Are Indians willing to pay to reduce air pollution? Findings from close-end double-bound contingent valuation study

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Abstract:

Ambient air pollution has become a severe environmental threat in India, as most Indian states lag behind the World Health Organisation (WHO) air quality standards. Such an alarming situation has forced the government to design various mitigation measures to curb emissions from anthropogenic sources. However, to successfully implement those interventions, policymakers must be aware of individual attitudes and preferences, which can be reflected in their willingness to pay (WTP) for air quality improvement. The current research employs the Contingent Valuation Method (CVM) to elicit individual WTP for air quality improvements and its determinant using the closed-end double bound (CE-DB) technique. Moreover, the study also investigates the source of preference anomalies common in the CE-DB method, leading to overestimating the mean WTP. The findings from our empirical model suggest that place of residence, educational qualification, air pollution awareness level, and monthly household income are the key determinants of individual WTP for air quality improvements. However, the existence of preference anomalies because of shifting and anchoring effects validates the overestimation of mean WTP. After correcting those anomalies, the estimated mean WTP is ₹ 255.69 (or $3.09) per month, around 15 per cent lower than the estimated mean WTP without correcting any anomalies.

Keywords: Ambient air pollution, India, Contingent Valuation Method, double-bound, anchoring effect, shifting effect

JEL classifications: Q50, Q51

1. Introduction:

In the twenty-first century, ambient air pollution has become a severe environmental threat worldwide. According to Greenstone et al. (2022), 97.3 per cent of the global population live in areas where ambient air pollution levels[1] exceed the prescribed limits of the World Health Organization (WHO). However, the associated burden of ambient pollution is relatively high for developing nations due to their large population, rapid and unplanned development strategies, and lower environmental concerns among citizens. In countries like India, ambient air pollution has emerged as a serious environmental concern, as more than 63 per cent of its population is experiencing pollution levels beyond the country's national standards (Greenstone et al., 2022), which are already lagging behind the WHO guidelines.

The data from the Global Burden Diseases Collaborative Network (2021) show that ambient air pollution is not sudden in India, as pollution concentrations have been rising at a menacing rate since the end of the last century. For instance, between 1990 and 2019, the average concentration levels have increased by approximately 16% (Global Burden of Disease Collaborative Network, 2021), the majority of which is attributed to various anthropogenic sources like emissions streaming from vehicular sources, industrial processes, coal-based thermal power plants and crop residual burning (Guttikunda et al. 2014; Gurjar et al., 2016; Centre for Environmental Health, 2017).

Exposure to these severe pollution levels increases the likelihood of adverse respiratory and cardiovascular diseases, leading to premature deaths. According to an estimate, air pollution killed around 1.7 million Indians, accounting for 17% of the country's total deaths in 2019 (India State-Level Disease Burden Initiative Air Pollution Collaborators, 2021). Most of these deaths are associated with exposure to ambient air pollution, making it India's fifth major

[1] By ambient air pollution levels, we mean the concentration of Particulate Matter (PM) which is generally used as a proxy indicator for the ambient air pollution level (WHO, 2021).

health risk factor (Centre for Environmental Health, 2017). From an economic perspective, ambient air pollution costs ₹ 7 lakh crore (or 3% of India’s GDP) every financial year to the Indian business sector in terms of loss of labour productivity, consumer footfall, and premature mortality (Dalberg Advisors, 2021).

To address these adverse health consequences and negative economic externalities associated with ambient air pollution, the Government of India initiated the nationwide programme known as the National Clean Air Programme (NCAP) as a long-term and time-bound strategy to improve air quality levels by cutting down the emissions from anthropogenic sources (Ministry of Environment, Forest & Climate Change, 2019). Under NCAP, the government has introduced new emission standards, adopted sustainable technologies, and used clean fuels to control emissions from anthropogenic sources. However, implementing those pollution abatement policies requires substantial investments and may increase the market prices of many goods, negatively affecting the country’s economic growth and the welfare of millions of households. Moreover, the effectiveness of those policies remains uncertain due to limited knowledge about individual preferences for clean air. Therefore, policymakers must understand the economic value of clean air, which can be used for evaluating the scope and involvement of those mitigation strategies.

For any marketable goods or services, the market equilibrium price is considered the economic value, indicating the preferences for that good or service. However, environmental good like clean air has no well-established market in a conventional sense. So, the market equilibrium price can no longer be used as an indicator of economic value. Therefore, the present study follows the Contingent Valuation Method (CVM) – a survey-based stated preference technique to identify the individual’s preference for a given improvement in air quality based on a hypothetical situation designed by researchers. These identified responses are linked with various individual-specific characteristics to estimate the Willingness to Pay (WTP) – a conventional indicator for economic value based on the Hicksian welfare measure. The primary objective of our study is to understand the individual preferences for ambient air quality improvement with a focus towards the Indo-Gangetic Plain – the major ambient air pollution hotspot in India (Chandrashekhar, 2017; Bernard and Kazmin, 2018; Cusworth et al., 2018). The current study utilises the closed-end double bound (CE-DB) elicitation technique to find answers to the following research questions:

- How much are Indians willing to pay for improvements in ambient air quality?
- Does the type of city (where the respondent lives) impact individual preference for air quality improvements? Are inhabitants of large cities, which are more polluted, more inclined to pay for air quality improvements?
- Does awareness regarding air pollution and related health consequences positively affect individual preference for air quality improvements?
- Is there a positive income effect on WTP for air quality improvement when substantial spatial heterogeneity is present in the sample?
- Does the presence of starting-point bias in the survey designs reduce the efficiency of the mean WTP estimate for air quality improvements?

The rest of the paper is organised as follows. Section 2 reviews CVM literature on the air pollution problem and indicates our research contributions. The analytical framework is mentioned in Section 3, followed by the discussion on survey design and variables utilised in the study in Section 4. The empirical findings are presented and discussed in Section 5. Finally, Section 6 concludes the study by summarising essential findings and policy recommendations.

