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ASSESSING THE WILLINGNESS TO PAY FOR CLEAN AIR: ANALYSIS OF INDIAN POPULATION

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Abstract: The paper studies the value that people put on the resource of clean air and their willingness to pay (WTP) for the same, while also analyzing the potential influence of certain socio-demographic factors upon people's spending choices in this regard. The study is conducted via the collection of cross-sectional primary data from different parts of India. The Contingent Valuation Method is used to evaluate the willingness to pay, and the econometric tool of multiple regression is applied to analyze the data. Further, the cardinal voting system is used to find the preferences of people regarding the reasons behind their WTP for clean air, among various options like prevention of mortality, morbidity, ecosystem damage, visibility loss, and material damage. The average willingness to pay across the sample was found to be around Rs.1581 per month. Factors like health status, air quality, residence type, income level, and age are significant determinants of WTP. The study provides a direction in understanding common people's viewpoint towards this environmental problem.

Keywords: Willingness to pay, Air pollution, Contingent Valuation method, Value of clean air, Cardinal Voting System

1. INTRODUCTION

"We still think of air as free. But clean air is not free, and neither is clean water. The price tag on pollution control is high. Through our years of past carelessness, we incurred a debt to nature, and now that debt is being called" - Richard Nixon (37th US President)

The consumption of vastly abundant natural resources has commonly been taken for granted over the years. Conscious observation would reveal that some resources have always been consumed as free goods. 'Water is no longer a free good' is something we might have heard often in the recent past. However, there is another natural resource that is potentially being fetched under the umbrella of economic goods; the change being difficult for us to accept at one go. The resource under concern here is clean air.

According to a study conducted in 2019, 21 out of 30 most polluted cities are in India (IQAir, 2020). Air pollution has intense effects on human health and the environment as a whole. One of the highest disease burdens from air pollution in the world is faced by India. An estimated 100% of the Indian population lives in areas with PM2.5 concentrations above the World Health Organization Guideline which is 10 ìg/m3 annual average (Brauer *et al.*, 2019). Inhalation of particulate matter (PM) can damage the respiratory system and lead to cardiovascular diseases, dysfunctions related to reproduction and the central nervous system, and can even cause cancer (Manisalidis *et al.*, 2020). Balakrishnan *et al.* (2019) estimated that 1.24 million deaths in India in 2017 were attributable to air pollution, where 0.67 million were caused due to ambient particulate matter pollution, while 0.48 million were caused due to household air pollution. They found that an estimated increase of 1.7 years could be expected in life expectancy in India if the existing pollution levels could be reduced and brought to be lower than the minimum levels that lead to health loss. These figures present a compelling picture of the hazards of air pollution concerning mortality and morbidity. But the damages caused by air pollution are not limited to human health alone.

Air pollution also poses a significant threat to the ecosystem. According to information from the United Nations for Europe (UNECE), air pollution affects the ecosystem's ability to function and grow. It hampers the growth and development of plants as increased ground-level ozone causes damage to their cell membranes. The consequent loss of plant cover affects all living beings since it implies a decline in natural air filtering capacity. Air pollution also affects aquatic ecosystems through nutrient overloads, which cause algae blooms, ultimately leading to a loss of oxygen.

Loss of visibility is another serious damage caused by air pollution. It has been confirmed that severe foggy conditions during the winter period are experienced in India each year, especially in the northern regions (Tiwari *et al.*, 2011). Apart from this, impacts of air pollution have also been observed on buildings, cultural monuments, and national heritage sites. N Venkat Rao *et al.* (2014) highlighted the seriousness of this damage as it leads to a remarkable decline in the service life of buildings, and causes discoloration, material loss, structural failing, and soiling.

The effects of air pollution extend to the economy. According to an analysis conducted by Dalberg, 2021, Indian businesses lose 7 lakh crores every year because of air pollution. It affects labour and asset productivity and hampers consumer footfall. Approximately 1.3 billion working days per year are lost by Indian employers as a result of air pollution. This has a destructive effect on the GDP of India. For instance, according to the report, published in April 2021, the IT sector lost 0.7% of its GDP to air pollution, while the tourism sector saw a GDP decline of 1% (Dalberg, 2021).

The assessment of willingness to pay for natural resources like clean air and water has been an appealing topic of interest at the international level. There have been quite a few studies done previously in the field of air quality-related willingness to pay (WTP) across the world, such as in countries like China (Liu *et al.*, 2018), Poland (Ligus, 2018), Mexico (Filippini & Martínez-Cruz, 2016), Thailand (Vassanadumrongdee & Matsuoka, 2005), as well as in India (Kumar & Rao, 2006). Istamto *et al.* (2014) conducted a combined study of willingness to pay for avoiding health risks caused due to road-traffic-related air and noise pollution in five European countries. A comparative study was done by Ning & Lee (2019) to study how the willingness to pay for air quality improvement differed between the two countries China and Korea.

The Contingent Valuation Method (CVM) as a method for measuring willingness to pay has commonly been used in many of these studies. Liu *et al.* (2018) in their study conducted among manufacturing workers in China, used the CV method to determine whether respondents are willing to pay for cleaner air or not. However, this study did not estimate the willingness to pay (WTP) in direct monetary terms. Ligus (2018) estimated the mean total WTP to be 21.172 PLN per month, in their research study conducted in Poland. This paper also inculcated the analysis of people's preferences for various damage components of air pollution as reasons behind their willingness to pay. Guha (2007) conducted a study in Calcutta, India, analyzing WTP for clean water supply, which again used the CV method for the evaluation of WTP.

