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Jie-Sheng Tan-Soo, Eric Finkelstein, Ping Qin, Marc Jeuland, Subhrendu Pattanayak and Xiaobing Zhang

Central America
Research Program in Economics and Environment for Development in Central America Tropical Agricultural Research and Higher Education Center (CATIE)

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Peking University

Colombia
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University of Economics
Ho Chi Minh City, Vietnam

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Jie-Sheng Tan-Soo[1]; Eric Finkelstein[2]; Ping Qin[3]; Marc Jeuland[4]; Subhrendu Pattanayak[4]; Xiaobing Zhang[5]

Abstract

Due to worsening air quality across many cities in developing countries, there is an urgent need to consider more aggressive air pollution control measures. Valuation of the benefits of clean air is crucial for establishing the rationale for such policies, but is methodologically challenging, often expensive, and therefore remains limited. This study assesses the potential for more standardized and cost-effective measurement of the demand for air quality improvements, applying a contingent valuation procedure via online surveys, in three Asian megacities facing severe but varying pollution problems – Beijing, Delhi, and Jakarta. The study's primary contribution is to demonstrate the viability of this approach, which significantly enhances comparability of valuations and their drivers across locations, and thereby has great potential for informing policy analysis and targeting of specific interventions. A second contribution is to supply sorely needed data on the benefits of clean air in these three particular Asian cities, which collectively have a population of about 50 million people. The annual willingness-to-pay for air quality to reach national standards is estimated to be US$150 in Jakarta (where average PM2.5 concentration, at 45µg/m3, exceeds national standards by the smallest amount, specifically a factor of 1.3), US$1845 in Beijing (PM2.5 at 58µg/m3, 1.7 times the standard), and US$1760 in Delhi (PM2.5 at 133µg/m3, 3.3 times the standard). The methods deployed could be applied more widely to construct a worldwide database of comparable air quality valuations.

Keywords: Low and middle-income countries, air pollution, contingent valuation

JEL Codes:

[1] Lee Kuan Yew School of Public Policy, National University of Singapore

[2] Duke-NUS Medical School, Singapore

[3] School of Applied Economics, Renmin University of China

[4] Sanford School of Public Policy, Duke University, USA

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Due to worsening air quality across many cities in developing countries, there is an urgent need to consider more aggressive air pollution control measures. Valuation of the benefits of clean air is crucial for establishing the rationale for such policies, but is methodologically challenging, often expensive, and therefore remains limited. This study assesses the potential for more standardized and cost-effective measurement of the demand for air quality improvements, applying a contingent valuation procedure via online surveys, in three Asian megacities facing severe but varying pollution problems – Beijing, Delhi, and Jakarta. The study's primary contribution is to demonstrate the viability of this approach, which significantly enhances comparability of valuations and their drivers across locations, and thereby has great potential for informing policy analysis and targeting of specific interventions. A second contribution is to supply sorely needed data on the benefits of clean air in these three particular Asian cities, which collectively have a population of about 50 million people. The annual willingness-to-pay for air quality to reach national standards is estimated to be US$150 in Jakarta (where average $PM_{2.5}$ concentration, at 45μg/m^3, exceeds national standards by the smallest amount, specifically a factor of 1.3), US$1845 in Beijing ($PM_{2.5}$ at 58μg/m^3, 1.7 times the standard), and US$1760 in Delhi ($PM_{2.5}$ at 133μg/m^3, 3.3 times the standard). The methods deployed could be applied more widely to construct a worldwide database of comparable air quality valuations.

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1 Introduction

Due to rapid industrialization, agricultural expansion, increased usage of fossil fuels, and extreme climatic conditions, air quality has been deteriorating rapidly in many places in recent years (Health Effects Institute, 2020; WHO, 2014).[1] While the World Health Organization has advocated 10 μg/m^3 as the 'safe' level of exposure to $PM_{2.5}$, it is estimated that over 90% of the world's population lives in places where air quality fails to meet this guideline (Health Effects Institute, 2020).[2] In fact, a majority of the world's population resides in locations that fail to meet the least stringent "interim target 1" of annual $PM_{2.5}$ exceeding 35 μg/m^3 (Health Effects Institute, 2020; WHO, 2018). In countries as diverse and populous as China, India, Nigeria, Pakistan, and Bangladesh, 80-100% of the population live in areas above the latter guideline (Health Effects Institute, 2019). In recognition of this trend of worsening air quality, research on the human impacts of exposure to air pollution in LMICs has greatly expanded. Various studies have found that exposure to high levels of air pollution causes higher morbidity and mortality, reduced labor participation, lower schooling attainment, and shorter height, among other negative health consequences (e.g., see Arceo, Hanna, & Oliva, 2016; Bharadwaj, Gibson, Zivin, & Neilson, 2017; Hanna & Oliva, 2015; Tan-Soo & Pattanayak, 2019).

Air quality is especially poor in urban areas in low- and middle-income countries (LMICs). According to a database of air quality compiled by the World Health Organization, all of the top 50 most polluted (using 2016 annual $PM_{2.5}$ levels) cities in the world are located in LMICs, mostly in Asia (WHO, 2018). Decision makers wanting to take policy action to address air quality problems in such cities confront a complex problem that is driven by a web of causes and sources

[1] There are however anecdotal accounts that the economic and social lockdowns implemented during the Covid-19 pandemic in many cities have improved air quality, and overall environmental conditions.
[2] The World Health Organization updated their air quality guidelines in 2021. The earlier guideline of 10 μg/m^3 for $PM_{2.5}$ is now relegated to interim target 4 whereas the safe level is now set at 5 μg/m^3 (WHO, 2021).

that are extremely difficult to manage (Kandlikar, 2007; Oanh et al., 2006), and which necessitate the creation of holistic air quality management plans. For instance, China – an oft-cited example of severe air pollution in developing countries – has implemented a host of aggressive measures in the last 5-10 years to improve air quality (Health Effects Institute, 2019; Jin, Andersson, & Zhang, 2016). These measures include mandatory cuts to industrial production, vehicle use restrictions, stringent emissions standards, and many others (Chen, Jin, Kumar, & Shi, 2013; Feng & Liao, 2016; Zhang, He, & Huo, 2012). Descriptive work suggests that these efforts coincided with a 33% decline in $PM_{2.5}$ levels in China between 2013 to 2017 (Huang, Pan, Guo, & Li, 2018), and rigorous evaluation of some of these efforts has confirmed their role in improving air quality (Viard & Fu, 2015).

Despite such evidence, many governments (e.g., in India) have been unwilling or unable to enact solutions that substantially mitigate worsening air pollution (Bernard & Kazmin, 2018; Bibhudatta & Saxena, 2018). One possible reason for the reluctance to enact bold measures is that air pollution is caused by increased economic activity, and that the opportunity costs of air quality improvements are therefore potentially significant (Gao et al., 2016; Jin et al., 2016; Wu, Xu, & Zhang, 2015). Declines in economic activity may be highly salient to policymakers, compared to the relatively less observable nonmarket, long-term human capital and quality of life damages imposed by pollution (Bharadwaj et al., 2017; Frankenberg, McKee, & Thomas, 2005). In light of this tradeoff, an economic efficiency rationale dictates that policy makers should weigh the value of cleaner air against the costs of reducing pollution when choosing among potential responses. Unfortunately, policymakers in many LMICs typically lack critical information on the value of clean air, and are hamstrung in their efforts to carry out this crucial calculation.

This study aims to fill that gap by demonstrating a rigorous, cost- and time-efficient, and generalizable method for estimating the value of clean air, as well as its determinants, using internet surveys deployed in three Asian mega-cities facing severe pollution problems – Beijing, Delhi, and Jakarta. The approach relies on the contingent valuation method (CVM), a well-established stated preference approach to eliciting valuations for nonmarket goods in a wide range of settings (Johnston et al., 2017; Whittington, 2010).

Research on the value of improved air quality dates back to the late 1960s, when economists first developed and began to utilize non-market valuation techniques. While the literature has grown in sophistication and relevance since those origins, data from developing countries remains limited. To date, a total of about 60 such studies have focused on LMIC locations.[3] There are at least two reasons why so few such studies have previously been conducted in LMICs. First, for many years, ambient air pollution was not recognized as a major public health issue in poor countries that were also facing multiple nutrition and environmental health problems (e.g., hunger, poor water and sanitation, and malaria) (Prüss-Ustün et al., 2017). As these regions' economies have developed, many of the aforementioned problems have become less severe, but burdens from air pollution have worsened, often driven by persistent household use of polluting fuels, and by industrialization and urbanization (Cohen et al., 2017; Jeuland, Pattanayak, & Bluffstone, 2015; Landrigan et al., 2018). Second, there are considerable data constraints to conducting high quality air quality valuation studies.[4] Most existing studies pertain to Chinese cities and apply stated

[3] This number is based on an ongoing review of air quality valuation studies in LMICs compiled by a co-author of this study from peer-reviewed publications on this topic. The list is available from the authors and will be provided upon request.

[4] SP valuation methods are those that rely on survey questions to elicit measures of willingness-to-pay for a good or service, and are commonly used for nonmarket valuation due to the inability to find real world prices that allow measurement of demand for such goods, which include for example, environmental amenities such as improved air quality. Revealed preference (RP) measures for such goods, on the other hand, rely on tradeoffs made between other related goods and the nonmarket good, such as paying higher prices for property in qualities with better air quality

preference (SP) methods. In comparison with their RP counterparts that tend to rely on hedonic valuation and therefore require administrative data as well as spatially-refined direct measures of air pollution (Tan-Soo & Pattanayak, 2019), SP studies draw on survey-based elicitation of valuation data collected from a relevant population. For these reasons, air quality valuation has most often been done using SP methods and/or in relatively data-rich locations (e.g., China) where it is possible to match location-specific air quality measures to other relevant data (WHO, 2018).

