Valuing individuals' preferences for air quality improvement: evidence from a discrete choice experiment in South Delhi

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Abstract

Air pollution is one of the most pressing problems in India, taking millions of lives annually. Despite unprecedented air quality deterioration, little is known about individuals' preferences for air quality improvement in India. As a first step, this study presents results from a discrete choice experiment eliciting the preferences for air quality improvement of inhabitants in South Delhi, India, which is part of the city of Delhi and where air pollution is causing extensive health hazards. Adequate knowledge about individuals' preferences can help in designing more effective health and environmental policies. Overall, we find a significant willingness to pay for improving the air quality in South Delhi. As expected, people with a higher level of education and a higher income are more willing to pay to alleviate and prevent the effects of air pollution. At the same time, significant gender effects are identified; women seem to have more homogeneous preferences regarding air quality than men. Furthermore, due to income inequalities, a significant number of respondents are not willing to pay.

Keywords: air quality improvement, discrete choice experiments, willingness to pay, South Delhi, individuals' preferences

JEL codes: C25, N55, Q51

1. Introduction

Ambient air pollution is the world's biggest environmental health threat (World Health Organization, 2016). The recent State of Global Air 2020 Report estimated that air pollution caused 6.67 million premature deaths globally in 2019 and that 58 per cent of these global deaths occurred in China and India (Health Effects Institute, 2020). This implies that controlling air pollution is a major concern across developing countries. In India, for instance, the annual concentration of fine particulate matter (PM2.5) was the highest in the world, and it contributed around 17.8 per cent (1.67 million) of the total death toll in 2019 (Pandey *et al*., 2020). According to the Swiss Air Quality Index (2020), 35 of the world's top 50 cities in 2020 in terms of the highest levels of annual PM2.5 were in India, and its capital territory, Delhi, was the 10th most air-polluted city in the world.

To alleviate the unprecedented impact of air pollution on big cities, the Indian government has launched a series of control measures together with a substantial increase in the total investment of INR44 billion (US$600 million) in the annual budget 2020–21 to improve air quality (Chatterji, 2020). For instance, an initial INR3 billion (US$42.6 million) was directly allocated to the five-year National Clean Air Programme (NCAP) initiated in 2019 to curb PM2.5 levels by 20–30 per cent by 2024, with 2017 as the base year. The NCAP mitigation programme focused on 102 cities in India that had crossed the limit of the National Ambient Air Quality Standards (NAAQSs). Moreover, the central government announced the Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) programme in India with an outlay of INR85 billion (US$1.15 billion) in 2015.

In recent years, the Indian government has introduced several measures to combat air pollution. Firstly, in 2015, it introduced the air quality index to analyse the day's air quality based on a set of air quality descriptors along with health advice, and comprehensive air monitoring stations were installed in public areas (Central Pollution Control Board, 2015).

Secondly, in 2017, the government introduced an emergency and comprehensive action plan called the Graded Response Action Plan (GRAP) (Chatterji, 2020). The purpose of the GRAP was to enforce emergency measures, such as suspending construction sites, restricting heavy vehicles in the city and imposing odd–even rules when the air pollution exceeds a dangerous level. Moreover, the aforementioned NCAP mitigation strategy followed the prevailing policies and strategies, such as the National Action Plan on Climate Change, promoting electric transportation and the smart cities plan.

Finally, in April 2020, the Indian government imposed the Euro VI emission standards (referred to in India as Bharat Stage VI) to regulate the emission of air pollutants by motor vehicles (Centre for Science and Environment, 2018). Moreover, in recent years, several power plants, including large power generators, construction sites, brick kilns and hot mix plants, have been shut down, and street air filters and smog towers have been introduced to remove particulate matter and dust. In addition, the authorities in Delhi have recently introduced the odd–even rule, which allows private vehicles to use the roads only on specified days, depending on their registration number (Chatterji, 2020).

Nonetheless, none of the above measures have been effective in reducing air pollution in India, and it remains a major concern for policymakers due to its huge economic cost in terms of air pollution-related mortality and morbidity (Balakrishnan *et al*., 2019; Watts *et al*., 2020). Pandey *et al*. (2020) showed that air pollution causes economic losses of nearly INR2,714.46 billion (€30.2 billion), which is 1.36 per cent of India's gross domestic product. Moreover, additional co-benefits of improving the air quality are closely linked to other environment-related issues, such as greenhouse gas emissions, climate change and technological innovation (Bollen, 2015).

For the city of Delhi, the Delhi Pollution Control Committee appointed by the Government of Delhi is committed to sustainable development and thus is also responsible for dealing with the air pollution problem in this area. It implements policies set by the Delhi division of the Ministry of Urban Development. According to Ministry of Urban Development, Delhi division (2007), the future air pollution mitigation plans must include public transportation planning (frequency, intermodal integration, single ticketing system, parking policy) and policy measures related to the operation of existing power plants and other industries.

However, little information is available about individuals' preferences regarding air pollution that could be used in economic evaluations, such as a cost-benefit analysis. In this paper, as a step towards mapping individuals' preferences for air quality improvement in India, we therefore conducted a survey in South Delhi, India because, especially in the megacities, air pollution is an extensive health hazard (Vohra *et al.*, 2021). Focusing on the second-largest urban district of Delhi, i.e. South Delhi, we provide data related to the benefits of air pollution reduction for a largely unexplored region of the world. Most studies concerned with the valuation of benefits due to improved air quality have focused on OECD (Organisation for Economic Co-operation and Development) countries. The air quality problems in OECD countries, however, can be quite different from those in developing countries. Our study represents, to the best of our knowledge, the first analysis of individuals' preferences for air quality in India elicited by the use of a Discrete Choice Experiment (DCE), while the technique has already been applied in other East Asian countries (see, e.g., Yoo *et al.*, 2008; Yao *et al.*, 2019; Nguyen *et al.*, 2021).

One of the main recommendations of an OECD report that analyses the air pollution impacts in the OECD countries together with China and India that stresses the importance of studies like ours is that "A defensible calculation of the economic cost of health impacts must be based on economic first principles" (OECD, 2014, p. 2). Given the relatively high amount of resources OECD countries devote to achieving this goal, the literature presenting value estimates in the OECD countries is extensive. Therefore, the OECD was able to initiate in 2011 a meta-analysis of SP studies of mortality risks related to the environment, transport and health (Lindhjem et al. 2011; OECD, 2012). But similar studies cannot be performed in many other parts of the world, including India, because of the lack of information related to environmental improvements.

Valuing the environmental goods and services in developing and transition economies can be seen as an extremely important task given that rapid economic development can be achieved at the cost of extensive destruction of renewable resources and degradation of the environment (Barbier and Cox, 2003). The cost of this destruction can be very high when future generations are considered. That is why the use of economic valuation techniques such as DCEs is of utmost importance as it contributes to a better resource allocation and better management of natural resources.

