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Economics of clean air: Valuation of reduced health risks from Household Air Pollution – A study of rural Indian Households

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Abstract

The rate of adoption of preventive measures for avoiding environmental and health risks arising from household air pollution remains quite low in developing countries, particularly in rural areas.. To successfully implement interventions for mitigating such risks, it is necessary for policymakers to understand the public attitude and perception towards such mitigations, which is reflected in their willingness to pay for reducing such health risks. This paper takes a contingent valuation approach to estimate the willingness to pay for reduction in such health risks using a double bounded dichotomous choice approach analysing its potential determinants. Concurrently, this paper also investigates the presence and potential sources of anomalies in such model. Results suggests that the estimated mean annual willingness to pay for reduction in health risks related to household air pollution is INR 678.14, accounting for approximately 1% of annual household income. Furthermore, the results demonstrate the presence of anomalies like internal inconsistency and anchoring effect validating the existence of starting point bias. The analysis of within-sample heterogeneity of the estimated mean annual willingness to pay further enables us to recommend policies like generating public awareness about health risks from household air pollution and targeting potential beneficiaries based on observable characteristics.

Keywords: willingness to pay; anchoring effect; contingent valuation method; estimated propensity score; household air pollution

JEL classification code: Q51, Q5

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1. Introduction

Household Air Pollution (HAP, hereafter) caused primarily by the incomplete combustion of dirty cooking fuels such as firewood and solid bio-mass fuels is a salient environmental and health risk particularly in developing countries. Estimates of the burden of HAP in India alone show approximately 1.04 million premature deaths as well as 31.4 million disability adjusted life years (Balakrishnan et al., 2014).

Health risks associated with HAP can be adequately prevented through exposure reduction via the usage (adoption) of modern cooking fuels (technologies) particularly in developing economies. However, regardless of the expected health benefits from such behaviour, several factors such as, liquidity constraints (e.g., Bensch et al., 2015) and a failure to perceive the seriousness of such health risks (Mobarak et al., 2012) may pose significant barriers to the usage (adoption) decision. Thus, it transpires that the implementation of suitable intervention policies to mitigate the HAP-related health risks may face numerous logistic challenges that in turn may reduce its effectiveness. To ensure the effectiveness of such interventions, understanding the attitude of the potential beneficiaries towards the mitigation of such health risks often reflected through their perceived private health benefits from the reduced exposure to HAP, becomes necessary (Shannon et al., 2019).

Perceived private health benefits of the individuals may be evaluated by estimating the valuation of reduction in health risks related to HAP as has been attempted in this study. In particular, we attempt to assess the individuals' valuation of reduced health risk from HAP exclusively, derived from a hypothetical improvement in household air quality.

Since the valuation of reduced health risk is non-amenable to market valuation, we have employed the contingent valuation method (CVM, hereafter). CVM is particularly useful for estimating the economic valuation of non-market goods owing to its greater flexibility in creating specific markets with proposed improvement (Andersson et al., 2016). Off late, the application of CVM to estimate the economic valuation of environmental resources and/or health risks related to ambient air pollution, smog mitigation and nuclear power among others, have garnered attention (Du and Mendelsohn, 2011; Sun and Zhu, 2014; Sun et al., 2016).

Compared to the wealth of literature related to environmental valuation , research on the valuation of economic cost of HAP is relatively small (Jeuland et al., 2015). To the best of our knowledge, only the study by Shannon et al. (2019) have implemented the CVM approach to estimate the valuation of HAP-related health risks in tandem with other environmental health risks. In this paper, we have tried to extend the literature related to the valuation of environmental health risks from HAP exclusively in the context of a developing economy using CVM. In particular, we exploit the double bounded dichotomous choice (DBDC, hereafter) approach under CVM.

Although DBDC method is preferred because of its relative statistical efficiency (Hanemann et al., 1991), its criticisms are widespread. DBDC responses may suffer from anomalies such as internal inconsistency arising from the difference in incentive compatibility across the two responses (Carson et al., 1998) and starting point bias (Gelo and Koch, 2015). In this study, we have tried to investigate the presence of such anomalies in DBDC models in the context of reduction in HAP-related health risks.

We analyse a unique contingent valuation dataset from 557 survey respondents in rural West Bengal, India. The annual mean WTP from the double bounded dichotomous approach is estimated to be INR 734.91 (~US$13). It is significantly lower than the estimated mean WTP obtained from the single bound dichotomous choice conforming to the presence of internal inconsistency in DBDC response. Furthermore, the results demonstrate the presence of anchoring effect validating the existence of starting point bias. Controlling for this, the estimated mean annual WTP for reduction in health risks related to HAP is estimated to be INR 678.14 (~US$12), accounting for approximately 1% of annual household income.

Given the evidence of the influence of individual-specific covariates in the individuals' WTP decision, we further attempt to explore the within-sample heterogeneity of the estimated mean WTP based on contextually relevant judiciously selected covariates. Our analysis of the within-sample heterogeneity of estimated mean WTP further indicates that any variation in individual-specific covariates may result in sufficient fluctuation in estimated mean WTP within the sample. This analysis may be particularly useful in designing effective policies for smooth implementation of interventions targeted towards HAP mitigation.

The contribution of this study is three-fold. First, this study attempts to provide a direction to understand the revealed preference for the reduction in health risks related to HAP of the potential beneficiaries by assessing the WTP values. This is possibly needed to understand the individual preferences and attitude for reduction in HAP for successful implementation[1]. Second, this study attempts to address the issue of starting point bias that may arise in DBDC approach in the context of health risks from HAP in developing countries. Finally, the analysis of within-sample heterogeneity of the estimated mean annual WTP further enables us to recommend policies like generating public awareness about HAP risk and targeting potential beneficiaries based on observable characteristics. Such policy is expected to ensure smooth implementation and enables one to assess the effectiveness of intervention programs to reduce HAP.

[1] Studies have elaborated that despite the implementation of several interventions targeted for low-income households in developing countries, few have delivered desired results. This is mainly due to the tendency of the households to reduce the sustained usage of modern cooking technology due to lack of maintenance or reversion to former behaviour once, the promotion period is over (Hanna et al., 2016). Therefore, for successful and sustained implementation, it is necessary to understand the attitude and preference of the potential beneficiaries about reduction in HAP-related health risks before such interventions,

The remainder of the paper is organized as follows. Section 2 presents the theoretical background of the CVM, highlighting on the potential anomalies in DBDC setup. Section 3 describes the survey methodology and variables considered for the study along with their summary statistics. It also elaborates on the methodology to elicit the bid responses. The next section presents our empirical models and estimation results. Section 5 presents the analysis of the within-sample heterogeneity of the estimated mean WTP based on contextually relevant covariates and its policy implications. The paper concludes by discussing directions of future research.

2. CVM and DBDC anomalies: Background

The theoretical underpinning of the CVM essentially follows from the cost-benefit analysis. A rational individual is willing to pay the proposed bid for any environmental resource and/or risk reducing goods (services) if and only if his or her utility from the resources and/or risk reduction is at least equivalent to the utility without them. The equivalent analogous condition states that a rational individual will agree to pay the proposed bid if and only if the willingness to pay for such goods (services) is at least equal to the proposed bid (Donfuet et al., 2014). It may be noted that the estimation of the mean WTP is dependent on the distributional assumption of the stochastic component of the utility function.

To estimate the individuals' WTP, elicitation of bid responses using a single dichotomous approach (referred to as single bounded dichotomous choice, SBDC) has been preferred over other approaches for being incentive compatible (Carson et al, 1998). However, critics argue that since, individual preferences are developed through repetition and practice, the estimated WTP obtained by SBDC approach may suffer from uncertainty reflected through high dispersion due to lack of well-defined preference (Plott et al., 2005). Thus, to incorporate the dynamic aspect of individual preferences, the DBDC approach is introduced, where the elicitation of bid response is supplemented with a follow-up dichotomous choice question (Cameron and Quiggin, 1994). This improves the statistical efficiency of the estimated WTP by exploiting the combination of responses from both the rounds.

