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# Air Quality Valuation Using Online Surveys in Three Asian Megacities

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## Abstract

Due to worsening air quality across many cities in developing countries, there is an urgent need to consider more aggressive measures to control air pollution. While valuation for clean air would help in the evaluation of such policies, there is a significant knowledge gap in this area. This study contributes to this literature by using online surveys to conduct contingent valuation for air quality improvements in three Asian megacities facing severe pollution problems – Beijing, Delhi, and Jakarta. Our primary contribution is to demonstrate the viability of this data collection and analytical methodology, which significantly enhances comparability of valuations and drivers of valuations across locations, and thereby has great potential for informing policy analysis and targeting of interventions. A second contribution is to supply sorely needed data on the benefits of clean air in these three Asian cities, which collectively have a population of about 50 million people. In all, we estimate that the annual willingness-to-pay for air quality to reach national standards is around US$150 in Jakarta, US$1700 in Beijing, and US$2400 in Delhi.

**Keywords**: low- and middle-income countries; air pollution; contingent valuation

**JEL Codes**: Q51; Q53; H41

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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, 2019; 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 92% of the world's population lives in places where air quality fails to meet this guideline (Health Effects Institute, 2019). Even with the least stringent "interim target 1" of annual $PM_{2.5}$ between 25 to 35 μg/m$^3$, more than half the world's population (54%) resides in locations that fail to meet this standard (Health Effects Institute, 2019; WHO, 2018). In countries as diverse and populous as China, India, Nigeria, Pakistan, and Bangladesh, around 80%-100% of the population live in areas above the WHO interim target 1 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 Lower and Middle-Income Countries (LMICs) has greatly expanded in recent years. Various studies have found that exposure to high levels of air pollution causes higher morbidity and mortality, reduced labor participation, lower schooling attainment, and stunting of growth, among other negative health consequences (e.g., see Arceo, Hanna, & Oliva, 2016; Bharadwaj et al., 2017; Hanna & Oliva, 2015; Tan-Soo & Pattanayak, 2019).

Air quality is especially poor in urban areas in 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). On the policy front, decision makers wanting to address air quality problems in such cities are faced with a complex problem that is driven by a web of causes and sources that can be 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 et al., 2013; Feng & Liao, 2016; Zhang, He, & Huo, 2012). Evaluation of these policies has shown that they have improved air quality substantially. Viard and Fu (2015) showed that Beijing's driving restriction policies decreased air pollution by around 8%. A descriptive study by Huang et al. (2018) observed that $PM_{2.5}$ levels in China decreased by about 33% between 2013 to 2017, which they largely attributed to the national air

[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.

quality management plan. Yet, many other governments (e.g., in India) have been unwilling or unable to enact solutions that substantially mitigate worsening air pollution.[2] One possible reason for this reluctance to act boldly is that air pollution is caused by increased economic activity, and that the opportunity costs of air quality improvements are thus 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 and long-term human capital and quality of life damages imposed by pollution (Bharadwaj et al., 2017; Frankenberg, McKee, & Thomas, 2005).

In light of this policy 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 information on the value of clean air, and are therefore hamstrung in their efforts to make this calculation.

This study aims to fill that gap by demonstrating a rigorous, and cost- and time-efficient 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. Our primary contribution is to demonstrate the viability of this data collection and analytical methodology, which significantly enhances comparability of valuations and drivers of valuations across locations, and thereby has great potential for informing policy analysis and targeting of interventions. A second contribution is to supply sorely needed data on the benefits of clean air in these three Asian cities, which collectively have a population of about 50 million people.

