents the conceptual framework for the analysis and estimation models. Section 3 provides background on the study area, the cookstoves used in the DCE, the sample stratification, the modules to elicit risk aversion and time preferences, and the design of the DCE. Section 4 discusses the results of the regression analysis of the DCE in terms of WTP for changes in attributes of the cookstove. We also report the estimated premium for biogas by different 'types' of households. Section 5 summarizes our study and the main policy implications.

2. Conceptual framework

In this paper, we study how the WTP for clean energy for cooking varies depending on technology type and cookstove attributes — smoke emissions, fuel requirements, and availability of maintenance assistance. We then look at how respondent experience and characteristics (risk aversion and time preferences) moderate demand. To do this, we use a random parameter logit model that allows us to consider unobserved heterogeneity at the individual level, as described in Section 2.2. Additionally, we deploy interaction terms to test specific sources of observed heterogeneity, as described in Section 2.3.

2.1. The random utility model

The theoretical framework for our study is the random utility model (Manski, 1977), where household i's utility can be decomposed into a non-stochastic indirect utility component $V_i(\cdot)$, which depends on the cookstove chosen, and a stochastic term ε_i, which captures idiosyncratic tastes or shocks. Following Lancaster (1966), we consider the cookstove as a bundle of attributes, each of which contributes to the household utility. In particular, we assume that the indirect utility of each stove jt (that is, technology j as described in choice-card t) is a function of observable characteristics of the stove included in vector X_{ijt} – price, maintenance assistance, smoke emissions, fuel requirements, and technology type (biogas, rocket stove, and traditional *chulha*) offered to individual i[3]:

$$U_{ijt} = V(X_{ijt}) + \varepsilon_{ijt}. \quad (1)$$

We start by specifying the non-stochastic indirect utility component in 'preference space' (Train and Weeks, 2005):

$$V_{ijt} = \alpha_i' \,(X_{ijt}) \; - \beta_i^{price} \,(price_{ijt}) \quad (2)$$

where the vector α_i consists of the marginal utilities of non-monetary characteristics (attributes and technology-specific premiums) and β_i^{price} is the marginal utility of the monetary characteristics (price). These parameters characterize the household preferences. The marginal utility parameters can then be translated into a marginal WTP for the attribute or for the technology-specific premium by dividing them by the coefficient of the price (i.e., the marginal utility of money):

$$WTP_i^l = \beta_i^l = \frac{\alpha_i^l}{\beta_i^{price}} \quad (3)$$

where l represents an attribute or a technology type, $l \in \{$*maintenance, fuel efficiency, smoke, biogas, rocket stove*$\}$.

We can therefore reparametrize the utility function from the preference space into the 'WTP space' (also called 'surplus model'), so that the coefficients are directly interpreted as WTP (Hole and Kolstad, 2012; Scarpa et al., 2008; Sonnier et al., 2007; Train and Weeks, 2005):

$$V_{ijt} = \beta_i^{price}[\beta_i' \,(X_{ijt}) \; - price_{jt}] \, . \quad (4)$$

In principle, different individuals might have different parameters and we allow for this heterogeneity in two ways. First, by using a random parameter logit model (RPL) we estimate an entire distribution for each parameter to account for unobserved heterogeneity in the sample. Second, we account for specific sources of observed heterogeneity by estimating different parameters for different types of respondents through interaction terms. We then test whether the estimated WTP are indeed statistically different between types.

As non-traditional technologies are new and tend to have much higher upfront costs compared to the traditional *chulha*, their net benefits might be unclear and the returns from investing in these cookstoves uncertain. Thus, what we have in mind is a learning process — those who have previously used the new technology will better understand the potential hidden costs and benefits of adopting it relative to households with no experience. Our main hypothesis is that households who have already used a biogas stove might have a clearer idea of the direct and indirect costs and benefits, the likelihood of their realization, and their time frame. In the case of biogas, costs and benefits include the time required to collect, feed, and stir the manure into the biogas digester, the need for careful cleaning and correct use of the system, the need for specialized maintenance and repair, and the amount of energy that can be produced given the available livestock. Additional indirect benefits of biogas are the possibility of using the byproduct slurry in place of purchased fertilizer and the health benefits from reduced smoke emissions and improved waste disposal (see Section 3.1). While some of these elements are captured by the attributes of our DCE (fuel-related time requirements, availability of maintenance assistance, smoke emissions), the others are not and should be captured by the biogas-specific premium. We might therefore expect that households who have no experience with biogas have a different WTP for the biogas-specific premium compared to households who have experience with the technology. In turn households who experienced malfunctions may have a lower WTP than those who have had a smooth experience, as each group adjust their expectations of costs and benefits accordingly.

Because the landscape is littered with past trials and partial successes, some households are better informed and this reduces their uncertainty. To delve more into this hypothesis, we also consider time and risk preferences as indicators of aversion to uncertainty. That is, we test if more risk-averse and more impatient households have a lower WTP for the improved yet less familiar technologies and the attributes. Further, we also test whether experience with a specific technology moderates the influence of time and risk preferences.

2.2. Random parameters: Accounting for unobserved heterogeneity

McFadden (1981) shows that when the stochastic term ε_{ijt} follows an i.i.d. type-one extreme value distribution and households choose the alternative that maximizes their utility in each choice-task, the probability that an alternative is chosen among all the alternatives in a given choice-task t is given by the conditional logit model (CL):

$$Pr(\text{choice } j = k \text{ by } i \text{ in task } t) = Pr(U_{ikt} > U_{ijt} \;\forall j \neq k) = \frac{e^{V(X_{ikt},\beta)}}{\sum_{j=1}^{J} e^{V(X_{ijt},\beta)}} \quad (5)$$

where the probability of choosing an alternative over the others is a function of the characteristics of the alternative itself, but also of the characteristics of all the other available options. In this case, $j \in \{$*biogas, rocket stove, traditional stove*$\}$.

This model can then be estimated using maximum likelihood, but it relies on two particularly restrictive assumptions: independent and identically distributed (i.i.d.) error terms and independence of irrelevant alternatives (IIA). The latter has often been found to be violated when tested in real-life decision-making situations, while the former is especially unrealistic when the same respondent makes repeated choices – as in the DCE analyzed in this paper – and decisions are therefore likely to be correlated (Lancsar et al., 2017).

[3] In the discrete choice experiment, individuals are asked to choose their preferred cookstove among 3 shown on a card; they are shown a total of 5 cards and asked to make a choice for each card.

For this reason, we relax these assumptions and use a random parameter logit model (RPL) introduced by Revelt and Train, 1998) instead. The RPL has been commonly used to analyze DCE data in studies of transportation (Greene and Hensher, 2003), health (Hole, 2008), environment (MacKerron et al., 2009), and energy (Van der Kroon et al., 2014; Jeuland et al., 2015a), among other applications.

The RPL allows us to consider heterogeneity of preferences and tastes in two ways. First, different households are allowed to have different preferences by modeling the WTP β as a random parameter with density function $f(\beta|\theta)$ rather than as a fixed parameter. The density function is characterized by the vector of parameters θ such as the mean and standard deviation of the assumed distribution that are estimated in the regression model. In this way, we can model unobserved heterogeneity. Second, following typical practice in the DCE literature, we consider heterogeneity in the demand for the different attributes and technologies by interacting indicators for different characteristics of the respondents (for example risk aversion, time preferences, and level of experience) with indicators for the levels of the attributes and the technology label.[4] These interactions represent the observed heterogeneity in our model. The combination of these two elements allows us to estimate the parameter distributions of different groups of people. Thus we can not only test the difference in the mean WTP, but also compare the estimated WTP distributions.

To obtain an expression for the probability of each choice under the basic RPL, the previous expression needs to be integrated over the distribution of the unknown random parameter:

$$Pr(\text{choice } j \text{ by } i \text{ in task } t) = \int \frac{e^{V(X_{ijt},\beta)}}{\sum_{j=1}^{J} e^{V(X_{ijt},\beta)}} \, f(\beta|\theta)\, d\beta. \tag{6}$$

This expression cannot be solved analytically to obtain an explicit likelihood function to maximize, so we use a maximum simulated likelihood approach instead (Train, 2009). This model is better suited to capture heterogeneity of preferences across respondents, as parameters (either some or all) are allowed to be randomly distributed across households according to a given continuous distribution, rather than being constrained into a single value as in the CL model. The model can also take into account the panel structure of the data by considering the probability that an individual makes a sequence of choices rather than the probability of a single choice:

$$\begin{aligned} &Pr(\text{sequence of choices } j \text{ by } i \text{ in task } t) \\ &= \int \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{e^{V(X_{ijt},\beta)}}{\sum_{j=1}^{J} e^{V(X_{ijt},\beta)}} \right]^{\mathbb{I}_{ijt}(k=j)} f(\beta|\theta)\, d\beta \end{aligned} \tag{7}$$

where $\mathbb{I}_{ijt}(k=j)$ is an indicator function that equals 1 if household i selected alternative $k=j$ in choice task t and 0 otherwise.

To estimate the model, we need to make assumptions on the distribution of the coefficients. Estimating the model in WTP space means that the estimated parameters directly describe the distribution of the WTP (Train and Weeks, 2005), so that distributional assumptions also translate directly into implications and constraints to the WTP. This can provide some advantages over the specification in preference space, where WTP is calculated as the ratio of the estimated coefficients for the attribute and for price. If both coefficients are modeled as random, the resulting distribution of the WTP is not easily characterized, nor are the implications of the distribution assumptions on the coefficients. As common in the literature (Hole and Kolstad, 2012; Scarpa et al., 2008), we use negative price in our equation and assume β_i^{price} to be log-normally distributed,[5] while the WTP are assumed to be normally distributed. This means that we constrain the marginal utility of price to always be non-positive, while the sign of the WTP for the attributes and the technology premiums is unrestricted. A negative WTP would mean that respondents need to be compensated to accept the proposed change in the attribute's levels or to switch from the default stove to the non-traditional ones. Given that attribute levels are all coded as improvements with respect to the baseline, we might want to constrain the WTP of the attributes to be non-negative too. Therefore, we conduct robustness checks assuming a log-normal distribution for these WTP and find very similar results.[6] On top of the advantages of interpretation of the coefficients and of the distribution assumptions, empirical applications have found estimations in WTP space to be more realistic. In some cases this modeling approach has also been shown to fit the data better (Train and Weeks, 2005; Scarpa et al., 2008; Sonnier et al., 2007).