Despite the advantages, the criticisms of DBDC are widespread. For example, difference in the estimated mean WTP from SBDC and DBDC models may exist due to variation in incentive compatibility, which is referred to as internal inconsistency in literature (Donfuet et al., 2014). However, repeated valuation question may offer familiarity to the respondents resulting in the attenuation of this difference over time (Bateman et al., 2008). In addition, empirical evidence suggests that WTP in two rounds of DBDC approach are often driven by the heterogeneity in preference, which results in divergence in WTP in both rounds (Herriges and Shogren, 1996).

The key explanation behind this divergence is starting point bias where individuals' response in follow up round is dependent on that of the initial round. Starting point bias may be broadly categorised into anchoring effect and shift effect; both of which arise when individuals are uncertain about the true value of the non-market good and perceive the initial bid to be the true value.

Anchoring effect arises when uncertain individuals update their follow-up WTP in a Bayesian perspective, conditioned on their prior beliefs of WTP and initial bid (Herriges and Shogren, 1996). Mathematically, under the anchoring effect, the WTP in follow-up round, w_{i2}^* can be represented as: $w_{i2}^* = \gamma b_{1i} + (1 - \gamma) w_{i1}^*$, where γ is the anchoring effect parameter with $0 < \gamma < 1$, assumed to be constant across all individuals; w_{i1}^* is the WTP in initial round and b_{1i} is the initial bid for representative individual *i*. Alternatively, under the shift effect, individuals consider the increasing (decreasing) follow-up price to be an unfair request to pay an additional amount for the same good (indicator of an under-quality good) resulting in a tendency to understate the WTP in the follow-up round (Alberini et al., 1997). Thus, under the shift effect, the WTP in the follow-up round is specified as $w_{i2}^{*} = w_{i1}^{*} + \delta$, where δ is the shift effect parameter with $\delta < 0$. In the simultaneous presence of anchoring and shift effects, the follow-up WTP may be expressed as $w_{i2}^{*} = \gamma b_{i1} + (1 - \gamma) w_{i1}^{*} + \delta$ (Gelo and Koch, 2015).

3. Data

3.1. Survey design

To collect the data, we have conducted a contingent valuation survey in 17 villages under the Dhapdhapi-II village council in the state of West Bengal, India. The rural areas of West Bengal show a high incidence of dirty fuel usage (92.7%) as their primary cooking fuel (NSSO, 2015). This indicates that the issue of HAP is quite prevalent in the rural regions of West Bengal, thus motivating our research design.

The survey site is located approximately 40 kilometers from the state capital, Kolkata and are densely populated with a population density of 700 per square kilometer as on January 2016. Due to its proximity to the metropolis, these villages have easy access to modern amenities but at the same time retain the typical traits of a rural area in any developing country.

We have conducted the survey following the procedure outlined below. A random sample of 600 households has been chosen for analysis. Our respondents are the individuals primarily responsible for cooking in the households; consequently, all of them are females. Our enumerator team has conducted the survey by door-to-door interview method between December 2017 and January 2018; ensuring a high response rate (98%). For the analysis, we exclude from our sample the respondents who have no spouse or provide no information on the spouse, thus, our effective sample size reducing to 557.

<Table 1 approximately here>

3.2.Description of the variables and their summary statistics

Self-reported health status

The association of HAP with various respiratory and vision-related diseases is well-established in literature (Smith and Pillarisetti, 2017). To account for this, following, Hanna et al. (2016) and based on our initial analysis of pilot study data, we have selected the three most common symptoms namely, dry cough, sore or runny eyes and difficulty in breathing in the final questionnaire .

The self-reported health status of the respondent refers to whether the respondents have experience at least one of three above mentioned minor yet common symptoms caused by HAP in the last 30 days. These physical symptoms are indeed, found to be prevalent among the respondents; around 76% of them have experienced at least one of the above-mentioned physical symptoms in the last 30 days (see Table 1).

Cooking fuel usage pattern

In this study, the cooking fuel usage pattern of the household is an important covariate and is represented by the fraction of days the dirty cooking fuel has been used for cooking in a 30-day period. We have computed the fraction of days of dirty fuel usage using the information on the number of days the respondent used coal/charcoal, solid biomass fuels, and firewood[2] in 30 days prior to the previous month.

[2] Although WHO (2018) classified kerosene to be dirty cooking fuel, we have conducted our survey in 2017-18, before this classification was published. In our study, we have consistently followed the nomenclature referred by Duflo et al. (2008) among others, where kerosene is classified as clean cooking fuel. In our study, we have consistently followed the nomenclature referred by Duflo et al. (2008) among others, where kerosene is classified as clean cooking fuel. In our effective sample, there is no observation that uses kerosene as the primary cooking fuel. Only 4% of the households use kerosene at least once in a 30-day period, thereby, having a non-zero value in the share of days of kerosene usage, keeping the remaining 96% observations as same. Even if we include kerosene to be a dirty cooking fuel, the variable 'fraction of days of dirty fuel usage in a 30-day period' is not

The fraction of days of dirty fuel usage is found to be 0.68 on an average, suggesting the higher prevalence of dirty fuel usage in rural India (see Table 1). At a cursory glance, this may suggest that despite the significant burden of HAP related symptoms, respondent households tend to show a relatively high-risk behaviour related to cooking fuel usage. This also supports the necessity of such valuation assessment.

Perception of health risks related to HAP

The approach to incorporate individuals' risk perception in the form of verbal scales (like Likert scale) to represent subjective likelihood is often criticised due to non-verifiability of the assessment and difficulty with inter-personal comparability of the subjective risk (Anglewicz and Kohler, 2009). Therefore, we include the individuals' perceived subjective health risk related to HAP in the form of probabilistic expectations on a scale of zero to ten elicited through interactive elicitation method using visual aids[3].

We presume that the respondents' perceived risk of suffering from above-mentioned HAP related symptoms in the next 30 days depends only on their current health status and fuel usage. In other words, the risk of being sick[4] is assumed to follow a first-order Markov process conditional on cooking fuel usage (Ross, 1996). Based on this assumption, we have elicited the respondents' perceived likelihood of becoming sick from HAP-related physical symptoms in the next 30 days from dirty fuel usage for two alternative situations, namely, currently being *sick* and *not sick*.

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changed much (mean changes from 0.682 to 0.689; standard deviation changes from 0.373 to 0.374). Therefore, we have preferred to retain kerosene as clean fuel, to maintain internal consistency among the survey, data and analysis.

[3] The methodology to elicit the individuals' subjective perception in probabilistic form, through interactive method using visual aids is elaborated in the study by Delavande and Kohler (2016).

[4] By "sick," we refer only to the situation of having suffered from at least one of the three HAP-related physical symptoms—dry cough, sore or runny eyes, and difficulties in breathing in a 30-day period.

Using these two elicited perceptions conditional on dirty fuel usage, we calculate the equilibrium distribution of the Markov process denoted as $SP[s = 1|d]$. Under the assumption of first-order Markov dependence, this represents the perception about the long-term fraction of periods during which the respondent would be sick provided that she uses dirty fuels. In other words, $SP[s = 1|d]$ may be interpreted as the perceived health risk from dirty fuel usage. Likewise, we derive the other equilibrium distribution of the Markov process conditional upon clean fuel usage denoted by $SP[s = 1|c]$. We include the difference in the perceptions of health risks from dirty and clean fuel usage (i.e., $SP[s = 1|d] - SP[s = 1|c]$) in our analysis. This difference, being non-negative, may be interpreted as the individuals' perceived increase in health risk from using dirty cooking fuels instead of clean cooking fuels.

Although the respondents have exhibited relatively low risk-averting behaviour, they seem to perceive an association between dirty fuel usage and deterioration of their health. The mean difference of 0.57 between $SP[s = 1|d]$ and $SP[s = 1|c]$ suggests that individuals on an average perceive that the dirty fuel usage is 57 percentage points more likely to degrade their health than the clean fuel usage.

Methodology to elicit the bid responses & their description

As our survey respondents are individuals from a rural area, it has been presumed that they are not much familiar with the sophisticated preventive measures from HAP. Therefore, to facilitate their understanding, the enumerators referred to the preventive device to be something similar to electric chimneys or exhaust fans that will reduce the incidence and extent of smoke in the cooking area, as an example.