## 2. Background

Research on the value of improved air quality first surfaced in the late 1960s when economists developed and began to utilize non-market valuation techniques (e.g., Nelson, 1978; Ridker & Henning, 1967). While the literature has grown in sophistication and relevance since then, there remains a glaring lack of studies from developing countries. To date, there are only around 60 studies focusing on LMIC locations, only slightly more than the total number of hedonic pricing studies conducted in the United States alone before 1995 (Smith & Huang, 1995).[3]

There are at least two reasons why so few such studies have been conducted in LMICs. First, for many years, ambient air pollution was not recognized as a major public health issue in

[2] https://economictimes.indiatimes.com/news/politics-and-nation/view-politicians-have-no-answer-to-indias-increasingly-toxic-air/articleshow/71965394.cms?from=mdr; https://ig.ft.com/india-pollution/

[3] Jie-Sheng Tan-Soo is currently working on a review of air quality valuation studies in LMICs and has compiled a list of peer-reviewed articles on this topic.

poor countries that were also facing many other 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 the 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, we can infer from the choice of methodologies and locations of LMIC urban air pollution studies, most of which are in Chinese cities and apply stated preference (SP) methods, that there are considerable data constraints in conducting air quality valuation studies. In comparison with their revealed preference (RP) counterparts (Tan-Soo & Pattanayak, 2019), SP studies have lower data requirements that can more easily be addressed by researchers lacking access to administrative data on property values or even location-specific measures of air quality. For these reasons, air quality valuation has most often been done using SP methods and/or in relatively data-rich locations (e.g., China), even though air quality problems are nearly ubiquitous across LMIC cities (WHO, 2018).

Our study and low-cost methodology, which uses the contingent valuation (CV) method, aims to address four major limitations in the existing valuation literature. The first is the lack of standard and consistent SP framings across studies, locations, and time, which leads to comparability problems. The second is the high cost of most SP data collection efforts, which rely heavily on in-person interviews and require specialized training of survey teams (Whittington, 2002). Third, there are heavy data requirements of most revealed preference methodologies, which require careful assembly of hedonic (property or wage), spatially-resolved environmental (air quality) and administrative (e.g., on crime or other locational attributes) data. And fourth, we improve on the restrictive behavioral assumptions of the most practical revealed preference methodologies. The next section of this paper provides a detailed description of how we obtain valuation estimates for clean air in our study locations using internet surveys. Data description and results follow in Section 4, and we discuss these results and lessons in Section 5.

## 3. Method/Model

To obtain air quality valuations in these three Asian cities, we rely on a standardized internet-based CV survey. This method allows us to circumvent many of the limitations discussed above, and yet meet the objective of informing policies on air quality management.

### *3a. Survey Implementation Plan*

To prepare the internet survey, and cognizant of the intricacies of design details in CV studies (Carson, 2000; Whittington, 2002), we began by organizing and conducting small focus

group discussions (FGDs) 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, and iii) face varying levels, sources, and temporal patterns of air pollution. In each city, we conducted three FGD sessions on consecutive days with about 6-8 participants per session, who were chosen to represent a spectrum of age, sex, income, and educational levels. In each session, we first had participants fill out a draft version of a printed version of the survey instrument, paying close attention 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, thereby collecting their feedback. In these sessions, we were particularly interested in participants' understanding and views of the contingent valuation scenario framing and questions – from which valuations for air quality would eventually be derived. Following each FGD session, we modified the questionnaire based on participants' feedback prior to using the updated instrument in the next session. In this way, the FGDs helped us to fine-tune the survey instrument and to determine an appropriate range of city-specific bid values for eventual use in the eventual internet survey.

Next, following completion of the FGDs, we conducted pilot surveys using the same internet platform as that for the main survey, with approximately 150 respondents per city. The purpose of these pilots was to obtain additional insight into whether the survey instrument was ready and suitable for mass deployment. Specifically, we checked for the distribution of socioeconomic characteristics of our respondents, and responses to the 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 on-line panel that is managed by a commercial survey company. Based on our pilots and on prior similar survey experiences (Campbell, Venn, & Anderson, 2018; Determann et al., 2017; Evans & Mathur, 2018), we anticipated that internet survey-takers would tend to have a higher level of education and income compared to the general population. Therefore, as much as possible, we tried to over-sample from groups with lower socio-economic status. Surveys for the three cities took place simultaneously, and 1,500 responses were collected within 10 days.