Kumar & Rao (2006) in their case study of Panipat thermal power stations in India, determined the significance of income and health status variables in impacting peoples' willingness to pay (WTP) for air quality improvements. Gupta (2016) in their study of Indian road passenger transport and the willingness to pay for the carbon tax, highlighted that education, income, and age have a significant role in determining WTP.

The effects of air pollution on normal life are indubitable. This brings up a question regarding the attitude of common people towards availing clean air. The research paper, therefore, studies how much do people value the resource of clean air and what is their willingness to pay for the same. As a further objective, the study aims to find the extent to which various social demographic factors like pollution levels, income per person, age, self-reported health status, residence type, education level, and the number of family members impact the willingness to pay for clean air. The paper adds to the existing literature by a combined perusal of all these factors and their influence on willingness to pay (WTP), through a country-wide sample, while also ingressing into the role of damage components as reasons behind people's WTP. The results are substantiated by our Pan India study, where some of these factors come out to be significant determinants of WTP, along with other factors that were included in our research study with the motive of obtaining a greater picture of people's attitude towards air pollution. In addition, it aims to examine the sensitivity of people towards various damage components of air pollution discussed above, namely mortality, morbidity, visibility loss, ecosystem damage, and material damage.

The analysis leads to some policy recommendations regarding potential governmental initiatives for combating air pollution, and modification possibilities in the government's taxation and expenditure plans in the area of air pollution. The study additionally aims to provide a direction to businesses and entrepreneurs in the field of air purification products with their pricing strategies and help environmentalists in further understanding the intensity of this problem from people's perspectives.

The overall flow of the paper is therefore divided into the following sections: the second section discusses the data and methodology used for the study. Regression analysis to measure the influence of the aforementioned socio-demographic factors upon WTP is done in the third section. The fourth section makes use of the cardinal voting system to study how people belonging to different socio-demographics rate the five damage components of air pollution discussed above, as reasons behind their WTP. The fifth section explores potential policy recommendations based on the results of previous sections. This section increases the applicability of the research study and brings out useful conclusions which can be applied in tackling the problem of air pollution.

2. DATA AND METHODOLOGY

2.1. Sample Selection

A Cross-sectional primary data was obtained through a questionnaire using Google forms, through link-sharing and phone calls, covering Indian residents from different income slabs, age groups, and residence types. Green's (1991) rule of thumb for determining sample size in regression analysis is "Ne"50 + 8m for testing the multiple correlations and Ne"104+m for testing individual predictors, where N is the sample size and m is the number of predictors (assuming a medium-sized relationship), If testing both, the larger sample size should be used."

Harris (1985) suggests that to use multiple regression analysis, the number of survey respondents should exceed the number of predictors by at least 50, while (Bartlett *et al.*, 2001) states that a conservative ratio of observations to independent variables of at least 10 should be maintained, where the dummy variable should be dummy coded and counted.

Thus, a sample size of 325 was selected, where the ratio of the number of responses to independent variables is over 20 and the number of responses is way over the minimum requirement placed by the rule of thumb. This helps improve the probability of detecting the contrast and association and maintain proper effect sizes and power (VanVoorhis & Morgan, 2007).

The responses were collected from various states and union territories across India naming Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chandigarh, Chattisgarh, Delhi, Gujarat, Haryana, Jammu and Kashmir, Jharkhand, Karnataka, Kerala, Ladakh, Madhya Pradesh, Maharashtra, Manipur, Odisha, Punjab, Rajasthan, Tamil Nadu, Telangana, Tripura, Uttar Pradesh, Uttarakhand, and West Bengal.

2.2. Questionnaire

Contingent Valuation Method was used to evaluate the willingness to pay, where the respondents take clean air as a hypothetical good and are directly requested to ascertain the amount of money that they are willing to pay (WTP) for a change in the quality of ambient air. The method has been considered ideal here since the idea of a realistic yet hypothetical market for buying a non-market natural resource can be credibly communicated to the respondent (Robert Cameron Mitchell & Carson, 1990). Thus, the value placed on clean air was quantified for each respondent through the questionnaire by asking: "How much are you willing to pay in rupee terms every month to improve the current air quality that you are experiencing, to a level such as natural reserves, scenic spots, etc.?"

In addition to a willingness to pay for cleaner air, the respondents were also asked about age, state/union Territory, type (rural/semi-rural/urban) of residence, ambient air quality (very good/good/average/bad/very bad), self-reported health status (very healthy/decent health/no serious condition/serious health issues), educational qualification (8th pass/12th pass/completed graduation/completed post-graduation), monthly family income (chosen from slabs of Rs. 20,000 each), rating from 1-5 for various damage components and the number of family members which is used to find the average income per person using the formula:

$$Average\ Income\ per\ person = \frac{L + U}{2 * N}$$

where L is the lower limit of the income slab and U is the upper limit of the income slab chosen by the respondent and N is the number of family members. The years of education were estimated using the highest educational qualification and age[1].