To control for any hypothetical bias arising from over-stating (under-stating) WTP from the true value, we have tried to present the scenario as realistic as possible. Before the elicitation, the enumerator team elaborated the benefit that the respondent may accrue and the cost they may have to incur for using the hypothetical preventive device[5]. For elicitation of bid responses, the following question was asked to the respondents:

"Are you willing to pay [initial bid] per year for using this preventive device?"

Informal interview during the pilot test helped us to choose three levels of initial bid: INR 100, INR 500 and INR 750. To avoid the problem of initial bid bias, we have randomly assigned these initial bids to the respondents. Following the standard norms of the DBDC approach, the follow-up bid has been doubled (halved) if the respondents give affirmative (negative) responses for the initial bid.

Characteristics of the bid responses

Since the bids are randomly assigned, following Imbens and Rubin (2015), we try to ensure the balance among the covariates in the assignment mechanism. Table 2 indicates that the number of individuals assigned to each initial bid level is more or less the same. Figure 1 presents the histograms along with the kernel density estimates of the estimated propensity score for each bid category[6] resulting from such random allocation of the survey units in three categories.

<Figure 1 approximately here>

A visual inspection of Figure 1 suggests that the estimated propensity scores in the three categories are more or less similar and are lying in the range of 0.1 to 0.6 with the mode in the range of 0.3 to 0.4. Thus, it may be concluded that the propensity score matching has been ensured in the three categories resulting in covariate balance among the three bid groups. Such

[5] The instructions and survey instruments used to elicit the bid responses are presented in the appendix (4.A1).

[6] The estimated propensity scores are obtained through the multinomial discrete choice logistic regression model, as a natural generalization of the method suggested by Imbens and Rubin (2015), p 286-287, to accommodate the three bid categories as the dependent variable.

covariate balance among the bid groups ensures that the groups are otherwise similar, and thus the bid responses are not biased in favour of any particular group.

Table 2 presents the distribution of proportion of acceptance across various bid levels. As the levels of bid increases, the proportion of acceptance to pay the bid level decreases. As an example, out of 197 individuals who are assigned the initial bid of INR 100, approximately 68% of them have expressed willingness to pay both the initial and the follow-up bid. But the share of individuals having affirmative responses in both rounds steadily declines to 8.65% (out of 185) when the initial bid assigned is INR 750.

<Table 2 approximately here>

Other covariates

In addition to the respondents' health status, cooking practice and perception of health risks, individual and household-specific factors may affect the respondents' valuation of reduced health risks. Therefore, in our model, we control for a set of factors including number of cooks (surrogate of household size), total monthly household expenditure (surrogate for household income), age, respondents' years of schooling, dummy for holding decision-making authority in the household (respondent holds the household decision-making authority), dummies for the occupation of the spouse (spouse works in informal sector and that in the agricultural sector), dummy for the location of the cooking area (cooking area located inside the dwelling area), dummy for ventilation (cooking area has ventilation facility) and dummy for the ownership of television.

4. Estimation models and results

To estimate the individuals' valuation of reduced health risks from reducing HAP exposure and thereby improving indoor air quality, we try to estimate a DBDC model. As a benchmark, we start with the most generalised DBDC model allowing the individuals' WTP to vary over the two rounds. Let the latent WTP (expressed in the logarithmic form[7]) of individual i in round k (w_{ik}^*) be a linear function of her prior experiences of HAP-related symptoms (s_i), cooking fuel usage pattern ($cook_i$), individual and household characteristics (z_i), and the perception of health risks ($risk_i$) where k = {1,2} representing initial and follow-up rounds respectively. In particular, the individual's WTP given the observed characteristics may be specified as:

$$\begin{bmatrix} \boldsymbol{w}_{i1}^* \\ \boldsymbol{w}_{i2}^* \end{bmatrix} = \begin{bmatrix} \boldsymbol{X}_i' \\ \boldsymbol{X}_i' \end{bmatrix} \boldsymbol{\beta} + \begin{bmatrix} \boldsymbol{u}_{i1} \\ \boldsymbol{u}_{i2} \end{bmatrix}, \tag{1}$$

where $X_i = [1 \quad \boldsymbol{z_i} \quad cook_i \quad s_i \quad risk_i]$and $\boldsymbol{u_i} = \begin{bmatrix} u_{i1} \\ u_{i2} \end{bmatrix}$ is the idiosyncratic error term uncorrelated with X_i. We further assume, with the usual notation $\begin{bmatrix} u_{i1} \\ u_{i2} \end{bmatrix} \sim N_2\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}\right)$. Since the individual's WTP is latent, it is estimated using the observed bid responses. Assuming $\begin{bmatrix} Y_{i1} \\ Y_{i2} \end{bmatrix}$ to be individual i's bid response, let $\mathbb{I}(\cdot)$ be an indicator function that links the individual's latent WTP to bid response in the following way:

$$\boldsymbol{Y_{ik}} = \mathbb{I}(\boldsymbol{w_{ik}^*} \geq \boldsymbol{b_{ik}}), \tag{2}$$

The indicator function $\mathbb{I}(\cdot)$ takes the value 1 if $w_{ik}^* \geq b_{ik}$ where, b_{ik} is the bid value of individual i for round k, $k = 1,2$. Ignoring the bid response from the follow-up round further simplifies the model, thereby representing the SBDC model.

On the basis of these assumptions, a likelihood function can be written based on the response probabilities for each response category in two rounds. The parameters associated with the covariates X_i and bid variables are obtained through the maximum likelihood method of estimation. Given the log-normal specification of the model, the estimated mean willingness

[7] The lognormal specification of WTP distribution appears to fit the skewed pattern of survey responses in a better way (Herriges and Shogren, 1996). It also allows us to ignore the negative WTP by restricting the distribution in the interval$(0, +\infty)$.

to pay can be computed as $\hat{E}(w^*) = \exp\left(\frac{\bar{X}'\hat{\boldsymbol{\beta}}}{\hat{\theta}} + 0.5\hat{\sigma}^2\right)$ where, $\hat{\beta}, \hat{\theta}$ are the estimated parameters of covariates and bids respectively; $\bar{X}$ is the average of other covariates based on the data (Du and Mendelsohn, 2011). Apart from providing the point estimates of mean WTP, we also report its confidence intervals using the Monte Carlo simulation method developed by Krinsky and Robb (1986)[8] by employing the parametric bootstrap procedure.

There are two primary concerns regarding the above model which we want to investigate. First, there is a possibility of internal inconsistency where, the mean WTP obtained from DBDC approach and SBDC approach may differ significantly. Second, the model described in equation (1) may suffer from starting point bias. We try to address these two concerns as detailed in the subsections below.

4.1. Base WTP estimates & internal inconsistency in DBDC responses

Estimation model

We start with restricting the parameters of equation (1) such that the individual's WTP remains invariant over the two rounds ($w_{i1}^* = w_{i2}^*$) and the randomness of the error term is only responsible for any variation. Under these cross-equation parametric restrictions, the model specified in equations (1) and (2) reduces to the following restricted bivariate probit model.

$$\begin{bmatrix} \boldsymbol{Y_{i1}} \\ \boldsymbol{Y_{i2}} \end{bmatrix} = \mathbb{I}\left(\begin{bmatrix} \boldsymbol{X_i'\beta} + \boldsymbol{u_{i1}} \\ \boldsymbol{X_i'\beta} + \boldsymbol{u_{i2}} \end{bmatrix} \geq \begin{bmatrix} \boldsymbol{b_{i1}} \\ \boldsymbol{b_{i2}} \end{bmatrix}\right), \tag{3}$$

with $\begin{bmatrix} u_{i1} \\ u_{i2} \end{bmatrix} \sim N_2\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{bmatrix}\right)$. Equation (3) suggests for the joint estimation of parameters through the maximum likelihood estimation method.