2. Literature review and contribution to current research

Numerous studies have been published that employ various methodologies like stated preference (i.e., CVM and choice-experiment) or revealed preference (i.e., hedonic, travel cost) approach to estimate the WTP for clean air (or air quality improvements). However, the present study restricts the literature review to empirical studies that use the CVM technique to evaluate the individual WTP for air quality improvements. These CVM literature are categorised into two groups for better understanding and convenience of readers. The first group indicates studies from China and India, where air pollution emerges as a national environmental problem as the majority of the population is exposed to high pollution concentration levels. In the second group, we mention the CVM studies from countries other than China and India, where the severity of the problem is relatively low.

Studies from China and India:

Hammitt and Zhou (2006) find the economic value of air pollution-related health risks in China using the double-bound dichotomous choice format. The study conducts in-person interviews with 3,700 individuals to collect individual-specific data from three different areas – Beijing, Anqing, and rural areas near Anqing. The authors separately estimate the economic value of preventing health risks from cold, chronic bronchitis, and fatality. They use the maximum likelihood technique to estimate the relationship between WTP and individual characteristics, assuming that WTP follows normal, lognormal, and Weibull distributions. However, based on the post-estimation test, they conclude that the lognormal distribution fits the data better. The estimated results show that the respondent’s educational qualification and income level have a positive impact, while age negatively impacts the inclination to prevent air pollution-related health risks. The study concludes that findings are consistent between Beijing and the rural area near Anqing. Moreover, the study also indicates that individual willingness to prevent health risks varies across different health issues.

Wang and Zhang (2009) follow the open-ended survey technique to estimate the individual willingness for air quality improvements in Jinan, China. The study uses stratified sampling to select 1,500 adults and conducts face-to-face interviews to collect individual-level information.

The authors estimate the univariate probit model to find the probability of positive responses for various characteristics of respondents. The estimated results suggest that annual household income, expenditure on respiratory illness treatment, and education levels positively influence the individual decision to pay. Du and Mendelsohn (2011) employ the double-bound in-person survey technique to collect information from 566 individuals and estimate the WTP for air quality improvement in Beijing, China. Unlike previous studies, authors avoid the hypothetical nature of CVM and explore what people are willing to pay to maintain the air quality during the Summer Olympic Games 2008. The study relies on univariate and bivariate probit models to identify the factors influencing individual WTP. The findings indicate that income levels and awareness about air pollution have positive impacts on individuals' inclination for air quality improvements.

Pu et al. (2019) aim to elicit individual preferences for clean air by conducting an online survey to collect information from 9,744 individuals across 31 provinces in China. Unlike previous studies, they compare the individual willingness and participation cost of mitigation to address the hypothetical bias in predicting the effectiveness of the air pollution policies. The study employs the payment card technique to estimate WTP while examining the air purifier cost (APC) to identify the individual participation cost. In the first part, the authors employ the probit model to estimate the probability of positive WTP and APC. In the second part, they use linear regression to explain the variations in positive WTP and APC numbers. Their analysis shows that the mean value of APC is lower than the mean WTP, suggesting individuals are spending less than their willingness. Moreover, the study finds a significant spatial difference in APC, mainly driven by pollution concentration levels. However, for WTP, no such difference is observed.

In the case of India, very few studies empirically model individual preference for air quality improvements. Some significant research findings on the non-market valuation of air quality are offered by Kumar and Rao (2001), Murty et al. (2004), and Gupta (2008). However, these studies have some limitations. First, these studies are based on the revealed preference approach, which only indicates the use value of air quality improvements and ignores the associated altruistic value. Second, during these studies, the market for air pollution-related commodities was not well developed in India, which might have restricted the effectiveness of the revealed preference approach to estimate the individual preference for air quality improvements. Recently, Chattopadhyay (2021) has used the CVM technique to estimate individual willingness to reduce health risks from household air pollution in rural areas of West Bengal. She follows the double-bound in-person interview method to collect individual-specific information. The study uses the bivariate probit model to identify the potential factors affecting individual willingness. The findings suggest that an individual's experience of air pollution-related symptoms is positively associated with WTP, while the respondent's age is negatively linked. Furthermore, the study reveals a positive income effect on reducing the health risk from household air pollution, i.e., with increased income, an individual is willing to pay more for a reduction in health risk by lowering indoor air pollution. The estimated annual mean willingness to pay for the reduction in health risk is ₹678.14, accounting for approximately 1% of the annual household income.

Studies from the rest of the world:

Donfouet et al. (2015) use a three-stage cluster technique to select 496 household heads and investigate the effect of 'time to think' and 'ballot box' experiments on individual WTP estimates for air quality improvements in Douala, Cameroon. In the first subsample (or control group), respondents answer the single-bound and double-bound (only for those respondents whose initial response is 'yes') questions about their preference for air quality improvement programs. The second subsample of respondents (or the first experimental group) receives a similar treatment but is given overnight time to think about their response. The respondents in the third subsample (or the second experimental group) are asked to mark their responses on a card and put them in a sealed envelope for privacy. The authors utilise probit and interval regression models to analyse individual responses. The findings suggest that individual-specific characteristics like income and educational qualification have positive impacts on the individual WTP for air quality improvements. Furthermore, the study indicates that the estimated mean WTP decreases when respondents are allowed time to think but increases for the ballot box approach relative to the control group.

Winden et al. (2018) utilise the WTP method to understand the public support for climate change mitigation by comparing adults and college students from China and the United States. The study follows the double-bound dichotomous choice model and uses online and offline survey methods to collect information from 3,110 adults (1,220 American and 1890 Chinese) and 3,485 (2,140 American and 1,345 Chinese). The empirical results of the bivariate probit model suggest that both countries have strong public support for climate change mitigation. However, after adjusting for differences in per capita incomes, Chinese (adult and student) WTP is two times larger than the US counterparts. Moreover, the study observes that higher environmental concerns cannot influence students to pay more than adults in the US. However, for the Chinese sample, the study observes a strong contrast.