The primary contribution of this study is to demonstrate the viability of a practical data driven and analytical methodology that aims to address two major limitations in this existing valuation literature as applied in LMICs. First, there is a lack of standard and consistent SP framings across studies, locations, and time, which leads to comparability problems that inhibit targeting of interventions and policy-making to the locations where benefits would be greatest. Second, most previous similar efforts are very costly, because of the heavy data requirements of revealed preference methodologies, which require careful assembly of hedonic measures (property or wage values), spatially-resolved environmental (air quality) and administrative (e.g., on crime or other locational attributes) information, and which typically rely on restrictive behavioral assumptions – namely a lack of accounting for regional sorting. Even for SP studies, the standard approach depends heavily on in-person interviews and specialized training of survey teams (Whittington, 2010). A second contribution is to provide updated estimates of the benefits of clean air in three very important Asian megacities. All three of these locations continue to face severe and frequent air pollution problems, and collectively have a population of about 50 million people. Their air pollution trajectories, however are quite different: Beijing's air quality is poor but improving,

(hedonic valuation), or spending money on travel (travel cost method) or coping behaviors (averting expenditures) that improve air quality.

Delhi's air quality is poor and shows no signs of improvement, and Jakarta's air quality is somewhat better but worsening.

The rest of the paper is organized as follows. The specific methods and surveys are described in Section 2. Descriptive statistics and results follow in Section 3. Finally, Section 4 discusses these results and concludes.

2 Method/Model

This section provides a detailed description of the low-cost internet survey approach that is used to value air quality improvement in the three study cities. The application of this standardized CV survey circumvents many of the limitations of typical methods, while still meeting the objective of informing air quality management and policy-making.

2.1 Survey planning and implementation

To prepare the internet survey, and cognizant of the intricacies of design details and the potential for bias in CV studies (Johnston et al., 2017), the study began with small focus group discussions (FGDs) conducted in each of the three selected locations – Beijing, Delhi, Jakarta. These cities were chosen because they are i) located in LMICs, ii) are large and economically important metropolises with more than 20 million residents each, and iii) face varying levels, sources, and temporal patterns of air pollution. In each city, three FGD sessions were conducted on consecutive days with about 6-8 participants per session, who were chosen to represent a spectrum of age, sex, income, and educational levels (see Figure 1 for the full study timeline). In each session, participants started by filling out a draft version of a printed version of the online survey instrument. During this portion of the FGD, close attention was paid to the variation in time taken to complete the questionnaire. After all participants had completed their questionnaires, a moderator initiated a discussion of each question with participants to collect their detailed feedback on the instrument. A key goal of these sessions was to assess participants' understanding and views of the CVM scenario framing and questions – from which valuations for air quality would eventually be derived. Following each FGD session, the questionnaire was modified based on participants' feedback prior to using the updated instrument in the next session. In this way, the FGDs helped guide the fine-tuning of the survey instrument and the specification of an appropriate range of city-specific bid values. These bid values would then be randomized to respondents to allow the tracing out of city-specific demand curves in the final internet survey.

Next, following completion of the FGDs, pilot surveys were conducted using the internet platform deployed for the main survey, with approximately 200 respondents per city. The purpose of these pilots was to obtain additional insight on whether the survey instrument was ready and suitable for mass deployment, and whether the range of hypothetical prices associated with an improved air quality policy had been well selected. Specifically elements examined included the distribution of socioeconomic characteristics of respondents, and whether responses varied across different bid values. On the basis of this piloting, minor adjustments were made to the survey instrument.

Links to the finalized survey were then sent to members participating in an online panel survey that is managed by a commercial survey company. Specifically, members of the panel are randomly invited to participate in the survey where the number of invites is based on estimated response rate for each city.[5] Based on the pilots and on prior similar survey experiences (Campbell, Venn, & Anderson, 2018; Determann, Lambooij, Steyerberg, de Bekker-Grob, & De Wit, 2017;

[5] For example, if the estimated response rate is 15%, 10,000 invites are needed to yield approximately 1,500 responses.

Evans & Mathur, 2018), it was anticipated that internet survey-takers would have a higher level of education and income on average when compared to the general population. Therefore, as much as possible, groups with lower socio-economic status were oversampled. Surveys for the three cities took place simultaneously (Figure 1), and just over 1,500 responses were collected from each location within 10 days (n=1,503 in Beijing. n=1,501 in Delhi, and n=1,506 in Jakarta).

2.2 Survey format

The survey consisted of four main modules: screening, socioeconomic and attitudinal questions, a CVM module, and a section on air pollution averting behaviors.[6]

First, the screening section was used to ensure that respondents were at least 21 years old and had resided in the city for at least nine months in the prior year. These screening criteria were applied to guarantee that respondents had sufficient experience of air quality in their city and were also in position to make financial decisions that would accurately reflect their private valuations for clean air.

The socioeconomic questions were designed to obtain basic information about the respondents and their households, e.g. age, sex, individual and household income, educational level, marital status, household size. The survey also elicited perceptions of air pollution, e.g., satisfaction with prevailing levels of air quality, and beliefs about air pollution causes. Responses to such questions are thought to shed light on responses to later valuation questions (Orgill, Shaheed, Brown, & Jeuland, 2013; Whitehead, 2006).

Third, the CVM scenario and question were crafted to be consistent with guidelines first established by NOAA, and incorporating, to the extent possible with an internet survey, recent

[6] The final English-language survey instruments used in each city are available at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/QQFSZA.

additions to that guidance (Arrow et al., 1993; Johnston et al., 2017). The respondent first received information on the current air quality in their city. The severity of air pollution was depicted in two ways: i) compared to national standards and ii) using images of city landmarks on days exhibiting varying, but experienced, levels of air quality.[7] The purpose of providing this information was to establish a common understanding among respondents within a city concerning different air pollution conditions[8], and the images served to simply and quickly illustrate the visual implications of different levels of experienced pollution. The respondent was then presented with a hypothetical scenario in which the local government would enact measures to improve air quality from the current levels of $PM_{2.5}$ to the location's national standards. This specific pollutant was selected for two main reasons. First, respondents often had difficulty distinguishing between different types of air pollutants, but fine particulate matter was generally salient. Second, while it is true that certain countries use air quality indices that combine several air pollutants, these indices i) often change over time within a given setting, and ii) include pollutants that vary across locations,[9] whereas measurement of $PM_{2.5}$ is based on a standard and objective approach. Examples of specific potential measures were provided, including limits on industrial polluter emissions, new standards for vehicular emissions, and enacting policies limiting crop burning in the broader regions and increasing tree planting. To minimize protest votes, respondents were asked to assume that the policies would work to achieve the required pollution reductions. In order to support the effort, all residents in a location would be required to pay a randomly assigned annual fee that would be collected from all residents.

[7] For Jakarta, the average $PM_{2.5}$ in 2016 is 45 μg/m^3 compared to the national standards of 35 μg/m^3. For Delhi, the average $PM_{2.5}$ in 2016 is 120 μg/m^3 compared to the national standards of 40 μg/m^3. For Beijing, the average $PM_{2.5}$ in 2016 is 59 μg/m^3 compared to the national standards of 35 μg/m^3.
[8] For instance, the FGDs in Jakarta reveal that some respondents associate air pollution with foul smell.
[9] For instance, China relied on the "Air Pollution Index" prior to 2012, but then changed to the "Air Quality Index".

Given this framing, respondents were asked to vote 'Yes' or 'No' and were asked to imagine that the policy would only be adopted if a majority of respondents voted in favor (see Appendix A for full depiction of the CVM question). In this regard, the CV question is based on a single-bound dichotomous choice design, within a referendum voting framework (an incentive compatible design for a public good). As this was a hypothetical choice, reminders about budget constraints and costs of coping with air pollution were included to ensure that respondents took these factors into consideration when deciding on whether to vote in favor of, or against, the policy. Finally, the survey included a brief cheap talk script aimed at minimizing yay-saying (Cummings & Taylor, 1999), specifically saying: "Before responding, please consider that if you contribute money towards this air quality improvement program, you are not going to be able to spend money on other things. In other surveys, we have seen that people sometimes give very high amounts because they have not carefully considered the other things they could buy with the money. Others give very small amounts because they do not think about all benefits."

Following the CVM vote question, respondents were asked to indicate the main reasons for their votes. Using their responses, further robustness checks were carried out to explore the sensitivity of the valuation estimates. The last module of the survey was on averting behaviors. Respondents were asked to report on behavioral responses for coping with air pollution during the past year, and to specify the amount spent for each type of behavior.[10]

Aside from the randomized bid amount, two additional randomized treatments were introduced into the survey instrument. First, around 50% of the respondents received information on the increased mortality risks from exposure to air pollution at current levels in their city, as compared to exposure to air quality at the location's national standards. These mortality risks were computed

[10] As the most common behavioral responses varied somewhat across contexts (as determined in FGDs), this module was tailored appropriately.

using the dose-response function for fine particulate matter (or $PM_{2.5}$) found in Burnett et al. (2014). The intention of this randomized information treatment was to assess whether willingness-to-pay (WTP) for cleaner air may be suppressed by a lack of understanding about the public health risks of air pollution. Second, half of the respondents completed the module on averting behaviors before the CV module. The intention of this switch in the order of the modules was to determine whether respondents correctly account for their coping costs (that would be avoided with clean air) when deciding on how to vote for the improvement. Acknowledging that coping costs are typically thought to only provide a lower bound on valuations for pollution reduction, it was nonetheless hypothesized that respondents whose coping expenditures were relatively higher, and especially those whose costs were higher than the randomly assigned value in the CV question, would be significantly more likely to vote "Yes", and *vice versa* (Pattanayak, Yang, Whittington, & Bal Kumar, 2005).