2.3. Random parameters & interactions: Accounting for observed heterogeneity

To allow for interactions, we first split the biogas technology type (represented by a dummy indicator for whether alternative j is a biogas stove) into three distinct technology dummies – one for each level of experience – indicating whether (i) alternative j is a biogas stove that is offered to an individual who had *good experience* with biogas, (ii) alternative j is a biogas stove that is offered to an individual who experienced malfunctions with biogas (*bad experience* for short), and (iii) alternative j is a biogas stove that is offered to an individual with *no experience* with biogas. The new vector of attributes and technologies therefore becomes: {*maintenance, fuel efficiency, smoke, biogas if good experience, biogas if bad experience, biogas if no experience, rocket stove*}. To test the role of time and risk preferences, each element of the vector is then interacted with an indicator for i's type:

$$\begin{aligned} V(X_{ijt}, \beta_{patient}, \beta_{impatient}) = \gamma [&\beta'_{patient}(X_{ijt})\, \mathbb{I}_i(i = \text{patient}) + \\ &+\beta'_{impatient}(X_{ijt})\, \mathbb{I}_i(i = \text{impatient}) \; - price_{jt}] \end{aligned} \tag{8}$$

and

$$\begin{aligned} V(X_{ijt}, \beta_{lessriskav.}, \beta_{moreriskav.}) = \gamma [&\beta'_{lessriskav.}(X_{ijt})\, \mathbb{I}_i(i = \text{lessriskav.}) + \\ &+\beta'_{moreriskav}(X_{ijt}) \\ &\times \mathbb{I}_i(i = \text{moreriskav.}) \; - price_{jt}]. \end{aligned} \tag{9}$$

To test our hypotheses, we use the estimated means of $f(\beta)$ to conduct a Wald test on whether the distributions of the WTP for each characteristic have statistically different means. In particular, we wish to test if preferences for cooking attributes and for cooking technologies vary by whether households are impatient or risk-averse. In the case of a relatively new technology, like biogas, risk-averse individuals should assign a penalty because of the uncertainties linked to its novelty. At the same time, there is also a temporal mismatch between costs and benefits, as the price for purchasing the stove is paid in the short-run, while fuel savings, smoke reductions, and other co-benefits of the cookstoves are realized in the long-run.[7] Following this argument, we wish to test if experience with a technology helps reduce uncertainty about how risky the investment is and what the payback period should be. Therefore, we hypothesize that experience reduces the valuation penalty that risk-averse and impatient respondents assign to biogas. This is tested by examining how the WTP for biogas changes by risk aversion and impatience separately by level of experience.

[4] The analysis is based on Jeuland et al. (2015a), as well as on the best practices for DCE (Hauber et al., 2016; Johnston et al., 2017; Lancsar et al., 2017).

[5] The change in the sign of the price is needed because a log-normal distribution is defined for non-negative values, while we want to constrain the marginal utility of the price to always be non-positive.

[6] All the models in the paper are estimated in Stata 16. RPL models in WTP space are estimated using the *mixlogitwtp* package described in Hole (2016), which is based on the *mixlogit* package by Hole (2007).

[7] Respondents with higher time discount rates (i.e., 'impatient') assign a higher weight to the present and a lower weight to the future compared to more 'patient' households; their net present value for the non-traditional improved stove should therefore be lower.

3. Background & data

3.1. Policies & technologies

Biogas has been shown to deliver substantial benefits in rural contexts with a hot and humid climate, typical of many parts of India. These benefits include not only reduced smoke emissions from cooking, cheaper energy, and reduction in the use of fuelwood, but also improved waste disposal (and therefore sanitation) and production of high-quality fertilizer for agriculture as a byproduct of the anaerobic digestion (Brown, 2006; Chen et al., 2010; Hazra et al., 2014; Insam et al., 2015; Lewis et al., 2016).

Bond and Templeton (2011) give an overview on the use of family-size biogas plants in LMICs, including details on policies implemented in India and China to promote biogas. We draw on this report to briefly summarize how a biogas digester works since readers are likely less familiar with this technology compared to other ICS or *chulhas*. In the simple fixed-dome design used in our study area, the digester consists of a pit outside the house, lined with bricks and cement and covered by a dome of the same materials (see Figure 4). The structure is custom-made on the spot by a mason. A mix of manure and water in fixed proportions is then regularly fed into the digester and let to ferment. This process releases methane gas, which is funneled into the gas burner through pipes and to be burnt for cooking. By capturing the methane into the digester and burning it, this process avoids methane leaks from manure into the atmosphere, therefore reducing the release of this greenhouse gas. Methane is clean-burning and, as long as the household has access to manure, the fuel for this technology is basically free. However, the system requires constant maintenance and cleaning and a reliable feed source, so there is an expense in terms of time and resources required to keep livestock, which is still a barrier for poor households (Walekhwa et al., 2009; Sun et al., 2014). The slurry that remains in the digester after the fermentation process can be used as fertilizer in agriculture, replacing commercially bought fertilizers and providing better performance than using (unfermented) manure. Moreover, this process provides safer waste disposal.

In India, the development and adoption of biogas in rural areas has been supported since the 1980s with the National Project on Biogas Development (NPBD) and subsequent national-level programs such as the National Biogas and Manure Management Programme. Further, Indian states also participated in information and subsidy schemes. These are provided by the Odisha Renewable Energy Development Agency (OREDA) in our study area, as confirmed by the surveyed households. Biogas development in India targets not only cooking but also lighting and other energy uses that can be fueled by biogas (Shukla, 2007). The scarce literature on biogas in this setting largely comprises case studies of (i) successes of biogas development programs (Rao and Ravindranath, 2002; Ravindranath and Balachandra, 2009; Vijay et al., 2015), (ii) barriers to bioenergy diffusion (Bhat et al., 2001; Raha et al., 2014; Reddy, 2004), and (iii) commercialization and diffusion of biogas in urban areas and at the industrial level (Mittal et al., 2018).

3.2. Survey & sample

Data for this paper come from a survey administered to 503 households in 42 villages in 8 different districts of Odisha, India.[8] The survey was conducted between November 2011 and February 2012. Several co-authors of this paper designed and supervised the initial data collection. The household sample was stratified in four groups: groups 1 and 2 are households that have *working* and *broken biogas* digesters respectively, households in group 3 do not have a biogas but have at least one other type of non-traditional cookstove (for example LPG or electric), and group 4 includes households who only have the traditional *chulha* (biomass cookstove). Note that while households in group 1, 2, and 3 have at least one improved cookstove, 88% of them also have a traditional *chulha*, as fuel stacking is common in the area. To ensure comparability and similar contextual factors for all groups, the enumerators attempted to interview 3 households from each group in each village, although in a limited number of cases this was not possible. Thus, the final sample includes 503 households: 133 are in group 1 (working biogas plant), 120 are in group 2 (broken biogas plant), 121 are in group 3 (other clean stoves), and 129 are in group 4 (traditional stoves only).

The interview was conducted with the head of the household in most cases. The survey collected data on household assets – such as land and livestock holdings – and other socio-economic characteristics. Detailed questions were asked about cooking, in particular the types of cookstoves available in the house and the time and resources spent in different cooking-related activities. A detailed summary of household characteristics and characteristics of biogas plants is provided in Appendix C with tables of descriptive statistics (Tables 6, 7 and 8).

Bond and Templeton (2011) estimate that to satisfy the energy demand of a household, the digester should be between 2 and 10 m^3 and at least five cows are needed to provide enough gas for cooking two meals a day for a family of five. All the biogas plants in the sample are fixed-dome (*Deenbandhu* model), with a capacity of either 1 m^3 (15% of the households) or 2 m^3 (85% of the households) and 65% of the households have less than 1 head of cattle per household member. This suggests that biogas in our study area might be insufficient to cover the full demand of energy for cooking and this might be one of the reasons why households keep using traditional stoves even when the biogas plant is working. This issue was highlighted in focus groups in the study area during the preparatory stage of the study (Hazra et al., 2014). Most plants were installed between 2004 and 2010, with some going back as far as the 1980s. Everyone in the sample received subsidies for the construction of the plant, ranging from 17% to 82% of the overall cost; the vast majority (91%) reported receiving them from OREDA and the remaining 9% from other support schemes from the Government of Odisha. OREDA also played an important role in spreading awareness about the technology, as 72% of the households heard about the program from them, while 22% found out through the person who installed the plant and 6% through family or friends.

3.3. Levels of experience

The sample stratification described above together with information from the survey allows us to classify households in three different levels of experience with biogas. We classified households as having had a *bad experience* if their biogas plant is currently broken or have experienced malfunctions in the past. We classified households as having had a *good experience* if their biogas plant has never broken down. The rest of the households are classified as having *no experience*.

3.4. Factors associated with cookstove ownership & biogas functionality

We conduct a descriptive analysis of what factors and characteristics are associated with the type of cookstoves owned and the level of experience with biogas. Detailed information and robustness checks are presented in Appendices C, D and E. While we use multivariate regressions to analyze patterns, these findings should be treated as descriptive associations. The insights obtained can nonetheless guide the interpretation of the results of the DCE analysis.