Under the SBDC specification, the model defined in equation (1) reduces to:

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[8] The point estimates along with the 95% confidence intervals by Krinsky- Robb method of mean WTP may be computed using the user-written command *wtpcikr* (10000 replications) in statistical software STATA (Jeanty, 2007).

$$\boldsymbol{w_i^*} = \boldsymbol{X_i'\beta} + \boldsymbol{u_i}, \tag{4}$$

where u_i is the idiosyncratic error term. The observed bid response of the individual (Y_i) is an indicator variable that takes the value unity if the respondent is willing to pay the bid. We assume that Y_i and w_i^* are associated in the following way: $Y_i = 1 \; if \; w_i^* \geq b_i$ and $Y_i = 0 \; if \; w_i^* < b_i$. We further assume that u_i is normally distributed with 0 mean and variance σ^2. Under these assumptions, the parameters of the SBDC model stated in (4) may then be estimated using a naïve probit model.

Estimation results

<Table 3 approximately here>

Table 3 presents the estimation results of equation (3). We start with the individual- and household-specific covariates (columns 1a and 1b) and sequentially incorporate the covariates related to health (columns 2a and 2b) and risk perception (columns 3a and 3b) in the estimation model. In line with the previous literatures, the results show a negative price effect that remains uniform across all model specifications (p < 0.01) Several other uniform patterns in the estimation results are also observed once we increase the number of controls.

Individual's experience of being sick with HAP related symptoms is positively and significantly associated with her probability of paying the proposed bids. In addition, households having a higher fraction of days of dirty fuel usage have a lower tendency to pay the proposed bid. This may indicate that individuals' cooking practices may have some role in individuals' valuation of the reduced health risks from HAP. Besides, individuals with higher household income and holding household decision-making authority have a higher tendency to pay the proposed bid. Interestingly, younger individuals tend to pay the proposed bid more in comparison to the older individuals.

Individuals' perception of health risk seems to play a role in bid response decision only for the follow-up bid. As presented in column 3b, the perceived increase in health risks from dirty fuel usage significantly increase the individuals' probability to pay the follow-up bid (p <0.01). This may suggest that an enhancement in the perceived increase of health risks from dirty fuel usage will increase the likelihood of paying the follow-up bid.

Columns 1 to 3 in Table 4 present the estimated coefficients of the SBDC model specified in equation (4). Similar to the previous estimation results described in Table 3, we sequentially increase the number of covariates in the estimation model. The value of the proposed bid is negatively and significantly associated with the likelihood to pay it (p < 0.01) and this is invariant with the number of covariates in the model. Over-all, the results of the DBDC model for the initial round response remains largely unchanged both quantitatively and qualitatively, even when the follow-up response is ignored. as has been frequently observed in literatures (e.g., Du and Mendelsohn, 2011).

<Table 4 approximately here>

Table 5 presents the estimated WTP from the SBDC and DBDC approach along with the 95% confidence interval. Using the results presented in columns 3a and 3b of Table 3, the mean annual WTP from the DBDC model (μ_{DBDC}) is estimated as INR 731.68 (~US$13) per year; the ratio of 95% confidence intervals to mean is 0.58. Analogously, using the findings presented in column 3 of Table 4, the annual mean WTP from the SBDC model (μ_{SBDC}) is estimated as INR 734.91 (~US$13.05) with the ratio of 95% confidence intervals to mean as 0.59. Thus, we may conclude that the DBDC model yields more efficient welfare estimates, however, the magnitude of the efficiency gain may be low.

<Table 5 approximately here>

To investigate the presence of internal inconsistency, it is sufficient to test whether μ_{DBDC} is significantly different from μ_{SBDC} (Donfuet et al., 2014). In other words, we need to test if the difference between μ_{SBDC} and μ_{DBDC} differs significantly from *zero*. For testing this hypothesis, we need to control for a key econometric issue, as indicated here.

The estimation of μ_{SBDC} exploits the response data from the initial round while the same response supplemented with the follow-up response data is used to compute the estimate of μ_{DBDC}. This may result in dependence structure in the sample leading to difficulty in obtaining a known closed form estimate of the standard error of the difference (Bateman et al., 2008). To address this, following Donfuet et al. (2014) we have estimated the standard error of the difference through bootstrapping (with 500 replications).

As shown in Table 5, the null hypothesis of $\mu_{SBDC} - \mu_{DBDC}$ being zero gets rejected at one per cent level of significance. The difference between the estimated mean annual WTP for the preventive device through the two approaches is obtained as INR 3.23 with a bootstrap standard error of INR 0.033. This suggests that although the efficiency gain is only 1% as observed earlier, the mean WTP from the SBDC and DBDC approaches differs significantly indicating the presence of internal inconsistency.

4.2. WTP estimates correcting for starting point bias

Estimation model

We attempt to investigate the potential sources of starting point bias in our DBDC model (if present). For this purpose, modeling the data in the panel format becomes particularly useful. Since we have two responses for each respondent, it is possible to represent the data in the panel structure defined in the following way:

$$\boldsymbol{w_{it}^{*}} = \boldsymbol{X_i'\beta} + \boldsymbol{u_{it}}, \tag{5}$$

where, the unobserved error term $u_{it} = (\alpha_i +, r_{it})$ captures the individual-specific (random) effect α_i and idiosyncratic effect, r_{it}, t = {1,2} representing initial and follow-up rounds respectively.

The panel data structure specification allows for the inclusion of shift effect and anchoring effect in the model. The shift effect is introduced in the model as an indicator variable $(t-1)$ that takes the value unity if the response is from the second round (Alberini et al., 1997). Alternatively, the anchoring effect is introduced in the model as $(t-1)b_{it}$ that captures the possibility that response in the follow-up question depends on the initial bid (Gelo and Koch, 2015). Therefore, in the presence of shift effect and anchoring effect, equation (5) may be reorganized in the following way:

$$\boldsymbol{w_{it}^{*} = X_i'\beta + \delta(t-1) + \gamma(t-1)b_{it} + u_{it}}, \tag{6}$$

where, δ is the shift effect parameter, and γ is the anchoring effect parameter. If an individual's observed sequence of bid response is defined as Y_{it}, then she will be willing to pay the bid if, $w_{it}^{*} \geq b_{it}\ \forall\ t = 1{,}2$. Under the assumption that u_{it} is normally distributed, we can estimate equation (6) using a random effect probit model.

Estimation results

<Table 6 approximately here>

Columns 1 to 4 in Table 6 presents the estimation results of the random effect probit model defined in equation (6). We start assuming the absence of any starting point bias and alternatively include shift effect (column 2) and anchoring effect (column 3) in the model. Finally, to ensure whether the shift (anchoring) effect is not capturing any other effect inappropriately, the simultaneous presence of both the effects is also considered in the estimation (column 4).

We observe that the anchoring effect is present within the DBDC model, but its effect is marginal (p <0.1) (see columns 3 and 4 of Table 6). This suggests that the initial bid may have influenced the individuals' decision in the follow-up round. In absolute terms, the value of the effect is approximately 0.217 (see column 4); indicating that the individuals refer 21.7% of their WTP to the initial bid while responding to the follow-up question. We also find that the coefficient of the shift effect is not statistically significant at 10% level. In other words, there is little evidence that shift effect is the source of starting point bias in our model. As indicated in Table 6, the rest of the results are more or less similar to those based on the DBDC model presented in Table 3.

Using the results presented in column 4 of Table 6 that include for both shift effect and anchoring effect, the mean annual WTP correcting for the starting point bias (μ_{WTP}) is estimated as INR 678.14 (~US$12) with 95% confidence intervals between INR 547.22 and INR 1036.96 (see Table 5). This estimated WTP accounts for approximately 1% of the respondents' annual household income on an average and lies in a comparable range with the existing studies.