2.3 Empirical model

Using respondents' votes on the CVM scenario, their willingness-to-pay ia estimated in the following manner. First, individual i's true willingness-to-pay (y) for improving air quality to the level of national standards is expressed as follows:

$$y_i = \mathrm{X}\beta + \varepsilon_i \tag{1}$$

X in Equation (1) is a vector of explanatory variables (e.g. socioeconomic status, attitude toward air quality issues) and ε_i is a normally-distributed disturbance term where $\varepsilon \backsim N(0, \sigma^2)$. Hence, when a randomly-chosen individual is faced with a bid of B for improving air quality to the level of national standards, the probability of voting "Yes" is:

$$P(Vote = \text{Yes} \mid \mathrm{X}) = P(\mathrm{X}\beta + \varepsilon_i > B) = P(\varepsilon_i > B - \mathrm{X}\beta) = P\left(z_i > \frac{B - \mathrm{X}\beta}{\sigma^2}\right) \tag{2}$$

The final expression in Equation (2) is the standard normal cumulative probability after normalizing the disturbance term. Hence, the entire probability distribution for individual *i* can be expressed as:

$$P(Vote = \text{Yes} \mid \mathrm{X}) = P(Vote = 1 \mid \mathrm{X}) = 1 - \Phi\left(\frac{B - \mathrm{X}\beta}{\sigma^2}\right) \qquad (3)$$

$$P(Vote = No \mid \mathrm{X}) = P(Vote = 0 \mid \mathrm{X}) = \Phi\left(\frac{B - \mathrm{X}\beta}{\sigma^2}\right).$$

Equation (3) can be estimated using a probit model with the following likelihood function:

$$L = \prod_{y=1}\left[1 - \Phi\left(\frac{B - \mathrm{X}\beta}{\sigma^2}\right)\right] \cdot \prod_{y=0}\Phi\left(\frac{B - \mathrm{X}\beta}{\sigma^2}\right) \qquad (4)$$

The $\hat{\beta}s$ are next recovered using Equation (4); mean WTP is then obtained by substituting the estimated coefficients into Equation (1).

In the empirical analysis, several specification of equation 3 are estimated. The most basic specifications only includes the randomized fee. Additional specifications progressively add groups of covariates: indicators for the experimental treatments (the randomized order and information treatments, and their interaction), a group of survey variables, controls for respondents' demographics and socio-economic status (namely age, gender, household composition, income and education), and finally attitudinal variables related to perceptions of pollution and the role of government. Robustness checks then impose sample restrictions that remove surveys that were completed very quickly or exceedingly slowly or exclude respondents who might have rejected the CVM scenario based on their responses to debriefing questions as described in Section 2.2, or use alternative specifications of the averting expenditures variables.

3 Results

3.1 Descriptive statistics

Descriptive statistics from the survey respondents are presented in Table 1. As respondents to an internet survey may not be representative of the general population, basic socioeconomic data from the survey are first compared against city-wide statistics to determine the extent to which the sample differs from the general population. Compared to the population average (for Beijing – taken from 2016 China Family Panel Survey; for Delhi – taken from 2012 consumer survey; for Jakarta – taken from 2010 Indonesian census)), and despite efforts to oversample groups anticipated to be underrepresented using the internet survey mode, respondents remain slightly younger and have larger household sizes than the typical resident in each city. The largest and most important difference, however, is in education (and even literacy), where respondents are unsurprisingly much more educated than the general population. On the other hand, there are no discernible differences in sex distribution and marital status. In all, this comparison between survey respondents and the general population informs us that this study's findings are representative of a subgroup that is of higher educational level than the general population, and therefore also likely higher in income.

Next, respondents' attitudes toward air quality in their respective cities are examined. Interestingly, residents of Jakarta appear most unsatisfied with their air quality, even though objective measures of air quality are best in that city. Respondents from all three cities share similar confidence in the potential for policy actions to improve air quality in their location. Beijing residents most frequently check air quality reports (about once a week on average), while Jakarta residents only check such information about once a month. Given the increased attention to air pollution in China in recent years, it is also not surprising that Beijing residents spend the most on coping with air pollution, even though Beijing and Delhi have similar levels of air quality. Among other differences, respondents in the former city have higher incomes, have experienced severe air pollution for a much longer period, and are more fastidious in checking air quality data regularly.

Third, the relationship between the proportion of "Yes" votes and the randomized annual fee for the policy change is explored. There were five randomly assigned bid amounts in each city, and Figure 2 shows their respective graphs. Through the focus group discussions and pilot surveys, it was determined that bid values should range from US$70-US$1,400 for Beijing, US$70-US$1,120 for Delhi, and US$4.3-US$142 for Jakarta. The proportion of "Yes" votes expectedly follows a downward trend as bid values increase. Across the three cities, around 80% of respondents that received the lowest bid value voted "Yes" for the policy. For the Beijing and Jakarta, this proportion decreases to around 57% at the highest bid value. In contrast, the proportion of "Yes" votes is around 65% for Delhi, indicating relatively inelastic demand for air quality improvements, in Delhi, relative to the other two cities.[11]

Lastly, the explanations for respondents' voting behaviors are examined, to provide insight on their WTP for air quality improvements. Respondents voting "Yes" in each city had the same rank order of reasons. Specifically, their reasons are ranked in the order of health improvements, participating in more outdoor activities, alleviating smell nuisances, decreasing mortality, reducing fear of worsening future air quality, and lowering stress in thinking about air pollution (Figure 3). Similarly, reasons for voting "No" were also ranked in the same manner across all three cities – already paying sufficient taxes, problem is from neighboring states, lack of trust in government, household budget constraints, difficulty of improving the situation, other reasons, and lack of concern about air pollution (Figure 3). Based on responses highlighting only aversion to taxes, a

[11] It is important to highlight that these high levels of "yes" responses even at high prices may be indicative of substantial hypothetical bias that is possible in stated preferences valuation studies. It may be particularly difficult to fully mitigate such bias in online surveys.

lack of confidence in the government or that the policy changes would be effective, it appears that 126 (8.4%), 110 (7.3%), and 135 (9.0%) respondents might have rejected the scenario, and these responses are excluded in the less conservative WTP estimates discussed below.

3.2 Determinants and estimates of willingness to pay

The probit model and likelihood function in Equation (4) was next estimated to obtain coefficients for the bid amount as well as for the list of explanatory variables. The first model discussed only controls for the randomized bid amount (Table 2, Panels A to C, Column 1). As expected, *bid* has a negative and highly significant effect on "Yes" responses across the three cities.

Second, the following covariates are added to the basic model: the health information treatment indicator, module order indicator, and the interaction term between module order and the information treatment (Column 2). These treatments do not appear to have strong impacts on responses, and when they do, the effects are not consistent. In the Beijing sample, for example, completion of the averting expenditures module before the CVM module increases WTP, as expected, perhaps because it increased the salience of those expenditures. In Delhi and Jakarta, however, this treatment had no significant effect on WTP. This may be because such spending is more than three times higher on average in Beijing. The health information treatment, meanwhile, had no effect on WTP in any of the cities, and the combined treatment similarly had no meaningful effect.

The indicator comparing the relative size of averting expenditures and the randomized bid amounts, plus its interaction with the early completion of the averting behavior module, is examined next (Column 3). These variables again generally do not have statistically significant coefficients, and among the statistically significant coefficients, there do not appear to be any discernible patterns across the three cities. For instance, respondents in Beijing whose averting expenditures are larger than the randomized bid amount are much more likely to respond “Yes”. In the two other cities, the coefficients are positive for this indicator, but the estimates are imprecise. This may again be due to the lower averting expenditures in Jakarta and Delhi, which reduce the precision for identifying this impact. Moreover, the combination of completing the AE module first and averting expenditures exceeding the randomized fee has no consistent relationship with WTP, and actually appears negative in Delhi, counter to expectations.

Fourth, variables representing socioeconomic factors are added to the regression models (Column 4). Age and age-square respectively have a negative and positive relationship with probability of voting “Yes” across all three cities. This means that age has a U-shaped relationship with willingness-to-pay for the air quality improvement policy, with the youngest and oldest respondents being most likely to vote “Yes”. Individual income has a positive and statistically significant impact on voting “Yes”. This is to be expected as it has been shown that willingness-to-pay for air quality improvements is positively correlated with income, indicating that air quality is a normal good (e.g., Hökby & Söderqvist, 2003; Shao, Tian, & Fan, 2018). Respondents from larger households are less likely to vote “Yes” in Jakarta, perhaps reflecting tighter budget constraints, though neither the number of children nor the number of elderly members in the household are consistently significant predictors.

Fifth, attitudes about current air quality are added to the model (Column 5). Across all three cities, respondents unsatisfied with current air quality are found to be more likely to vote “Yes” for the policy. However, it is somewhat surprising that respondents in Jakarta who think it is possible to improve air quality are less likely to vote “Yes”. One possible explanation is that respondents to the survey may have interpreted this question as whether they think air quality *will* improve in the future. If so, those who answered in the positive to this question would be less likely to vote "Yes" for an additional hypothetical improvement. Respondents in Delhi and Jakarta who check air quality information less frequently are also less likely to vote "Yes", indicating that efforts to obtain information about air quality are also reflective of higher willingness-to-pay. However, in Beijing, where respondents tend to be more aware of air quality, this variable is not statistically significant. The amount spent on averting behaviors also has different relationships with voting patterns across different cities. Beijing's respondents, who have the highest such coping costs, are more likely to vote "Yes" when they have higher averting expenditures, whereas Delhi's respondents, who spend much less on average, appear to show the opposite relationship, and finally there is no discernible relationship for Jakarta. One possible explanation is that the Chinese respondents view averting expenditures as substitutes for city-level policies, while Delhi respondents view them as complements.[12]

From the model results, willingness to pay (WTP) to improve air quality from current levels to national standards is computed using Equation (1). The average WTP for Beijing for the various models is summarized in Figure 3. The first five bars in Panel A of Figure 3 correspond to the results in Columns 1-5 of Table 2. The value of improved air quality ranges from US$1,526 to US$2,034 across the five specifications. Additionally, respondents are separated into sub-samples based on whether their averting expenditures (AE) are higher or lower than the median. The latter two bars of Panel A in Figure 3 show a clear difference between these two groups where respondents with higher AE also have greater WTP compared to respondents with lower AE

[12] As noted previously, alternative specifications for the role of averting expenditures were also applied (in Appendix Table A2). These results are not substantively different, except that the negative relationship in Delhi is no longer apparent, and there is a concave relationship between averting expenditures and WTP in Beijing.