### *3b. Survey Format*

The survey consisted of four main modules: screening, socioeconomic and attitudinal questions, contingent valuation (CV), and averting behaviors.

First, the screening section was used to pick respondents who 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

to ensure that respondents had sufficient experience of air quality in their city and were also in a position to make financial decisions that would accurately reflect their private valuations of 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. We also asked about perceptions of air pollution in this section, e.g., eliciting satisfaction with prevailing levels of air quality, inquiring on beliefs about air pollution causes, etc. Responses to such questions are thought to shed light on responses to valuation questions (Orgill et al., 2013; Whitehead, 2006).

Third, the CV scenario and question were crafted to be consistent with guidelines first established by the U.S. National Oceanic and Atmospheric Administration (NOAA), and incorporating suggestions from recent additions to that guidance (Arrow et al., 1993). 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 with varying degree of air quality.[4] The purpose of providing information on current air quality was twofold. First, it was to establish a common understanding among respondents within a city concerning different air pollution conditions[5], and the images served to simply and quickly illustrate typical consequences of different levels of pollution. Second, the ensuing hypothetical improvement to air quality is thus based on the current level. While it is theoretically possible to implement a CV where we do not provide any information on current air quality, the results would likely be noisy (and less informative) to the extent that respondents have differing baseline understand of air quality.

The respondent was then presented with a hypothetical scenario in which the local government would enact measures to improve air quality from current standards to reach national standards. All respondents are subsequently presented with a randomly-assigned annual fee for which they were asked to vote 'Yes' or 'No' (see Appendix A for full depiction of the CV 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). Because this was a hypothetical choice, we also included reminders about budget constraints and costs of coping with air pollution to ensure that respondents took these factors into consideration when deciding on their votes.

[4] For Jakarta, the average $PM_{2.5}$ in 2016 was 45 μg/m$^3$, compared to the national standards of 35 μg/m$^3$. For Delhi, the average $PM_{2.5}$ in 2016 was 120 μg/m$^3$, compared to the national standards of 40 μg/m$^3$. For Beijing, the average $PM_{2.5}$ in 2016 was 59 μg/m$^3$, compared to the national standards of 35 μg/m$^3$.

[5] For instance, the FGDs in Jakarta reveal that some respondents associate air pollution with foul smell.

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 last year and the amount spent for each type of behavior. As the most common behavioral responses varied somewhat across contexts (as determined in FGDs), this module was tailored appropriately.

Aside from the randomized bid amount, we introduced two additional randomized treatments 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 national standards. These mortality risks were computed 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 (which would be avoided with clean air) when deciding on how to vote for the improvement. Examples of such coping costs are expenditures on face-masks, purchase and operations of air purifiers, medical expenses related to respiratory illness, etc… Acknowledging that coping costs are typically thought to only provide a lower bound on valuations for pollution reduction, we nonetheless hypothesized that respondents whose coping expenditures were higher than the randomly assigned value in the CV question would be significantly more likely to vote "Yes", and *vice versa* (Pattanayak et al., 2005). *A priori* to conducting the survey, we expected the coefficient for health information would be positive, as we suspected that respondents would tend to underestimate these health consequences, such that providing information about the health implications of exposure to air pollution would increase WTP. Similarly, we thought that receiving the averting behaviors module before the CV module would make these costs more salient to respondents, and thereby increase WTP (acknowledging, however, that respondents with low levels of averting behavior might not be affected in this way).

### *3c. Empirical Model*

Using respondents' votes on the contingent valuation scenario, we estimate their willingness-to-pay in the following manner. First, we assume that individual *i*'s true willingness-to-pay (*y*) can be 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 $\varepsilon_i$ is a normally-distributed disturbance term where $\varepsilon \backsim N(0, \sigma^2)$.