The following patterns emerge: We find that biogas is more likely to be used by households in the lower and middle part of the income distribution and by households who have more livestock, while higher

[8] Specific districts include Angul (60 households), Cuttack (84), Jagatsingpur (60), Jajpur (48), Jharsuguda (96), Keonghar (60), Sambalpur (84), and Sundargarh (11), where numbers of household subsamples are listed in brackets. These districts capture the geographical and cultural diversity of the state.

income households tend to use other clean cookstoves (such as LPG and electric). The poorest households tend to have only a traditional *chulha* (Table 10). The association between livestock and ownership of a biogas plant is expected, as a functional biogas plant needs a reliable feed of manure. This is a barrier for poorer households, who may not have the resources to purchase and keep large animals (Walekhwa et al., 2009; Sun et al., 2014). Robustness checks in Appendix E are conducted to control for differences in livestock availability and income level between the groups. Focusing on the households who own a biogas plant, we find that malfunctions and failures are correlated with the age and size of the biogas system, as well as time spent on operating and cleaning the systems.[9] We do not find major differences in observed socio-demographic characteristics across households with good and bad experiences (Table 9).

3.5. Time & risk preferences

We elicited risk preferences and time preferences using two hypothetical dichotomous choice exercises. In each exercise, we asked the respondent to imagine that someone is offering them a gift in the form of an amount of money and reminded them that there are no right or wrong answers, just personal preferences. (See Appendix B for the script used for these questions).

In the time preference module, the respondent chose between a *sooner smaller* amount and a *later larger* amount. The first question asked whether they prefer a smaller amount of money (1,000 INR) tomorrow or prefer to wait for 12 months to receive double that amount (2,000 INR).[10] If they chose the smaller sooner amount, they were asked a second question in which the later larger amount was increased to 2,500 INR. If they chose the later larger amount at first, they were asked a second question in which the later larger amount was decreased to 1,500 INR. Using these sets of responses, we create an *impatience* dummy with value 1 if the respondent chose the *sooner smaller* amount in both questions. Sixty six percent of the our study sample are in this category.

The risk aversion module was similar, asking the respondent to choose between a *smaller safer* or a *larger riskier* amount. Specifically, they chose between a certain amount now (500 INR) or to flip a coin for the chance to receive a larger amount (1,200 INR) if it is heads but 0 if it is tails.[11] The expected value of this option was therefore 600 INR. If they preferred the safer option first, next they were asked to choose between the same safer smaller option or an uncertain amount with a higher expected value than the first choice. That is, to flip the coin to receive 1,250 INR if it is heads or 250 INR if it is tails, an expected value of 750 INR. If they instead preferred the riskier option in the first question, they were then asked to choose between the certain 500 INR or to flip a coin for a 1,000 INR if heads but 0 if tails (the expected value is 500 INR, the same as the certain amount). The responses are then used to create a *risk aversion* dummy with value 1 if the respondent chose the *safer smaller* amount in both questions. Sixty four percent of our study sample are in this category.

For both risk aversion and time preferences, we also create a 4-level ordinal index with the four possible combination of decisions and conduct robustness checks using these measures instead of the dummy, which confirm the results (Tables available on request). While there is considerable overlap between risk-averse & impatient (54% of overall sample), some respondents are risk-averse & patient (about 10%) and others less risk-averse & impatient (about 13%).

3.6. The discrete choice experiment (DCE)

Focus groups during the design phase identified some challenges of biogas adoption. These included: (i) inadequate repair services and assistance, as digesters need careful and constant maintenance to ensure functionality; (ii) affordability, as the upfront construction costs are still very high even after subtracting the subsidy; (iii) biogas is usually insufficient to cover all of the family cooking needs, and (iv) alternative uses of dung as fertilizer and fuel (dung cakes).[12]

Information from the focus groups were thus used to design the DCE to assess household preferences for two types of cleaner cooking technologies – a *biogas system* and a biomass ICS (*rocket stove*) – and for cookstove attributes – *smoke emissions*, *fuel & time requirements*, and *maintenance assistance*. Each bundle of technology and attributes is presented with a *price* tag, described as the one-off payment needed to acquire the stove. In all survey questions and analysis, the traditional *chulha* (a simple biomass mud stove) served as the outside option.

The DCE consisted of 5 hypothetical decision scenarios, each presented through a choice-card. The 3 alternatives in each choice-card are 'labeled' using the names of the most common cookstove available in the sample area for each type: *gobar gas* (biogas plant), *rocket stove* (biomass ICS), and the traditional *chulha* (the outside option). Pictures of these types of stove are included in Figure 4 in Appendix A. Each alternative was presented with a picture of the stove itself, followed by sketches of levels of (i) its price (as a number and as a picture of the corresponding banknotes), (ii) maintenance assistance, (iii) smoke emissions, and (iv) fuel requirement. Before the DCE module was started, each stove and each attribute was explained in detail using information cards with pictures and sketches. Note, while the fuel requirement was represented by wood logs in the choice card for simplicity's sake, the enumerator explained that this also included the resources (money and time) needed to fuel the stove. That is, the enumerator described this attribute as "the fuel needed for cooking with the stove — both the amount and the time required to collect and prepare it" to ensure that the attribute would be comparable between stoves that use different fuels. An example of a choice card is shown in Fig. 1. In Appendix B, we present the script used by enumerators to describe the attributes and to explain the DCE itself.

The attributes for the traditional stove (*chulha*) are fixed for all the decisions and are set to low maintenance assistance, high smoke emissions, and medium fuel requirements; the price is stated as 100 INR (equivalent to 2.5 USD in 2021 terms). The attributes and attribute levels used are summarized in Table 1. A total of 25 combinations of attributes for the rocket stove and biogas system were obtained using a D-efficient fractional factorial design. The 25 choice cards were grouped into 5 sets of 5 cards each and respondents in each stratification group were randomized into a choice set. The final dataset consists of 503 respondents, each presented with 5 choice cards, resulting in 2,515 choices.[13] In the empirical analysis, attributes are coded as being

[9] Bond and Templeton (2011) also highlight age of biogas digester as a key predictor of performance.

[10] The conversion rate used in the paper to translate 2011–12 prices into present day values is: 1,000 INR at the time of the study (2011–2012) is equivalent to 1,850 INR in 2021. To convert the values into present day USD: 74 INR is equivalent to 1 USD (all in 2021 terms). Therefore the *sooner smaller* amount of 1,000 INR offered in the survey is equivalent to 25 USD in present-day terms. For reference, in the sample the median monthly expenditures excluding food, a proxy for the household disposable income, was 1,350 INR, which is equivalent to 2,500 INR or 34 USD in present-day terms. So the amounts offered were substantial.

[11] The amount of 500 INR offered in the survey is equivalent to 925 INR or 12.5 USD in present-day terms; 1,200 INR is equivalent to 2,220 INR or 30 USD in present-day terms.

[12] Note that the slurry leftover in the biogas digester after the fermentation process can also be used as fertilizer and in fact should be more effective than using the fresh manure (Bond and Templeton, 2011).

[13] The choice-cards are presented to all respondents in a choice set following the same order. We do not see potential for anchoring as the combinations of stove types and attribute levels do not follow any systematic pattern within a set nor between the first cards of different sets. While randomizing the order of the cards would allow us to formally control for anchoring, it introduces some additional field complexities for the enumerators in terms of logistics and data collection in this paper-based survey.

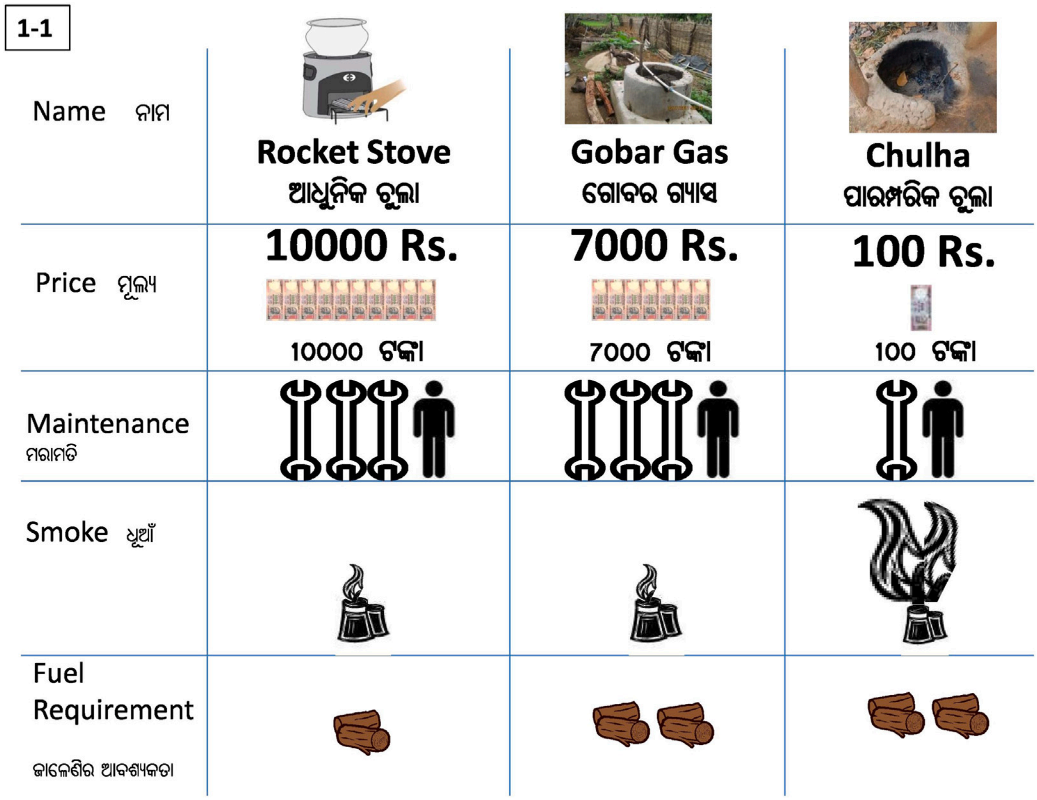


Fig. 1. Example of choice-card used in the discrete-choice experiment.