As a comparison[9], Shannon et al. (2019) have estimated the mean monthly WTP for reducing HAP exposure to be in the range of \$1.09 −\$1.68 which is approximately 1−2 % of the monthly household income in their revealed preference study of rural Indian households. It should be noted that Shannon et al (2019) have conducted the survey in rural India during 2013

[9] To compare our estimated valuation for reduced health risks from HAP with that in existing literatures, we express the estimated mean WTP in *monthly* terms. Based on our analysis, the estimated mean WTP per month is approximately INR (678.14/12)=56.51 which is, on an average, around 1% of the respondents' monthly household income.

and in their sample the average monthly household income was reported as approximately \$100. On the basis of our sample collected in 2017-2018, the average monthly household income is obtained as INR 7510 (~\$120). During the period of 2013-2017, India has witnessed a growth in GDP from 6.39 in 2013 to 7.17 in 2017 (World Bank, 2019). As a result of this economic development, the average income of the people is expected to increase as has been reflected in our sample. However, this increase in household income does not alter the households' proportional valuation of reduced health risks related to HAP which remains unchanged at approximately 1% of the average monthly household income. The findings from these revealed preference studies may suggest that individuals in rural India have consistently attributed a low valuation to the reduction in HAP-related health risks from a hypothetical indoor air quality improvement. In this context, it is noteworthy that Mobarak et al. (2012) provided similar evidence in their stated preference study related to valuation of HAP-related risk mitigation among the households in rural Bangladesh. Therefore, we may conclude that, individuals in rural areas of developing countries may perceive a lower valuation of the reduction in HAP-related health risks, which is robust across time and study area as well as, invariant of the nature of the study design.

It is not unreasonable to assume that the estimated WTP may appear to be negligible in nominal terms. However, McPhail (1993) argue that, , provision of basic amenities like piped water in developing countries is considered to be affordable if it is approximately 5% of the household income. Drawing reference to this frequently quoted "five-percent rule" (Shannon et al., 2019), we may conclude that, while the estimated mean WTP appears to be negligible in nominal terms, it may be non-trivial in the context of low-income economies particularly in rural areas.

4. Heterogeneity of the estimated mean annual WTP and its policy implications

Individuals' WTP may be commodity specific and also depends on space and time (Sun et al., 2016). Since, for a given commodity, the individuals are quite likely to develop their valuation based on their individual specific characteristics, the estimated mean WTP is expected to be sensitive to these individual-specific attributes. This gives us a rationale to explore the within-sample heterogeneity of estimated mean WTP, given our evidence that some of the relevant and indicative covariates influence the individuals' WTP decision.

We focus on three contextual attributes related to individuals' WTP for mitigating health risks from HAP exposure – self-reported health status, cooking fuel usage pattern and perception of increased health risk from dirty fuel usage. Unlike the first variable, the latter two is continuous in the interval [0,1]. For this reason, for the latter two variables, we focus on the estimated mean annual WTP evaluated at the median and that at the two endpoints.

For this analysis, we use the results presented in column 4 of Table 6. We also present the kernel density of the bootstrapped estimates of the mean across the variation in covariates in Figure 2. The possible heterogeneity in the estimated mean within the sample, along with the 95% confidence intervals under various scenarios is presented in Table 7.

<Figure 2 approximately here>

Panel I of Figure 2 presents the heterogeneity in estimated mean with respect to self-reported health status. Although the distribution of the two groups *sick* and *not sick* is positively skewed, they somewhat differ in shape in terms of spread. The estimated mean of the latter group (INR 412.61) is much lower than that of the former (INR 793.76) (see Table 7); the *sick* individuals, on an average are willing to pay a higher annual premium[10] for the preventive device than their *not sick* counterparts, with a larger confidence interval.

The within-sample variation in the estimated mean with respect to cooking fuel usage is presented in Panel II of Figure 2. The kernel densities of the quantities at all the levels of fraction of days of dirty fuel usage is positively skewed. Although there is some overlap among the densities, it is evident from the figure that exclusive clean (dirty) cooking fuel users have the highest (lowest) WTP for the preventive measure despite possibly requiring it the least (most). To be specific, the estimated mean annual WTP of the former group (INR 1077.12) exceeds that of the latter group (INR 543.61) by almost two times. Panel II further indicates that, the exclusive dirty fuel users consistently have the lowest perceived private health benefit from reduced health risk related to HAP which results to the lowest spread among the three groups.

Given the evidence that individuals' self-reported health status and cooking fuel usage may result in within-sample variation in estimated mean, we attempt the investigate the joint impact of these variables on the heterogeneity of the quantity. For this purpose, we classify the categories based on the two groups of self-reported health status (*sick* and *not sick*) and that of fuel users (*exclusive clean fuel users* and *exclusive dirty fuel users*[11]). We plot the distributions of the bootstrapped estimates of the quantity corresponding to these four groups in panel III of Figure 2. This figure shows that the group *exclusive clean fuel users and sick* has the highest

[10] Incidentally, it is interesting to compare the estimated mean WTP of the *sick* individuals with their 'actual' expenditure to reduce the most recent event of the above-mentioned physical symptoms, which can be considered to be a defensive expenditure. In monthly terms, the estimated mean for the sick individuals is INR 66.15. On the other hand, it is available from the data that these individuals spend INR 57.25 on average per month to treat their recent events of ailment from the aforementioned symptoms. Our result conforms with the economic theory that actual defensive expenditure underestimates the true WTP (Alberini and Krupnick, 2000); the magnitude of the ratio between defensive expenditure to the elicited WTP, although more than unity, is comparatively low in our study. This may be due to economic, cultural, and institutional differences between India and other countries and also, our emphasis on few common but minor physical symptoms associated with HAP.

[11] In the sample, around 12% (44%) households are exclusive clean (dirty) fuel users.

valuation of reduced health risks related to HAP among the four groups, while an exactly opposite pattern is not observed for the group *exclusive dirty fuel users and not sick*. The individuals in the group *exclusive dirty fuel users and not sick* seem to consistently express the lowest perceived private health benefits from reduction in health risks related to HAP, resulting in the lowest dispersion in the distribution. Panel III further reveals that the distribution of the remaining two groups is more or less overlapping, indicating similar perception of private health benefits from reduced health risks related to HAP.

Finally, we present the within-sample heterogeneity of estimated mean with respect to different levels of perceptions of increased health risk from dirty fuel usage in Panel IV of Figure 2. The figure shows that the groups assigning maximum value of the perception is likely to have the highest valuation of the reduced health risks related to HAP. This is quite evident given our finding that perception positively influences the individuals' likelihood to pay the bid as discussed in previous sub-section. To be specific, the individuals assigning the maximum value of the perceived increase in health risk has an estimated annual mean WTP as INR 931.03 which is approximately, 2.08 times that of the group expressing minimum value to the perceived risk.

<Table 7 approximately here>

Summarizing the observations of the within-sample heterogeneity of the estimated mean WTP, we may conclude that it is sensitive to both health and non-health factors. The respondents in the group expressing the highest WTP, have a larger spread on their perceived private health benefit from reduced health risks related to HAP. Concurrently, respondents in other groups, who are more conservative in nature with lower WTP, hold a more consistent view. This finding may appear to be in contrast to the findings of previous literature (Sun and Zhu,2014) in the context of WTP for avoidance of nuclear power. However, it is to be noted that the risk perception or threat related to nuclear power is enormous in magnitude and seldom encountered in reality. Concurrently, the individuals in developing countries particularly in rural areas perceive the risk from HAP to be a trivial one, not to speak of any threat whatsoever, because of their prior experience with prolonged and regular exposure of it owing to habitual and age-old practices over generations[12]. Furthermore, we have elicited the bid responses by mentioning about common symptoms related to HAP, of which they are often ignorant in the short run[13]. Therefore, it will not be unreasonable to argue that individuals belonging to the group expressing higher WTP may have their perceived private health benefit deviated further from each other in the context of reduced health risks from HAP. Thus, some individuals of the group have expressed a higher valuation of reduced health risks than others. This may result in the heterogeneity of the perception of private health benefit within the groups, resulting in the larger spread.