2.3. Statistical Analysis

The following regression model is estimated as the base model where the log of willingness to pay (WTP) is the dependent variable. Since the log-level functional form is used for conducting the regression analysis, the model, therefore, aims to study the percentage changes in WTP as the independent variables change. The independent variables are the various socio-demographic factors where X_1 to X_4 are quantitative variables and the variables X_5 and X_6 are dummy variables.

$$\ln(WTP) = \beta_0 + \sum_{i=1}^{4} \beta_i X_i + \sum_{j=5}^{6} \beta_j X_j + \mu$$

where X_1 is years of education, X_2 is age, X_3 is the average income per person, and X_4 is the number of family members. X_5 and X_6 are the dummy variables for residence type (semi-rural and urban, rural being the control group). The base model is further extended by incorporating self-reported variables.

$$\ln(WTP) = \beta_0 + \sum_{i=1}^{4} \beta_i X_i + \sum_{j=5}^{13} \beta_j X_j + \mu$$

where X_7, X_8, X_9, and X_{10} are the dummy variables for self-reported ambient air quality (good, average, bad, and very bad, very good being the control group), X_{11}, X_{12}, and X_{13} are the dummy variables for self-reported health status (controlled health issues[2], decent health[3], and very healthy, serious health issues being the control group). The estimation of the base and extended version of the model is done to separate the influence of objective factors based on facts, and subjective factors based on perception, upon people's willingness to pay for clean air. The ordinary least squares (OLS) technique is used to analyze how changes in X variables impact the WTP.

The assumptions of classical linear regression models have been tested for both these models. The third set of variables are the different damage components of air pollution i.e. various after-effects of air pollution which people would like to reduce such as mortality (reduction in life expectancy), morbidity (health issues caused due to air pollution), visibility loss (due to pollution-related fog), ecosystem damage (global warming, etc) and material damage (to property, monuments, etc). The cardinal voting system is used to analyze the importance placed on different damage components since it allows for the respondents to give an independent valuation for each of the factors and express their degree of preference (Baujard *et al.*, 2017). The respondents rated their preference for each of the damage factors – mortality, morbidity, visibility loss, ecosystem damage, and material damage, on a scale of 1-5, where 5 represented the highest rating. These ratings were then used to estimate the corresponding rankings of these factors where rank 1 was given to the factors with the highest ratings. The analysis of these rankings is done for different socio-demographic factors by calculating the ranks separately for each socio-demographic factor to study the preferences of the respondents and observing patterns that reflect the psychological attitude of different categories of respondents towards the repercussions of air pollution as presented in the fourth section.

3. ESTIMATION RESULTS

The mean WTP (calculated by taking an average of all the 325 responses for WTP) for cleaner air per month came out to be Rs 1581.43 per month with standard deviation of

4293.63. To further evaluate the determinants of WTP the base model is estimated with socio-demographic factors as independent variables i.e., years of education, age, income, number of family members, and residence type (urban/rural/semi-rural). The results presented in column 1 of Table 1 show that except for years of education, all other variables are significant. The variable for age is included in the model keeping in mind a usual association of increase in age with greater fears of health hazards and damage risks. It was therefore interesting to answer the question regarding a potential relationship between age and WTP for reducing air pollution. 'Age' is found to be a significant determinant with a p-value of 0.006 indicating that with an increase in age by a year, WTP increases by 2.033%, keeping other variables constant. This finding suggests that elderly people value clean air more than younger ones. In addition to increased concern for damage possibilities, this can be attributed to higher consciousness among the elderly which is shaped by their experience.

The income per person is also significant at 1% level of significance suggesting an expected result that people who are more able to pay are the ones who are more willing to pay for clean air.

The number of family members came out to be significant with a p-value of 0.024 indicating that as the number of family members increases by one person, willingness to pay also increases by 14.90763%. One possible reason behind this could be that the presence of more children and aged people, who are more prone to air pollution damages and health risks, could imply a greater extent of fear against air pollution in the families with a higher number of members.

Finally, for the dummy variable 'residence type', with rural being the base category, a significant relationship is noted as we move from rural to urban residents, wherein the WTP increases by 174.23%, keeping other variables constant. The results obtained reflect that urbanization influences the amount of money people are ready to spend for air quality improvement. The difference in the attitude of people towards clean air WTP derived from our study can be ascribed to possibly greater awareness levels in urban areas as compared to rural areas, instead of factors like exposure level and vulnerability as Ravishankara *et al.* (2020) had used satellite-derived data to show a similarity between air pollution scenarios in urban and non-urban areas in India.

The base model is further extended to include self-reported variables namely, health status, and ambient air quality. These variables are subjective in the sense that they are self-reported by the respondents based on their perception of health conditions and surroundings. The results of this extended model can be seen in column 2 of Table 1. Both the additional variables, i.e., health status and ambient air quality are found to be significant. Various socio-demographic factors i.e. age, income, number of family members, and residence type continue to be significant in the extended model too,