Kim et al. (2019) adopt the close-end single-bound dichotomous choice format to elicit the WTP of Koreans for a reduction in particulate (PM_{10} and $PM_{2.5}$) levels via green electricity in Seoul. The authors follow a convenience survey approach using the snowballing technique to select 171 parents from different types of schools (i.e., international schools or domestic schools) where they send their children and aim to understand their preferences to mitigate PM_{10} and $PM_{2.5}$ in residential areas of Seoul. They use an online survey technique to collect individual-specific information and employ the probit model to link the WTP question with individual-specific characteristics. Empirical findings indicate that female respondents are inclined to pay more for air quality improvements than male respondents. Apart from the gender variable, the study also finds that income level, personal experience with air pollution-related illness, and awareness regarding environmental policies positively affect the individual WTP. A sub-sample analysis shows the mean WTP differs significantly between respondents belonging to two socio-cultural groups (the ‘international school’ and ‘domestic school’). The authors conclude that awareness regarding the strong linkage between the current emissions of particulates and green electricity needs to be raised in society.

Tantiwat et al. (2021) employ the double-bound elicitation format to estimate the individual WTP for air quality improvements in Bangkok, Thailand. The study uses online (face-to-face, voice and video call) survey methods based on convenience sampling to collect information from 602 individuals. The authors use the maximum likelihood estimation technique, assuming that WTP follows normal, lognormal, and Weibull distributions. Regression results indicate that income level, educational qualification, and knowledge about air pollution problems positively influence individual WTP for air quality improvements. People concerned about air pollution when using road transport are more willing to pay for air quality improvements. Regression results show that city-dwelling has a negative impact on WTP for air quality. People who live in the city are less likely to pay for improvements in air quality. Moreover, the study finds that if respondents believe that existing government policies are insufficient to protect air quality, they are inclined to pay more for clean air.

Cho and Cho (2023) employ the WTP concept to find the economic value of building a new monitoring and information system for ultrafine particles in Korea. The study follows an online survey to collect information from 1,040 Korean individuals and develops the one-and-one-half-bound dichotomous choice model. They use the spike model to estimate the individual WTP and its determinants. The estimated results show that although the Korean people are satisfied with the existing air pollution monitoring system, they are willing to pay for the new one. The study finds that individuals with greater knowledge about ultrafine particles have higher WTP than their counterparts.

Diallo and Seck (2023) use the WTP approach to understand public attitudes toward improving air quality in Dakar (Senegal). Based on the face-to-face interview of 427 individuals, they developed a double-bound dichotomous choice model to estimate individual willingness. The study uses the bivariate probit model to identify the WTP determinants. The findings suggest that most respondents are willing to pay for air quality improvements. However, the study observes a heterogeneity in individual preferences as the willingness for air quality improvement varies with awareness about air pollution and life expectancy gains, payment methods, and individual-specific characteristics (like income levels, education, and family size). The study also suggests that seasonal temperature variations influence the respondent's WTP for air quality improvements.

Research contributions

Among different available WTP elicitation formats, the present study chooses the CE-DB format – where individuals are asked a follow-up valuation question based on their response to the initial valuation question (Hanemann et al., 1991). An advantage of the close-end method is that it minimises extreme and ambiguous WTP responses, while the double-bound technique offers more precise WTP bounds with more individual responses[2] (Haab and McConnell, 2003). The proposed empirical strategy is somewhat similar to Chattopadhyay (2021), which focuses on avoiding health risks arising from indoor air pollution and is based on a sample of rural households from one particular district in the state of West Bengal, India. However, our

[2] The DB format offers four possible combination of individual responses – (yes, yes), (yes, no), (no, yes), and (no, no). Thus, the total number of individual responses is increased without increasing total number of respondent observations.

study aims to estimate individual preference for ambient air quality improvements and intends to make the following contributions to the existing literature:

- The individual covered in the current work comes mainly from India's northern and western states. To the best of our knowledge, WTP for ambient air quality improvement for such a large geographical location in India has not been studied before.
- The current study explores the role of residential areas (i.e., city types) on individual preferences as pollution concentration levels in India vary across cities and states.
- Although the current study prefers the CE-DB strategy due to its relative statistical efficiency, its findings may be affected by starting point bias. Therefore, we investigate the presence of such anomalies to obtain more accurate WTP estimates

3. Methodology:

In order to answer the above research questions, the present study follows the CVM – a survey-based non-market valuation technique. Under CVM, researchers first construct a hypothetical market for the environmental good or service under consideration and then ask individuals to state their maximum WTP for a unit change in that environmental good or service. The CVM technique uses the utility difference model to estimate the individual WTP.

We follow a closed-end survey format to minimise extreme and ambiguous WTP responses, as the individual is asked whether they are willing to pay a specific monetary amount (aka bid amount), say ₹ A (or $ B), for the proposed air quality level improvement. Here, the positive response implies that the respondent believes he or she will be better off due to the proposed improvement, and his or her actual WTP is greater than equal to the proposed bid amount, ₹ A. Symbolically,

$$\mathrm{Pr}(\mathrm{Yes_i}) = \mathrm{Pr}(\mathrm{WTP_i} \geq \mathrm{A}) = 1 - \mathrm{F_i}(\mathrm{A}) \tag{1}$$

here, $F_i(A)$ denotes the cumulative distribution function of the bid amount ₹ A for i^{th} respondent. Under CVM studies, it is generally assumed that each response is linked with corresponding utility functions which are partially observable. The present study assumes that the observable portion of the utility function is additive and further divided into individual characteristics (Z) and bid amount (A). Similarly, the unobservable part or stochastic component (ϵ) is assumed to be independent, identically and normally distributed with zero mean and unknown variance (σ^2). Therefore, Eq.1 can be rewritten as

$$\begin{aligned} \Pr(\mathrm{Yes_i}) &= 1 - \Pr(-(\alpha Z_i - \beta A_i) \geq \epsilon_i) \\ &= \Pr(\epsilon_i \leq \alpha Z_i - \beta A_i) \\ &= \Phi(\frac{\alpha}{\sigma} Z_i - \frac{\beta}{\sigma} A_i). \end{aligned} \tag{2}$$

Here α and β are the parameters for individual covariates and bid amount, respectively, and $\Phi(.)$ is the cumulative standard normal distribution, showing the probability of a “Yes” response up to a specific bid amount A at a given value of covariates describing individual characteristics.