The application of these techniques in developing and transition economies can be however related to local conditions and culture that may be very different from developed economies where these techniques have been applied and their results used in policy making for decades (Navrud and Mungatana, 1994; Rakotonarivo et al., 2016; Quah, 2013). This can be one of the reasons of the lack of environmental studies in these economies and it also increases the importance of an environmental valuation study focused on the severe problem of air pollution carried out in the second most populous country with a rapid growth economy.

The Environmental Valuation Reference Inventory (https://www.evri.ca/), a worldwide and searchable compendium of summaries of environmental and health economics valuation studies (Morrison, 2001) provides, as of March 1st, 2022, more than 2,100 entries for North America and more than 1,500 for Europe out of an approximate total of 5,200 entries. In contrast, for India, this inventory has only 74 entries. This indicates that more evidence about the value of non-market goods and externalities is urgently needed to monitor the environmental and health conditions in such a rapidly developing economy.

That is why there is a need for primary valuation studies focused on this topic. The emphasis on valuation studies is relevant in order to assess the effectiveness of government outlays in meeting the objectives of abatement policies, and to provide a possible roadmap for government policymaking that broadens societal benefits. It can also assist policy-makers in determining when to spend money on mitigation policies, bearing in mind the benefits of abatement policies.

The remainder of the study is organised as follows. Section 2 summarises the literature on the economic evaluation of air pollution to reconfirm the knowledge gap. Sections 3, 4 and 5 present the case study, survey design and data collection, respectively. Section 6 describes the applied methodology, and Sections 7 and 8 gather the main results and willingness to pay (WTP) estimates before the conclusion in Section 9.

2. Literature Review

A number of revealed preference (RP) and stated preference (SP) studies have investigated the economic and health benefits of reducing air pollution (Alberini and Krupnick, 2000; Yoo *et al.*, 2008; Yao *et al.*, 2019; Pandey *et al.*, 2020). Amongst these methods, SP techniques are usually the most suitable tool for the economic evaluation of air pollution due to the fact that they can analyse both market and non-market goods or services.

Baby (2009) represents an example of the scarce SP valuation studies related to air pollution in India. This limited contingent valuation study, conducted in the industrial agglomeration of Cochin, state of Kerala, was devoted to valuing only one aspect related to the air pollution, specifically the additional 'symptom days'. The RP literature focused on India is slightly broader and the papers are usually based on hedonic pricing (Murthy, Gulati and Banerjee, 2003; Murty and Gulati, 2005) or health production function (Kumar and Rao, 2001).

The impact of air pollution on human health has been studied in India using different approaches. For instance, the World Bank-funded study by Cropper *et al.* (1997) was one of the first attempts to tackle this issue. Since then, many physiological and RP studies investigating the impact of air pollution on health status have emerged in the literature (Tyagi *et al*., 2016; Balakrishnan *et al*., 2019; Ishita and Dholakia, 2019; Pandey *et al*., 2020; Vohra *et al*., 2021).

In spite of the extensive environmental valuation DCE literature in various fields, only a few air quality valuation studies seem to have been carried out using a DCE. Most of these studies have focused on OECD and East Asian countries. The most recent examples of an air pollution valuation study are represented by Nguyen *et al.* (2021), who estimated the economic benefits associated with air quality improvements in Hanoi City, the capital of Vietnam, and Moon *et al.* (2021), who examine the public perception of air quality improvement of the South Korean population.

Table 1 summarises the DCE studies focusing on air pollution that have been conducted in different geographical regions over the past 20 years. The first and second columns show the author(s) of the study and the country where the DCEs were conducted. The third column indicates the number of individuals in the sample, ranging from 286 to 3,000. The most important column for our analysis is the fourth column, which presents the attributes related to air pollution. These attributes were used as a baseline in the focus group discussion described below, which led to the final definition of our DCE. The fifth column shows the types of models used, which include a wide range of standard discrete choice approaches. Finally, the last column of Table 1 shows the field of study.

Table 1

Studies employing discrete choice experiments to value the effects of air pollution.

Author and Year	Country	No. of Individuals	Attributes	Model Estimated	Area of Study
Muller *et al*. (2001)	Canada	515	Odour, black fallout, visibility, health effects, property tax/rent	Conditional logit (CL)	Environment
Wardman and Bristow (2004)	UK	398	Noise, air quality, car, bus	Binary logit	Transportation
Collins (2007)	US	403	Visibility, healthy days, gas price, vehicle inspection cost, electricity bill	Mixed logit (MXL)	Environment
Yoo *et al*. (2008)	S. Korea	600	Mortality, morbidity, soil damage, poor visibility, price	MNL	Environment
Carlsson *et al*. (2010)	Sweden	3,000	Marine environment, lakes and streams, clean air	Random parameter logit (RPL)	Environment
Ghorbani *et al*. (2011)	Iran	286	Health effects, high particulate count, foul odours, reduced visibility, price	MNL	Environment
Banfi *et al*. (2012)	Switzerland	635	Rent, mobile antenna, air quality, traffic noise exposure	CL	Transportation
Rizzi *et al*. (2014)	Chile	321	Visibility, health of children, health of adults, health of the elderly, cost	MXL	Health
Tang and Zhang (2016)	China	988	Smog days, mortality, policy content, policy delay, cost	CL	Environment
Boyle *et al*. (2016)	US	1,271	Visibility improvements, ecosystem impacts, health impacts, timing, cost	CL	Environment
Valeri *et al*. (2016)	Italy	2,400	Measures, cost, mobility habits, eating habits, premature deaths, polluters pay more	MNL, Latent class model (LCM)	Transportation
Huang *et al*. (2017)	China	475	Changes in the number of times with cold symptoms, morbidity, mortality, cost of programme, payment vehicle	Generalised multinomial logit (GMNL), LCM	Health
Yao *et al*. (2019)	China	394	Air quality, price	MXL	Environment
Li (2019)	China	759	Illness duration, daily activity restriction, price of cure	RPL	Health
Jin *et al*. (2020)	China	1,107	Morbidity, mortality, delay, cost	MNL, MXL, LCM	Health
Nguyen *et al.* (2021)	Vietnam	1,028	Morbidity, mortality, urban tree cover area	CL, MXL, GMNL, LCM	Health, Environment
Moon *et al.* (2021)	S. Korea	1000	Air pollutants (TSP, PM10, PM2.5, NOx, SOx, VOC), cost	MXL, Hierarchical Bayesian (HB) logit model	Environment

3. The Case Study

Air pollution is mainly prevalent in big cities in India, creating massive public health and environmental crises (Chatterji, 2020). Across all the megacities in India, the city of Delhi has witnessed detrimental levels of air pollution. For this reason, we chose South Delhi, the second-largest urban district of Delhi, for our case study (see Figure 1). This district has been affected by a severe deterioration in air quality over the past decades.