Table 1
Attributes and attribute levels used in the discrete choice experiment (DCE).

Attributes	Reference level (chulha = traditional stove)	Levels for biogas & rocket stove
Price (in 2011-INR)	100 INR	4,000/7,000/10,000 INR
(in 2021-USD)	(2.5 USD)	(100/175/250 USD)
Maintenance	Low	Low/High
Smoke	High	Low/High
Fuel requirement	Medium	Low/Medium/High

lower or higher than the baseline attributes of the traditional stove, which are fixed across all questions. Price is considered a continuous variable.[14]

The choice variable in our DCE is the alternative chosen among the biogas system, the rocket stove, or the traditional *chulha*. After the respondent selected their preferred alternative for a choice card, they were asked to confirm whether they would indeed purchase that cookstove at the proposed price and in 73% of the cases the respondent answered affirmatively. In the analysis we only use responses that are confirmed in the follow-up question and remove the responses that were not confirmed.[15]

Because of our reliance on stated preferences, there is a risk of hypothetical bias. For at least three reasons, however, we believe this is the best approach for the context. First, we pursue the stated preference approach in this paper because we wish to understand how different attributes of this household energy system matter to households. As detailed in over 50 years of development of stated preference methods, these methods are essential when the real choice sets that households face either do not contain all attribute combinations or the relevant variations is simply unavailable. Therefore we can introduce such variations into a DCE whereas the revealed preferences is not an option in our study setting. Second, our paper adheres to the many recommendations for how to minimize biases in stated preference studies (Whittington, 2010). That is, first we implement a variety of procedures in the design stage such as careful scenario development, focus groups, pre-testing, enumerator training, field verification. Additionally, in the analysis stage we also screen the data carefully and check for expected correlations (e.g., with income) to minimize the risk of such biases. We also draw on previous applications of stated preference to household cooking such as Jeuland et al. (2015a) to minimize obvious biases. Finally, the fact that the good offered is tangible and commonly marketed reduces the risks of getting spurious, overly strategic, or thoughtless responses. Risks of such responses are heightened if respondents are asked to consider exotic settings or unfamiliar non-market goods.

4. Results

4.1. The basic random parameters logit

We report the results from the DCE analysis in a set of tables and graphs. In the tables, we present the estimated mean and estimated

[14] As a robustness check, we run additional regressions using price as a categorical variable, as suggested by Lancsar et al. (2017), and find that the coefficients respond close to linearly. For this reason, in the main specifications presented in the paper price is modeled as continuous.

[15] The following question was used to confirm whether they would indeed purchase: "Would you purchase the alternative you have chosen at the given price?". Most of the "no" answers are cases in which the selected option is the rocket stove (only 55% of the cases where a rocket stove is selected are then validated, compared to 70% for the biogas and 87% for the traditional *chulha*) or cases in which the respondent selected the biogas plant or the traditional *chulha* but already has one. As a robustness check, we repeat the analysis with the full sample of choices. These results are similar to the main results described in the text, especially for the ASCs, while the WTP for attributes are slightly higher but still comparable.

Table 2
Regression table for the DCE.

	WTP	
	(mean)	(SD)
biogas ASC, if good experience	7348***	5655***
	(596)	(832)
biogas ASC, if bad experience	5744***	4185***
	(525)	(559)
biogas ASC, if no experience	2837***	6881***
	(801)	(764)
rocket stove ASC	−2768**	6147***
	(919)	(654)
maintenance assistance	609	3213***
	(404)	(591)
smoke reduction	4785***	1389***
	(456)	(385)
fuel efficiency	3074***	520
	(320)	(379)
N	5484	
aic	2655	
bic	2761	

Standard errors in parentheses; * p<0.05 ** p<0.01 *** p<0.001.

standard deviation (SD) of the WTP distribution, with corresponding standard errors for the level of precision of each estimate. In the graphs we plot the distribution of the WTP, based on the estimated means and standard deviations. The distribution is obtained from the individual-level coefficients using 1,000 Halton draws for the simulation, following the approach in Revelt and Train (2000).[16] Density functions are then estimated using Epanechnikov kernel density.

First, in Table 2 we report the parameters of a basic RPL model with attributes and alternative-specific constants (ASC), distinguishing the biogas ASC by the respondent's level of experience with biogas. The signs of the coefficients for the attributes are positive, as expected. The mean WTP for smoke reductions is INR 4,785 and for fuel efficiency is INR 3,074. The mean WTP for maintenance assistance is instead low and not statistically different from zero (INR 609).[17] The low WTP for maintenance is consistent with another DCE (Jeuland et al., 2015a), which suggest that maintenance is not a main concern for fuelwood stoves. However, focus groups in our study area highlighted maintenance as important for biogas functionality, so households might consider this to be a biogas-specific issue that is captured in the biogas ASC discussed next.

Second, we estimate technology-specific premiums (the ASCs). That is, with our labeled DCE design, we can measure cookstove-specific tastes, holding all other attributes (smokiness, fuel efficiency, and maintenance assistance) as constant. Thus, we can report if respondents are willing to pay a premium (or need to be compensated) for a specific technology (biogas or rocket stove) without regard to the attributes. We find that the mean WTP for the rocket stove premium is negative and statistically significant at conventional levels, suggesting that the traditional *chulha* (outside option) is preferred to the rocket stove. The average respondent needs compensation of at least INR 2,768 (or USD 69 in current value). There are two possible reasons for lack of enthusiasm for rocket stoves in our study area. First, these stoves did not have wide penetration at the time of the survey and so respondents may have been unfamiliar with it. In contrast, biogas systems were heavily advertised and subsidized in the surveyed villages. Second, the rocket stoves marketed in the area during the study period were early designs that often failed to deliver the promised improvements.[18]

On the contrary, the biogas system is on average strongly preferred to the *chulha*, all else equal. In the case of biogas, this premium should capture some combination of the indirect costs and benefits of the technology that are not included as attributes, such as the improved waste disposal, the fertilizer obtained as byproduct of the fermentation process, and the space taken up by the biogas digester on small house plots. The magnitude of the WTP for the biogas premium nonetheless depends on respondent experiences. Those with a good experience have the largest mean WTP (INR 7,348), followed by those who experienced malfunctions (INR 5,744), and then by those with no experience (INR 2,837).[19] The valuation of the technology *per se* (without considering attributes) therefore appears to be counteracted by negative experiences and failures, when compared to households who have had positive experiences. Thus, construction quality, maintenance services, and customer assistance could sustain interest in the technology and avoid abandonment, as noted in a different context by Gould et al. (2018).

Finally, we find that the level of experience is not the only source of heterogeneous WTP. The estimated SDs of the WTP distributions that capture unobserved heterogeneity are all large in magnitude and significantly different from zero. To better understand and explain these variations, we report on the analyses using interaction terms in the next sub-section.

4.2. Considering experience and risk & time preferences

Here we present on two specific potential sources of preference heterogeneity – risk and time preferences – that are modeled by including interaction terms as described in Eqs. (8) and (9). We include risk and time preferences in two separate models due to power and computational limitations of the flexible specification we use.[20] We present the estimated means and SDs of the WTP for interactions with time preferences in Table 3 and for interactions with risk aversion in Table 4. To better understand the results, plots of the WTP distributions simulated using the estimated parameters are shown in Figs. 2 and 3. Note that even after controlling for these household types, we see unobserved heterogeneity in the WTP for each attribute and each ASC. This is shown by the highly significant SDs of the WTP and can be visualized in the corresponding spread of the estimated density functions in Figs. 2 and 3. The only exception is the case of risk-averse respondents' WTP for fuel efficiency, as the SD is not significantly different from zero.

The results in Table 3 and Fig. 2 suggest that compared to patient respondents, respondents who are more impatient appear to have (i) larger mean WTP for maintenance assistance, (ii) lower WTP for fuel efficiency, and (iii) similar WTP for smoke reduction. The rocket stove premium and the biogas premium also tend to be lower for households who are more impatient, although in the case of biogas this is true only in the group with no experience. These results are intuitive, as impatient respondents likely discount future fuel savings and other

[16] The simulations are performed using the package *mixlbeta* (Hole, 2007, 2016).

[17] To better understand what these numbers mean, in present-day USD: the mean WTP for smoke reductions is USD 120, for fuel efficiency is USD 77, and for maintenance is USD 15.

[18] Some well-designed experimental studies (incidentally also in Odisha — our study site) that evaluated poor stove designs (traditional chulhas with a chimney) found null effects on various outcomes (Hanna et al., 2016). Other studies that evaluated more recent and more efficient natural draft biomass-burning improved cookstoves found positive outcomes for fuel efficiency, time savings, and health (Brooks et al., 2016; Jeuland et al., 2020; Lewis et al., 2015; Pattanayak et al., 2019; Krishnapriya et al., 2021).

[19] In present-day USD, these correspond to USD 184 (good experience), USD 144 (malfunctioning), and USD 71 (no experience).

[20] In general, we consider risk aversion and impatience to capture related preferences and tolerance towards uncertainty. As mentioned previously, though there is some overlap between risk-averse & impatient (54% of overall sample are both risk-averse and impatient), this overlap is not perfect.

Table 3
Regression table, model with time preferences.