Under the double-bound format, individuals are initially offered a bid amount, say A_1, for the proposed improvement. If the individual gives a positive response, then in the follow-up question, the surveyor asks a relatively higher bid (A_2) for the same level of improvement. If the individual agrees to pay the higher bid amount, then his or her actual WTP amount is higher (or at least equal) to the follow-up bid amount A_2. However, if the respondent refuses to pay the follow-up bid amount, then his or her actual WTP lies between A_1 and A_2.

Similarly, if the individual’s initial response is negative, the surveyor offers a lower bid in the follow-up question. If the individual response to the follow-up question is positive, then the actual WTP is lower than the initial bid but higher (or at least equal to) the follow-up bid. However, for the negative follow-up response, the individual’s WTP is lower than the follow-up bid amount. Carson and Hanemann (2005) and Haab and McConnell (2003) provide detailed econometric modelling that can be used to derive the econometric model for individual preferences and the probability for each combination of responses. For instance, the probability of (Yes, Yes) response for the ith individual is given by

$$\begin{aligned}\Pr(\text{Yes},\text{Yes}) &= \Pr[(\epsilon_{i1} \leq \alpha Z_i - \beta A_{i1}), (\epsilon_{i2} \leq \alpha Z_i - \beta A_{i2})] \\ &= \Phi_{\epsilon_1\epsilon_2}\left(\frac{\alpha Z_i - \beta A_{i1}}{\sigma_1}, \frac{\alpha Z_i - \beta A_{i2}}{\sigma_2}, \rho\right).\end{aligned} \tag{3}$$

The subscripts 1 and 2 specify the initial and follow-up responses, respectively. The $\Phi_{\epsilon_1\epsilon_2}$ is the standard bivariate normal cumulative distribution with zero means, constant variances (σ_1^2, σ_2^2), and correlation coefficient ρ. Here, Z denotes the vector of individual covariates, while A_1 and A_2 are initial and follow-up bid amounts, respectively. Similarly, one can also define the probabilities for the other three possible responses (i.e., Yes-No, No-Yes, and No-No). Based on those probabilities, the bivariate probit model is adopted to explain variation in the individual responses, and the corresponding likelihood function can be written as

$$L(\alpha,\beta|Z,A) = \prod_{i=1}^{N}\left[\Phi_{\epsilon_1\epsilon_2}\left\{I_{1i}\left(\frac{\alpha Z_i - \beta A_{i1}}{\sigma_1}\right), I_{2i}\left(\frac{\alpha Z_i - \beta A_{i1}}{\sigma_1}\right), I_{1i}I_{2i}\rho\right\}\right] \tag{4}$$

where I_{1i} and I_{2i} are the indicator variables to indicate the individuals' initial and follow-up responses, respectively.

In order to obtain meaningful WTP, the CE-DB method assumes that the preference for the environmental good or service remains consistent across initial and follow-up WTP questions. However, studies by Herridges and Shogren (1996) and Flachaire and Hollard (2006) find a violation of this standard assumption. They argue that the starting point bias (where the initial bid amount is perceived as the actual value of the good or service) affects an individual's follow-up preferences, leading to divergence in the WTP estimates. The studies by Gelo and Koch (2015) and Choi et al. (2016) have identified anchoring and shifting as the reasons for the starting point bias.

Under the shifting effect, a respondent assumes the initial bid amount as the price of the proposed environmental good or service. Under this perception, if an individual responds positively to the initial bid amount, he or she might consider the follow-up higher bid amount unfair to the same proposed improvement. Here, the individual shifts his or her actual preference between initial WTP (WTP_1) and follow-up WTP (WTP_2) based on a shifting parameter (δ): $WTP_{2i} = WTP_{1i} + \delta$, where $\delta < 0$. The negative sign of the shifting parameter ensures the rejection of the follow-up bid amount, leading to a decline in WTP value. If the respondent is uncertain about the true value of the given environmental good or service, then he or she uses the initial bid as the anchor and follows the anchoring preference (γ) to update his or her follow-up preference based on prior beliefs regarding initial WTP (WTP_1). Under the anchoring effect, the follow-up WTP (WTP_2) is the weighted average of WTP_1 and the initial bid amount (A_1). Symbolically, $WTP_{2i} = (1-\gamma)WTP_{1i} + \gamma A_1$, where $0 \leq \gamma \leq 1$. Here, positive anchoring preference implies that a rise in the anchoring parameter increases the bias in the WTP_2 estimates.

Following Gelo and Koch (2015), the present study hypothesises the simultaneous presence of both shifting and anchoring effects: $WTP_{2i} = \gamma A_1 + (1-\gamma)WTP_{1i} + \delta$. To verify our hypothesis, we follow Whitehead (2002) to transform our survey data into a pseudo-panel structure and estimate the following econometric model

$$WTP_{it} = \alpha_i + \delta D_i + \gamma D_i A_{it} + \beta Z_{it} + \epsilon_{it}. \tag{5}$$

Here, WTP_{it} is the response of i^{th} individual at t^{th} round[3], which takes value one for a positive response and zero otherwise. The variable D_i is called the shifting variable, which takes value one to indicate the follow-up response in our CE-DB survey and zero otherwise. Similarly, the D_iA_{it} variable (i.e., an interaction between shifting dummy and bid amount) captures the

[3] In present study, individual i (=1, 2,…,539) is faced the valuation question t (=1,2) times.

anchoring effect. To estimate Eq. 8, we employ the random-probit model, assuming that our random error term (ϵ_{it}) follows the standard normal distribution.