In some econometric specifications, we also interact these randomized treatments with information obtained from the respondents to obtain additional insights about their valuations. Specifically, we generate two such interaction terms: i) an indicator variable for whether averting expenditures are larger than randomized bid amount, and ii) the interaction of the indicator variable in (i) with the treatment variable of receiving the averting behaviors module before the CV module. We hypothesize interaction term (i) to have a positive coefficient because the averting expenditure is a revealed measure of WTP for air quality. The second interaction term is also hypothesized to be positive because respondents who do in fact spend more on averting expenditures could be subtly reminded after completing that module. Hence, when an individual is faced with a randomly-assigned bid of *B*, the probability of voting "Yes" is:

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

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:

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

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

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

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

We can recover $\hat{\beta}s$ using Equation (4); mean WTP is then obtained by substituting the estimated coefficients into Equation (1).

## 4. Results

### *4a. Descriptive Statistics*

Descriptive statistics from the survey respondents are presented in Table 1. As we are cognizant that respondents from an internet survey may not be representative of the general population, we compare basic socioeconomic data from the survey against city-wide statistics to determine the extent to which our sample differs from the general population. In comparison 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 our efforts to oversample groups we anticipated to be underrepresented using this survey mode, our internet survey respondents are on average slightly younger, and have larger household sizes.

The largest and most important difference, however, is in education (and even literacy), where our 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 our findings are more representative of a sub-selection of the population that is of higher educational level than the general population, and therefore also likely higher income.

Second, we examine in detail respondents' attitudes toward air quality in their respective cities. It is interesting to note that Jakarta residents are the most unsatisfied with their air quality even though they have the best air quality amongst the three cities. Respondents from all three cities share similar confidence in the possibility of improving 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 (Health Effects Institute, 2019), it is also not surprising that Beijing residents spend the most in coping with air pollution, even though Beijing and Delhi have similar levels of air quality. Among other differences, respondents in Beijing have higher incomes, have experienced severe air pollution for a much longer period, and are more fastidious in checking air quality data regularly.

Third, we examine how the proportion of "Yes" votes changes with respect to the randomized bid amount (which are at the annual level). There were five randomly assigned bid amounts in each city, and Figure 1 shows their respective graphs. Through our focus group discussions and pilot surveys, we 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. We can see that the proportion of "Yes" votes expectedly follows a general downward trend as bid values increase. Across 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.

Lastly, we collected explanations for respondents' voting behaviors to generate additional insights 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 nuisance smells, decreasing mortality, reducing fear of worsening future air quality, and lowering stress in thinking about air pollution (Figure 2). 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 2).

### *4b. Determinants and Estimates of Willingness to Pay*

We estimated a probit model using the likelihood function in Equation (4) to obtain coefficients for the bid amount as well as for the list of explanatory variables. We begin by estimating a bid-only model where the only covariate is the randomized bid amount (Table 2, Panels A to C, Columns 1 to 3). As expected, *bid* has a negative and highly significant effect on "Yes" responses across the three cities.

Second, we add the following set of covariates to the basic model: the health information treatment indicator, module order indicator, and the interaction term between module order and the relative size of averting expenditures and bid amounts. The majority of these variables 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". However, this relationship is not observed in the two other cities.

Third, variables representing socioeconomic factors are added to the regression models. Age and age-square respectively have a negative and positive relationship with probability of voting "Yes" across all three cities. This means that younger respondents are more likely to vote "No" for the air quality improvement policy, while older respondents are more 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 (e.g., Hökby & Söderqvist, 2003; Shao, Tian, & Fan, 2018). Respondents from larger households are less likely to vote "Yes" in Jakarta, and it is surprising that neither the number of children nor the number of elderly members in the household are statistically significant predictors.