(US$1,998 vs. US$1,077). The full model estimates for these two subsamples are shown in Table 2 Columns 6 and 7.

Average WTP for Delhi's respondents is computed in the same manner (Figure 3, Panel B). Across the four models, WTP ranges from US$1,759 to US$2,407. In contrast to Beijing, there is hardly any disparity in WTP for the sub-samples based on AE in Delhi (US$2,223 vs. US$2,169). However, the 95% confidence interval for the AE above median group is much wider and extends to over US$6,000, indicating greater dispersion in this group. Jakarta follows a similar pattern to Delhi but has much lower WTP for clean air. Results from the four models are narrowly bound between US$146 to US$151 (Figure 3, Panel C), and WTP for respondents with AE above the median is only slightly higher than for respondents with AE below it (US$159 vs. US$151).

In terms of average individual income in Beijing, Delhi, and Jakarta, these WTP estimates amount to about 7%, 15%, and 1.8% respectively. The estimated WTP amounts as a proportion of income align well with the current situation in each city. At the time of the survey, Beijing's annual air pollution levels were 1.68 times the national standard threshold on average, Delhi's was 3.33 times the standard, and Jakarta's was 1.28 times the standard. As such, WTP for Delhi is highest and this is possibly driven by the high level of air pollution relative to national standards. On the other hand, Jakarta has the best air quality among the three cities, and thus logically could have lower WTP as a proportion of income.

The elasticity of WTP with respect to income can also be obtained, to further investigate if the difference in WTP across cities is driven by air quality differences or innate preferences. To do so, the income coefficient from the probit WTP regression is examined.[13] The implied income elasticities of demand are similar at 0.35, 0.19, and 0.24 respectively for Beijing, Delhi, and Jakarta.

[13] The elasticity of WTP with respect to income is calculated as $\beta_{income} \frac{\overline{income}}{\overline{WTP}}$.

They can be interpreted as follows: A 1% increase in income is associated with around 0.2%-0.35% increase in WTP for air quality improvement across the three cities. Given that incomes are very different across these cities (lower in Jakarta, higher in Beijing), this suggests that their divergent WTP levels are partly driven by income, and partly by local air pollution differences (i.e., the income differences across cities cannot explain the substantial cross-city variation in WTP).[14]

4 Discussion and conclusions

4.1 Summary and discussion of findings

This study used an internet survey methodology with about 1,500 respondents per city to elicit willingness to pay for improved air quality in three Asian mega-cities – Beijing, Delhi, and Jakarta. Responses were collected in each city over a period of about two weeks, relying on a standardized contingent valuation module. Individual annual WTP for air quality improvements from current levels to national standards was found to be about US$150 in Jakarta (95% CI: US$130-US$175), US$1,760 in Delhi (95% CI: US$1,415-US$2,630), and $US1,845 in Beijing (95% CI: US$1,310-US$2,820). These WTP estimates largely reflect the extent to which current air pollution levels currently exceed the national standards in each locations. The regression models that generated these WTP also showed that higher income respondents are more likely to vote in favor of air quality improvement policies, as are those who check air quality information more frequently. On the other hand, the cost of the policy improvement and satisfaction with current air quality are negatively correlated with WTP. The WTP estimates are also similar in a model excluding

[14] As robustness checks, sample restrictions were imposed that removed surveys that were completed very quickly or exceedingly slowly or excluded respondents who might have rejected the CVM scenario based on their responses to debriefing questions as described above, and using alternative specifications of the averting expenditures variable. The results with these restictions are generally unchanged (See Table A1).

covariates (indicating that the randomization of prices worked properly), and when the sample is restricted based on the completion time of the survey.

This study provides two main scientific and policy contributions. First, it demonstrates that consistent and comparable WTP for air quality can be obtained in a cost- and time-efficient manner. Just as the World Health Organization maintains an annually-updated database of air quality in cities around the world, one could also deploy such standardized surveys to measure WTP for air quality improvements for cities around the world on an annual basis. The benefits of having such a database to policymakers would be multiple. First, given that air quality is deteriorating quickly in many cities, city planners need to decide if it is prudent to allocate scarce resources to manage air quality. As such, a database with up-to-date valuations of air quality would enable the decision-making process, and track progress and the demand for further improvements over time. Second, while the method that is demonstrated is cost- and time-efficient, it is still unlikely that all cities could be easily covered. In this regard, if the database has sufficient time- and spatial-variation, it could be leveraged to more easily and accurately impute valuations for cities not covered in it, accounting e.g., for difference in air pollution levels, incomes, population demographics, and other important correlates of demand. Analyzing a rich set of geographic, spatial, and temporal variables could also pay dividends for better establishing empirical relationships between such variables and preferences for environmental quality. Third, resources aside, using internet surveys is also more practical than face to face surveys, given the recent experience of the COVID-19 pandemic. The second contribution this study provides is updated valuations for clean air in these three megacities. There are very few studies on air quality valuation from developing country contexts, and in particular for this study, from Delhi and Jakarta, even though these cities are extremely large and have poor air quality. In this regard, the study findings provide valuable data points for policymakers in these locations seeking to formulate air quality management plans. For instance, a district court in Jakarta recently ruled against the Indonesian government for poor air quality in the city, and ordered the president to impose tighter regulations (Rayda, 2021).

There are also two key limitations of this study. First, by design, 100% of respondents are literate and internet users. This is obviously not a representative sample of the general population in these cities, and there would be an even more significant divergence with general representativeness in lower-income contexts, where access to the internet and high-quality education are more unequal. Indeed, comparison with representative surveys shows that the samples in each city are more educated and have higher income than the general population in each location. The impact of this may explain why this study's estimates are somewhat higher than those from other, albeit not fully comparable, CV studies conducted in the same cities (mostly Beijing). In future work, researchers with sufficient resources should consider using experimental sampling, through which respondents contacted in person and via an online approach would be randomized to each of these two survey modes, to better understand the extent of sample selection and survey mode bias. This approach would also help to address the second major limitation of this study, which relates to the validity of internet survey responses. In particular, while the regression model results mostly conformed to expectations, there were a few instances where the randomized treatments did not, and considerable voting in favor of policy action was observed even when the proposed fee was very high. In face-to-face surveys, enumerators can check for respondents' attentiveness or understanding of questions, and somewhat counter the propensity for yeah-saying, but there are fewer avenues to detect anomalies in results obtained from an internet survey. Developing and testing the effectiveness of validity checks that work for online valuation surveys remains a useful exercise in future similar work.

4.2 Conclusion

Due to escalating air pollution levels around the world, many cities are in urgent need of actions or policies to improve air quality. Air quality management plans and interventions are costly, however, so policymakers need estimates of the value of air quality improvements to determine which actions to pursue, and specifically, where the benefits of air quality improvements from interventions will outweigh their costs. Unfortunately, valuation studies are in short supply in just the places where they are most urgently needed, due to the cost and data requirements of standard valuation techniques, and most existing valuation studies are ill-suited to guide prioritization of actions due to the lack of comparability of the measures they produce. This study demonstrated a standardized and cost-effective approach to generating such estimates in three Asian mega-cities facing pollution problems today, which could be deployed more widely to construct a global database of comparable and policy-relevant air quality valuations.

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Tables and figures

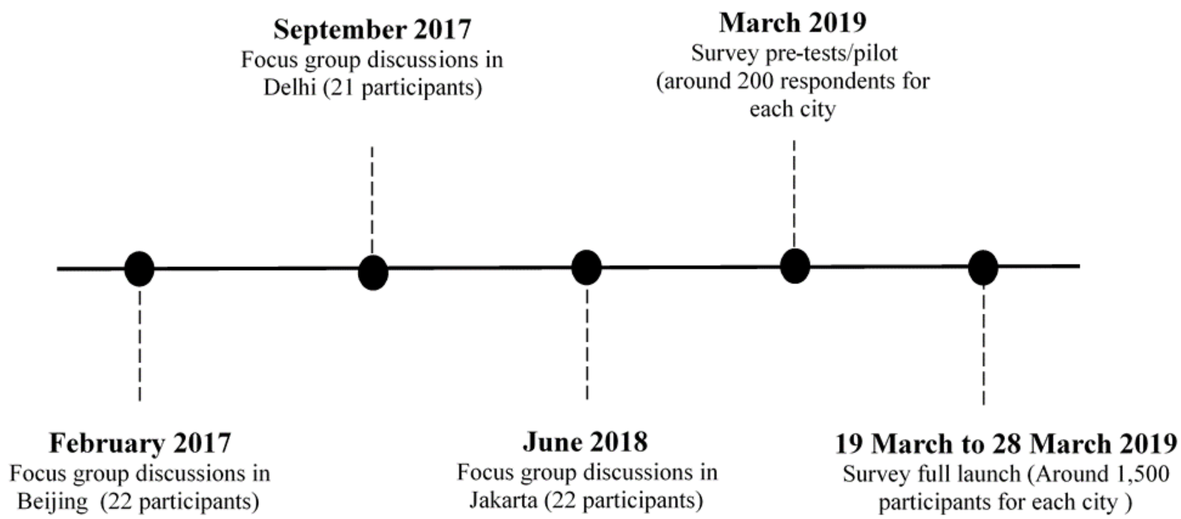

Figure 1. Timeline of survey implementation.