Table 1: Estimation Results

Log of Willingness to Pay [ln(WTP)]	*Base Model*	*Extended Model*
Years of Education [X_1]	0.0046902 (0.907)	0.0049539 (0.899)
Age [X_2]	0.0203338*** (0.006)	0.0151738** (0.038)
Income per Person [X_3]	0.0000107*** (0.000)	0.0000104*** (0.000)
Number of Family Members [X_4]	0.1490763** (0.024)	0.1308163** (0.040)
Residence Type:		
Semi-Rural [X_5]	0.6205533 (0.128)	0.2303956 (0.566)
Urban [X_6]	1.742253*** (0.000)	1.109235*** (0.002)
Ambient Air Quality:		
Good [X_7]	-	1.140297*** (0.008)
Average [X_8]	-	1.498752*** (0.001)
Bad [X_9]	-	1.946812*** (0.000)
Very Bad [X_{10}]	-	2.239102*** (0.000)
Health Status:		
Controlled Health Issues [X_{11}]	-	-1.110049** (0.036)
Occasional Medical Problems [X_{12}]	-	-1.253784** (0.012)
No Medical Conditions [X_{13}]	-	-1.182302** (0.018)
Constant (5Ø7ß$_0$)	2.352073*** (0.001)	2.736337*** (0.002)
Number of observations	325	325
F(6, 318)	15.86	10.96
Prob > F	0.0000	0.0000
R-squared	0.2303	0.3142
Adjusted R-squared	0.2158	0.2855
Root MSE	1.8482	1.7641

Note: Values in parenthesis are the p-values. *, **, and *** indicates level of significance at 10%, 5% and 1% respectively.

while years of education remain insignificant, confirming the robustness of the base model results. Also, the fit of the model has improved since the Adjusted R squared value has increased from 0.2158 to 0.2855 as we move from the base model to the extended model.

The beta coefficient of 'age' is 0.0151738, meaning that as age increases by one year, the willingness to pay for clean air increased by 1.51738%, other variables remaining constant. This relationship is significant with a p-value of 0.038. This provides substance for the association under the question to be established. The relationship between WTP and income per person came out to be highly significant, with a p-value of 0.000 again. The beta coefficient for this relationship was 0.0000104. Therefore, other variables remaining constant, with an increase in income per person by one rupee, WTP increases by 0.00104%. This similarly implies that if a person's income increases by an amount of Rs.10000, the WTP will rise by around 10.4%. In addition to the role of greater spending power due to higher income, increased standards of living associated with income rise can be potential reasons behind this finding. For the number of family members, it is observed that with an increase in the number of family members by one person, WTP increases by 13.08%, keeping other variables constant.

For the variable residence type, a significant difference in WTP was noticed between the respondents belonging to rural and urban areas, the p-value for this relationship being 0.002 where the base category was taken to be rural. The coefficient shows that the WTP for clean air increased by 110.92% as we moved from people residing in rural areas to those living in urban areas, keeping other variables constant. The coefficient for the difference in WTP between respondents living in rural and semi-rural areas was 0.2303956, representing a positive trend in this regard too, however, this relationship could not be proved to be significant through our analysis, which can be a result of a limited sample size. This is a potentially important relationship that can be strengthened by further research in this area. The motive behind studying this variable was to explore the trend of increase in WTP as the development status of people's residence place improves.

The high level of variedness in the air quality of India brings up an important question regarding the influence of ambient air quality that people place upon WTP for clean air. It is indeed observed that WTP increases as the air quality worsen. The results show that other variables remaining constant, WTP rises by 114.03% as the air quality deteriorates from very good to good, by 149.88% as it worsens from very good to average, by 194.68% for the change in air quality from very good to bad, and by 223.91% as the air quality further worsens from very good to very bad. This finding signifies the vulnerability of people who are exposed to very bad air quality as compared to those living in better conditions.

Considering the severe effects that air pollution can potentially have upon a person's health it is desirable to check whether the current health status of a person influences their WTP for cleaner air. The results obtained are in line with the possibility of increased concern for air pollution among people with serious medical conditions, which is the base category for this variable in the model. This can be attributed to a rise in fear of further harm to health due to air pollution among the people with serious medical conditions, who are already struggling against critical health issues. The WTP declines by 111.0049% as the health status improves from serious medical diseases to controlled medical problems, keeping other variables constant. Further, it is noted that WTP declines by 125.3784% as we move from serious medical diseases to decent health conditions that are the ones who only occasionally suffer from illnesses. Finally, it is observed that the WTP of respondents who recognized themselves to be very healthy is lesser than those with serious medical conditions by the extent of 118.2302%, keeping other variables fixed.

For the quantitative variable X_1 measuring years of education, an insignificant relationship with WTP is observed, as was the case in the base model. The p-value came out to be 0.899. This result points to an interesting observation regarding a greater role of awareness levels than the number of years of formal education. It shows that literacy level is not a determinant of people's attitude towards air pollution, and that awareness is a psychological attribute that cannot be measured by traditional educational qualifications.

On testing the assumptions of the classical linear regression model, it is successfully tested using White's test of heteroskedasticity that the model is homoscedastic, while correlation coefficients between the dependent variables show that there is no perfect/ high multicollinearity in the model. Further, Kernel density estimate, is used to test for the normality of residuals. The Ramsey RESET test is used to determine that the models are free of omitted variable bias. (refer to appendix)

4. DAMAGE COMPONENTS AS REASONS FOR WTP

Figure 1 presents the results of the overall ranking evaluation conducted under this study. It plots the sum of ranks obtained where the factor with the lowest sum of ranks came out to be the most preferred. It was deduced that the prevention of morbidities as