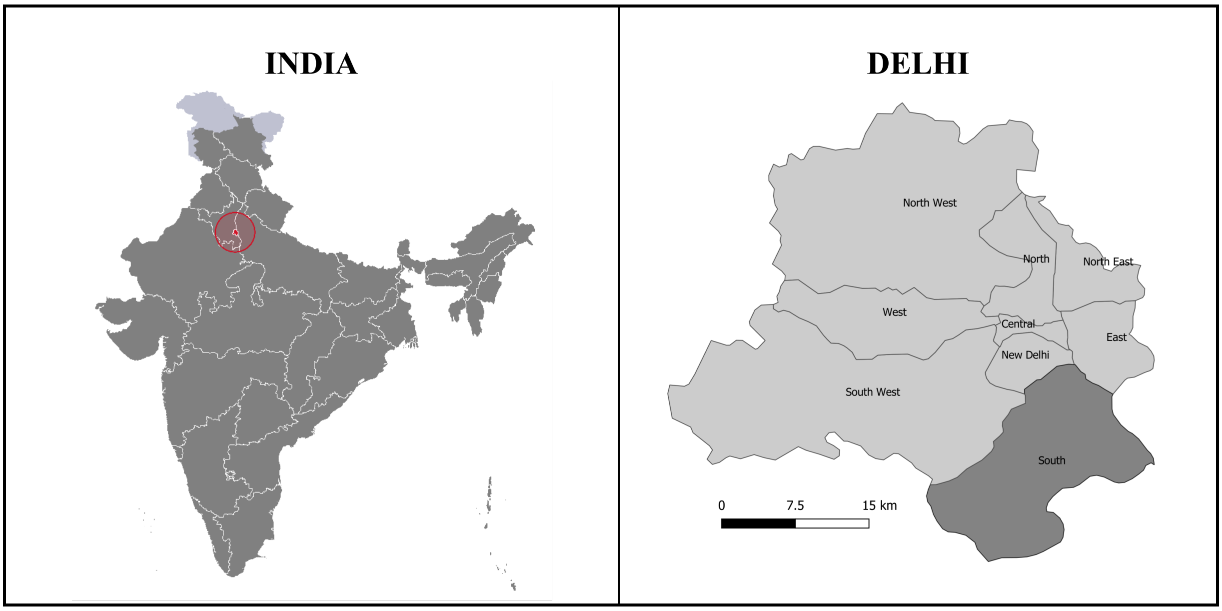

Figure 1. Location of South Delhi in Delhi (India).

Source: https://commons.wikimedia.org/wiki/File:IN DL.svg#/media/File:IN-DL.svg, under the CC BY-SA 4.0 licence, and http://www.arcgis.com/home/item.html?id=7c4f1b9be6cc4cecbcd28ee5136898f7, under the Creative Commons Attribution 2.5 India licence.

According to the Census of India (2011), South Delhi has a population of over 2.7 million permanent residents and a population density of 11,000 people per square km. Moreover, 86.60 per cent of the population of South Delhi is literate, meaning that the majority of respondents are able to understand and answer potentially complex DCE surveys. In addition, South Delhi's residents are aware of the level of air pollution in their neighbourhood and can easily think of a monetary value for reducing the level of pollution to a level that they would like. The main reason for this is that there are 10 air quality monitoring stations in Delhi, and three of them are located in the district of South Delhi; they provide people with comprehensive and real-time information about the current air pollution levels (Central Pollution Control Board, 2016).

The economic liberalisation policy of 1991, which brought about rapid industrialisation and urban mobilisation in South Delhi, is considered to be the main reason for its negative trend in air quality. This alone led to a huge increase in industrial emissions, accounting for 35 per cent of the total air pollution in the city Delhi, which includes the analysed area of South Delhi (Ishita and Dholakia, 2019). Moreover, this led to rapid growth in the real estate, power and transportation sectors, coupled with an increase in planned and unplanned urbanisation (Gordon *et al*., 2018). The steep increase in the number of motor vehicles from 4.2 million in 2004 to 10.9 million in 2018 (Economic Survey, 2019) has further exacerbated the deterioration of the air quality. As a result, vehicular emissions are now recognised as one of the major contributors, accounting for 30 per cent of Delhi's total air pollution (Ishita and Dholakia, 2019).

Likewise, with the rise in income and consumption, the city of Delhi produces 9,500 tons of waste every day, making it the city with the second-largest amount of waste in India (Sharma, 2017). This gigantic amount of waste is managed through landfills (located in South Delhi) and biomass burning, which produces deadly methane, and the estimated emissions contribute about 20–30 per cent of the total air pollution in Delhi. Moreover, a recent study by Bikkina *et al*. (2019) found that the share of stubble burning in the neighbouring states of Punjab and Haryana has greatly worsened the air pollution in Delhi in recent years, as it can range from 17 per cent to 43 per cent from winter to autumn.

The above evidence shows that the intensity of the deterioration in air quality standards in South Delhi is unprecedented. To address this challenge, as previously explained, the government has implemented a number of control measures over the last 5 years. For example, it has shut down power plants, banned waste incineration and restricted emissions from polluting vehicles to improve the air quality. Nevertheless, as mentioned earlier, South Delhi had the highest annual average PM2.5 concentration in India in 2019, 98 micrograms per cubic metre, which is higher than the NAAQS. Therefore, despite the efforts of the government to improve the air quality, the city is far from achieving the Geneva Action Agenda to Combat Air Pollution target by 2030 (International Institute for Sustainable Development, 2018), and improving the air quality remains the inevitable priority.

4. Survey Design

The objective of the survey was to analyse individuals' preferences for improving the air quality in South Delhi. The survey consisted of four parts. The first part contained an introduction to environmental policies to reduce the air pollution in South Delhi and general questions regarding this issue. The second part was devoted to the DCE, and the third part asked some contingent valuation (CV)-type questions that are not analysed in this study. Finally, some attitudinal questions were posed, and basic socio-demographic information about the interviewees was collected in the fourth part.

The DCE presented the respondents with different alternatives for tackling air pollution in South Delhi. The three main pollutants in Delhi – vehicular emissions, industrial emissions and the burning of waste – were used to define the alternatives. The alternatives were specific solutions to these main pollutants and were represented by *improved public transportation*, *improved technology* and *building waste recycling plants* in addition to the *no action* option. All these solutions have been used previously in the literature (Wang *et al*., 2019; Kaur, 2020; Watts *et al*., 2020).

The attributes were defined during a focus group discussion, a collaborative process that sought advice from 20 air quality experts, residents, environmental economists and local government professionals. This focus group discussion was organised in a series of online meetings during January 2019. The participants in the focus group completed a questionnaire in which they indicated on a scale from one to five the importance of the attributes defined in Table 1 based on the literature review and discussed possible solutions to the air pollution issue. The focus group's outcome was used to define the final set of attributes and their respective levels. To achieve a balance between the number of attributes and the complexity of the design, the four most highly valued attributes in the focus group were selected.

The final set of attributes comprised *infant mortality*, *reduced visibility*, *morbidity* and *cost*. The definitions of these attributes, together with their corresponding levels, are presented in Table 2. The first attribute, *infant mortality*, represented the number of annual premature deaths under the age of five due to air pollution. According to the Ministry of Health and Family Welfare (MHFW) (2017), the actual number of premature deaths in Delhi due to air pollution in 2016 was 15,000. Therefore, the *no action* level of this attribute was set to 15,000, and the three assumed reduction levels were set to 4,000, 8,000 and 12,000.