The final objective of the current study is to estimate the mean WTP for air quality improvements based on individual responses. Given the standard normal specification, the mean WTP for the overall sample can be computed as

$$E(WTP) = [(\frac{\sum \bar{Z}'\hat{\beta}}{\hat{\alpha}}) - 1] \quad (6)$$

where, $\hat{\beta}$ and $\hat{\alpha}$ are the estimated parameters of individual covariates and bid amount, respectively. The $\bar{Z}$ is the average value of the individual covariates based on our data (Gunatilake et al., 2007). However, our Stata 14 estimates of Eq. 4 and Eq. 5 do not correspond to the direct estimates of the required parameters (Lopez-Feldman, 2012). Therefore, we utilise the user-defined doubleb and singleb Stata commands developed by Lopez-Feldman (2012) to get direct estimates of the parameters and then utilise the post-estimation Stata command (nlcom) to estimate Eq. 6.

4. Survey design and data descriptions:

All data used to estimate our bivariate probit model in the previous section come from a primary survey conducted in 2019. The present study follows the National Oceanic and Atmospheric Administration (NOAA) panel recommendations (Arrow et al., 1993) as much as possible in designing the survey format. Our focus group is the parents or guardians of newly admitted undergraduate students of premier academic institutions located in two northern states of India – Uttar Pradesh and Uttarakhand. Parents or guardians attending the orientation program for their children are chosen randomly to participate in face-to-face interviews. However, their participation in the survey is voluntary. The advantage of our data collection strategy is two-fold: first, given resource constraints, it minimises the cost of the survey, and second, it ensures sufficient heterogeneity in the samples as the majority of the students getting admission to these institutions come from various states of the northern and western part of India.

Our questionnaire is divided into three sections. Section A collects individual-level socio-economic information like educational qualification, income, and wealth, while Section B gathers information on individual willingness for air quality improvements. Finally, section C asks questions about the respondent's awareness and concern about air pollution. In the present study, more than 600 individuals are approached. However, after removing incomplete questionnaires, information on 539 north Indian respondents constitutes the final data set for empirical analysis.

During the survey, each respondent is asked: "Would you be willing to pay ₹A every month to the government as an additional component of your tax if the government spends this money to improve air quality?" However, before asking the WTP question, each respondent is requested to read three paragraphs of information to ensure a homogeneous knowledge base across respondents. The first paragraph briefly mentions India's ambient air pollution situation and possible health incidences. The second paragraph indicates the policies to mitigate air pollution levels and the related costs of those mitigation activities. The final paragraph reminds the respondents about their budget constraints to obtain an informed WTP response. During the survey, each respondent is randomly assigned an initial bid (i.e., ₹A) from a set of three values – 100, 200, and 500[4]. Figure 1 shows the proportion of positive (i.e., "Yes") and negative (i.e., "No") responses across bid amounts and suggests a negative relation between the bid amount and positive response.

<**Figure 1:** Proportion of initial responses against different initial bid amounts>

[4] All bid values asked in the survey are in Indian currency. The selection of the bid amount is done subjectively, keeping in the mind of its acceptability and reliability. For international references, one may wish to convert those bid amounts into United States Dollar (USD), by dividing those values by average official exchange rate 70.42 for the period 2019 (World Bank, 2020).

Under the DB strategy, every individual is asked a follow-up WTP question based on his or her initial WTP response. Therefore, each initial bid has two follow-up bids: A higher follow-up bid (if the initial response is positive) and a lower follow-up bid (if the initial response is negative). Table 1 shows the distribution of individual responses across different bid amounts. Here, Panel A presents the distribution of initial responses, while Panel B represents the distribution of follow-up responses. For example, 128 respondents have faced the initial bid amount of ₹ 100, out of which only 41 respondents give a negative response and receive ₹ 50 as their lower follow-up bid amount. However, 87 respondents have been offered ₹ 200 as their higher follow-up bid amount. From Panel B, we observe that only nine respondents have changed their response and are willing to pay ₹ 50 to improve air quality. Regarding a higher follow-up bid amount, we observe that only 27 respondents are unwilling to pay the follow-up bid amount (i.e., ₹ 200). Table 1 also indicates an unequal distribution of initial bids among individuals, possibly because (i) the initial bid is assigned randomly and (ii) only correctly filled forms are considered.

<**Table 1:** Distribution of responses across both WTP questions>

The present study assumes that an individual's response to the WTP question depends on the bid amount and various socio-economic variables. In the present study, we have also collected individual-specific information and summaries in Table 2. The sample covers 14 states[5], a union territory (Chandigarh), and the National Capital Territory (Delhi). However, the majority of our sample comes from the five largest states – Uttar Pradesh (21.15% observations), Rajasthan (20.04% observations), Maharashtra (11% observations), and Madhya Pradesh (10.02% observations). The location variable indicates the respondent's place of residence,

[5] These 14 states are Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Madhya Pradesh, Maharashtra, Odisha, Panjab, Rajasthan, Uttar Pradesh, Uttarakhand, and West Bengal.

which can be further grouped into three categories – Tier 1 city, Tier 2 city, and other city[6]. In the present study, most of the respondents belong to Tier 2 cities (73.84%), followed by Tier 1 cities (15.40%) and other cities (10.76%). The education variable shows the highest education level of respondents, which are grouped into three categories – higher secondary (i.e., class XII) or less, graduation, and master's degree and above. Table 2 shows that around 91% of our respondents have at least a graduation degree.