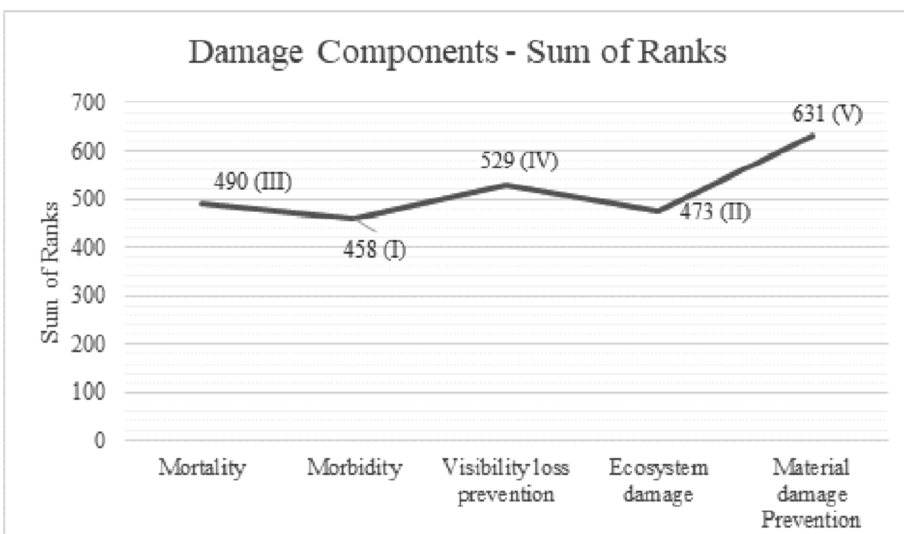

Figure 1: Damage Components - the sum of ranks

a reason behind the willingness to pay for clean air was the most prevalent. This preference was followed by a concern for ecosystem damage. The apprehension of mortality was the third-ranked factor, followed by prevention of visibility loss. Material damage prevention came out to be the least preferred reason behind people's WTP.

The study of the damage components gives a glimpse of the fears, concerns, and awareness levels that frame the way people approach the subject of air pollution in their daily lives. It is evident from the results presented in Figure 1 that the fear of catching morbidities caused by air pollution is a major concern among people. It reflects that people are aware of the dangerous health hazards caused by air pollution and are eager to find ways of keeping away from them.

The result about ecosystem damage being the second most important reason for WTP among respondents indicates success in increasing the concern level of common people for the environment, which has been an agenda of many stakeholders like NGOs, governmental initiatives over the past few years. Prevention of mortality fears against air pollution hazards and increase in life expectancy, being the average factor, reflects moderate sensitivity to the fatality of air pollution. It shows that the possibility of death due to air pollution-related reasons is still a factor that people, on average, don't consider to be much concerned about.

Visibility loss due to pollution-related fog came out to be the fourth important factor. This can be explained by the fact that recognizable difficulties majorly arise during the winter season. Therefore, its impact on common life is not as severe and regular as compared to the other factors. The fear of damage to materials, property, and historical monuments remains a factor that is least important for the common person, in comparison to other concerns that relate to life and the environment. This reflects the approach of people while prioritizing their preferences towards loss prevention, where material belongings come below the health and living.

Analysis of damage components based on social demographic factors

It can be observed from Figure 2 that for the lower age groups, i.e., the age groups of <=18 years and 19-25 years, ecosystem damage is the highest-rated concern. This shows that the awareness regarding environmental well-being is greater among the children and youth population. A naturally expected yet interesting observation is that the higher age groups i.e. age 25 years and above have voted morbidity to be the most important reason behind their willingness to pay, roughly indicating a trend that the concern for morbidity increases with age. Material damage remained the least preferred concern across all age groups.

In Figure 3 it is observed that for people living in areas with very good air quality, the concern for ecosystem damage is comparatively less as compared to those living in

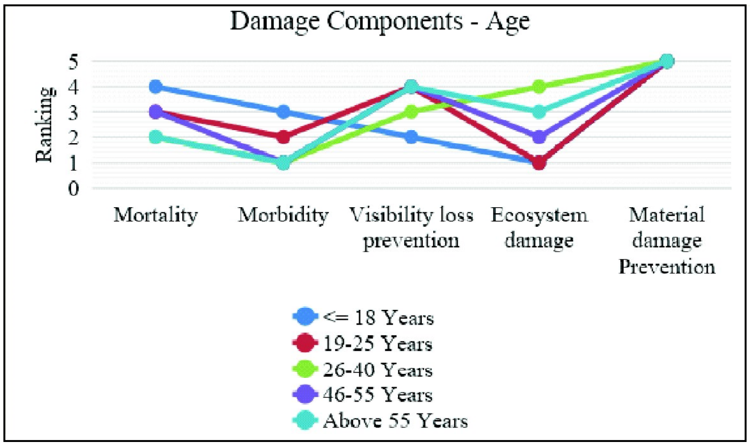

Figure 2: Rankings by Age Groups

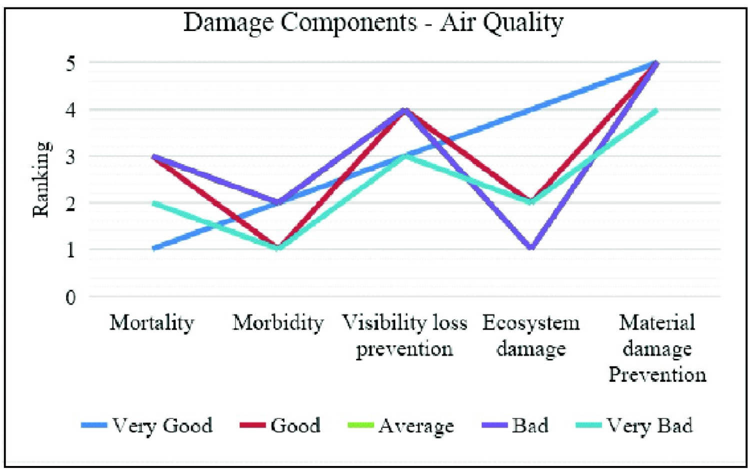

Figure 3: Rankings By Residents of Areas With Varying (Self Reported) Air Quality