The second attribute, *reduced visibility*, showed the annual number of days with reduced visibility (i.e. less than 1 km of visibility per day). The actual number of days with reduced visibility due to air pollution in 2018 was 25 days, as reported by Tyagi *et al.* (2016) and the Meteorological Department (2018). Therefore, the *no action* level of this attribute was set to 25 annual days of poor visibility and the three expected levels of reduced visibility were set to 10, 15 and 20 days.

The third attribute was *morbidity*; this was also reported by the MHFW (2017), which mentioned that the outdoor air pollution in Delhi caused 10,000 extra hospital admissions in 2016. For this reason, the *no action* level of this attribute was set at 10,000 hospitalisations, and the three assumed reduction levels were set at 4,000, 6,000 and 8,000.

Finally, the monetary attribute was a monthly air pollution tax on the population of South Delhi, which would be collected by the government. The assumed tax rates in Table 2 range from INR150 to INR800 (€2 to €10). The cost vector level was set adequately in relation to the average income in the region, using information from the Economic Survey (2019), and adjusted according to the focus group discussion. Moreover, the cost vector was checked in the pilot study to determine whether the highest cost vector level was set in line with the rule of thumb that the maximum cost should not be selected in more than 5 per cent to 10 per cent of cases when presented (Glenk *et al*., 2019). To ensure that the survey and the attributes identified by the focus group were properly understandable, two pilot studies were also conducted with 30 individuals in March 2019.

Table 2

Attributes and levels of the DCE in South Delhi.

Attribute	Definition	Attribute Levels
Infant mortality	Annual premature deaths under the age of five due to air pollution in Delhi	4 k 8 k 12 k 15 k*
Reduced visibility	Annual number of reduced visibility days (less than 1 km visibility in a day)	10 days 15 days 20 days 25 days*
Morbidity	Annual number of hospital admissions due to air pollution in Delhi	4 k 6 k 8 k 10 k*
Cost	Cost per person (individual/month)	INR150 INR300 INR600 INR800 INR0*

Note: The status quo level is denoted by *.

To reduce the cognitive load of the choice task, we used icons to represent the attributes and their levels graphically. Figure 2 shows an example of the choice task. Each respondent was presented with five choice cards and asked to choose one of three hypothetical programmes or the *no action* alternative.

The use of a full factorial design was not possible because the four attributes and their levels would result in a large number of choice situations ($3^4 \times 5^1 = 405$). Thus, following the best practice of DCE design (Mariel *et al.*, 2021), we used the Ngene software to generate a D-efficient experimental design for a MNL with ten rows, which was sectioned into two blocks (ChoiceMetrics, 2018). Additionally, we included a budget and opt-out reminder at the bottom of each choice card to minimise the potential hypothetical bias. Specifically, the wording of these reminders was ‘If you do not like any of the three programmes or their costs are too high, you can choose the alternative NO ACTION’, and ‘Please keep in mind that the amount of money you would spend on the new air pollution tax would not be available to your budget for other expenses’, respectively.

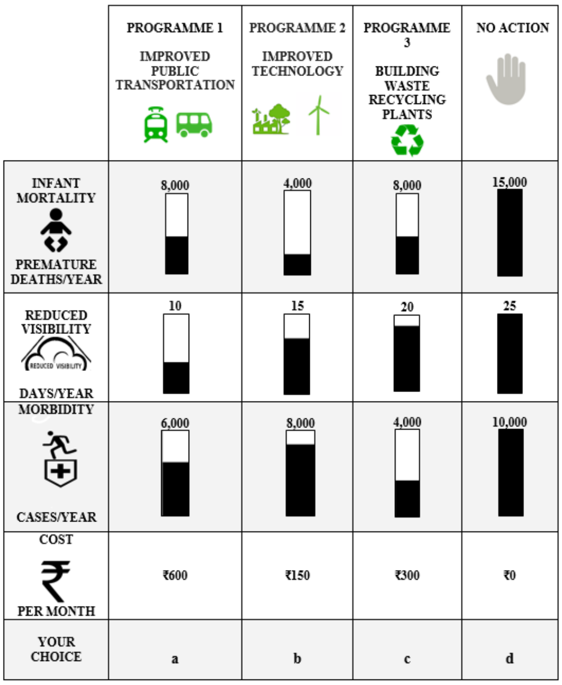

Figure 2. Sample choice card presented to the respondents.

5. Data

The data were collected from 4 July 2019 to 4 September 2019 at different sites in South Delhi. Stratified random sampling was applied based on the age, gender and education of the

Delhi population because the figures for South Delhi were not available. In total, 489 anonymous adult respondents aged 18 and over agreed to participate in the survey. Four respondents did not complete the entire survey, reducing the final sample to 485 individuals. Given that each participant responded to five choice cards, the number total of observations collected in the DCE part was 2,425.

Table 3

Descriptive statistics of the sample ($N = 485$).

Label	Definition	Mean	Median	Std Dev.	Min.	Max.	Expected Frequency
Age	Age of the respondent	32.6	27.5	13.61	18	76	39.2
		Value	**Frequency**				
Female	Gender (male = 0,	0	55%				54%
	female = 1)	1	45%				46%
Education	Education level						
	(primary = 1,	1	10%				21%
	secondary = 2,	2	16%				29%
	university = 3)	3	74%				50%
Income	Income level						
	< INR150,000,	1	20%				34%
	(INR150,001; INR600,000)	2	50%				32%
	> INR600,001	3	30%				34%

Table 3 displays the descriptive statistics of the final data. The last column of Table 3 presents the population values for Delhi (Census of India, 2011; Statista, 2016; National Family Health Survey, 2017). More than half of the respondents were between 18 and 35 years of age, and about 74 per cent had a university degree. A direct comparison with the last column shows a slight overrepresentation of people with a high level of education and a high income in our sample. This is because individuals with low or no education were more likely to decline participation in the survey despite the fact that the interviewer presented the survey to the respondents in a face-to-face manner. Another reason why our sample includes large shares of young and educated people might be that the study area includes many administrative and educational institutions, including three major public universities, and a growing commercial district.

To deal with this problem of the representability of the sample, we defined weights for all respondents according to their education and income category. The joint distribution of the expected and observed shares are presented in Table 4. The distribution of the expected values has been obtained from Bhattacharya (2016), ICE360 (2016), Statista, 2016 and the National Family Health Survey (2017).

Table 4

Expected/observed percentages for each education and income category.