Fourth, we add attitudes about current air quality to the model. We find that across all three cities, respondents unsatisfied with current air quality are more likely to vote "Yes" for the policy. However, it is somewhat surprising that respondents in Beijing and 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" to the hypothetical scenario. We also see that respondents in Delhi and Jakarta who check air quality information less frequently are less likely to vote "Yes", indicating that individuals who

make an effort to obtain information about air quality have higher willingness-to-pay. However, it should also be noted that this signal is not statistically significant for Beijing's respondents, who are generally most aware of air quality in the first place. In other words, air quality information is much more widely available in Beijing compared to the two other cities, and residents therefore need not expend significant effort to obtain information on air quality. 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. One possible explanation is that the Chinese respondents view averting expenditures as substitutes to city-level policies while Delhi respondents view them as complements.

Using the model results, we can also compute willingness to pay (WTP) to improve air quality from current levels to national standards using Equation (1). We first compute the average WTP for Beijing for the various models that were estimated (Figure 3). The first four bars in Panel A of Figure 3 correspond to the results in Columns 1, and 4-6 of Table 2. We can see that valuation for improved air quality ranges from around US$1,532 to US$2,031 across the four models. Additionally, we divided respondents into sub-samples based on whether their averting expenditure (AE) is higher or lower than the median level. 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 larger WTP compared to respondents with lower AE (US$1,006 vs. US$2,066).

Second, we compute average WTP for Delhi's respondents in the same manner (Figure 3, Panel B). Across the four models, WTP ranges from US$1,767 to US$2,474. The disparity in WTP for the sub-samples based on AE is, however, lower than that in Beijing, as we observe a much smaller difference (US$2,253 vs. US$2,170). However, the 95% confidence interval for the above-median AE group is much wider and extends to over US$6,000, indicating greater dispersion in this group.

Third, Jakarta follows a similar pattern, where the average WTP estimates across the four models are narrowly bound between US$146 to US$151 (Figure 3, Panel C). We observe the same pattern as with Delhi, where WTP for respondents with AE above the median is slightly higher than for respondents with AE below the median (US$158 vs. US$150).

In terms of WTP as a percentage of average individual income, these amount to about 7%, 15%, and 1.8% respectively. The estimated WTP amounts are also in line with the current situation in each city. At the time of the survey, Beijing's annual air quality was 1.68 times the national standards, Delhi's was 3.33 times, and Jakarta's was 1.28 times. The fact that WTP is highest in

Delhi may be driven by the high level of air pollution relative to national standards, even though incomes are somewhat lower than in Beijing. On the other hand, Jakarta has the best air quality among the three cities, and thus logically could have lower WTP.

We also conducted robustness checks to ensure our results are not driven by choice of covariates and respondents' attention span (or lack thereof). First, we estimated Equation (3) using a bid-only model (Table 2, Columns (1), (3), and (5)). The WTPs are around 3%-27% lower than those obtained from the full model, but similar otherwise. Second, we limited the dataset to respondents who took more than 6 minutes and less than around 50 minutes to complete the survey.[6] The reason is that, unlike a face-to-face interview, we cannot observe respondents' attitude in answering the survey questions. As such, we use survey completion time to exclude respondents who are possibly using too little or too much time to complete the survey. Respondents who use too little time to complete the survey most likely paid little attention to the questions. On the other hand, respondents who took too much time could have been distracted in the midst of answering the survey. While such survey responses would likely introduce more noise into the data (and hence attenuation bias), we find that the results are highly similar to the baseline estimates with this smaller sample (Table A1).