worse air quality conditions. This potentially indicates that people residing in such areas feel a greater need for environmental protection and feel more vulnerable to be a victim of ecosystem damage. The graphs for average and bad air quality coincided in this plot, showing a high level of similarity in the attitude of people living under the circumstance of moderate to poor air quality. This could also be a result of subjective evaluation on the part of the respondents in ascertaining the adverse outcomes of the quality of the air they experience.

It is also seen in figure 4 that respondents belonging to semi-rural areas voted ecosystem damage to be the most important factor behind their willingness to pay. This trend potentially indicates that people from areas that are in the process of development and urbanization feel more prone to environmental damage.

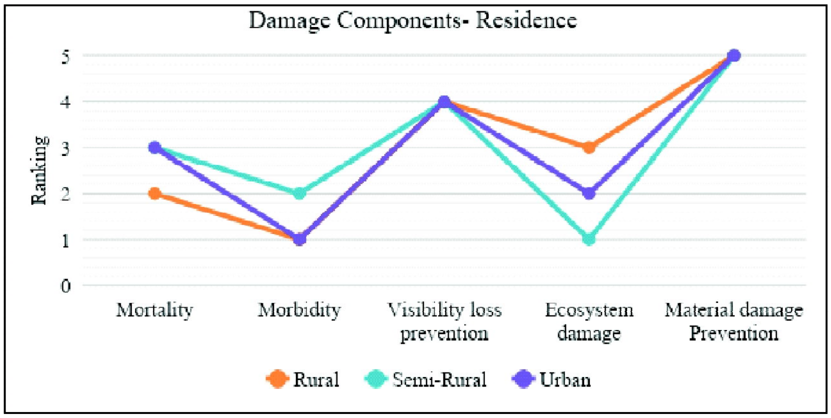

Figure 4: Rankings By Residents of Rural, Semi-Urban and Urban Areas

Figure 5 shows that respondents suffering from serious medical conditions and chronic diseases rated mortality prevention as the greatest reason behind their willingness to pay. This confirms an expected result regarding the psychological fear of death risk due to air pollution among people with serious illness. The fear of material damage again comes out to be the least important across all health groups, reflecting the overall trend.

Similar patterns are observed in analyzing the rankings placed by people with different educational qualifications and incomes (Figure 6). Morbidity and ecosystem damage comes out to be the main reasons for WTP, and concern for material damage is