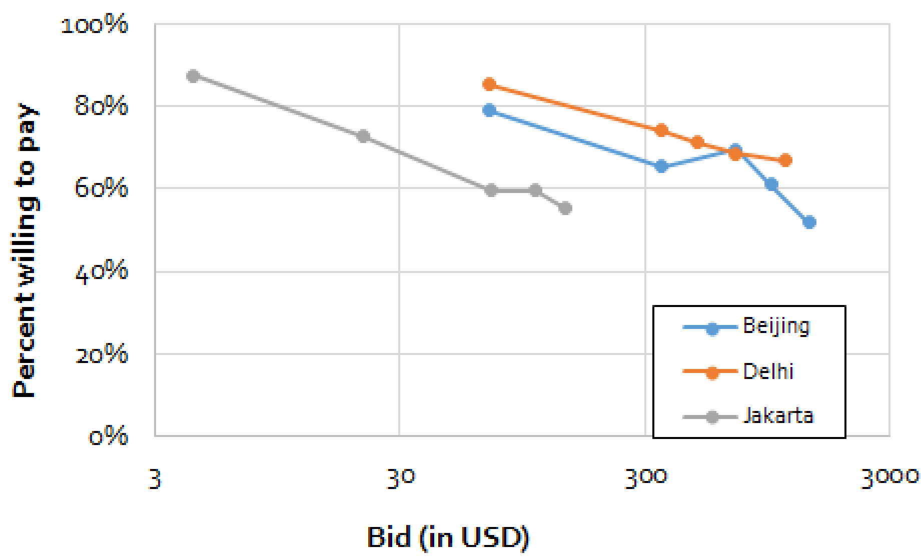

Figure 2. Proportion of “Yes” votes vs. Bid amount.

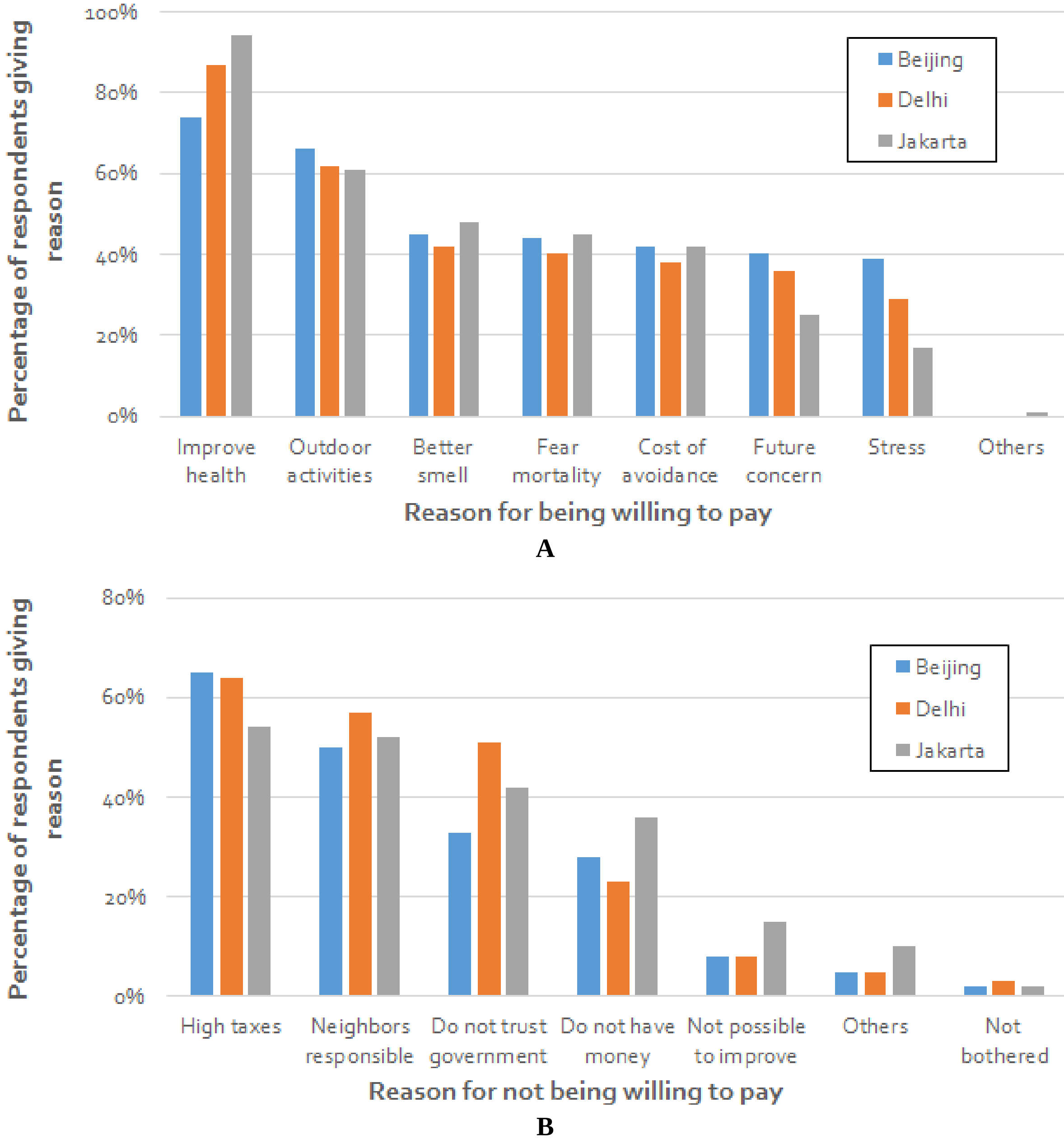

Figure 3. Reasons for voting A) "Yes" or B) "No" in the CVM scenario

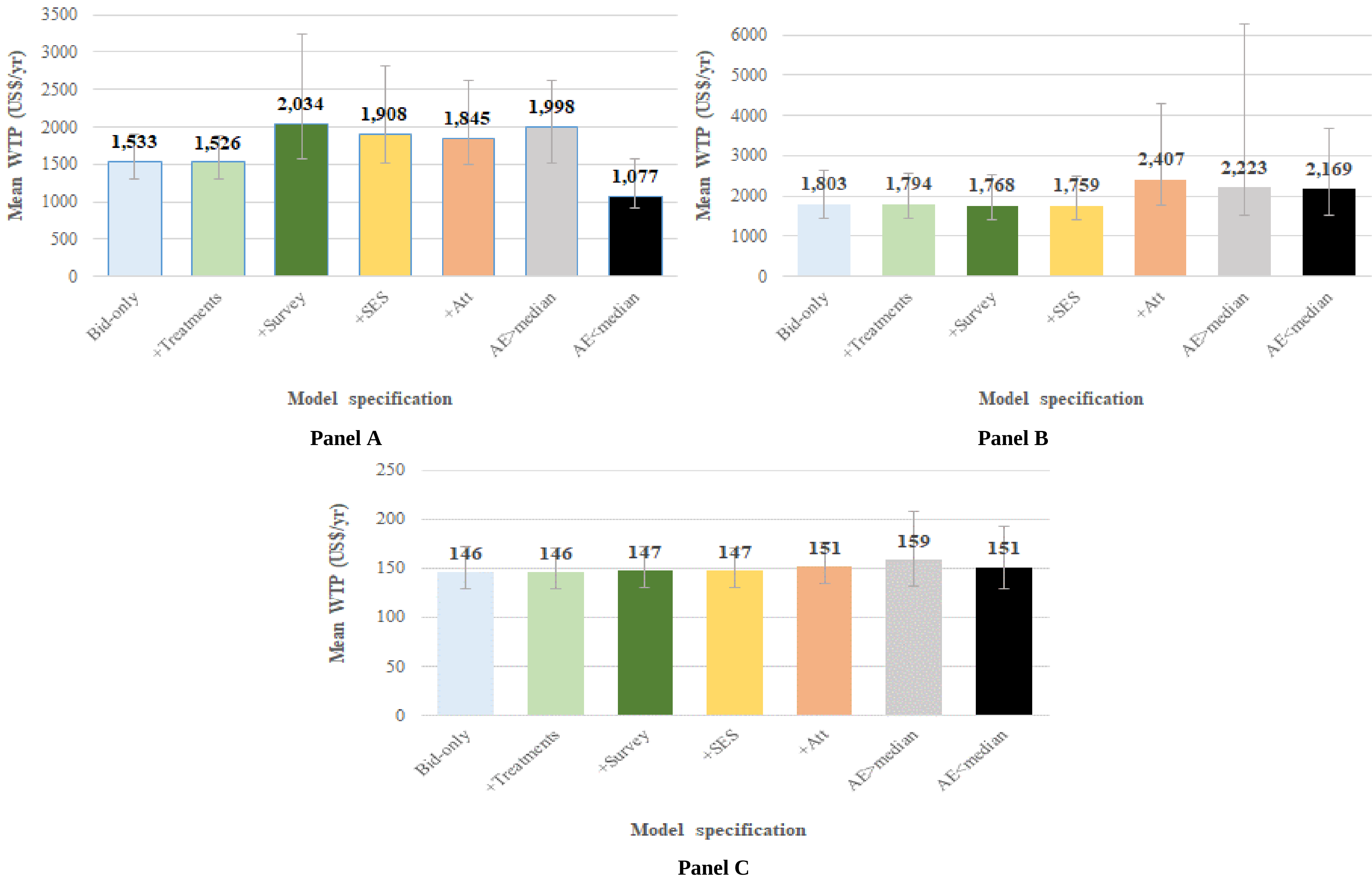

Figure 4. Willingness-to-pay (WTP) for air quality improvements in a) Beijing; b) Delhi; and c) Jakarta. (Notes: Different specifications correspond to the models presented in Table 2 Panels A-C. Each model through "+ Att" adds additional control variables: SES = Socioeconomic status; Att = Attitudinal variables. The final two are estimates for subsamples with averting expenditures above and below the median, respectively. Error bars correspond to 95% Krinsky-Robb Confidence Intervals)