<**Table 2:** Summary statistics>

Environmental concern is a derived variable that indicates the level of concern regarding air pollution in India. The variable is constructed based on section C of the questionnaire, where respondents are asked five questions regarding their awareness and concerns about the air pollution problem in India[7]. If the individual responds positively, his response is recorded as one, otherwise zero. The sum of all these five responses indicates the total environmental score of the individual, which varies between zero and five. Suppose the total environmental concern score is higher than or equal to the median score (viz., four), then the environmental concern dummy takes value one; otherwise, zero. In the present study, around 82% of respondents are highly concerned about air pollution problems in India.

Finally, the income variable indicates the monthly household income for each respondent, which is categorised into six different classes – less than ₹20,000, ₹20,000–40,000, ₹40,001–60,000, ₹60,001–80,000, ₹80,001–1,00,000, and more than ₹1,00,000. However, from the

[6] For classification of Tier 1 and Tier 2 cities, the present study uses the official memorandum on re-classification of cities based on 2011 census, by the Ministry of Finance, the Government of India (Department of Expenditure, 2015).

[7] These questions are as follows: (i) "Do you consider air pollution as major health problem in your locality?" (ii) "Do you think that firecrackers used during the festival celebrations may increase the air pollution level?" (iii) "Do you consider air pollution as one of the most important problems in India?" (iv) "Have you seen, heard or read about severity of air pollution related problems in last one year, in India?" and (v) "Stricter environmental regulation to reduce air pollution may result in higher prices, reduced economic growth and less opportunities for job creation. Do you think India should make such stricter environmental regulations even if the economy has to sacrifice its growth targets to some extent?"

analysis perspective, each class's mid-value is considered the representative income level[8]. Here, negatively skewed income variables suggest that most of our respondents belong to high-income groups.

5. Results and discussion

In this section, we report and discuss our empirical results, followed by the mean WTP estimate. We begin with Table 3, which summarises the parameter estimates (Panel A) and marginal effects (Panel B) of the bivariate probit model (i.e., Eq. 4) without accommodating the shifting and anchoring effects.

Panel A suggests that the impact of economic variables like initial bid amount and individual-specific characteristics like residential location and educational qualification are limited only to the initial response. For example, the negative significant initial bid coefficient implies a unit increase in the initial bid amount decreases the z-score[9] by 0.0010 units. The finding aligns with modern economic theory, which says an individual will purchase less if the commodity price is high. The positive and significant Tier 1 dummy suggests that if the respondent lives in Tier 1 cities, his or her z-score will increase by 0.7466 compared to the reference category. The finding implies a positive big-city dwelling effect on the individual's willingness for ambient air quality improvement (Carlsson and Johansson, 2000). The positive and significant education dummies imply that higher education levels lead to higher levels of WTP as individuals become more sensitive to environmental problems (Diallo and Seck, 2023). For instance, the z-score is increased by 0.4792 for graduate respondents, while for respondents with a master's degree and above, the estimated rise in z-score is 0.3698 relative to our base

[8] For open-end class, class width is assumed as same as close-end class.
[9] The probit function indicates the inverse of cumulative distribution function of a standard normal random variable (z). So, the estimated coefficient is interpreted as change in z-score which shows the distance from mean value measured in terms of standard deviation.

categories (Higher secondary or less). However, between graduation and master's degree and above, we fail to obtain any significant difference [10].

The estimated bivariate coefficients for income and environmental concern dummy show positive associations for both initial and follow-up responses; however, the impact of estimated coefficients remains the same across both responses[11]. Here, the household income variable shows a positive income effect, which states that with an increase in monthly household income, individuals may upgrade their consumption bundle with a higher quality of good or service (Wang and Zhang, 2009; Kim et al., 2019; Diallo and Seck, 2023). Similarly, the estimated environmental concern dummy suggests that individuals with more knowledge and awarness about ambient air pollution problems are willing to pay more than others (Du and Mendelsohn, 2011; Cho and Cho, 2023). Finally, the significant and positive correlation coefficient indicates a strong positive association between initial and follow-up responses and justifies the usage of the bivariate probit model. The significant Wald statistic suggests that our bivariate model is overall significant.

< **Table 3:** Findings based on bivariate probit model>

Note that in Panel A, the interpretation of the estimated coefficient is based on the standard-normal cumulative or z-score, which is difficult to understand. Therefore, we estimate the marginal (or covariate) effect for each independent variable and report them in Panel B of Table 3. First, the probability of a positive response is negatively related to the initial bid amount. For instance, a unit increase in the initial bid amount decreases the probability of a positive response by 0.01 percentage points. Second, for individuals living in Tier 1 cities, the probability of a positive response is increased by 17.75 percentage points. Third, for the income

[10] However, we fail to obtain any significant difference between estimated coefficients of graduation and master degree and above. Here estimated test statistics (i.e., Chi-square) is 0.81 with p-value 0.36.
[11] For income variable estimated test statistics value is 0.66 with p-value 0.41 and, similarly, for environmental concern variable, the estimated test statistics is 1.77 with p-value 0.1834.

variable, we observe that a unit change in monthly household income can increase the probability of a positive response by 0.20 percentage points. Finally, we find the highest marginal effect for the environmental concern dummy, suggesting an increase of 21.89 percentage points in the probability of a positive response to air quality improvements.

From the distribution of individual responses (see Table 1), we find that around 68% of individuals remain consistent about their WTP response with "Yes-Yes" or "No-No" types of responses, and only 32% of respondents have altered their responses during the follow-up question. The present study assumes that shifting and anchoring anomalies might influence individual responses during follow-up responses. The present study estimates Eq. 5 to verify the hypothesised anomalies, and the corresponding results of the random probit model are reported in Table 4. The baseline model in Column 1 assumes the absence of anomalies. In Columns 2, 3 and 4, we have introduced the shifting, anchoring, and shifting-anchoring anomalies, respectively.