## 5. Discussion

Due to escalating air pollution levels around the world, many cities are in urgent need of actions or policies to improve air quality. Because air quality management plans are costly, policymakers need valuation for air quality improvements to aid in their decision-making process, i.e. comparison of the costs vs. benefits of air quality improvement policies. Unfortunately, non-market valuation studies of air quality improvements are in short supply in places where they are most urgently needed. Compounding this problem is that most existing valuation studies are also ill-suited to the task, for four main reasons. First, even though stated preference studies are by far the most dominant style of air quality valuation studies in developing countries, the lack of consistent framing constraint the findings' comparability and usage beyond their immediate purpose. Second, SP studies are resource-intensive as they are traditionally conducted by in-person enumerators. Such efforts are constrained by the availability of the survey-teams and ease of access to households. Third, while revealed preference valuation studies allow the researcher to conduct more rigorous checks of the underlying theoretical and modeling assumptions, such studies can only be implemented in data-rich environment. In contrast, information on air quality and/or behaviors are difficult to obtain for developing countries. Lastly and related, while revealed

[6] This corresponds to the 5$^{th}$ and 95$^{th}$ percentile of time taken to complete surveys. Exact time differs slightly for each city.

preference valuation studies are empirically more robust than their SP counterparts, this advantage comes at a cost. Due to their restrictive modeling framework, revealed preference studies typically yield estimates of marginal willingness-to-pay, which, while convenient for comparison, are not easily scalable for meaningful policy analyses.[7] In this regard, this study attempts to conduct air quality valuation studies that can circumvent the limitations of earlier approaches. Specifically, we used internet surveys to conduct mass interviews on air quality valuations in three Asian mega-cities – Beijing, Delhi, and Jakarta. We collected around 1,500 responses from each city in around two weeks, using contingent valuation to recover willingness-to-pay for air quality improvements. While CV surveys have been widely utilized in many studies to recover valuations for non-marketed goods (commonly, environmental goods), our approach of conducting CV over the internet and using standardized survey instruments in three cities offers the following improvements over earlier attempts. First, we deploy consistent and more generalizable CV scenarios in our survey instrument. This allows comparison over different locations and over time (if we repeat the survey in the same location). Second, the data are collected using internet survey, which allows us to collect more responses in a shorter amount of time and more cheaply, compared to field surveys. Resources aside, using internet surveys are also more practical given the current pandemic outbreak in most of the world.

We found that individual annual WTP for air quality improvements from current levels to national standards are around US$151 in Jakarta (95% CI: US$134-US$176), US$2426 in Delhi (95% CI: US$1,786-US$4,397), and $US1,736 in Beijing (95% CI: US$1,438-US$2,356). These WTP are also in line with the extent to which current air quality are higher than national standards. The regression models that generated these WTP also showed that higher income and married respondents are more likely to be positively correlated with voting “Yes”. On the other hand, bid amount, age, satisfaction with current air quality, and frequency of checking air quality are negatively correlated. These WTPs are also robust to a no-covariate model, and to whether the sample is restricted by completion time of survey. In all these models, we are reassured that we have achieved the main purpose of this study: obtaining consistent and comparable WTP for air quality in a cost- and time-efficient manner.

However, there are several limitations of our findings. First, by design, 100% of the respondents in our survey are literate and are internet users. This is obviously not representative of their general population in most cities. In fact, comparison with representative surveys shows that our sample on average is more highly educated and has higher income. As such, our results are not inclusive of those at or near the bottom of the pyramid. The impact of this is shown in our

[7] Due to the non-linearity in the relationship between air quality improvement and marginal willingness-to-pay (MWTP), we cannot easily scale MWTP to total WTP for non-marginal improvements in air quality (Sieg et al., 2004).

WTP estimates, which are higher compared to other CV studies conducted in the same cities (mostly Beijing). Second, while the regression models are mostly in line with expectations, there are instances where the randomized treatments did not yield the expected results. Unlike a face-to-face survey where the enumerator could check for respondents' attentiveness or understanding the questions, there are fewer avenues for us to detect anomalies in results obtained from an internet survey.

## References

Arceo, E., Hanna, R., & Oliva, P. (2016). Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City. *The Economic Journal, 126*(591), 257-280.