	WTP, time preferences	
	(mean)	(SD)
biogas ASC, if good exp. and patient	6610***	5724***
	(1204)	(1657)
biogas ASC, if good exp. and impatient	7125***	6019***
	(971)	(1336)
biogas ASC, if bad exp. and patient	6471***	4506***
	(1033)	(1134)
biogas ASC, if bad exp. and impatient	5256***	3504***
	(728)	(939)
biogas ASC, if no exp. and patient	6001***	6518***
	(981)	(1238)
biogas ASC, if no exp. and impatient	1613	8131***
	(915)	(1244)
rocket stove ASC, if patient	−1732	7854***
	(1383)	(1241)
rocket stove ASC, if impatient	−4376***	6065***
	(1279)	(924)
maint. assist., if patient	198	3478***
	(660)	(733)
maint. assist., if impatient	1117*	3967***
	(527)	(738)
smoke reduct., if patient	5091***	1853*
	(722)	(869)
smoke reduct., if impatient	4932***	1409
	(589)	(1162)
fuel efficiency, if patient	4144***	2656***
	(530)	(691)
fuel efficiency, if impatient	2824***	1237*
	(344)	(543)
N	5484	
aic	2661.55	
bic	2859.84	

Standard errors in parentheses; * p<0.05 ** p<0.01 *** p<0.001.

future benefits of the non-traditional stoves more than their patient counterparts and therefore may not want to wait for repair in case of malfunctions.

Turning to risk aversion in Table 4 and Fig. 3, we find that compared to less risk-averse respondents, the more risk-averse have (i) larger mean WTP for maintenance assistance, (ii) lower mean WTP for smoke reduction, and (iii) similar WTP for fuel efficiency. We also find that the more risk-averse are willing to pay lower premiums for the rocket stove and for the biogas system. Risk-averse individuals may prefer maintenance service that decreases the risk of malfunctions, and in general are less likely to try new technologies as they are perceived as riskier than the traditional ones. The result on smoke reduction suggests that aversion to monetary risks may not directly translate into aversion to health risks, or that the latter are not evident to the respondent. This result may well be specific to our study sample because most respondents are men, while health risks from polluting cooking practices tend to disproportionately affect women and children.

Nonetheless, we find small differences in estimated WTP for each attribute and each technology between households who are impatient and those who are patient, with the notable exception of the biogas premium for respondents with no experience (Table 2). This can also be seen in the plots, as the peak of the distributions for each WTP for the impatient respondents tend to be close to the corresponding WTP for the more patient respondents and the density functions tend to overlap at least in part, except in the case of the biogas premium for the no-experience group (Fig. 2). The same patterns are true for risk-averse respondents: the mean WTP for the same characteristic between the two groups (more and less risk-averse) tend to be quite close and the corresponding density functions tend to overlap at least in part in all cases but the biogas premium for inexperienced respondents.

Given these findings, it is unclear to what extent time and risk preferences matter. We use a Wald test to formally assess whether the differences in mean WTP between impatient and patient respondents

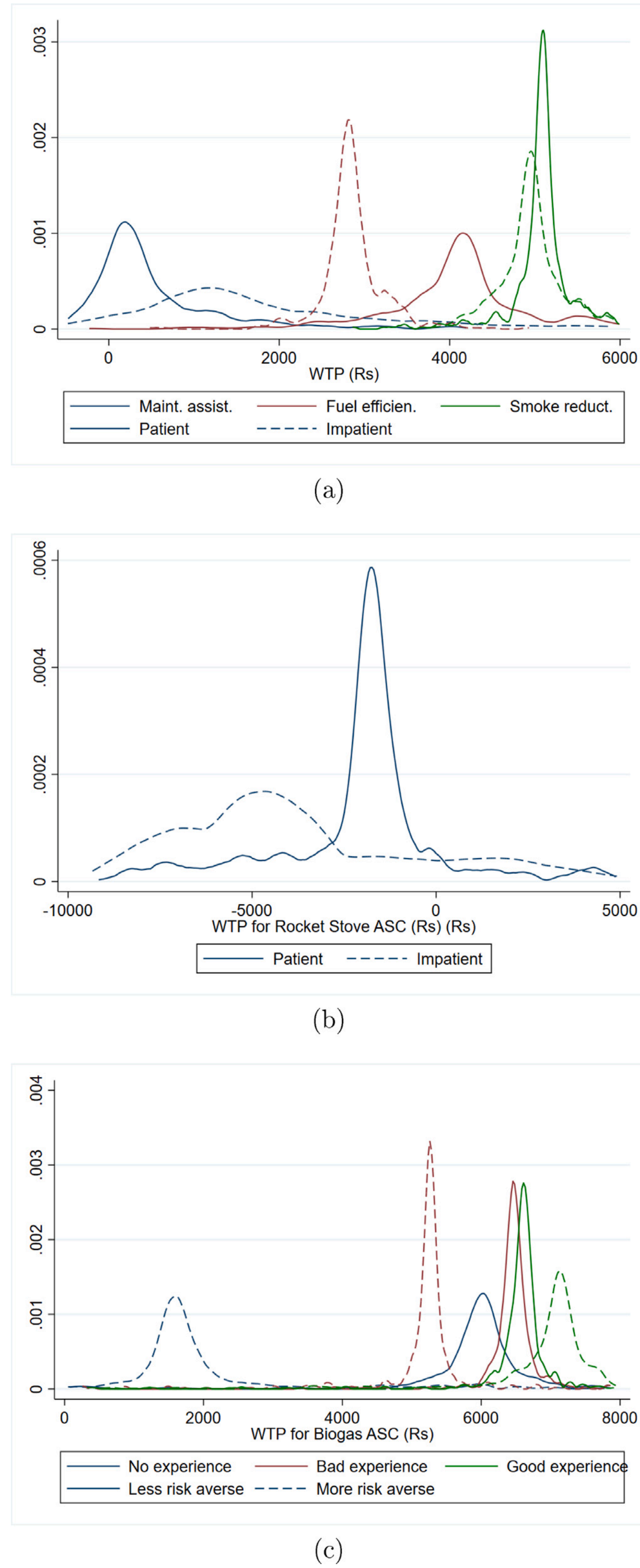


Fig. 2. Estimated distributions of the WTP of patient and impatient respondents. Density functions are estimated using Epanechnikov kernel density. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Regression table, model with risk preferences.

	WTP, risk aversion	
	(mean)	(SD)
biogas ASC, if good exp. and less risk averse	8038***	4810***
	(720)	(886)
biogas ASC, if good exp. and more risk averse	7100***	7323***
	(591)	(978)
biogas ASC, if bad exp. and less risk averse	5399***	3781***
	(641)	(635)
biogas ASC, if bad exp. and more risk averse	5014***	3311***
	(588)	(615)
biogas ASC, if no exp. and less risk averse	5148***	5332***
	(659)	(547)
biogas ASC, if no exp. and more risk averse	2781***	7677***
	(624)	(994)
rocket stove ASC, if less risk averse	−2315	6978***
	(1259)	(1090)
rocket stove ASC, if more risk averse	−3021**	4590***
	(1069)	(551)
maint. assist., if less risk averse	631	2386***
	(479)	(593)
maint. assist., if more risk averse	1223**	1545***
	(389)	(393)
smoke reduct., if less risk averse	5060***	2814***
	(659)	(424)
smoke reduct., if more risk averse	3927***	1846***
	(471)	(313)
fuel efficiency, if less risk averse	2929***	1972***
	(496)	(363)
fuel efficiency, if more risk averse	2863***	24
	(290)	(320)
N	5484	
aic	2676.12	
bic	2874.40	

Standard errors in parentheses; * p<0.05 ** p<0.01 *** p<0.001.

Table 5
Difference in WTP between impatient and patient respondents (top) and between more risk-averse and less risk-averse respondents (bottom).

Test of difference in means between impatient and patient respondents

	Difference in means (INR)	*p*-value
WTP for biogas, if good experience	518	0.738
WTP for biogas, if bad experience	−1215	0.335
WTP for biogas, if no experience	−4388**	0.001
WTP for rocket stove	−2644	0.114
WTP for maintenance assistance	919	0.274
WTP for smoke reduction	−160	0.846
WTP for fuel efficiency	−1320*	0.020

* p<0.05 ** p<0.01 *** p<0.001.

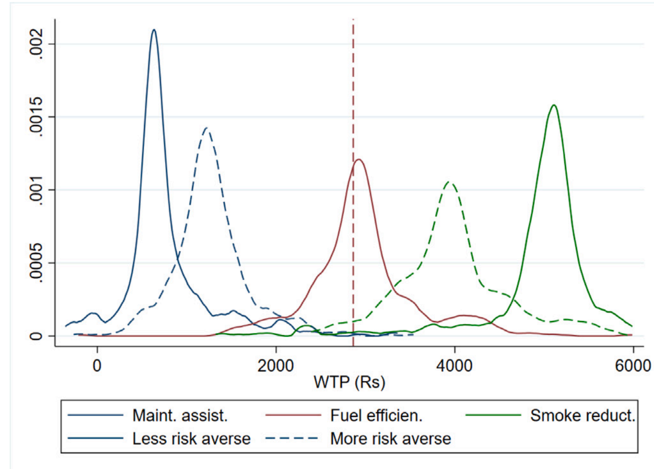
Test of difference in means between more and less risk averse respondents

	Difference in means (INR)	*p*-value
WTP for biogas, if good experience	−939	0.314
WTP for biogas, if bad experience	−384	0.657
WTP for biogas, if no experience	−2366**	0.008
WTP for rocket stove	−705	0.648
WTP for maintenance assistance	592	0.331
WTP for smoke reduction	−1134	0.135
WTP for fuel efficiency	−65	0.903

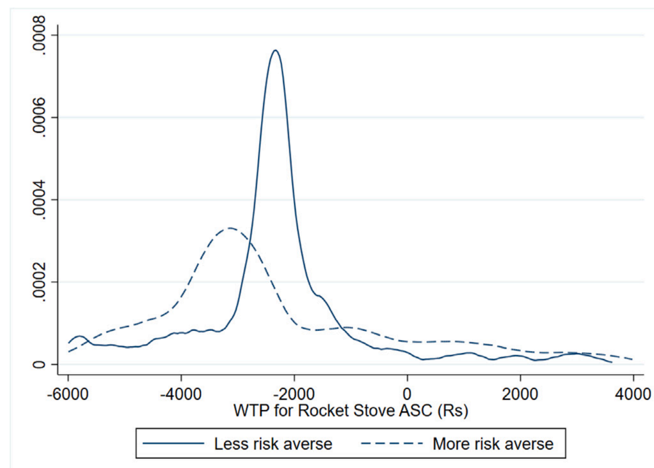
* p<0.05 ** p<0.01 *** p<0.001.

are statistically significant. We also conduct the same test for the differences in mean WTP between more risk-averse and less risk-averse respondents. The magnitude of the differences and the p-values from the tests are reported in Table 5. We find a marginally significant difference in the mean WTP for fuel efficiency between impatient and patient respondents, which is likely because impatient respondents more heavily discount the future fuel savings of an efficient stove.