		Income 1	2	3	Total
Education	**1**	10% / 7%	8% / 3%	3% / 0%	21% / 10%
	2	11% / 6%	9% / 9%	9% / 1%	29% / 16%
	3	13% / 7%	15% / 38%	22% / 29%	50% / 74%
	Total	34% / 20%	32% / 50%	34% / 30%	

6. Methodology

We applied the latent class model (LCM) to analyse the responses obtained from the DCE described above (Hensher and Greene, 2003). The LCM is based on the random utility theory (McFadden, 1974), which states that the utility U_{njt} of respondent n from alternative j on each choice card t is composed of observable term V_{njt}, called representative utility, and unobservable terms ε_{njt}. It can be represented as

$$U_{njt} = V_{njt} + \varepsilon_{njt} = X'_{njt}\ \beta + \varepsilon_{njt}, \tag{1}$$

where X'_{njt} is a vector containing attributes of the goods or service to be valued (in our case *infant mortality*, *reduced visibility*, *morbidity* and *cost*) and β is the vector of the corresponding parameters. The unobservable term of utility ε_{njt} is assumed to be extreme value type I distributed with location parameter 0 and scale parameter 1. The theoretical model commonly used for analysing discrete choices is the random utility maximisation model, which is based on the random utility theory assumption of the utility-maximising behaviour of individuals. Therefore, the choice probability of choosing the alternative i_{nt} corresponding to the basic MNL is

$$P_{ni_{nt}t} = Prob(V_{ni_{nt}t} + \varepsilon_{ni_{nt}t} > V_{njt} + \varepsilon_{njt}) = \frac{exp\ (V_{ni_{nt}t})}{\sum_{j=1}^{J} exp\ (V_{njt})} = \frac{exp\ (X'_{ni_{nt}}\ \beta)}{\sum_{j=1}^{J} exp\ (X'_{njt}\ \beta)}. \quad (2)$$

In the LCM, we assume that the preferences differ among individuals and that these can be filtered into C classes. The logit probability of alternative i_{nt} being chosen by decision maker n on the t choice card conditioned on a specific class c is defined as

$$P_{ni_{nt}t|c} = \frac{exp\ (X'_{ni_{nt}}\ \beta_c)}{\sum_{j=1}^{J} exp\ (X'_{njt}\ \beta_c)}. \quad (3)$$

Therefore, for a specific class c, the probability of the sequence of choices of decision maker n is

$$P_n(i_n|c) = \prod_{t=1}^{T} P_{ni_{nt}t}(i_{nt}|c) = \prod_{t=1}^{T} \left(\frac{exp\ (X'_{ni_{nt}}\ \beta_c)}{\sum_{j=1}^{J} exp\ (X'_{njt}\ \beta_c)} \right). \quad (4)$$

The probability π_{nc} of decision maker n belonging to specific class C is modelled as a logit probability:

$$\pi_{nc} = \frac{exp(\mu_{nc}+R'_n\lambda_c)}{\sum_{c=1}^{C} exp(\mu_{nc}+R'_n\lambda_c)}, \quad (5)$$

where μ_{nc} and λ_c are the parameters to be estimated and R'_n is a vector including the characteristics of respondent n, commonly socio-demographic variables. The vector of parameters λ_c together with the corresponding parameter μ_{nc} must be normalised to zero for one class to ensure the model identification. A positive sign of a parameter in λ_c corresponding to a specific socio-demographic variable means that an increase in this variable increases the probability of belonging to a specific class with respect to the benchmark class.

The unconditional probability of decision maker n in making the sequence of choices is the sum of the conditional probabilities over the classes weighted by the probability of belonging to each class:

$$P_n = \sum_{c=1}^{C} \pi_{nc} \cdot P_n(i_{nt}|c) = \sum_{c=1}^{C} \pi_{nc} \cdot \prod_{t=1}^{T} P_{nit}(i_{nt}|c). \quad (6)$$

Hence, the log-likelihood function in the estimation procedure, which maximises the observed choices for the sample of N decision makers, is defined as

$$LL(\beta) = ln(\prod_{n=1}^{N} w_n \cdot P_n) = \sum_{\mathrm{n}=1}^{\mathrm{N}} w_n \cdot ln[\sum_{c=1}^{C} \pi_{nc} \cdot \prod_{t=1}^{T} P_{\mathrm{nit}}(i_{nt}|c)], \quad (7)$$

where w_n represents the weights obtained from Table 4 to account for the over- and underrepresentation of some of the education–income groups.

7. Results

The number of classes in an LCM is usually determined by using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) (Swait and Erdem, 2007). However, the researcher's own assessment of the suitability of the model should also be considered (Hynes *et al.*, 2008) and, for example, the meaningfulness of the estimated parameter signs should be taken into account (Scarpa and Thiene, 2005). That means that the interpretability of the classes should play an important role in the determination of the number of classes. Table 5 summarises these values obtained for LCMs with two, three and four classes, along with the number of parameters and the value of the log-likelihood. As expected, the log-likelihood increased with the number of parameters and the number of classes. Nevertheless, the remaining statistics provided mixed results: the BIC supported a solution with three classes, while the AIC supported the model with four classes. Since the AIC tends to overestimate the number of classes, three classes were chosen in this analysis.

Table 6 presents the estimates of the three-class LCM. The corresponding distributions of the allocation probabilities defined in (5) are represented graphically in Figure 3. The highest probabilities corresponded to Class 3, with a median probability close to 0.79, followed by Class 2, with a median probability around 0.13. The smallest median value, less than 0.08, corresponded to Class 1. The class allocation coefficients for Class 1 were set to zero for identification purposes, so the coefficients for Classes 2 and 3, shown in the lower part of Table 6, were interpreted relative to Class 1. The main difference between the coefficients of the allocation function for Class 2 and Class 3 was represented by the coefficient of education. Class 2 seemed to be characterised by low education. In contrast, Class 3 was characterised by high income and high education.

Table 5

Information criteria statistics.

	Two classes	Three classes	Four classes
LogL	-2706.5	-2034.9	-2004.0
Number of parameters (K)	19	31	43
Sample size (n)	2395	2395	2395
AIC	5451.0	4131.8	**4094.0**
BIC	5560.8	**4311.0**	4342.6
CAIC	5579.8	**4342.0**	4385.6

As can be seen in Table 6, an increase in the cost reduced the propensity to choose environmental programmes across all classes, which is a conclusion consistent with microeconomic theory. Nonetheless, the cost sensitivities varied across classes, which has an important impact on the WTP values presented in the next section. The largest class, Class 3, showed the expected strong preference for a reduction in infant mortality and morbidity. This was an expected result that had previously been widely reported in the literature (Yoo *et al.*, 2008; Tang and Zhang, 2016; Jin *et al.*, 2020). An interesting finding in Class 3 was that the

ASCs had very similar values, indicating that respondents valued improved transportation, technology and the building of waste recycling plants equally.

Table 6

LCM parameter estimates.