Arrow, K., Solow, R., Portney, P. R., Leamer, E. E., Radner, R., & Schuman, H. (1993). Report of the NOAA panel on contingent valuation. *Federal Register, 58*(10), 4601-4614.

Bharadwaj, P., Gibson, M., Zivin, J. G., & Neilson, C. (2017). Gray matters: Fetal pollution exposure and human capital formation. *Journal of the Association of Environmental and Resource Economists, 4*(2), 505-542.

Burnett, R. T., Pope III, C. A., Ezzati, M., Olives, C., Lim, S. S., Mehta, S., . . . Brauer, M. (2014). An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. *Environmental Health Perspectives, 122*(4), 397.

Campbell, R. M., Venn, T. J., & Anderson, N. M. (2018). Cost and performance tradeoffs between mail and internet survey modes in a nonmarket valuation study. *Journal of Environmental Management, 210*, 316-327.

Carson, R. T. (2000). Contingent valuation: A user's guide: ACS Publications.

Chen, Y., Jin, G. Z., Kumar, N., & Shi, G. (2013). The promise of Beijing: Evaluating the impact of the 2008 Olympic Games on air quality. *Journal of Environmental Economics and Management, 66*(3), 424-443.

Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., . . . Dandona, R. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: An analysis of data from the Global Burden of Diseases Study 2015. *The Lancet, 389*(10082), 1907-1918.

Determann, D., Lambooij, M. S., Steyerberg, E. W., de Bekker-Grob, E. W., & De Wit, G. A. (2017). Impact of survey administration mode on the results of a health-related discrete choice experiment: Online and paper comparison. *Value in Health, 20*(7), 953-960.

Evans, J. R., & Mathur, A. (2018). The value of online surveys: A look back and a look ahead. *Internet Research*.

Feng, L., & Liao, W. (2016). Legislation, plans, and policies for prevention and control of air pollution in China: achievements, challenges, and improvements. *Journal of Cleaner Production, 112*, 1549-1558.

Frankenberg, E., McKee, D., & Thomas, D. (2005). Health consequences of forest fires in Indonesia. *Demography, 42*(1), 109-129.

Gao, J., Yuan, Z., Liu, X., Xia, X., Huang, X., & Dong, Z. (2016). Improving air pollution control policy in China—A perspective based on cost–benefit analysis. *Science of the Total Environment, 543*, 307-314.

Hanna, R., & Oliva, P. (2015). The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics, 122*, 68-79.

Health Effects Institute. (2019). *State of Global Air 2019*. Retrieved from www.stateofglobalair.org

Hökby, S., & Söderqvist, T. (2003). Elasticities of demand and willingness to pay for environmental services in Sweden. *Environmental and Resource Economics, 26*(3), 361-383.

Huang, J., Pan, X., Guo, X., & Li, G. (2018). Health impact of China's Air Pollution Prevention and Control Action Plan: An analysis of national air quality monitoring and mortality data. *The Lancet Planetary Health, 2*(7), e313-e323.

Jeuland, M., Pattanayak, S. K., & Bluffstone, R. (2015). The economics of household air pollution. *Annual Review of Resource Economics, 7*(1), 81-108.

Jin, Y., Andersson, H., & Zhang, S. (2016). Air pollution control policies in China: A retrospective and prospects. *International Journal of Environmental Research and Public Health, 13*(12), 1219.

Kandlikar, M. (2007). Air pollution at a hotspot location in Delhi: Detecting trends, seasonal cycles and oscillations. *Atmospheric Environment, 41*(28), 5934-5947.

Landrigan, P. J., Fuller, R., Acosta, N. J., Adeyi, O., Arnold, R., Baldé, A. B., . . . Breysse, P. N. (2018). The Lancet Commission on pollution and health. *The Lancet, 391*(10119), 462-512.

Nelson, J. P. (1978). Residential choice, hedonic prices, and the demand for urban air quality. *Journal of Urban Economics, 5*(3), 357-369.