Above evidence leads to at least two important directions for policy design. First, since the respondents' perception of increased health risks from dirty fuel usage has a significant positive effect on their WTP for reduced health risks related to HAP, a plausible policy may be suggested as follows. Government at the local level may launch programs to educate the people about the possible health hazards (both short term and long term) related to HAP as well as, the urgency to adopt/use modern cooking fuels (technology). It is likely that with an increased

[12] We do not disagree with the findings of Sun and Zhu (2014). Rather, this study may indicate that lower perceived private health benefit is likely to prevail over familiar facilities such as clean air and water which are regularly used. The observation by Takama et al (2012) further substantiate this finding; low-income households in Ethiopia have a higher WTP to reduce the risk associated with explosion of cook stoves which is an unfamiliar and rare kind of health hazard in comparison to the much familiar hazard of burning. Thus, the perceived private health benefit is likely to differ and expected to be higher for facilities which are rather uncommon in everyday use like hazards from nuclear power station or toxic chemical reactor. As a result, framing of policies for facilities which are in everyday use with a relatively low perception of hazard, although are more important and widespread, seems to be difficult and may take considerable amount of time and persuasion.

[13] In general, it is difficult to elicit the risk perception or valuation of risks for serious physical symptoms related to HAP like COPD or ALRI, as they occur less frequently (Yokoo et al., 2020).

knowledge, the individuals' concerns about HAP related issues will increase. This is expected to enhance the chance of success of the current or future intervention programs[14].

Second, following Yokoo et al (2020), the results may enable one to improve the efficiency of awareness generation and/or information provision programs by addressing the target group identified by observables. For example, the individuals belonging to the group *exclusive dirty fuel users and not sick* show a consistent but more conservative attitude towards HAP problems with the lowest valuation for reduction in health risks related to HAP. Any environmental policy in general and awareness generation and/or information provision policy towards reduction of HAP in particular, may be found to be more effective if such an understanding can be targeted and altered.

6. Conclusion

Health risk related to HAP is a salient feature of the households in developing countries particularly in the rural areas. We analyze data from a unique contingent valuation survey in rural India to estimate the individuals' valuation of reduced health risks derived from hypothetical improvement in indoor air quality. In particular, we estimate their WTP for a hypothetical preventive measure from HAP using DBDC approach, investigating for the possible anomalies in such model.

The potential impact of our results on the literature related to the valuation of environmental health risks related to HAP in the context of a developing economy, is worth noting. The results suggest that presence of internal inconsistency in DBDC response, the means from the SBDC

[14] It is to be noted that generation of public awareness particularly in the context of interventions targeted to HAP reduction is of much relevance for ensuring sustained success of such programs. For example, despite the initiative by the Government of India to provide free LPG connections to households lying below poverty line, a large section of the target households continues to use dirty cooking fuels either as their primary or as the secondary sources of cooking fuel (Gould and Urpelainen, 2018). This may reflect the necessity of a concurrent awareness generation about the health risks related to HAP along with the intervention policies to reduce such HAP. .

and DBDC approaches differ significantly; with the former being significantly higher than the latter. Furthermore, our study provides some evidence of the anchoring effect validating the presence of starting point bias in the DBDC model. The estimated value of the anchoring effect, in this context, is obtained to be approximately 0.217 ($p < 0.1$). Correcting for this starting point bias, the estimated mean WTP for the preventive measure is approximately obtained as INR 678.14 per year (~US$12). This amount accounts for approximately 1% of the annual household income on an average. Our analysis of such valuation of reduced health risks related to HAP suggests that ignoring the starting point bias may result in an overestimation of individuals' WTP. Sufficient within-sample heterogeneity of the estimated mean annual WTP with respect to judiciously selected covariates is also observed. This enables us to recommend policies like generating public awareness about HAP risk and targeting potential beneficiaries based on observable characteristics. Such policy is expected to ensure smooth implementation and enables one to assess the effectiveness of intervention programs to reduce HAP.

Our results should be interpreted with caution. First, our analysis of perceived private health benefits focuses on common but minor physical symptoms related to HAP which is often ignored by individuals in the short run. Consequently, the estimated mean WTP may yield an appropriate lower (upper) bound of the valuation. Second, it is to be noted that we have concentrated exclusively on the health risks related to HAP in this study. However, simultaneous presence of multiple health risks are rules rather than exceptions, particularly in developing economies. and this may affect the individuals' WTP for a specific risk. More detailed analyses on multiple health risks (for example, health risks related to HAP coupled with health risks from improper sanitization for women or consumption of contaminated water) are required, including relevant sensitivity analysis. Third, the results may not be generalizable for the entire rural India because they are not necessarily an unbiased representation of the population (that is, all the individuals in rural India). However, there may be several areas in

West Bengal similar to our study area in terms of ethno-socio-demographic features, which are located in the proximity of an urban metropolis. As such, it is expected that the findings here will be valid for those areas.

We have confined our attention to the perceived health benefit from the viewpoint of the respondent, and this may be an oversimplification. For a holistic analysis of the individuals' valuation of reduced health risks related to HAP, we need to include the household burden of diseases, especially that of the kids. Finally, for a comprehensive analysis of individuals' demand for the preventive device, we need to take up future studies that will also identify which attributes of this preventive measure is given priority by the potential beneficiaries apart from estimating the valuation. This may demand the necessity of a stated preference study. We would like to extend our research in these directions in future.

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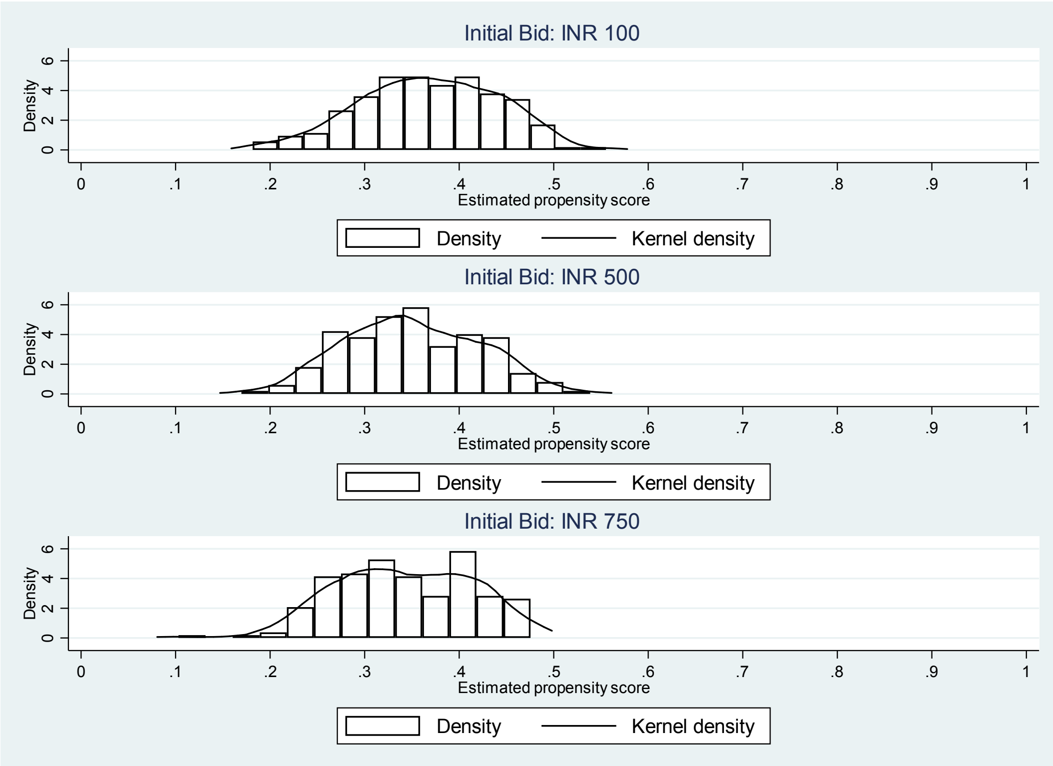

Figure 1. Histogram and Kernel density of the estimated propensity scores across three bid groups