Table 1: Descriptive statistics

Panel A: Beijing respondents

Variable	Definition/Unit	Mean	SD	Min	Max
Age		43.85	13.83	21	82
Age (from 2016 China Family Panel Survey)		*3.11*	*1.71*	*1*	*11*
Sex (1=Male, 0=Female)		0.54	0.50	0	1
Sex (1=Male, 0=Female) (from 2016 CFPS)		*0.52*	*0.50*	*0*	*1*
Marital status (1=Currently married, 0=Not married)		0.88	0.32	0	1
Marital status (1=Currently married, 0=Not married) (from 2016 CFPS)		*0.76*	*0.43*	*0*	*1*
Household size		3.27	1.01	1	8
Household size (from 2016 CFPS)		*3.11*	*1.71*	*1*	*11*
No. of children ≤12 in household		0.630	0.618	0	3
Number of health symptoms identified		4.66	2.26	1	12
Citizenship is responsible for clean air		0.47	0.50	0	1
Averting expenditures (USD)		1927.3	2432.6	0	18577.6
Income bracket (annual before tax in CNY)					
	No income	0.010	0.099		
	Less than 25,000	0.019	0.138		
	25,000 to 40,000	0.021	0.142		
	40,000 to 65,000	0.079	0.269		
	65,000 to 90,000	0.092	0.290		
	90,000 to 115,000	0.148	0.355		
	115,000 to 130,000	0.166	0.372		
	130,000 to 155,000	0.115	0.319		
	155,000 to 205,000	0.110	0.314		
	205,000 to 255,000	0.076	0.265		
	255,000 to 305,000	0.061	0.240		
	305,000 to 355,000	0.033	0.179		
	355,000 to 405,000	0.033	0.179		
	More than 405,000	0.037	0.188		
Highest educational level					
	No schooling	0.001	0.036		
	Primary school	0.005	0.068		
	Middle school	0.023	0.149		
	High school	0.073	0.259		
	Technical secondary school	0.051	0.221		
	Junior college	0.170	0.376		
	Bachelor's degree	0.581	0.494		
	Master's degree	0.088	0.284		
	Doctoral degree	0.008	0.089		
College education (1=Yes, 0=No) (from 2016 CFPS)		0.34	0.47	0	1
Employment status					
	Salaried employee	0.723	0.448		
	Head of own business	0.080	0.271		
	Not working but looking	0.004	0.063		
	Not working -- retired	0.124	0.330		

	Work from home (telecommute or run business from home)	0.047	0.211
	Student	0.012	0.109
	Homemaker	0.010	0.099
Satisfaction with current AQ			
	Very satisfied	0.055	0.228
	Satisfied	0.357	0.479
	Neutral	0.395	0.489
	Unsatisfied	0.164	0.371
	Very unsatisfied	0.029	0.167
Whether air quality has improved in 2018			
	Improved significantly	0.100	0.301
	Some improvement	0.708	0.455
	Remained the same	0.169	0.375
	Some deterioration	0.020	0.140
	Worsened significantly	0.003	0.052
Whether air quality will improve in next 5 years			
	Will improve significantly	0.218	0.413
	Will have some improvement	0.657	0.475
	Will remain the same	0.076	0.265
	Will have some deterioration	0.033	0.178
	Will worsen significantly	0.005	0.073
	Don’t know/ No way of forecasting	0.011	0.106
Frequency of checking air quality			
	At least daily	0.34	0.47
	At least once a week	0.40	0.49
	At least monthly	0.10	0.31
	Very infrequent/never	0.15	0.36

Panel B: Delhi respondents

Variable	Definition/Unit	Mean	SD	Min	Max
Age		35.54	11.20	21	88
Age (from 2012 consumer survey)		*39.40*	*14*	*21*	*92*
Sex (1=Male, 0=Female)		0.533	0.499	0	1
Sex (1=Male, 0=Female) (from 2012 consumer survey)		*0.54*	*0*	*0*	*1*
Marital status (1=Currently married, 0=Not married)		0.755	0.430	0	1
Marital status (1=Currently married, 0=Not married) (from 2012 consumer survey)		*0.76*	*0*	*0*	*1*
Household size		4.414	1.525	1	15
Household size (from 2012 consumer survey)		*3.90*	*2.22*	*1*	*18*
No. of children $\geq$12 in household		0.980	0.832	0	7
Number of health symptoms identified		5.62	2.75	1	12
Citizenship is responsible for clean air		0.46	0.50	0	1
Averting expenditures (USD)		355.4	865.6	0	21370.6
Income bracket (monthly before tax in INR)					
	No income	0.037	0.190		
	Less than 5,000	0.015	0.120		
	5,000 to 12,000	0.023	0.151		
	12,000 to 17,000	0.025	0.157		
	17,000 to 22,000	0.031	0.174		
	22,000 to 27,000	0.055	0.229		
	27,000 to 32,000	0.065	0.246		
	32,000 to 37,000	0.065	0.246		
	37,000 to 42,000	0.095	0.293		
	42,000 to 47,000	0.087	0.281		
	47,000 to 52,000	0.097	0.296		
	52,000 to 57,000	0.124	0.330		
	More than 57,000	0.281	0.450		
Highest educational level					
	No schooling	0.001	0.036		
	Primary school	0.002	0.045		
	Secondary school	0.003	0.058		
	Higher secondary school	0.042	0.201		
	Vocational school	0.007	0.085		
	Bachelor’s degree	0.323	0.468		
	Master’s degree	0.602	0.490		
	Doctoral degree	0.019	0.135		
College education (1=Yes, 0=No) (from 2012 consumer survey)		*0.30*	*0.45*		
Employment status					
	Salaried employee	0.787	0.410		
	Head of own business	0.070	0.255		
	Not working but looking	0.021	0.142		
	Not working -- retired	0.015	0.120		
	Work from home (telecommute or run business from home)	0.035	0.185		
	Student	0.052	0.222		

	Homemaker	0.021	0.142
Satisfaction with current AQ			
	Very satisfied	0.318	0.466
	Satisfied	0.119	0.323
	Neutral	0.105	0.306
	Unsatisfied	0.266	0.442
	Very unsatisfied	0.193	0.394
Whether air quality has improved in 2018			
	Improved significantly	0.292	0.455
	Some improvement	0.273	0.446
	Remained the same	0.217	0.412
	Some deterioration	0.136	0.343
	Worsened significantly	0.082	0.275
Whether air quality will improve in next 5 years			
	Will improve significantly	0.336	0.473
	Will have some improvement	0.283	0.451
	Will remain the same	0.093	0.291
	Will have some deterioration	0.109	0.311
	Will worsen significantly	0.146	0.353
	Don’t know/ No way of forecasting	0.033	0.178
Frequency of checking air quality			
	At least daily	0.32	0.468
	At least once a week	0.27	0.444
	At least monthly	0.12	0.328
	Very infrequent/never	0.28	0.451

Panel C: Jakarta respondents

Variable	Definition/Unit	Mean	SD	Min	Max
Age		36.73	10.76	21	75
Age (from 2010 census)		*41.16*	*14.62*	*21*	*98*
Sex (1=Male, 0=Female)		0.50	0.50	0	1
Sex (1=Male, 0=Female) (from 2010 census)		*0.50*	*0.50*	*0*	*1*
Marital status (1=Currently married, 0=Not married)		0.74	0.44	0	1
Marital status (1=Currently married, 0=Not married) (from 2010 census)		*0.78*	*0.41*	*0*	*1*
Household size		4.01	1.48	1	15
Household size (from 2010 census)		*3.80*	*2.07*	*1*	*30*
No. of children $\geq$12 in household		1.05	0.87	0	6
Number of health symptoms identified		4.75	2.83	1	13
Averting expenditures (USD)		479.5	1053.0	0	16122.0
Income bracket (monthly before tax in IDR)					
	I have no income	0.02	0.15		
	Less than 2 million	0.04	0.19		
	2 million to 3 million	0.07	0.25		
	3 million to 4 million	0.10	0.30		
	4 million to 6 million	0.18	0.38		
	6 million to 8 million	0.16	0.37		
	8 million to 10 million	0.14	0.35		
	10 million to 12 million	0.06	0.24		
	12 million to 15 million	0.05	0.21		
	15 million to 20 million	0.05	0.22		
	20 million to 25 million	0.03	0.18		
	25 million to 30 million	0.05	0.22		
	More than 30 million	0.05	0.21		
Highest educational level					
	No schooling	0.00	0.03		
	Primary school	0.00	0.03		
	Secondary school	0.01	0.10		
	Higher secondary school	0.19	0.39		
	Vocational school	0.07	0.25		
	Bachelor’s degree	0.67	0.47		
	Master’s degree	0.06	0.24		
	Doctoral degree	0.01	0.07		
College education (1=Yes, 0=No) (from 2010 census)		*0.05*	*0.22*		
Employment status					
	Salaried employee	0.60	0.49		
	Head of own business	0.23	0.42		
	Not working but looking	0.02	0.15		
	Not working -- retired	0.01	0.11		

	Work from home (telecommute or run business from home)	0.07	0.25
	Student	0.03	0.16
	Homemaker	0.04	0.20
Satisfaction with current AQ			
	Very satisfied	0.09	0.29
	Satisfied	0.14	0.35
	Neutral	0.24	0.43
	Unsatisfied	0.42	0.49
	Very unsatisfied	0.10	0.30
Whether air quality has improved in 2018			
	Improved significantly	0.12	0.32
	Some improvement	0.21	0.41
	Remained the same	0.43	0.50
	Some deterioration	0.19	0.39
	Worsened significantly	0.05	0.22
Whether air quality will improve in next 5 years			
	Will improve significantly	0.17	0.38
	Will have some improvement	0.19	0.39
	Will remain the same	0.15	0.36
	Will have some deterioration	0.24	0.43
	Will worsen significantly	0.19	0.39
	Don’t know/ No way of forecasting	0.05	0.22
Frequency of checking air quality			
	At least daily	0.16	0.36
	At least once a week	0.24	0.43
	At least monthly	0.18	0.38
	Very infrequent/never	0.43	0.49