< **Table 4**: Random probit estimation results>

The significant coefficient for shifting and anchoring variables in Columns 2 and 3 suggests that preference for air quality improvements differs substantially between initial and follow-up responses. However, the negative anchoring coefficient in Column 3 violates the standard assumption of the positive anchoring effect. Whitehead (2002) argues that violation in the anchoring assumption might arise because of model misspecification due to the interaction between the bid amount and the shifting dummy. Therefore, we re-estimate the model with shifting and anchoring effects and report them in Column 4. We use the log-likelihood ratio to evaluate model fitness, which indicates a significant improvement for the empirical model in column 4. Therefore, we decide to consider the presence of both anomalies in individual preferences.

The findings in Column 4 show that both shifting and anchoring coefficients are statistically significant. Unlike Column 3, the positive anchoring coefficient in Column 4 follows the standard anchoring assumption. Here, the estimated anchoring coefficient indicates that the initial bid can only influence 0.11% of an individual's decision in the follow-up WTP question. Furthermore, the negative shifting coefficient (like Column 2) also suggests a downward shift in individual WTP during follow-up questions.

The final objective of the study is to determine the individuals' WTP for ambient air quality improvements in India. Table 5 summarises the point estimate for the mean WTP values, standard errors, z statistics and p-value based on Eq. 6. For the bivariate model, our estimated mean WTP value is ₹303.38 (or $3.66) per month, which is less than 1% of the average monthly household income of our sample. However, our estimated mean WTP value might be biased as the bivariate model does not account for the shifting and anchoring effects.

<**Table 5**: Mean WTP estimates>

Therefore, we re-estimate the mean WTP based on the random-effect probit model estimates. Based on the shifting-anchoring specification in Table 4, the estimated mean WTP becomes ₹255.69 (or $3.09) per month and is around 15 per cent lower than the mean WTP estimates based on the bivariate probit model. This finding suggests that correcting the starting point bias in our CE-DB design minimises the bias in the mean WTP estimate.

6. Conclusion:

The current study relies on the CE-DB CVM technique to determine how the variety of socio-economic factors, including place of residence, educational qualification, income level, and awareness regarding air pollution and related health consequences, can influence the individual WTP for air quality improvements in the context of India, particularly for the Indio-Gangatic Plain. To obtain individual preferences for ambient air quality improvement, we employ the bivariate probit model on a sample of parents or guardians attending the orientation program of their newly admitted children in premier academic institutions. As mentioned earlier, our research work is probably the first that covers a large geographical location to examine the role of residential areas and other socio-economic variables on individual willingness for improvements in ambient air quality. Furthermore, the study has investigated the possible sources of starting point bias in the CE-DB design, leading to overestimating mean WTP.

The findings of our study indicate that various socio-economic factors play a significant role in determining the individual's preference for ambient air quality improvements. For example, inhabitants of large cities pay more as pollution problems are more common in those cities. Similarly, higher-income respondents are more willing due to the positive income effect. For education and environmental awareness variables, the positive associations with WTP suggest that a well-informed respondent can easily relate his or her contribution towards mitigation activities. From a policy perspective, these empirical findings are helpful to policymakers in designing a successful air pollution mitigation strategy. The study has also identified shifting and anchoring anomalies as possible sources of starting point bias in the current CE-DB design. After correcting those anomalies, our estimated mean WTP suggests that, on average, individuals are willing to pay ₹255.69 (or $3.09) per month to improve the air quality.

The findings of the current research work are subject to at least two limitations. First, due to a lack of external funding, the study uses a moderate sample size generated in a somewhat non-random manner that might reduce the generalisation power of our findings. Second, unlike Mariel et al. (2022), the present study follows a single dichotomous elicitation format, providing little evidence of individual preference for various air pollution attributes. Moreover, our study collects information from the parents or guardians of newly admitted undergraduate students who came to help their children settle down on campus. Therefore, we restrict ourselves to using a small and straightforward survey questionnaire to collect information.

Despite such limitations, our study has tried to portray a simplified demand-side indicator for air quality improvements, which can be interpreted as public support for air quality improvement in India. It is recommended that further air pollution-related CVM research be undertaken in the following areas. For instance, one may study the role of payment vehicles to determine individuals' willingness for air quality improvements. It would also be interesting to compare individual preferences across various air pollution mitigation strategies in the Indian context.

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Table 1: Distribution of responses across both WTP questions

	Panel A			Panel B	
	Initial response			Follow-up response	
Initial bid (₹)	No	Yes	Follow-up bid (₹)	No	Yes
100	41	87	Low: 50	32	09
			High: 200	27	60
200	92	195	Low: 100	73	19
			High: 500	77	118
500	53	71	Low: 200	36	17
			High: 1000	25	46
Total	186	353		270	269

Source: Authors’ calculation

Table 2: Summary statistics

Original Variable	Derived variables and labels	Frequency	Percentage
Location	Tier 1 cities	83	15.40
	Tier 2 cities	398	73.84
	Other	58	10.76
Education	Higher secondary or less	48	8.91
	Graduation	246	45.64
	Master degree & above	245	45.45
Environmental concern	High (1)	440	81.63
	Low (0)	99	18.37
Affluent	High (1)	175	32.47
	Low (0)	364	67.53
		Mean	Median
Household monthly income	Income (in ’000 ₹)	80.35	90

Note: all percentages are calculated based on sample size (i.e., N) 539
Source: Authors’ calculation