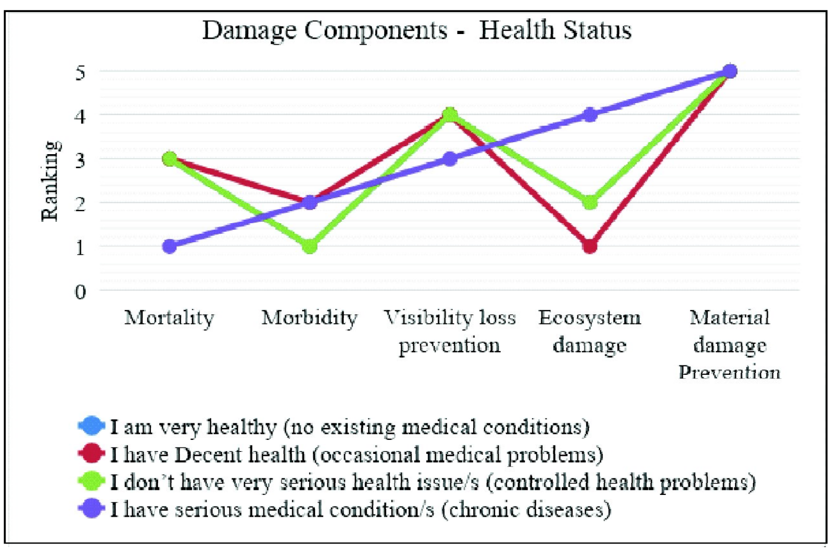

Figure 5: Rankings By Respondents with Different Health Status

6a: Rankings by Educational Groups

6b: Rankings by Income Groups

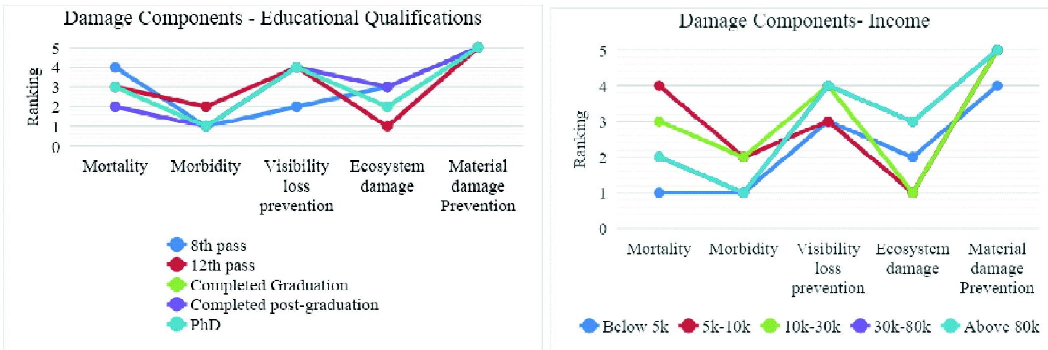

Figure 6: Rankings By Educational and Income Groups

often ranked low in the preference hierarchy, reflecting preference towards health and living over material belongings, a similar trend as that of the overall rankings.

5. CONCLUSIONS AND POLICY RECOMMENDATIONS

The study on the assessment of willingness to pay for clean air in India brought us to some captivating results. The aim was to form a quantitative measurement of people's attitude towards air pollution, which was done using the Contingent Valuation Method (CVM). The application of regression methods yielded important information about the influence of demographic factors upon WTP. It was concluded that factors including health status, air quality, residence type, age, and income had a significant impact on the WTP. Further evaluation of the damage components was done using the cardinal voting system, which informed that morbidity and ecosystem loss form the two most important reasons behind the willingness to pay for cleaner air. Prevention of mortality and visibility loss were averagely voted, while material damage was the least important concern.

The research work throws light upon the eagerness of common people to improve the air quality that they experience. It re-confirms the fact that air pollution is one of the greatest threats both for the present and future generations. It is therefore imperative that firm steps are taken to increase vigilance against rising pollution levels, and culture of strengthened awareness is promoted among the common people.

The results are useful in deriving policy recommendations in the direction of combating air pollution. It is observed from the regression results that income plays a significant role in determining willingness to pay, and a higher WTP was associated with an increase in income. Therefore, one potential policy option is the usage of a progressive income tax (cess) regime for clean air by the government, wherein higher collection of funds for clean air projects is done from richer households.

An important observation obtained from the analysis is that the willingness to pay for cleaner air among people residing in urban areas is significantly higher than that of people residing in rural areas. Therefore, a disproportionate burden of funding clean air projects can be put on urban populations (via both direct and indirect taxation). A similar approach can be followed for the population residing in areas with very poor air quality since the WTP for those respondents is higher as compared to those residing in areas with average, good, and very good air quality conditions.

In the questionnaire, there was an open-ended optional question, where respondents were asked to suggest steps for the government to ensure better air quality. There was the active participation of respondents with this question, with 215 respondents giving various suggestions, despite the question being optional. This showed a good picture of how people have great expectations from the government for taking steps to combat air pollution. The suggestions regarding steps the government should take to curb air pollution are summarized below.

It is suggested that improved planning is required in a way to reduce the exposure of residents to emissions, using AQI and emissions data. Infrastructure should be designed to encourage the use of cycling, walking, etc. Improving the road quality to reduce road dust and implementing restrictions on vehicle crowd on roads, promotion of public transport by making it safer and cheaper, promotion of car-pooling system, strict compulsion on the industries to check their emissions in residential areas, compulsory plantation drives for any developmental project to compensate for the loss of trees, informative advertising about steps people can take at individual and community level to prevent pollution, stricter punishments against violation of pollution control norms by non-abiding citizens, increasing incentives for the use of environmentally efficient energy resources and fuels, both at domestic and industrial level, enhanced real-time monitoring of air pollution, adoption of IoT-enabled air pollution monitoring, promotion of electric vehicles (EVs) through subsidization and incentivization, development of EV Supportive infrastructure, promotion of CNG vehicles, affirmative laws for prevention of stubble burning and burning of plastic waste, installation of air purifiers and air cleaning towers across cities, strict regulation of construction activities in residential areas, promotion of environment friendly (non-plastic) products and waste-free production are the main suggestions that came across.

While the government has taken many steps to tackle the problem of air pollution, like setting emission standards and reduction in energy consumption by energy-intensive industries. State-specific policies to efficiently control particulate matter emissions have been put in place in states with high pollution levels. India has pledged in the Paris Climate Agreement to generate 40% of its electricity from renewable sources by 2030 when two-thirds of the electricity in India is produced from fossil fuels now. But still, there is a long way to go, more awareness needs to be created about the harmful impact of ambient particulate matter and household air pollution among policymakers and the general public, which would help further escalate the air pollution control efforts in India (Balakrishnan *et al.*, 2019).

India should implement both long-term and short-term comprehensive mechanisms and policies to reduce the high levels of air pollution that pose a major threat to the long-term development of India. It is encouraging to see that the discussion on air pollution in India by the public, media, and other stakeholders has been increasing substantially and policymakers seem keen to address the problem (Balakrishnan *et al.*, 2019). This positive momentum could be boosted further by the evidence presented in this paper to enhance the planning and implementation of air pollution control efforts across India in a sustainable manner, by taking into account the value placed by people on this resource and public opinion on this pressing issue. It is important to note that besides benefitting human health, the reduction of air pollution in India would also have a broader beneficial impact on other aspects of the economy (Lvovsky, 1998) and the ecosystem.