	Class 1			Class 2			Class 3		
Variables	*Coef.*	*Std Error*		*Coef.*	*Std Error*		*Coef.*	*Std Error*	
ASC-Transportation	-1.952	1.547		8.938	9.331		3.801	0.584	***
ASC-Technology	-2.664	1.519	*	8.585	10.010		3.472	0.594	***
ASC-Recycling Plants	-2.377	1.560		7.594	10.005		3.532	0.588	***
Infant mortality	0.145	0.087	*	-0.723	0.622		-0.131	0.013	***
Reduced visibility	-0.176	0.069	**	0.064	0.359		-0.002	0.009	
Morbidity	0.325	0.156	**	-0.318	0.471		-0.143	0.027	***
Cost	-0.031	0.014	**	-0.644	0.103	***	-0.013	0.001	***
Class allocation									
Constant				0.559	0.349		-1.053	0.337	***
Age				-0.019	0.005	***	-0.024	0.004	***
Female				0.661	0.166	***	0.884	0.153	***
Education				-0.658	0.108	***	0.668	0.098	***
Income				1.092	0.110	***	0.907	0.100	***
Allocation Probability (Median)		0.08			0.13			0.79	
Log-likelihood	-2034.90								
Parameters	31								
Observations	2395								
AIC	4311.00								
BIC	4342.00								

Note: *, ** and *** indicate the 10%, 5% and 1% significance levels, respectively.

Although the focus groups and piloting pointed to reduced visibility as one of the main air pollution issues in South Delhi, our results suggested that the respondents did not pay the expected attention to this attribute in their decision-making processes. One possible explanation could be the season of data collection. The data were collected during the summer, which is characterised by days with good visibility, but the focus group was carried out in the winter (January 2019).

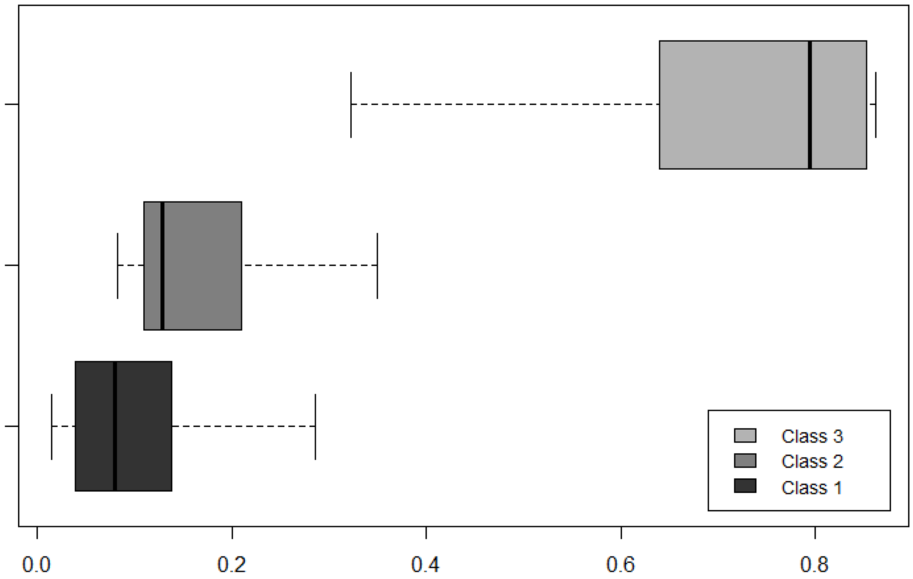

Figure 3. Allocation probabilities obtained from the LCM estimation.

Perhaps the most striking results were the positive coefficients for the infant mortality and morbidity attributes in the smallest class, Class 1, and the non-significant coefficients for all non-cost attributes in Class 2. The pronounced taste heterogeneity in preferences was evident from the enormous class differences in the analysed population.

Class 2 likely represented individuals with very low education and low income, as supported by the coefficients in the allocation function and the significant cost coefficient, the other utility coefficients being non-significant. This could imply some sort of lexicographic preference (Sælensminde, 2006) leading to a choice based on the alternative with the lowest or zero cost.

The smallest class, Class 1, had an unexpected positive coefficient for health attributes, which may indicate that individuals' preferences were not well defined. Therefore, both Class 1 and Class 2 could be labelled as classes with 'non-trading behaviour', as the corresponding responses appeared to violate one or more standard assumptions (Hess *et al*., 2010). This non-trading behaviour was probably related to the cultural setting and the large class differentiation present in the analysed population.

8. WTP Estimates

Based on the LCM estimates presented in Table 6, we derived the WTP for each attribute in all the classes. The WTP values for individual n and the non-cost attribute were computed as the weighted average of the non-cost/cost coefficients and weighted by the probability defined by the allocation function (5). If β_{cr} is the coefficient of the non-cost attribute ($r = 1,2,3$) and β_{c4} is the cost attribute in class C, then the WTP can be defined as

$$WTP_{nr} = \pi_{n1}\frac{\beta_{1r}}{\beta_{14}} + \pi_{n2}\frac{\beta_{2r}}{\beta_{24}} + \pi_{n3}\frac{\beta_{3r}}{\beta_{34}}.$$

Table 7 presents the descriptive statistics of the WTP distributions based on the estimates shown in Table 6. Figure 4 shows the same outcome graphically using box plots.

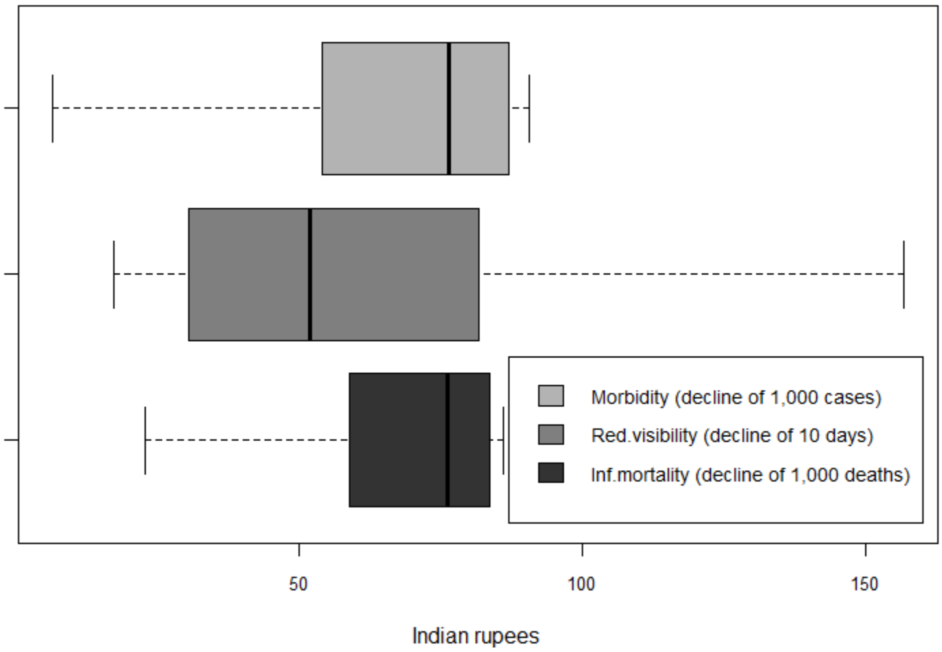

Figure 4. WTP distribution obtained from the LCM estimation.