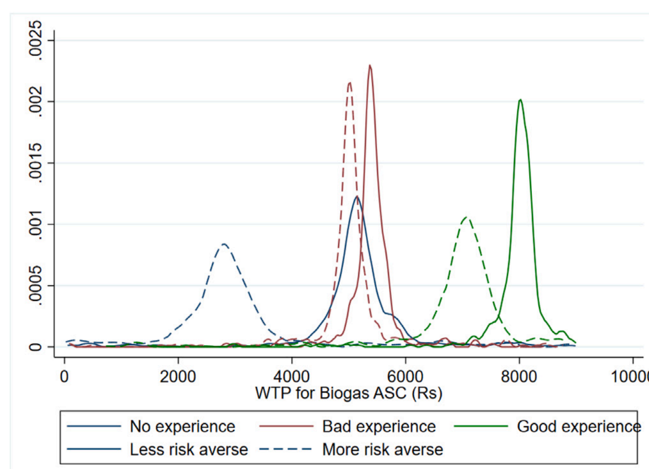
Only in the case of households with no experience, impatience and risk aversion is correlated with significantly lower mean WTP for biogas. That is, in the subgroup of households with no experience,



(a)



(b)



(c)

Fig. 3. Estimated distributions of the WTP of less risk-averse and more risk-averse respondents. Density functions are estimated using Epanechnikov kernel density. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

impatient respondents are willing to pay on average INR 4,388 less for biogas than patient respondents, while more risk-averse respondents are willing to pay on average INR 2,366 less than less risk-averse respondents. Moreover, the distribution of the WTP for biogas for respondents who have no experience and are impatient do not overlap almost at all with the corresponding distribution for respondents who are more patient, suggesting that the difference in WTP is not confined to the average respondent but to the whole distribution (compare the dashed and solid blue curves in Fig. 2.c). A similar but less extreme result can be observed for risk aversion, as the distributions are closer but still have almost no overlapping (compare the dashed and solid blue curves in Fig. 3.c). Collectively, these results suggest that while risk aversion and impatience depress demand for biogas, both positive and negative experiences mitigate these effects, possibly because they make this new technology and all its benefits more familiar.

4.3. Further reflections on modeling experience

Given the focus on experience in our analysis, we conduct robustness checks and offer a few caveats. First, households who have experience with biogas might have had a pre-existing interest in the technology. Comparing them with households who intend to install soon might therefore provide more meaningful insights. We distinguish the group that has no experience into those who are planning to install biogas soon (55% of this subsample) and those who have no plans to install (45% of this subsample). These subgroups are almost equally split between households who already have another ICS and households who rely exclusively on *chulhas*. Results of the analysis with this additional distinction are presented in Appendix F. Predictably, we find that those who plan to install biogas have a much larger WTP for biogas than those who do not.

Second, experience with biogas could imply that the household has already faced a specific price for the system when it was purchased. We might be concerned therefore that households 'anchor' their responses to the price they have already experienced rather than stating their real preferences. In a further robustness check, we find that whether the price presented in the choice-card is lower or higher than the price paid at time of purchase is insignificant when controlling for the general price level and the other attributes used in the DCE (tables available on request).

Third, we cannot rule out that households who already have a biogas system had systematically different preferences for biogas even before adoption, or that those who experienced malfunctions had a more pessimistic opinion about the technology, which is what led to the malfunctions in the first place. In Appendix D and in Table 10 in Appendix E we do not find major differences between households with good and bad experience along observed demographics characteristics. Nonetheless, to control for the role of other observable characteristics of the respondents, such as livestock and disposable income, we conduct two robustness checks (Appendix E). Both the semi-parametric analysis (using inverse probability weighting) and the non-parametric analysis (achieving balance on key observables) confirm the main findings reported thus far. Nonetheless, given the nature of the data, we caution that these results are best viewed as careful correlations rather than causal effects of experience on WTP and more research is needed to confirm the direction of causality.

Finally, despite the numerous robustness checks, our experience categories are simplifications. Future researchers could explore the continuum of experiences that individuals may have with a technology. For example, future data collections could include questions on the severity of the malfunctions, how long and how often the system has been used, and a subjective satisfaction scale for the experience. Further, while we focus on first-hand personal experience, future research may expand our findings by looking at how individuals learn from their peers (e.g., Bonan et al., 2021). Future research should also more formally integrate qualitative research on experience, for example by using mixed methods.

5. Summary & conclusions

Part of the reason energy poverty is both pernicious and persistent is because lack of access to energy-efficient technologies can keep people in socio-economic poverty, which in turn makes it harder to adopt and use clean energy. Biogas has the potential to break this cycle and to deliver important benefits in rural areas with a hot and humid climate, which often are the hotspots for energy poverty. Understanding which types of households are interested in what aspects of biogas and other clean cooking technologies can help design better promotion efforts, therefore making sure the products offered match the needs of the energy poor. In this paper, we try to fill this gap by using a DCE to better characterize household preferences for biogas and other ICS in India. We find that respondents have a high WTP for biogas, on average. In contrast, WTP for rocket stoves (a biomass ICS alternative promoted by the private sector) is much lower, especially when contrasted with the familiar traditional biomass-burning *chulha*. Households appear to assign high values to smoke reduction and fuel savings, two dimensions on which biogas can deliver substantial improvements.

However, these general results hide substantial preference heterogeneity, especially with respect to previous experience with biogas. While none of the following findings is surprising *per se*, we find that households who have had a good experience have a higher mean premium for biogas compared to households who have a bad experience (such as cracked structure, inlet or outlet problems, or pipe problems). We also find that while risk aversion and impatience are associated with lower WTP for biogas, previous experience of any kind (good or bad) attenuates this gap. While these are new findings in the household energy poverty literature in LMICs, they resonate with lessons about learning processes from the broader technology diffusion literature (Gillingham and Palmer, 2014; Schleich et al., 2019).

These findings collectively clarify our main contributions to the small yet growing microeconomics literature on household cooking and energy poverty. Many of the published studies of demand in rural areas of LMICs inadvertently assume that the technology is new for everyone, when in reality households have varied experiences with past trials and distribution programs. This phenomenon likely introduces demand variation through learning. Thus, our findings lend themselves to two kinds of recommendations. First, monetary incentives for adoption of biogas should be complemented not just with generic demonstration campaigns, but also with technology trials that allow households to gain hands-on experience. Such efforts could be organized by having household ambassadors for the technology in each village, or by a local promoter who could, for example, install biogas in local schools or other community facilities. Second, beyond ensuring that the technology is locally-relevant and matches household-specific needs, the product must be of high quality and must come with easily accessible after-sales customer service, including but not limited to affordable maintenance and repair services.[21] Note that while the National Biogas and Manure Management Programme promises warranties, training, and subsidies for repair, ground implementation falls woefully short (Raha et al., 2014). Maintenance and repair services can in turn also limit disinterest, discontent, abandonment, and negative opinions that reduce adoption by others.[22] Our results also have a methodological implication, as they show the importance of controlling for previous experiences when conducting a DCE because

[21] See for example the training programs, customer service centers, and repair campaigns envisioned by the Africa Biogas Partnership Program (Clemens et al., 2018).

[22] A small fraction of the households in our sample that have bad experiences (16%) stated that they have no interest in repairing the plant. Poor quality systems may therefore result in abandonment and low valuation of the technology. If negative opinions spread faster than positive opinions as found by Miller and Mobarak (2015), this might further reduce uptake of the technology.

some households may already be familiar with the technology being offered. We provide a first attempt on how to do this, as well as caveats and suggestions on how to better collect data and model experience.

We conclude with two reflections. First, even though positive experiences boost demand, many households face a litany of constraints — income, credit, and liquidity, among others. Moreover, tastes for biogas are heterogeneous and some households have simply low interest in the technology. These households might therefore be unable or unwilling to cover the upfront costs of building a biogas system. Because biogas use can reduce a host of social costs of cooking related to health, environment, and climate (including methane and $PM_{2.5}$ emissions), households should be offered subsidies that are framed as payments for reducing negative externalities. Second, while there is substantial interest in biogas in the study area, our findings suggest that penetration could be improved by complementing the existing subsidy schemes both with technology trials at the start and customer support (maintenance and repair service) over the lifetime of the biogas system. Experience can sustain use if and only if behavioral and engineering malfunctions do not generate discontent, leading to abandonment. Collectively, this shows how eliciting tastes (e.g., stated preference surveys) and explaining demand heterogeneity (e.g., random parameter logit modeling) can aid the design and supply of clean energy solutions in rural areas of LMICs, the hotspot for energy poverty.