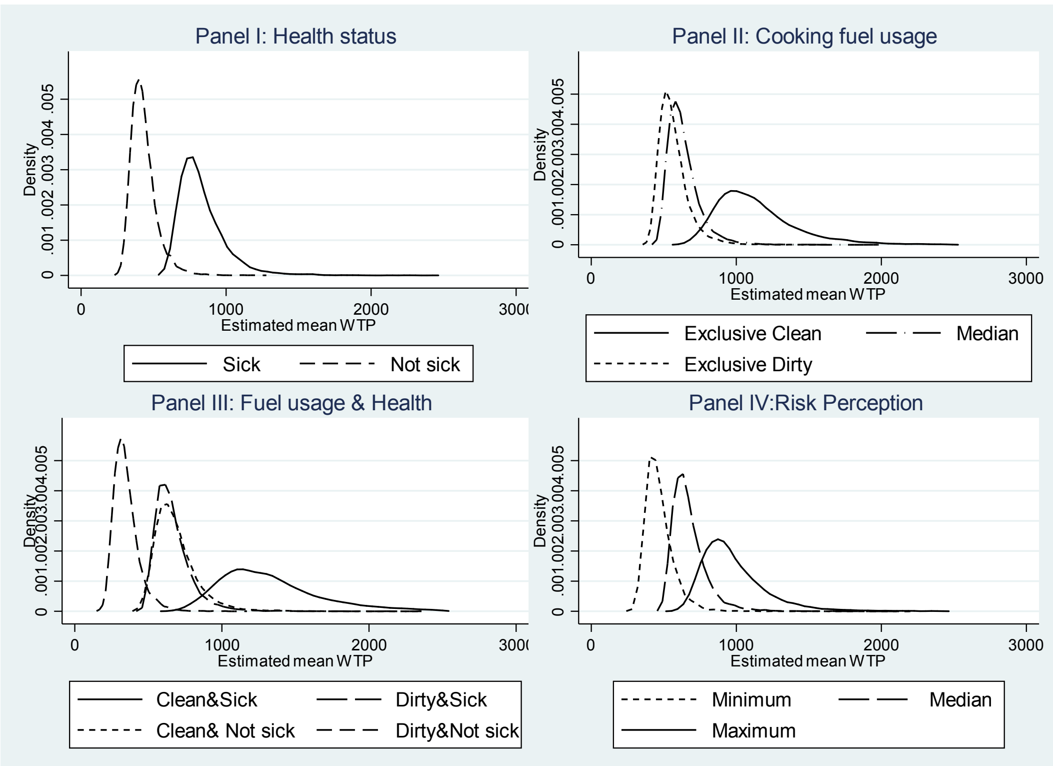

Figure 2. Kernel density of the bootstrapped estimates of mean WTP

Table 1. Descriptive statistics

Variable	Mean	SD	Min	Max
Health-related variable				
Sick in last 30 days with at least one physical symptom (binary)	0.76	0.43	0	1
Cooking practice-related variable				
Fraction of days of dirty fuel usage in last 30 days	0.68	0.38	0	1
Risk perception-related variable				
$SP(s\|d) - SP(s\|c)$	0.57	0.22	0.14	1
Other control variables				
Number of cooks	1.13	0.41	1	4
Age	37.78	10.79	17	76
Years of schooling	4.83	4.13	0	17
Holds household decision-making authority (binary)	0.06	0.24	0	1
Spouse works in informal sector (binary)	0.3	0.46	0	1
Spouse works in agricultural sector (binary)	0.27	0.44	0	1
Expenditure (in INR 1,000)	7.51	3.74	2.3	55
Kitchen located inside dwelling area (binary)	0.16	0.36	0	1
Access to ventilation in cooking area (binary)	0.97	0.16	0	1
Owns television (binary)	0.86	0.35	0	1

Note: In risk perception-related variables, $SP(.|.)$, s denotes the likelihood of being sick from at least one of the physical symptoms (dry cough, sore or runny eyes and difficulties in breathing) and c(d) represents clean(dirty) cooking fuel usage. The sample size in 557.

Table 2: Distribution of the bid responses

Lower Follow-up Bid	Initial Bid	Higher Follow-up Bid	Yes-Yes	Yes-No	No-Yes	No-No	*N*
50	100	200	68.53%	17.77%	7.11%	6.60%	197
250	500	1000	10.29%	29.14%	38.86%	21.71%	175
375	750	1500	8.65%	20.00%	37.30%	34.05%	185

Note: This table presents the distribution of the bid responses across the respondents. Each value of the bid is expressed in Indian National Rupee (INR) where INR 62= US$1 (the average monthly exchange rate in December 2017- January 2018 when the survey was conducted). N represents the number of respondents who were assigned that level of bid random. The total sample size is 557.

Table 3. Results of the DBDC model (bivariate probit model)

	[1a]	[1b]	[2a]	[2b]	[3a]	[3b]
Initial Bid(log)	-0.86***		-0.866***		-0.866***	
	(0.074)		(0.074)		(0.073)	
Final Bid (log)		-0.676***		-0.672***		-0.676***
		(0.104)		(0.106)		(0.108)
Number of cooks	-0.073	-0.064	-0.066	-0.056	-0.066	-0.049
	(0.141)	(0.148)	(0.142)	(0.148)	(0.143)	(0.144)
Age	-0.012*	-0.009	-0.013**	-0.011*	-0.013**	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Years of schooling	-0.001	-0.007	-0.002	-0.008	-0.002	-0.008
	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)
Decision-maker	0.529**	0.438*	0.509*	0.403	0.505*	0.403
	(0.269)	(0.243)	(0.272)	(0.248)	(0.272)	(0.248)
Spouse works in informal sector	0.025	0.053	0.082	0.01	0.08	0.099
	(0.149)	(0.138)	(0.151)	(0.139)	(0.152)	(0.14)
Spouse works in agricultural sector	-0.219	-0.015	-0.188	0.0201	-0.192	0.012
	(0.151)	(0.143)	(0.152)	(0.144)	(0.152)	(0.146)
Household expenditure	0.041*	0.021	0.04*	0.02	0.04*	0.019
	(0.022)	(0.019)	(0.022)	(0.019)	(0.022)	(0.019)
Kitchen located inside	-0.118	0.046	-0.12	0.05	-0.125	0.026
	(0.159)	(0.154)	(0.16)	(0.154)	(0.160)	(0.151)
Ventilation	-0.109	0.102	-0.243	-0.014	-0.246	-0.033
	(0.328)	(0.357)	(0.343)	(0.356)	(0.338)	(0.343)
Owns television	0.044	-0.063	0.035	-0.08	0.026	-0.131
	(0.184)	(0.163)	(0.186)	(0.165)	(0.186)	(0.164)
Fraction of days of dirty fuel usage	-0.033	-0.168	-0.538**	-0.676***	-0.53**	-0.647***
	(0.178)	(0.160)	(0.257)	(0.233)	(0.257)	(0.233)
Sick			0.601***	0.596***	0.590***	0.554***
			(0.215)	(0.191)	(0.214)	(0.191)
$SP(s\|d) - SP(s\|c)$					0.217	1.001***
					(0.270)	(0.259)
ρ	0.298**		0.258**		0.237*	
	(0.121)		(0.121)		(0.122)	
Log likelihood	-647.7		-639.8		-632.5	
χ^2	169.2		185.7		202.4	
χ^2 for ρ	6.063		4.591		3.773	

Note: This table provides the estimation results for (3), where the dependent variable is the bid response (=1 if the respondent is willing to pay the proposed bid) for the initial round (in columns indicated by "a") and follow-up round (in columns indicated by "b"). The sample size is 557. ***, ** and * indicate statistical significance at the one, five and ten per cent levels respectively. Robust standard errors are presented in parenthesis. The constant terms are not reported for the sake of space.