The WTP values have been rescaled for ease of interpretation. For example, the median amount that respondents were willing to pay to avoid 1,000 premature deaths from air pollution was INR75.8/month. Similarly, the median amount that respondents were willing to pay to avoid 1,000 additional hospital admissions due to air pollution was INR77.2/month. Finally, the median value that respondents were willing to pay for 10 fewer days with reduced visibility was about INR57.3/month.

Given the allocation function (5), which depends on the socio-demographic variables, the WTP distributions shown in Figure 4 can be broken down into subgroups of the population that could shed some light on the underlying preference heterogeneity. Figure 5 shows box plots of the WTP distributions distinguished by gender, age, income and education level. It also provides a direct visual comparison of the differences in WTP distributions for the subgroup categories of socio-demographic variables for each attribute.

Table 7

WTP estimates.

Variables	**Median**	**Mean**	**Std. Dev.**
Infant mortality (reduction of 1,000)	INR75.8 (€0.95)	INR66.5 (€0.83)	INR22.4
Reduced visibility (reduction of 10 day)	INR57.3 (€0.72)	INR72.0 (€0.90)	INR54.5
Morbidity (reduction of 1,000)	INR77.2 (€0.97)	INR65.3 (€0.82)	INR30.3

Note: INR80 = approx. €1 (accessed 4 July 2019 www.rbi.org.in).

Figure 5 contains four graphs that present the WTP distribution for different subgroups of the population defined by four socio-demographic variables. The first graph in the upper-left corner presents the differences for younger and older individuals, the young group being defined as individuals under 22 years of age and the older group being defined as individuals over 40 years of age. The graph in the lower-left corner of Figure 5 represents the differences between men and women. The graph in the upper-right corner represents the differences between the three educational levels defined in Table 3. Finally, the last graph in the lower-right corner is based on the income levels defined in the same Table 3.

To test the differences between two WTP distributions corresponding to two subgroups defined by a specific socio-demographic variable, we applied the complete combinatorial test (Poe *et al*., 2005). This approach is a convolutions method, which consists of calculating the whole range of possible differences between two vectors generated from two different distributions. The ratio of negative outcomes divided by all the possible outcomes gives an exact *p-value* of the one-tailed test for the null hypothesis of equality against the negative difference of the two distributions. The results of the complete combinatorial test are shown in Table 8. According to Figure 5, young respondents and female respondents were willing to pay more for a reduction in infant mortality and morbidity, but these differences were not significant at the 5 per cent significance level (Table 8).

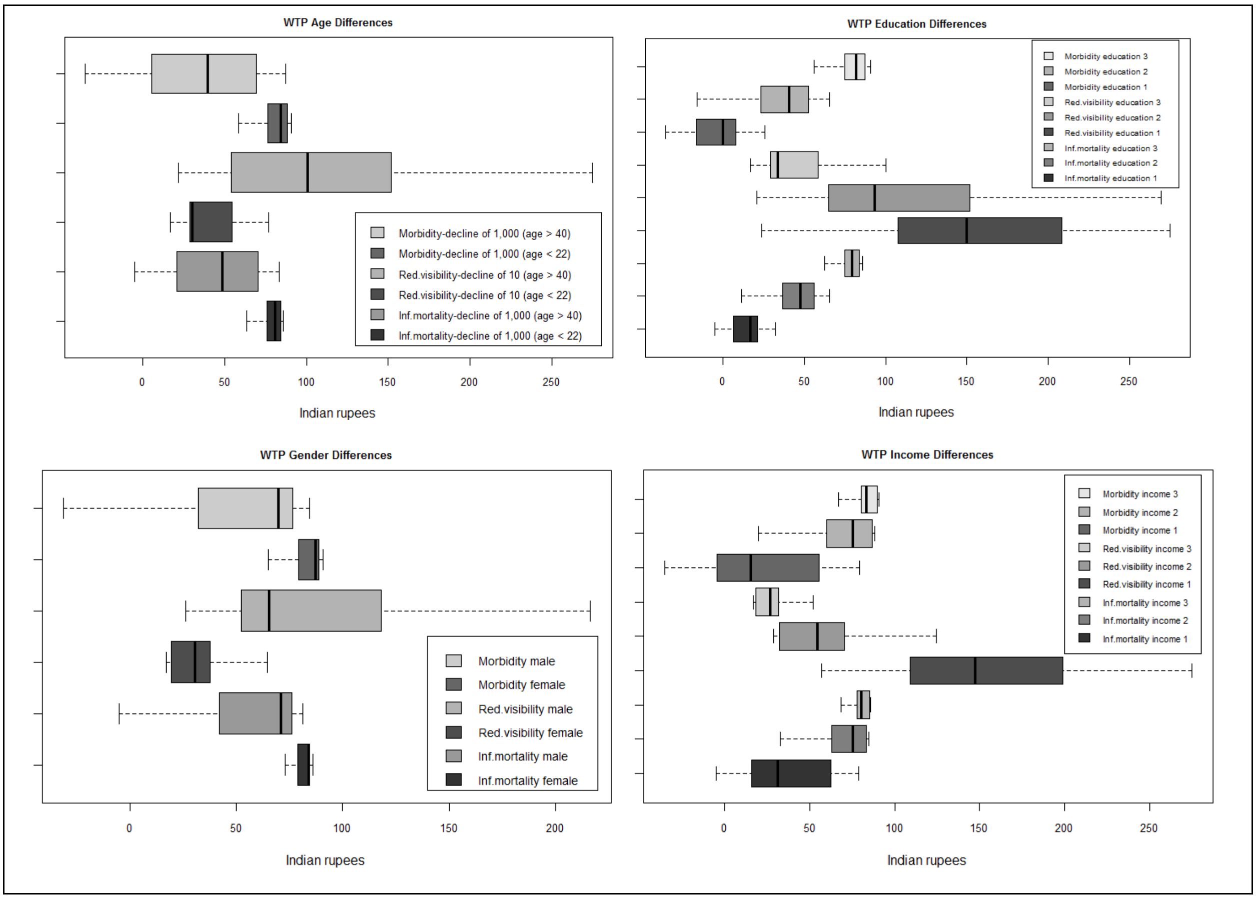

Figure 5. WTP differences in socio-demographic variables obtained from the LCM estimation.

Furthermore, young respondents and women seem to be more consistent as the spread of their distribution was narrower. This is similar to the finding of Jin *et al*. (2020, p. 11), who stated that 'female respondents have stronger preferences for programs with larger risk reductions and are more sensitive to the cost of the alternatives'. More information on gender differences and risk attitudes can be found in the study by Filippin and Crosetto (2016). As expected, higher-educated respondents and those with a higher income were willing to pay more for a reduction in infant mortality and morbidity than low-income and lower-educated respondents, as found in many studies (Muller *et al*., 2001; Rizzi *et al*., 2014; Tang and Zhang, 2016). These differences were significant, as can be seen in Table 8.

Table 8

Poe test for two WTP distributions of subgroups for each attribute.