CRediT authorship contribution statement

Marta Talevi: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Subhrendu K. Pattanayak:** Conceptualization, Fieldwork, Data curation, Methodology, Writing – original draft, Writing – review & editing, Supervision. **Ipsita Das:** Conceptualization, Fieldwork, Data curation, Writing – review & editing. **Jessica J. Lewis:** Conceptualization, Fieldwork, Data curation, Writing – review & editing. **Ashok K. Singha:** Conceptualization, Fieldwork, Data curation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We acknowledge support from SANDEE (the South Asian Network for Development and Environmental Economics) for the fieldwork and data collection stages. Talevi acknowledges the financial support provided by the UK Economic and Social Research Council (grant number ES/J500070/1) for subsequent stages of the research project after the data collection. We would like to thank Salvatore Di Falco, Steve Gibbons, Marc Jeuland, Erin Litzow, Robyn Meeks, Susana Mourato, Hisham Zerriffi, and participants at the 25th EAERE Annual Conference, EfD's 14th Annual Meeting, and the Initiative for Sustainable Energy Policy (ISEP) workshop for helpful comments. All errors are our own. Our gratitude also goes to the households who participated in the study and dedicated time to this project.

Inclusion and diversity

We worked to ensure ethnic or other types of diversity in the recruitment of human subjects. We worked to ensure that the study questionnaires were prepared in an inclusive way. While citing references scientifically relevant for this work, we also actively worked to promote gender balance in our reference list. The author list of this paper includes contributors from the location where the research was conducted who participated in the data collection, design, analysis, and/or interpretation of the work.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105796.

References

Atmadja, S.S., Sills, E.O., Pattanayak, S.K., Yang, J.-C., Patil, S., 2017. Explaining environmental health behaviors: evidence from rural India on the influence of discount rates. Environ. Dev. Econ. 22 (3), 229–248.

Bedi, A.S., Pellegrini, L., Tasciotti, L., 2015. The effects of Rwanda's biogas program on energy expenditure and fuel use. World Dev. 67, 461–474.

Bedi, A.S., Sparrow, R., Tasciotti, L., 2017. The impact of a household biogas programme on energy use and expenditure in East Java. Energy Econ. 68, 66–76.

Beltramo, T., Blalock, G., Levine, D.I., Simons, A.M., 2015. The effect of marketing messages and payment over time on willingness to pay for fuel-efficient cookstoves. J. Econ. Behav. Organ. 118, 333–345.

Bensch, G., Grimm, M., Peters, J., 2015. Why do households forego high returns from technology adoption? evidence from improved cooking stoves in burkina faso. J. Econ. Behav. Organ. 116, 187–205.

Bensch, G., Peters, J., 2013. Alleviating deforestation pressures? Impacts of improved stove dissemination on charcoal consumption in urban Senegal. Land Econom. 89 (4), 676–698.

Berkouwer, S.B., Dean, J.T., 2019. Credit and attention in the adoption of profitable energy efficient technologies in Kenya. Working Paper Series No. WPS-098. Center For Effective Global Action. University Of California, Berkeley.

Bhat, P., Chanakya, H., Ravindranath, N., 2001. Biogas plant dissemination: success story of Sirsi, India. Energy Sustain. Dev. 5 (1), 39–46.

Bonan, J., Battiston, P., Bleck, J., LeMay-Boucher, P., Pareglio, S., Sarr, B., Tavoni, M., 2021. Social interaction and technology adoption: Experimental evidence from improved cookstoves in Mali. World Dev. 144, 105467.

Bond, T., Templeton, M.R., 2011. History and future of domestic biogas plants in the developing world. Energy Sustain. Dev. 15 (4), 347–354.

Brooks, N., Bhojvaid, V., Jeuland, M.A., Lewis, J.J., Patange, O., Pattanayak, S.K., 2016. How much do alternative cookstoves reduce biomass fuel use? Evidence from North India. Resour. Energy Econ. 43, 153–171.

Brown, V.J., 2006. Biogas: a bright idea for Africa. Environ. Health Perspect. 114 (5).

Cameron, L.A., 1999. The importance of learning in the adoption of high-yielding variety seeds. Am. J. Agric. Econ. 81 (1), 83–94.

Chen, Y., Yang, G., Sweeney, S., Feng, Y., 2010. Household biogas use in rural China: a study of opportunities and constraints. Renew. Sustain. Energy Rev. 14 (1), 545–549.

Churchill, S.A., Smyth, R., Farrell, L., 2020. Fuel poverty and subjective wellbeing. Energy Econ. 86, 104650.

Clemens, H., Bailis, R., Nyambane, A., Ndung'u, V., 2018. Africa Biogas Partnership Program: A review of clean cooking implementation through market development in East Africa. Energy Sustain. Dev. 46, 23–31.

Daioglou, V., Van Ruijven, B.J., Van Vuuren, D.P., 2012. Model projections for household energy use in developing countries. Energy 37 (1), 601–615.

Foster, A.D., Rosenzweig, M.R., 2010. Microeconomics of technology adoption. Annu. Rev. Econ. 2 (1), 395–424.

Gillingham, K., Palmer, K., 2014. Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. Rev. Environ. Econ. Policy 8 (1), 18–38.

Gordon, S.B., Bruce, N.G., Grigg, J., Hibberd, P.L., Kurmi, O.P., Lam, K.-b.H., Mortimer, K., Asante, K.P., Balakrishnan, K., Balmes, J., et al., 2014. Respiratory risks from household air pollution in low and middle income countries. Lancet Respir. Med. 2 (10), 823–860.

Gould, C.F., Hou, X., Richmond, J., Sharma, A., Urpelainen, J., 2020. Jointly modeling the adoption and use of clean cooking fuels in rural India. Environ. Res. Commun. 2 (8), 085004.

Gould, C.F., Jagoe, K., Moreno, A.I., Verastegui, A., Pilco, V., García, J., Fort, A., Johnson, M., 2018. Prevalent degradation and patterns of use, maintenance, repair, and access to post-acquisition services for biomass stoves in Peru. Energy Sustain. Dev. 45, 79–87.

Gould, C.F., Urpelainen, J., 2018. LPG as a clean cooking fuel: Adoption, use, and impact in rural India. Energy Policy 122, 395–408.

Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis: contrasts with mixed logit. Transp. Res. B 37 (8), 681–698.

Hanna, R., Duflo, E., Greenstone, M., 2016. Up in smoke: the influence of household behavior on the long-run impact of improved cooking stoves. Am. Econ. J. Econ. Policy 8 (1), 80–114.

Hauber, A.B., González, J.M., Groothuis-Oudshoorn, C.G., Prior, T., Marshall, D.A., Cunningham, C., IJzerman, M.J., Bridges, J.F., 2016. Statistical methods for the analysis of discrete choice experiments: a report of the ISPOR conjoint analysis good research practices task force. Value Health 19 (4), 300–315.