Table 2 (Panel A). Probit estimation of willingness to pay in Beijing

VARIABLES	(1) Beijing bid only	(2) Beijing +treatment	(3) Beijing +survey	(4) Beijing +SES	(5) Beijing +Att	(6) Beijing AB>M	(7) Beijing AB<M
Bid amount (‘000)	-0.487***	-0.492***	-0.312*	-0.371**	-0.421***	-0.611***	-0.490***
	(0.072)	(0.072)	(0.077)	(0.080)	(0.085)	(0.119)	(0.106)
AE module before CV module		0.172*	0.076	0.031	0.083	0.138	0.314**
		(0.096)	(0.126)	(0.129)	(0.134)	(0.156)	(0.143)
Information treatment		0.022	0.003	-0.020	-0.009	-0.079	0.129
		(0.095)	(0.096)	(0.098)	(0.102)	(0.153)	(0.142)
Info*AE first		-0.211	-0.190	-0.161	-0.211	-0.169	-0.368*
		(0.135)	(0.136)	(0.140)	(0.145)	(0.218)	(0.200)
AE amount > bid			0.479***	0.347***	0.283**		
			(0.100)	(0.107)	(0.127)		
Interaction of "AE before" and "AE > bid"			0.091	0.141	0.134		
			(0.139)	(0.142)	(0.148)		
Age				-0.082***	-0.079***	-0.073**	-0.117***
				(0.021)	(0.021)	(0.033)	(0.030)
Age-squared				0.001***	0.001***	0.001***	0.001***
				(0.000)	(0.000)	(0.000)	(0.000)
Marital status				0.408***	0.397***	0.368**	0.561***
				(0.130)	(0.134)	(0.186)	(0.207)
Sex				-0.020	-0.039	-0.064	0.020
				(0.071)	(0.074)	(0.110)	(0.103)
Income (‘000)				0.012***	0.012***	0.009**	0.017***
				(0.003)	(0.003)	(0.004)	(0.005)
College education				0.241**	0.247**	0.443**	0.070
				(0.111)	(0.117)	(0.216)	(0.148)
Household size				0.073	0.066	0.010	0.128*
				(0.047)	(0.048)	(0.072)	(0.068)
No. of children $\leq$ 12				0.002	-0.008	0.050	-0.082
				(0.078)	(0.080)	(0.119)	(0.119)
No. of elderly $\geq$ 60				0.019	0.005	0.107	-0.054

				(0.057)	(0.059)	(0.089)	(0.084)
Satisfied with current AQ					-0.301***	-0.236***	-0.344***
					(0.044)	(0.063)	(0.062)
Feels its possible to improve AQ					-0.089	-0.078	-0.119
					(0.061)	(0.094)	(0.081)
Symptoms identified					-0.105***	-0.094***	-0.119***
					(0.017)	(0.025)	(0.025)
Frequency of checking AQ					0.019	-0.074	0.056
					(0.041)	(0.060)	(0.056)
Citizens are responsible					-0.039	0.316***	-0.349***
					(0.077)	(0.113)	(0.108)
log(averting expenditure)					0.047***		
					(0.015)		
Constant	0.746***	0.706***	0.309***	0.769*	2.010***	2.502***	3.172***
	(0.063)	(0.086)	(0.111)	(0.463)	(0.515)	(0.743)	(0.724)
Observations	1,503	1,503	1,503	1,503	1,447	750	749

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the estimation outcomes of probit regressions. Column (1) is the most basic model using only bid as covariate. Column (2) includes experimental treatments and their interaction, whereas column (3) adds survey variables related to averting expenditures compared to bids or interacted with the AE first treatment. Column (4) adds household and individual socioeconomic status (SES) to the model. Column (5) adds responses to attitudinal questions on air quality. Column (6) and (7) separates respondents according to whether their averting expenditures are above or below median.

Table 2 (Panel B). Probit estimation of willingness to pay in Delhi.

VARIABLES	(1) Delhi bid only	(2) Delhi +treatment	(3) Delhi +survey	(4) Delhi +SES	(5) Delhi +Att	(6) Delhi AB>M	(7) Delhi AB<M
Bid amount (‘000)	-0.502***	-0.506***	-0.519***	-0.557***	-0.466***	-0.441***	-0.626***
	(0.099)	(0.099)	(0.103)	(0.106)	(0.120)	(0.160)	(0.165)
AE module before CV module		-0.088	0.011	0.018	0.065	-0.350**	0.251
		(0.099)	(0.107)	(0.111)	(0.124)	(0.155)	(0.174)
Information treatment		-0.098	-0.094	-0.085	-0.051	-0.099	-0.026
		(0.100)	(0.100)	(0.104)	(0.115)	(0.161)	(0.166)
Info*AE first		0.093	0.088	0.098	0.072	0.113	0.013
		(0.140)	(0.140)	(0.145)	(0.160)	(0.218)	(0.244)
AE amount > bid			0.185	0.140	0.492***		
			(0.120)	(0.124)	(0.150)		
Interaction of "AE before" and "AE > bid"			-0.391**	-0.416**	-0.553***		
			(0.163)	(0.167)	(0.182)		
Age				-0.070***	-0.072***	-0.046	-0.104***
				(0.021)	(0.024)	(0.035)	(0.039)
Age-squared				0.001***	0.001**	0.000	0.001**
				(0.000)	(0.000)	(0.000)	(0.000)
Marital status				0.400***	0.281**	0.170	0.514***
				(0.109)	(0.123)	(0.161)	(0.196)
Sex				-0.117	0.084	0.051	0.087
				(0.074)	(0.083)	(0.114)	(0.128)
Income (‘000)				0.005***	0.003**	0.026	0.042*
				(0.001)	(0.002)	(0.023)	(0.023)
College education				-0.576***	-0.241	0.111	-0.588*
				(0.175)	(0.201)	(0.281)	(0.311)
Household size				-0.011	0.064*	0.049	0.092*
				(0.030)	(0.033)	(0.049)	(0.047)
No. of children $\leq$ 12				0.211***	0.099*	0.082	0.074
				(0.053)	(0.058)	(0.080)	(0.092)
No. of elderly $\geq$ 60				0.136***	0.025	-0.024	0.098

				(0.049)	(0.055)	(0.072)	(0.088)
Satisfied with current AQ					-0.318***	-0.270***	-0.383***
					(0.034)	(0.048)	(0.051)
Feels its possible to improve AQ					-0.046	-0.072	-0.011
					(0.047)	(0.067)	(0.069)
Symptoms identified					-0.021	-0.004	-0.034
					(0.017)	(0.023)	(0.025)
Frequency of checking AQ					-0.252***	-0.265***	-0.206***
					(0.037)	(0.050)	(0.055)
Citizens are responsible					-0.306***	-0.222*	-0.387***
					(0.086)	(0.116)	(0.132)
log(averting expenditure)					-0.020**		
					(0.009)		
Constant	0.906***	0.978***	0.940***	2.266***	3.899***	3.349***	4.636***
	(0.067)	(0.093)	(0.102)	(0.445)	(0.516)	(0.729)	(0.830)
Observations	1,501	1,501	1,501	1,501	1,501	746	747

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the estimation outcomes of probit regressions. Column (1) is the most basic model using only bid as covariate. Column (2) includes experimental treatments and their interaction, whereas column (3) adds survey variables related to averting expenditures compared to bids or interacted with the AE first treatment. Column (4) adds household and individual socioeconomic status (SES) to the model. Column (5) adds responses to attitudinal questions on air quality. Column (6) and (7) separates respondents according to whether their averting expenditures are above or below median.

Table 2 (Panel C). Probit estimation of willingness to pay in Jakarta.

VARIABLES	(1) Jakarta bid only	(2) Jakarta +treatment	(3) Jakarta +survey	(4) Jakarta +SES	(5) Jakarta +Att	(6) Jakarta AB>M	(7) Jakarta AB<M
Bid amount	-0.006***	-0.006***	-0.006***	-0.006***	-0.007***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
AE module before CV module		-0.033	0.005	0.067	0.053	-0.134	0.125
		(0.097)	(0.136)	(0.139)	(0.146)	(0.145)	(0.153)
Information treatment		-0.134	-0.134	-0.111	-0.091	-0.188	0.060
		(0.096)	(0.096)	(0.098)	(0.102)	(0.146)	(0.147)
Info*AE first		0.156	0.158	0.163	0.192	0.246	0.084
		(0.136)	(0.137)	(0.140)	(0.146)	(0.205)	(0.213)
AE amount > bid			0.121	0.068	0.242		
			(0.100)	(0.103)	(0.161)		
Interaction of "AE before" and "AE > bid"			-0.061	-0.158	-0.122		
			(0.143)	(0.147)	(0.155)		
Age				-0.110***	-0.107***	-0.114***	-0.116***
				(0.024)	(0.025)	(0.036)	(0.037)
Age-squared				0.001***	0.001***	0.001***	0.001***
				(0.000)	(0.000)	(0.000)	(0.000)
Marital status				0.128	-0.029	-0.034	0.021
				(0.099)	(0.102)	(0.149)	(0.145)
Sex				-0.234***	-0.225***	0.017	-0.472***
				(0.072)	(0.076)	(0.106)	(0.112)
Income (‘000)				0.035***	0.029***	0.033***	0.031**
				(0.006)	(0.007)	(0.009)	(0.013)
College education				0.095	-0.004	-0.065	-0.022
				(0.086)	(0.090)	(0.136)	(0.124)
Household size				-0.099***	-0.084***	-0.137***	-0.047
				(0.030)	(0.032)	(0.050)	(0.043)
No. of children ≤ 12				0.088*	0.049	0.079	0.020
				(0.052)	(0.053)	(0.077)	(0.075)
No. of elderly ≥ 60				0.126**	0.055	0.113	0.016

				(0.053)	(0.055)	(0.075)	(0.084)
Satisfied with current AQ					-0.145***	-0.149**	-0.094*
					(0.040)	(0.058)	(0.057)
Feels its possible to improve AQ					-0.214***	-0.259***	-0.131*
					(0.052)	(0.073)	(0.078)
Symptoms identified					-0.019	-0.015	-0.021
					(0.014)	(0.019)	(0.022)
Frequency of checking AQ					-0.316***	-0.210***	-0.450***
					(0.038)	(0.052)	(0.061)
Citizens are responsible					0.147	0.264*	0.088
					(0.095)	(0.146)	(0.129)
log(averting expenditure)					-0.007		
					(0.015)		
Constant	0.867***	0.915***	0.831***	2.973***	4.758***	4.918***	5.078***
	(0.060)	(0.086)	(0.109)	(0.457)	(0.514)	(0.748)	(0.749)
Observations	1,506	1,506	1,506	1,506	1,506	751	750

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the estimation outcomes of probit regressions. Column (1) is the most basic model using only bid as covariate. Column (2) includes experimental treatments and their interaction, whereas column (3) adds survey variables related to averting expenditures compared to bids or interacted with the AE first treatment. Column (4) adds household and individual socioeconomic status (SES) to the model. Column (5) adds responses to attitudinal questions on air quality. Column (6) and (7) separates respondents according to whether their averting expenditures are above or below median.