Attributes	**P-value**	
Infant mortality		
WTP (female) > WTP (male)	0.14	
WTP (young) > WTP (old)	0.13	
WTP (education 3) > WTP (education 2)	0.01	**
WTP (education 2) > WTP (education 1)	0.04	**
WTP (income 3) > WTP (income 2)	0.27	
WTP (income 2) > WTP (income 1)	0.17	
Reduced visibility		
WTP (male) > WTP (female)	0.16	
WTP (old) > WTP (young)	0.17	
WTP (education 2) > WTP (education 3)	0.16	
WTP (education 1) > WTP (education 2)	0.31	
WTP (income 2) > WTP (income 3)	0.13	
WTP (income 1) > WTP (income 2)	0.08	*
Morbidity		
WTP (female) > WTP (male)	0.14	
WTP (young) > WTP (old)	0.13	
WTP (education 3) > WTP (education 2)	0.02	**
WTP (education 2) > WTP (education 1)	0.07	*

WTP (income 3) > WTP (income 2)	0.26
WTP (income 2) > WTP (income 1)	0.16

Note: *, ** and *** indicate the 10%, 5% and 1% significance levels, respectively.

According to Table 8, there were no differences in the WTP distributions for reduced visibility across gender, age and education subgroups. The only difference that was significant at the 10% significance level was the difference between income groups 1 and 2 but not between income groups 2 and 3.

9. Discussion and Conclusions

This study examines individuals' preferences for improving the air quality in South Delhi, India, where air pollution has become an inescapable problem in recent years. Our results indicate two small classes of respondents characterised by non-trading behaviour related to a specific cultural context and large income inequalities in the society analysed. The largest class, however, was characterised by a clear preference for a reduction in infant mortality and morbidity, usually found in the context of developed countries. This was an anticipated finding that has emerged extensively in the literature (Yoo *et al*., 2008; Tang and Zhang, 2016; Jin *et al*., 2020).

To disentangle the observed preference heterogeneity, we analysed the effect of different socio-demographic variables, allowing us to test for equality between WTP distributions corresponding to the different subgroups defined by these socio-demographic variables. The main conclusion that can be drawn is that individuals with higher income and education levels have higher WTP values for a reduction in infant mortality and morbidity.

It has been widely described by the Health Effects Institute (2020) that mortality and morbidity due to air pollution are high in India and even higher in South Delhi. Therefore, this issue deserves more attention in the creation of future policies, which should be based on comprehensive research studies. Our sample was relatively large, and our conclusions are in line with the related literature. Therefore, our results can be considered as important input for local policymaking when it comes to air pollution.

How serious the situation is in Delhi was demonstrated by an interesting real-world experiment described in the *New York Times* (Raj and Schultz, 2019). In November 2019, the air pollution in Delhi reached dangerous levels, and people started buying fresh air called 'Oxy Pure' at an oxygen bar in South Delhi. Its price was around €4 (INR375) for 15 minutes of fresh air. While these values are not directly comparable to our results, as we are assessing different aspects of air pollution, the high demand described in the above newspaper article shows how concerned people in Delhi are about the air pollution in the city.

The proposed improvement measures in our study include the adoption of improved public transportation, improved technology and the building of waste recycling plants. Our results suggest that people place equal value on these three strategies. Hence, appropriate investment in transportation through the adoption of electric vehicles could be a valid and accepted policy, as also shown, for example, by Wang *et al*. (2019), thus supporting our first strategy. Similarly, Watts *et al*. (2020) indicated that focusing on technological innovation seems to be unavoidable to reduce both air pollutants and greenhouse gas emissions, thus supporting our second strategy. In addition, the third strategy is supported by the findings of Tarfasa and Brouwer (2018), who concluded that significant social benefits can be achieved through public investment in solid waste recycling services in developing countries, and by Kaur (2020), who showed that building waste-to-energy recycling plants is a valid solution to incentivise farmers not to practise stubble burning to improve the air quality.

For the Delhi Pollution Control Committee, cost–benefit analysis should be one of the tools used for the evaluation of policies aiming at air pollution reduction. It enables the net present value of investment expenditures (abatement policies) to be compared with the net present value of the benefits generated by the investment (avoiding damage from air pollution). However, cost–benefit analysis requires information concerning the costs of different mitigation policies and those related to the economic damage that has been avoided, which can be represented by the WTP for improvements or by the willingness to accept compensation for a deterioration in air quality. Thus, the results from our study can be seen as valuable input for future cost–benefit analyses devoted to air pollution mitigation strategies in South Delhi.

Our results regarding the effect of education, which support investment in a high-quality education, are in line with those of Hettige *et al.* (1996), who analysed several cases studies in South and Southeast Asia, focused on the determinants of pollution abatement. Their most relevant result indicated that community income and education are highly relevant determinants of informal environmental regulatory outcomes as communities with limited resources may trade air pollution, and environmental quality in general, against other social goods.

The Delhi Pollution Control Committee could also probably benefit from the results. Blackman (2010), who examined various pressures for improved environmental performance in developing countries and policy innovations that leverage these pressures, namely public disclosure and voluntary regulation, concluded that public disclosure is more promising. In spite of the fact that promoting policies that leverage informal regulation is not a general solution for the difficult challenges of air pollution regulation in developing countries, they can be effective in some situations. Collaboration with local communities located close to the main polluters could lead to more effective pressure being put on them.

Nevertheless, given the low effectiveness of the plans mentioned in the introduction, such as NCAP, FAME or GRAP, higher-level policymaking institutions, such as the Government of Delhi, should focus on strengthening their regulatory capacity. Although the study has been carried out in South Delhi, the use of weights according to education and income gives the opportunity to conduct benefit transfers (Johnston et al., 2015). The transfers would provide the first estimates of the benefits of air quality improvements at other policy sites in India, especially in other large cities. To easily enable these transfers, the raw data and the R-codes needed to replicate and transfer our results to a different target population are published at https://github.com/discretechoice/AirPollutionIndia. However, whether and to what extent the results can be incorporated into cost-benefit analysis of policies at other sites is an open question and must be tested in future benefit transfer studies also using survey data for the policy sites.

The environmental goods and services can be valued with different tools and methods that are steadily improving and being developed (Haque, Murty and Shyamsundar, 2011; Quah and Tan, 2021). Our latent class approach takes into account both non-observed as well as observed heterogeneity by the use of socio-demographic variables. This modelling approach could be extended in future studies by tackling with problems of environmental valuation studies related to developing and transition economies such as low confidence of policy decision makers, existence of informal markets or low literacy rates (Alam, 2006). Future studies could include in their surveys some additional questions related to general or specific attitudinal indicators and perceptions (Borriello and Rose, 2019) that could handle these issues. These indicators could enrich the modelling approach in many different ways that include the hybrid choice models (McFadden, 1986), the control function approach (Guevara and Ben-Akiva, 2012) or the multiple indicator solution (Guevara et al., 2020).

Like most other empirical studies, our application has some limitations related to the representativeness of the sample and the use of a limited number of air pollution attributes. Given the severe situation today regarding air pollution across many parts of India, future studies on the benefits of improving the air quality on a larger scale are urgently needed. Our results suggest that from an economic point of view, the air quality is extremely poor today.

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