Table 4. Results of the SBDC model (naïve probit model)

	[1]	[2]	[3]
Initial Bid (log)	-0.849***	-0.858***	-0.859***
	(0.073)	(0.073)	(0.073)
Number of cooks	-0.071	-0.064	-0.064
	(0.143)	(0.144)	(0.144)
Age	-0.012**	-0.014**	-0.013**
	(0.006)	(0.006)	(0.006)
Years of schooling	-0.001	-0.002	-0.001
	(0.017)	(0.017)	(0.017)
Decision-maker	0.543**	0.524*	0.517*
	(0.269)	(0.27)	(0.27)
Spouse works in informal sector	0.011	0.071	0.071
	(0.150)	(0.152)	(0.152)
Spouse works in agricultural sector	-0.222	-0.190	-0.193
	(0.151)	(0.152)	(0.152)
Household expenditure	0.041*	0.04*	0.04*
	(0.023)	(0.022)	(0.023)
Kitchen located inside	-0.109	-0.114	-0.119
	(0.157)	(0.159)	(0.158)
Ventilation	-0.111	-0.246	-0.247
	(0.327)	(0.341)	(0.337)
Owns television	0.07	0.056	0.044
	(0.185)	(0.185)	(0.186)
Fraction of days of dirty fuel usage	-0.029	-0.537**	-0.525**
	(0.178)	(0.255)	(0.254)
Sick		0.604***	0.589***
		(0.211)	(0.211)
$SP(s\|d) - SP(s\|c)$			0.238
			(0.273)
Log likelihood	-299.0	-294.5	-294.1
Pseudo R^2	0.224	0.236	0.237
χ^2	148.2	157.2	158.1

Note: This table provides the estimation results for (4), where the dependent variable is the bid response (=1 if the respondent is willing to pay the proposed bid). The sample size is 557. ***, ** and * indicate statistical significance at the one, five and ten per cent levels respectively. Robust standard errors are presented in parenthesis. The constant terms are not reported for the sake of space.

Table 5. Estimates and confidence intervals of mean WTP through various approaches

Entity	Estimate	95% Confidence Interval	
		Lower Bound	Upper Bound
μ_{DBDC}	731.68	589.08	1012.93
μ_{SBDC}	734.91	589.25	1025.13
$\mu_{SBDC} - \mu_{DBDC}$	3.23 (0.033)		
μ_{WTP}	678.14	547.22	1036.96

Note: The annual mean WTP for the preventive device under DBDC (SBDC) method is estimated using the results presented in column 3a & 3b of Table 3 (column 3 of Table 4). The annual mean WTP correcting for the starting point bias is estimated using the findings presented in column (4) of Table 4.6. The values are expressed in INR where US$1=INR 62 (average monthly exchange rate during December 2017 - January 2018). The confidence intervals of corresponding mean WTPs are computed using Krinsky and Robb method (number of replications 10000). The standard error of the difference of mean WTP in SBDC and DBDC method is computed using bootstrap (number of replications 500).

Table 6. Result of model addressing starting point bias (random probit model)

	(1)	(2)	(3)	(4)
Bid (log)	-0.964***	-0.958***	-0.959***	-0.972***
	(0.131)	(0.13)	(0.128)	(0.118)
Shift effect parameter		0.14		-1.143
		(0.089)		(0.718)
Anchoring effect parameter			0.027*	0.217*
			(0.015)	(0.121)
Number of cooks	-0.061	-0.062	-0.061	-0.059
	(0.133)	(0.133)	(0.132)	(0.122)
Age	-0.013**	-0.013**	-0.013**	-0.012**
	(0.005)	(0.005)	(0.005)	(0.005)
Years of schooling	-0.006	-0.006	-0.006	-0.005
	(0.015)	(0.015)	(0.015)	(0.014)
Decision-maker	0.549**	0.551**	0.545**	0.501**
	(0.237)	(0.238)	(0.235)	(0.219)
Spouse works in informal sector	0.101	0.100	0.1	0.097
	(0.132)	(0.132)	(0.131)	(0.122)
Spouse works in agricultural sector	-0.101	-0.104	-0.103	-0.089
	(0.139)	(0.139)	(0.137)	(0.128)
Household expenditure	0.035*	0.035*	0.034*	0.032*
	(0.018)	(0.018)	(0.018)	(0.017)
Kitchen located inside	-0.05	-0.052	-0.052	-0.046
	(0.149)	(0.149)	(0.148)	(0.137)
Ventilation	-0.157	-0.151	-0.148	-0.134
	(0.337)	(0.338)	(0.334)	(0.310)
Owns television	-0.06	-0.064	-0.064	-0.06
	(0.157)	(0.158)	(0.156)	(0.145)
Fraction of days of dirty fuel usage	-0.719***	-0.718***	-0.712***	-0.665***
	(0.234)	(0.234)	(0.232)	(0.216)
Sick	0.691***	0.690***	0.684***	0.636***
	(0.193)	(0.193)	(0.191)	(0.178)
$SP(s\|d) - SP(s\|c)$	0.751***	0.755***	0.750***	0.712***
	(0.250)	(0.251)	(0.248)	(0.231)
$ln\sigma^2$	-0.794*	-0.790*	-0.842*	-1.289*
	(0.475)	(0.471)	(0.483)	(0.696)
Log likelihood	-639.4	-638.1	-637.8	-636.6
χ^2	64.04	66.32	68.49	83.26

Note: This table provides the estimation results for equation (6), where the dependent variable is the bid response (=1 if the respondent is willing to pay the proposed bid). The sample size is 557. ***, ** and * indicate statistical significance at the one, five and ten per cent levels respectively. Robust standard errors are presented in parenthesis. The constant terms are not reported for the sake of space.

Table 7. Within-sample heterogeneity analysis of estimated mean WTP

	Estimated	95% Confidence Interval	
	Mean	Lower Bound	Upper Bound
Across categories of health status			
Sick	793.76	624.31	1249.30
Not sick	412.61	305.81	654.29
Across different levels of fuel usage			
Exclusive clean fuel usage	1077.12	751.26	1915.01
Median	609.37	490.80	925.29
Exclusive dirty fuel usage	543.61	430.06	840.68
Across different levels of fuel usage & health status			
Exclusive clean fuel user & sick	1261.09	831.35	2362.83
Exclusive dirty fuel user & sick	636.45	505.26	984.09
Exclusive clean fuel user & not sick	655.53	491.27	1047.93
Exclusive dirty fuel user & not sick	330.83	226.69	562.41
Across different levels of perceptions			
Minimum value	447.53	333.86	703.46
Median value	645.50	522.64	979.95
Maximum value	931.03	685.68	1591.93

Note: The mean WTP per year across different categories of individual-specific factors is estimated using the results presented in column (4) of Table 6. The estimated mean WTP per year is expressed in INR where US$1=INR 62 (average of the average monthly exchange rate in December 2017 and January 2018). The confidence intervals of corresponding mean WTPs are computed using Krinsky and Robb method (number of replications 10000).

Appendix

Appendix 4.A1

Instructions and question to elicit the bid responses

Willingness to Pay

We understand that the issue of smoke coming from the burning of cooking fuels while you cook is quite serious for the household health, especially yours. We request you to think of a situation where some public program has been implemented for the public interest in all the villages under this village council. In this program, some kind of preventive device similar to an electric chimney or exhaust fan is installed in the cooking area of the house at a minimal cost or for free. The expected benefit from the preventive device is the following: the incidence and extent of the smoke during cooking will be greatly reduced. This, in turn, will effectively reduce your chances of suffering from related physical symptoms like dry cough, sore or runny eyes, difficulties in breathing. Moreover, this will also improve the indoor air quality of the household such that your kids or other family members will also have a lesser chance of suffering from the above-mentioned diseases. However, please note that the program fund will not be sufficient to finance the usage or maintenance cost for the device. Once installed you need to pay [initial bid] per year for using the device. We shall now request you to kindly consider your household budget constraint and other financial obligations before answering this question

To the enumerator: *Please ask the* ***value according to the group id*** *randomly assigned to you*

i	Group ID	**A**	**B**	**C**
	Are you willing to pay this amount per year for the preventive device?	**Rs. 500**	**Rs. 750**	**Rs. 100**
		Yes	Yes	Yes
		No	No	No

To the enumerator: If ***YES*** *then* ***proceed to ii****; if* ***NO*** *then* ***proceed to iii***

ii	Group ID	**A**	**B**	**C**
	Are you willing to pay this amount per year for the preventive device?	**Rs.1000**	**Rs. 1500**	**Rs. 200**
		Yes	Yes	Yes
		No	No	No
iii	Group ID	**A**	**B**	**C**
	Are you willing to pay this amount per year for the preventive device?	**Rs.250**	**Rs. 375**	**Rs. 50**
		Yes	Yes	Yes
		No	No	No