Appendix A. Additional figures and tables

Table A1. Probit estimation of willingness to pay using limited samples

	Excluding short and long surveys			Excluding potential scenario rejectors		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Beijing	Delhi	Jakarta	Beijing	Delhi	Jakarta
Bid amount ('000, except in Jakarta)	-0.470***	-0.499***	-0.006***	-0.488***	-0.519***	-0.007***
	(0.089)	(0.126)	(0.001)	(0.094)	(0.133)	(0.001)
AE module before CV module	0.050	0.097	0.022	0.046	-0.005	-0.008
	(0.140)	(0.131)	(0.151)	(0.144)	(0.136)	(0.157)
Information treatment	0.008	-0.023	-0.093	-0.010	-0.162	0.007
	(0.106)	(0.120)	(0.105)	(0.110)	(0.126)	(0.113)
Info*AE first	-0.282*	-0.018	0.212	-0.139	0.214	0.134
	(0.152)	(0.168)	(0.151)	(0.158)	(0.175)	(0.161)
AE amount > bid	0.173	0.448***	0.292*	0.243*	0.563***	0.177
	(0.134)	(0.156)	(0.167)	(0.138)	(0.168)	(0.175)
Interaction of "AE before" and "AE > bid"	0.251	-0.532***	-0.092	0.180	-0.583***	-0.034
	(0.155)	(0.190)	(0.160)	(0.160)	(0.204)	(0.169)
Age	-0.085***	-0.079***	-0.106***	-0.090***	-0.079***	-0.081***
	(0.023)	(0.026)	(0.026)	(0.025)	(0.026)	(0.027)
Age-squared	0.001***	0.001**	0.001***	0.001***	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marital status	0.404***	0.346***	-0.007	0.376**	0.356***	-0.076
	(0.142)	(0.128)	(0.107)	(0.147)	(0.134)	(0.113)
Sex	-0.019	0.116	-0.223***	-0.101	0.066	-0.311***
	(0.077)	(0.087)	(0.079)	(0.081)	(0.092)	(0.083)
Income ('000)	0.013***	0.033**	0.031***	0.016***	0.054***	0.040***
	(0.003)	(0.017)	(0.007)	(0.003)	(0.017)	(0.008)
College education	0.286**	-0.410*	-0.020	0.408***	-0.231	0.031
	(0.122)	(0.228)	(0.093)	(0.125)	(0.214)	(0.098)
Household size	0.072	0.074**	-0.087***	0.064	0.064*	-0.097***
	(0.051)	(0.034)	(0.033)	(0.052)	(0.036)	(0.035)
No. of children ≤ 12	0.022	0.101*	0.048	0.019	0.102	0.030

	(0.084)	(0.060)	(0.055)	(0.087)	(0.063)	(0.058)
No. of elderly $\geq$ 60	-0.018	0.033	0.045	0.042	0.006	0.046
	(0.063)	(0.057)	(0.057)	(0.066)	(0.060)	(0.060)
Satisfied with current AQ	-0.308***	-0.343***	-0.146***	-0.245***	-0.288***	-0.146***
	(0.046)	(0.036)	(0.042)	(0.048)	(0.037)	(0.043)
Feels it is possible to improve AQ	-0.072	-0.030	-0.224***	-0.067	-0.003	-0.189***
	(0.063)	(0.049)	(0.055)	(0.066)	(0.053)	(0.057)
Symptoms identified	-0.104***	-0.014	-0.017	-0.122***	-0.036*	-0.033**
	(0.018)	(0.018)	(0.015)	(0.019)	(0.019)	(0.015)
Frequency of checking AQ	0.010	-0.234***	-0.316***	-0.008	-0.215***	-0.293***
	(0.042)	(0.039)	(0.040)	(0.044)	(0.040)	(0.042)
Citizens are responsible	-0.040	-0.334***	0.118	-0.025	-0.338***	0.187*
	(0.081)	(0.090)	(0.099)	(0.084)	(0.095)	(0.103)
log(averting expenditure)	0.057***	-0.016	-0.012	0.030*	-0.019*	-0.001
	(0.016)	(0.010)	(0.016)	(0.017)	(0.010)	(0.016)
Constant	2.015***	4.061***	4.766***	2.296***	3.966***	4.522***
	(0.543)	(0.558)	(0.535)	(0.573)	(0.565)	(0.548)
Willingness-to-pay (US$)	1,694.2	2,269.2	154.1	2,129.7	2,653.5	180.7
95% confidence interval	(1,410; 2,318)	(1,689; 3,923)	(136; 183)	(1,685; 2,943)	(1,890; 4,553)	(155; 210)
Observations	1,378	1,367	1,411	1,377	1,391	1,371

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the estimation outcomes of probit regressions using only observations where respondents used more than 6 minutes (5th percentile) and less than 30 minutes (95th percentile) to complete the survey (columns 1-3) and when potential scenario rejectors were excluded based on responses to debriefing questions (columns 4-6).

Table A2. Probit estimation with alternative averting expenditures specifications

	AE interacted with AE Before			AE Only Specification		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Beijing	Delhi	Jakarta	Beijing	Delhi	Jakarta
Bid amount (‘000, except in Jakarta)	-0.548***	-0.523***	-0.007***	-0.531***	-0.525***	-0.007***
	(0.078)	(0.113)	(0.001)	(0.150)	(0.113)	(0.001)
AE module before CV module	0.067	-0.118	-0.049	0.192*	-0.102	-0.025
	(0.111)	(0.117)	(0.108)	(0.103)	(0.113)	(0.104)
Information treatment	0.001	-0.074	-0.089	0.004	-0.066	-0.084
	(0.101)	(0.114)	(0.102)	(0.101)	(0.114)	(0.102)
Info*AE first	-0.234	0.095	0.194	-0.220	0.084	0.188
	(0.144)	(0.159)	(0.146)	(0.144)	(0.159)	(0.146)
Interaction of "AE before" and “Total AE”	0.070***	0.044	0.048			
	(0.026)	(0.075)	(0.058)			
Age	-0.082***	-0.068***	-0.106***	-0.084***	-0.067***	-0.108***
	(0.021)	(0.024)	(0.025)	(0.021)	(0.024)	(0.025)
Age-squared	0.001***	0.001**	0.001***	0.001***	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marital status	0.405***	0.285**	-0.026	0.427***	0.294**	-0.019
	(0.134)	(0.122)	(0.102)	(0.134)	(0.122)	(0.102)
Sex	-0.032	0.080	-0.223***	-0.024	0.074	-0.221***
	(0.074)	(0.083)	(0.076)	(0.073)	(0.083)	(0.076)
Income (‘000)	0.013***	0.035**	0.029***	0.012***	0.030*	0.028***
	(0.003)	(0.016)	(0.007)	(0.003)	(0.016)	(0.007)
College education	0.264**	-0.227	0.000	0.235**	-0.222	0.003
	(0.117)	(0.200)	(0.089)	(0.117)	(0.198)	(0.089)
Household size	0.072	0.063*	-0.084***	0.074	0.066**	-0.087***
	(0.048)	(0.033)	(0.032)	(0.048)	(0.033)	(0.032)
No. of children $\leq$ 12	-0.009	0.094	0.050	-0.001	0.086	0.051
	(0.080)	(0.058)	(0.053)	(0.080)	(0.058)	(0.053)
No. of elderly $\geq$ 60	0.006	0.028	0.058	0.006	0.020	0.060

	(0.059)	(0.055)	(0.055)	(0.059)	(0.054)	(0.055)
Satisfied with current AQ	-0.292***	-0.308***	-0.147***	-0.289***	-0.317***	-0.145***
	(0.044)	(0.034)	(0.040)	(0.043)	(0.033)	(0.039)
Feels it is possible to improve AQ	-0.097	-0.053	-0.212***	-0.108*	-0.057	-0.213***
	(0.061)	(0.047)	(0.052)	(0.060)	(0.047)	(0.052)
Symptoms identified	-0.109***	-0.021	-0.021	-0.107***	-0.024	-0.021
	(0.017)	(0.017)	(0.014)	(0.017)	(0.017)	(0.014)
Frequency of checking AQ	0.014	-0.255***	-0.319***	0.003	-0.242***	-0.315***
	(0.040)	(0.037)	(0.038)	(0.040)	(0.036)	(0.038)
Citizens are responsible	-0.051	-0.309***	0.150	-0.039	-0.318***	0.150
	(0.077)	(0.086)	(0.095)	(0.077)	(0.085)	(0.095)
Ln(averting expenditures)	0.065***	-0.013	0.007			
	(0.013)	(0.008)	(0.009)			
Total averting expenditure (‘000)				0.000***	0.000	0.000
				(0.000)	(0.000)	(0.000)
(Total averting expenditure)^2 /10^6				-0.000***	0.000	-0.000
				(0.000)	(0.000)	(0.000)
Constant	2.196***	3.941***	4.860***	2.396***	3.925***	4.880***
	(0.510)	(0.510)	(0.512)	(0.505)	(0.509)	(0.513)
Willingness-to-pay (US$)	1,582.4	2,186.9	149.4	1,602.0	2,179.4	149.6
95% confidence interval	(1,366; 1,941)	(1,692; 3,396)	(133; 173)	(1,375; 1,980)	(1,687; 3,366)	(133; 173)
Observations	1,503	1,501	1,506	1,503	1,501	1,506

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the estimation outcomes of probit regressions using only observations with alternative specifications for averting expenditures controls: interaction of AE with AE module prior to CVM (columns 1-3) and control for total AE and total AE squared, to look for evidence of nonlinearities (columns 4-6).