Notes

1. It is assumed, based on ideal scenarios, that respondents who have the highest qualification as 8th pass and are below the age of 18, have continued their education, and those above 18 have discontinued their education because had they continued with their education, they would have a higher degree (12th pass, here). Similarly, it is assumed that respondents classified as 12th pass and below the age of 22 have continued their education and hence years of education have been allotted accordingly. Further, since we do not have data if the student has pursued a 3 or 4-year degree in under graduation, it has been assumed that those with a graduate degree over the age of 21 have had 15.5 years of education. It has been assumed that the post-graduate degree is of 2 years and Ph.D. is of 5 years.
2. Respondents having controlled health problems are the ones having some morbities like diabetes, hypertension or cured from serious health issues like heart problems, cancer etc, and now leading a normal life.
3. Respondents with decent health are the ones having occasional medical problems for example frequent headaches or more prone to infections etc. These health issues do not have long term consequences.

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Appendix

A.1. Homoskedasticity

White's test for Ho: homoskedasticity

Against Ha: unrestricted heteroskedasticity

Cameron & Trivedi's decomposition of IM-test

Table 2: Test for Homoskedasticity

	Base Model			*Extended Model*		
Source	*chi2*	*df*	*p*	*chi2*	*df*	*p*
Heteroskedasticity	10.98	24	0.9891	88.31	83	0.3245
Skewness	14.27	6	0.0268	15.57	13	0.2732
Kurtosis	4.86	1	0.0275	0.96	1	0.3284
Total	30.11	31	0.5117	104.83	97	0.2757

A.2. Multicollinearity

Table 3: Correlation Between Xi Variables in Base Model

	Years of Education	*Age*	*Income per person*	*Number of family members*	*Residence Type*
Years of Education	1				
Age 0.5321	1				
Income per person	0.2665	0.2243	1		
Number of family members	-0.1223	-0.2009	-0.2698	1	
Residence Type	0.1718	0.13	0.2707	-0.2082	1

Table 4: Correlation Between Xi Variables in Extended Model

	Years of Education	*Age*	*Income per person*	*Number of family members*	*Residence Type*	*Air Quality*	*Health Status*
Years of Education	1						
Age	0.5321	1					
Income per person	0.2665	0.2243	1				
Number of family members	-0.1223	-0.2009	-0.2698	1			
Residence Type	0.1718	0.13	0.2707	-0.2082	1		
Air Quality	0.132	0.1478	0.1142	-0.0888	0.3581	1	
Health Status	-0.0617	-0.204	-0.0714	0.0282	0.0834	-0.0603	1

A.3 Normality

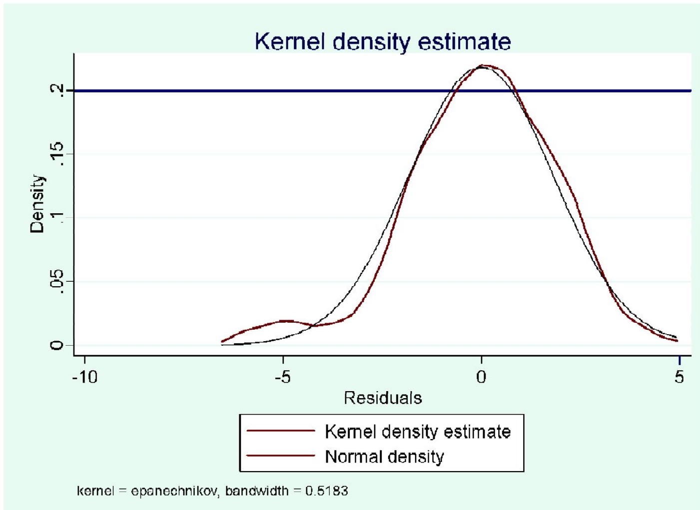

Figure 7: Kernel Density Estimate for Residuals in Base Model

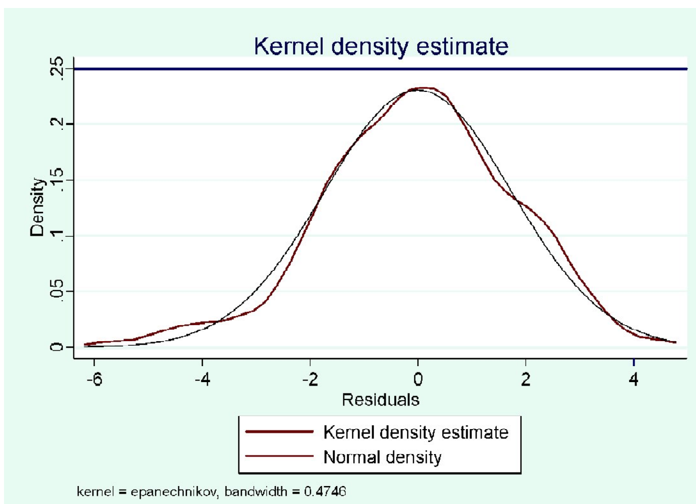

Figure 8: Kernel Density Estimate for Residuals in Extended Model

A.4. Omitted Variable Bias

Ramsey RESET test using powers of the fitted values of log of willingness to pay

Ho: model has no omitted variables

Base Model

F(3, 315) = 0.18 Prob > F = 0.9105

Extended Model

F(3, 308) = 0.61 Prob > F = 0.6086