Hazra, S., Lewis, J., Ipsita, D., Singha, A.K., 2014. Adoption and use of improved stoves and biogas plants in rural India. South Asian Network For Development And Environmental Economics (SANDEE) Working Papers.
Herington, M., Lant, P., Smart, S., Greig, C., van de Fliert, E., 2017. Defection, recruitment and social change in cooking practices: Energy poverty through a social practice lens. Energy Res. Soc. Sci. 34, 272–280.
Hole, A.R., 2007. Fitting mixed logit models by using maximum simulated likelihood. Stata J. 7 (3), 388–401.
Hole, A.R., 2008. Modelling heterogeneity in patients' preferences for the attributes of a general practitioner appointment. J. Health Econ. 27 (4), 1078–1094.
Hole, A., 2016. MIXLOGITWTP: Stata module to estimate mixed logit models in WTP space.
Hole, A.R., Kolstad, J.R., 2012. Mixed logit estimation of willingness to pay distributions: a comparison of models in preference and WTP space using data from a health-related choice experiment. Empir. Econ. 42 (2), 445–469.
IEA, IRENA, UNSD, World Bank, WHO, 2020. Tracking SDG7: The Energy Progress Report. International Energy Agency, Paris.
Insam, H., Gómez-Brandón, M., Ascher, J., 2015. Manure-based biogas fermentation residues – Friend or foe of soil fertility? Soil Biol. Biochem. 84, 1–14.
Jagger, P., Das, I., Handa, S., Nylander-French, L.A., Yeatts, K.B., 2019. Early adoption of an improved household energy system in urban Rwanda. EcoHealth 16 (1), 7–20.
Jeuland, M.A., Bhojvaid, V., Kar, A., Lewis, J.J., Patange, O., Pattanayak, S.K., Ramanathan, N., Rehman, I., Soo, J.T., Ramanathan, V., 2015a. Preferences for improved cook stoves: Evidence from rural villages in north India. Energy Econ. 52, 287–298.
Jeuland, M.A., Pattanayak, S.K., 2012. Benefits and costs of improved cookstoves: assessing the implications of variability in health, forest and climate impacts. PLoS One 7 (2).
Jeuland, M., Pattanayak, S.K., Bluffstone, R., 2015b. The economics of household air pollution. Annu. Rev. Resour. Econ. 7 (1), 81–108.
Jeuland, M.A., Pattanayak, S.K., Samaddar, S., Shah, R., Vora, M., 2020. Adoption and impacts of improved biomass cookstoves in rural Rajasthan. Energy Sustain. Dev. 57, 149–159.
Jeuland, M., Pattanayak, S.K., Soo, J.-S.T., Usmani, F., 2019. Preferences and the effectiveness of behavior-change interventions: Evidence from adoption of improved cookstoves in India. J. Assoc. Environ. Resour. Econ. http://dx.doi.org/10.1086/706937, URL: arXiv:https://doi.org/10.1086/706937.
Johnston, R.J., Boyle, K.J., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T.A., Hanemann, W.M., Hanley, N., Ryan, M., Scarpa, R., et al., 2017. Contemporary guidance for stated preference studies. J. Assoc. Environ. Resour. Econ. 4 (2), 319–405.
Kar, A., Pachauri, S., Bailis, R., Zerriffi, H., 2019. Using sales data to assess cooking gas adoption and the impact of India's Ujjwala programme in rural Karnataka. Nature Energy 4 (9), 806–814.
Kelebe, H.E., Ayimut, K.M., Berhe, G.H., Hintsa, K., 2017. Determinants for adoption decision of small scale biogas technology by rural households in Tigray, Ethiopia. Energy Econ. 66, 272–278.
Krishnapriya, P., Chandrasekaran, M., Jeuland, M., Pattanayak, S.K., 2021. Do improved cookstoves save time and improve gender outcomes? Evidence from six developing countries. Energy Econ. 102, 105456.
Van der Kroon, B., Brouwer, R., Van Beukering, P.J., 2014. The impact of the household decision environment on fuel choice behavior. Energy Econ. 44, 236–247.
Lancaster, K.J., 1966. A new approach to consumer theory. J. Political Econ. 74 (2), 132–157.
Lancsar, E., Fiebig, D.G., Hole, A.R., 2017. Discrete choice experiments: a guide to model specification, estimation and software. Pharmacoeconomics 35 (7), 697–716.
Lewis, J.J., Bhojvaid, V., Brooks, N., Das, I., Jeuland, M.A., Patange, O., Pattanayak, S.K., 2015. Piloting improved cookstoves in India. J. Health Commun. 20 (sup1), 28–42.
Lewis, J.J., Hollingsworth, J.W., Chartier, R.T., Cooper, E.M., Foster, W.M., Gomes, G.L., Kussin, P.S., MacInnis, J.J., Padhi, B.K., Panigrahi, P., et al., 2016. Biogas stoves reduce firewood use, household air pollution, and hospital visits in Odisha, India. Environ. Sci. Technol. 51 (1), 560–569.
MacKerron, G.J., Egerton, C., Gaskell, C., Parpia, A., Mourato, S., 2009. Willingness to pay for carbon offset certification and co-benefits among (high-) flying young adults in the UK. Energy Policy 37 (4), 1372–1381.
Mani, S., Jain, A., Tripathi, S., Gould, C.F., 2020. The drivers of sustained use of liquified petroleum gas in India. Nat. Energy 5 (6), 450–457.
Manski, C.F., 1977. The structure of random utility models. Theory Decis. 8 (3), 229.
Marra, M., Pannell, D.J., Ghadim, A.A., 2003. The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? Agric. Syst. 75 (2–3), 215–234.
McFadden, D., 1981. Econometric models of probabilistic choice. In: Structural Analysis of Discrete Data with Econometric Applications. MIT Press, pp. 198–272.
Meeks, R., Sims, K.R., Thompson, H., 2019. Waste not: can household biogas deliver sustainable development? Environ. Resour. Econ. 72 (3), 763–794.
Miller, G., Mobarak, A.M., 2015. Learning about new technologies through social networks: experimental evidence on nontraditional stoves in Bangladesh. Mark. Sci. 34 (4), 480–499.
Mittal, S., Ahlgren, E.O., Shukla, P., 2018. Barriers to biogas dissemination in India: A review. Energy Policy 112, 361–370.
Mobarak, A.M., Dwivedi, P., Bailis, R., Hildemann, L., Miller, G., 2012. Low demand for nontraditional cookstove technologies. Proc. Natl. Acad. Sci. 109 (27), 10815–10820.
Mohapatra, S., Simon, L., 2017. Intra-household bargaining over household technology adoption. Rev. Econ. Househ. 15 (4), 1263–1290.
Nussbaumer, P., Nerini, F.F., Onyeji, I., Howells, M., 2013. Global insights based on the multidimensional energy poverty index (MEPI). Sustainability 5 (5), 2060–2076.
Pant, K.P., Pattanayak, S.K., Thakuri, M., 2014. Climate change, cookstoves, and coughs and colds: Thinking global and acting local in rural Nepal. In: Barrett, S., Mäler, K., Maskin, E. (Eds.), Environment And Development Economics: Essays in Honor of Sir Partha Dasgupta. Oxford Univ Press, New York, pp. 145–168.
Pattanayak, S.K., Jeuland, M.A., Lewis, J.J., Usmani, F., Brooks, N., Bhojvaid, V., Kar, A., Lipinski, L., Morrison, L., Patange, O., et al., 2019. Experimental evidence on promotion of electric and improved biomass cookstoves. Proc. Natl. Acad. Sci. 116 (27), 13282–13287.
Pattanayak, S.K., Pakhtigian, E.L., Litzow, E.L., 2018. Through the looking glass: Environmental health economics in low and middle income countries. In: Handbook Of Environmental Economics. vol. 4, Elsevier, pp. 143–191.
Paudel, J., 2021. Beyond the blaze: The impact of forest fires on energy poverty. Energy Econ. 105388.
Raha, D., Mahanta, P., Clarke, M.L., 2014. The implementation of decentralised biogas plants in Assam, NE India: The impact and effectiveness of the National Biogas and Manure Management Programme. Energy Policy 68, 80–91.
Rao, N.D., Kiesewetter, G., Min, J., Pachauri, S., Wagner, F., 2021. Household contributions to and impacts from air pollution in India. Nat. Sustain. 1–9.
Rao, K.U., Ravindranath, N., 2002. Policies to overcome barriers to the spread of bioenergy technologies in India. Energy Sustain. Dev. 6 (3), 59–73.
Ravindranath, N., Balachandra, P., 2009. Sustainable bioenergy for India: Technical, economic and policy analysis. Energy 34 (8), 1003–1013.
Reddy, A.K., 2004. Lessons from the Pura community biogas project. Energy Sustain. Dev. 8 (3), 68–73.
Rehfuess, E.A., Puzzolo, E., Stanistreet, D., Pope, D., Bruce, N.G., 2014. Enablers and barriers to large-scale uptake of improved solid fuel stoves: a systematic review. Environ. Health Perspect. 122 (2), 120–130.
Revelt, D., Train, K., 1998. Mixed logit with repeated choices: households' choices of appliance efficiency level. Rev. Econ. Stat. 80 (4), 647–657.
Revelt, D., Train, K., 2000. Customer-Specific Taste Parameters and Mixed Logit: Households' Choice of Electricity Supplier. Technical Report, University of California at Berkeley.
Scarpa, R., Thiene, M., Train, K., 2008. Utility in willingness to pay space: a tool to address confounding random scale effects in destination choice to the Alps. Am. J. Agric. Econ. 90 (4), 994–1010.
Schleich, J., Gassmann, X., Meissner, T., Faure, C., 2019. A large-scale test of the effects of time discounting, risk aversion, loss aversion, and present bias on household adoption of energy-efficient technologies. Energy Econ. 80, 377–393.
Sharma, A., Parikh, J., Singh, C., 2019. Transition to LPG for cooking: A case study from two states of India. Energy Sustain. Dev. 51, 63–72.
Shukla, P., 2007. Biomass Energy Strategies For Aligning Development And Climate Goals In India. Netherlands Environmental Assessment Agency (MNP).
Somanathan, E., Bluffstone, R., 2015. Biogas: Clean energy access with low-cost mitigation of climate change. Environ. Resour. Econ. 62 (2), 265–277. http://dx.doi.org/10.1007/s10640-015-9961-6, URL: https://ideas.repec.org/a/kap/enreec/v62y2015i2p265-277.html.
Sonnier, G., Ainslie, A., Otter, T., 2007. Heterogeneity distributions of willingness-to-pay in choice models. Quant. Mark. Econ. 5 (3), 313–331.
Sovacool, B.K., 2012. The political economy of energy poverty: A review of key challenges. Energy Sustain. Dev. 16 (3), 272–282.
Sovacool, B.K., 2014. Defining, measuring, and tackling energy poverty. Energy Poverty Glob. Chall. Local Solut. 2, 21–53.
Sun, D., Bai, J., Qiu, H., Cai, Y., 2014. Impact of government subsidies on household biogas use in rural China. Energy Policy 73, 748–756.
Swain, S.S., Mishra, P., 2020. Determinants of adoption of cleaner cooking energy: experience of the Pradhan Mantri Ujjwala Yojana in rural Odisha, India. J. Clean. Prod. 248, 119223.
Takama, T., Tsephel, S., Johnson, F.X., 2012. Evaluating the relative strength of product-specific factors in fuel switching and stove choice decisions in Ethiopia. A discrete choice model of household preferences for clean cooking alternatives. Energy Econ. 34 (6), 1763–1773.
Thomson, H., Snell, C., Bouzarovski, S., 2017. Health, well-being and energy poverty in Europe: A comparative study of 32 European countries. Int. J. Environ. Res. Public Health 14 (6), 584.

Tinker, I., 1987. The real rural energy crisis: women's time. Energy J. 8, 125–146.
Train, K.E., 2009. Discrete Choice Methods With Simulation. Cambridge University Press.
Train, K., Weeks, M., 2005. Discrete choice models in preference space and willingness-to-pay space. In: Applications Of Simulation Methods In Environmental And Resource Economics. Springer, pp. 1–16.
Vijay, V.K., Kapoor, R., Trivedi, A., Vijay, V., 2015. Biogas as clean fuel for cooking and transportation needs in India. In: Advances in Bioprocess Technology. Springer, pp. 257–275.
Walekhwa, P.N., Mugisha, J., Drake, L., 2009. Biogas energy from family-sized digesters in Uganda: Critical factors and policy implications. Energy Policy 37 (7), 2754–2762.
Whittington, D., 2010. What have we learned from 20 years of stated preference research in less-developed countries? Annu. Rev. Resour. Econ. 2 (1), 209–236.
World Health Organization, 2016. Burning Opportunity: Clean Household Energy for Health, Sustainable Development, And Wellbeing of Women And Children. World Health Organization.
World Health Organization, 2021. Household energy database. www.who.int/data/gho/data/themes/air-pollution/who-household-energy-db. (Accessed 23 July 2021).