Table 3: Findings based on bivariate probit model

Variables	Panel A: Bivariate probit estimates — Initial response	Panel A: Bivariate probit estimates — Follow-up response	Panel B: Marginal effects
Initial bid (₹)	-0.0010***		-0.0001***
	(0.0004)		(0.0000)
Follow-up bid (₹)		-0.0003	-0.0001
		(0.0003)	(0.0001)
Tier 1 city	0.7466***	0.3479	0.1775**
	(0.2491)	(0.2271)	(0.0771)
Tier 2 city	0.2422	0.2333	0.0907
	(0.1887)	(0.1815)	(0.0577)
Graduation	0.4792**	0.1290	0.1000
	(0.2094)	(0.2067)	(0.0626)
Master degree & above	0.3698*	0.0581	0.0674
	(0.2107)	(0.2084)	(0.0627)
Income (in ’000 ₹)	0.0039**	0.0056***	0.0020***
	(0.0019)	(0.0018)	(0.0006)
Environmental concern	0.7123***	0.5113***	0.2189***
	(0.1436)	(0.1463)	(0.0428)
Intercept	-0.8881***	-1.0472***	-
	(0.2782)	(0.2576)	-
Correlation	0.7197***		-
	(0.1258)		-
Observations	539		539
Log-likelihood	-645.45		-
Wald statistics	68.08		-
p-value	0.00		-
AIC	1324.91[17]		-
BIC	1397.83 [17]		-

Note: (i) Robust standard errors in parentheses; (ii)*** $p<0.01$, ** $p<0.05$, * $p<0.1$; (iii) degrees of freedom are mentioned in box brackets;
Source: Authors’ calculation

Table 4: Random probit estimation results

Variables	(1) Baseline	(2) Shifting	(3) Anchoring	(4) Shifting and anchoring
Shifting		-0.5745***		-0.8591***
		(0.1073)		(0.1857)
Anchoring			-0.0012***	0.0011*
			(0.0004)	(0.0006)
Bid	-0.0018***	-0.0008*	-0.0002	-0.0017**
	(0.0006)	(0.0004)	(0.0006)	(0.0007)
Tier 1 city	0.9559**	0.8589***	0.9308***	0.8250**
	(0.3857)	(0.3334)	(0.3604)	(0.3263)
Tier 2 city	0.4195	0.3967	0.4195	0.3821
	(0.2921)	(0.2555)	(0.2759)	(0.2495)
Graduation	0.5755*	0.4932*	0.5312*	0.4852*
	(0.3210)	(0.2792)	(0.3004)	(0.2741)
Master degree & above	0.4200	0.3464	0.3727	0.3468
	(0.3173)	(0.2776)	(0.2984)	(0.2722)
Income (in ’000 ₹)	0.0090***	0.0078***	0.0084***	0.0077***
	(0.0030)	(0.0026)	(0.0028)	(0.0025)
Environmental concern	1.1482***	1.0141***	1.1001***	0.9806***
	(0.2736)	(0.2282)	(0.2482)	(0.2250)
Intercept	-1.6368***	-1.3692***	-1.7676***	-1.1139***
	(0.4211)	(0.3665)	(0.3999)	(0.3842)
Observations	1,078	1,078	1,078	1,078
Number of ids	539	539	539	539
Log-likelihood	-665.76	-651.28	-659.60	-649.66
ρ	0.7030	0.6293	0.6760	0.6111
	(0.0737)	(0.0719)	(0.0674)	(0.0777)

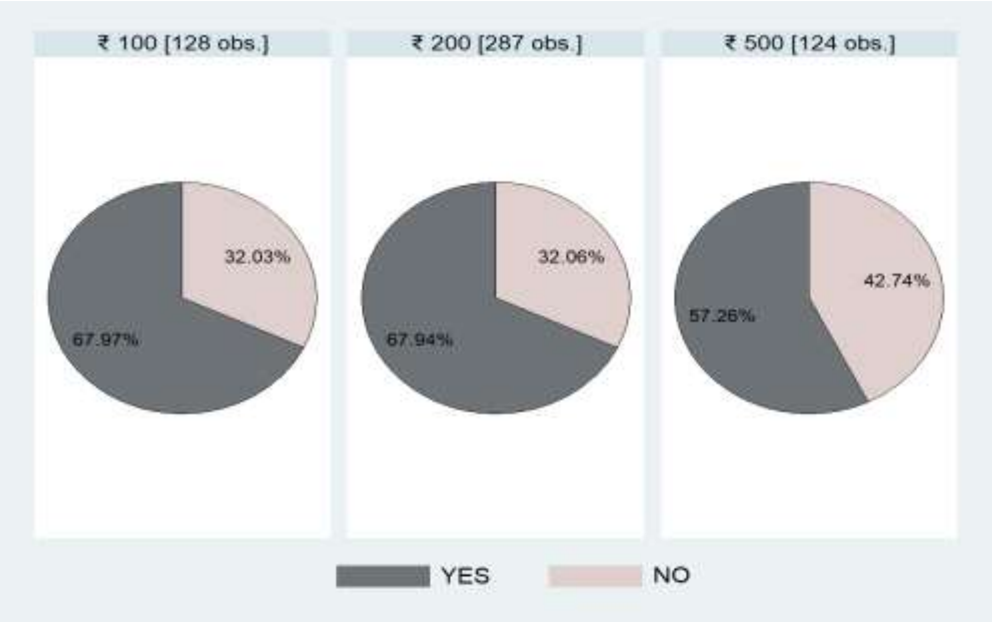
Note: (i) Robust standard errors in parentheses; (ii)*** p<0.01, ** p<0.05, * p<0.1; (iii) degrees of freedom is mentioned in box brackets; (iv) ρ indicates the portion of total variance contributed by the panel-level variance component
Source: Authors’ calculation

Table 5: Mean WTP estimates

	Mean WTP	Std. error	z statistic	p-value
Bivariate probit	303.38	84.78	3.58	0.00
Random probit	255.69	135.23	1.89	0.05

Note: Robust standard errors are reported
Source: Authors’ calculation

Figure 1: Proportion of initial response against different initial bid amounts



Source: Authors' creation