Oanh, N. K., Upadhyay, N., Zhuang, Y.-H., Hao, Z.-P., Murthy, D., Lestari, P., . . . Dung, N. (2006). Particulate air pollution in six Asian cities: Spatial and temporal distributions, and associated sources. *Atmospheric Environment, 40*(18), 3367-3380.

Orgill, J., Shaheed, A., Brown, J., & Jeuland, M. (2013). Water quality perceptions and willingness to pay for clean water in peri-urban Cambodian communities. *Journal of Water and Health, 11*(3), 489-506.

Pattanayak, S. K., Yang, J. C., Whittington, D., & Bal Kumar, K. (2005). Coping with unreliable public water supplies: Averting expenditures by households in Kathmandu, Nepal. *Water Resources Research, 41*(2).

Prüss-Ustün, A., Wolf, J., Corvalán, C., Neville, T., Bos, R., & Neira, M. (2017). Diseases due to unhealthy environments: an updated estimate of the global burden of disease attributable to environmental determinants of health. *Journal of Public Health, 39*(3), 464-475.

Ridker, R. G., & Henning, J. A. (1967). The determinants of residential property values with special reference to air pollution. *The Review of Economics and Statistics*, 246-257.

Shao, S., Tian, Z., & Fan, M. (2018). Do the rich have stronger willingness to pay for environmental protection? New evidence from a survey in China. *World Development, 105*, 83-94.

Sieg, H., Smith, V. K., Banzhaf, H. S., & Walsh, R. (2004). Estimating the general equilibrium benefits of large changes in spatially delineated public goods. *International Economic Review, 45*(4), 1047-1077.

Smith, V. K., & Huang, J.-C. (1995). Can markets value air quality? A meta-analysis of hedonic property value models. *Journal of Political Economy, 103*(1), 209-227.

Tan-Soo, J.-S., & Pattanayak, S. K. (2019). Seeking natural capital projects: Forest fires, haze, and early-life exposure in Indonesia. *Proceedings of the National Academy of Sciences, 116*(12), 5239-5245.

Viard, V. B., & Fu, S. (2015). The effect of Beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics, 125*, 98-115.

Whitehead, J. C. (2006). Improving willingness to pay estimates for quality improvements through joint estimation with quality perceptions. *Southern Economic Journal*, 100-111.

Whittington, D. (2002). Improving the performance of contingent valuation studies in developing countries. *Environmental and Resource Economics, 22*(1-2), 323-367.

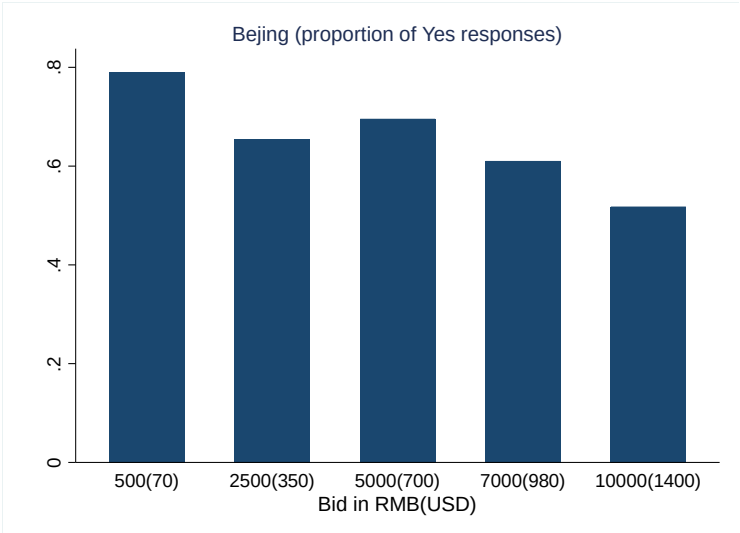
WHO. (2014). Burden of disease from Ambient Air Pollution for 2012. *Geneva: World Health Organization*.

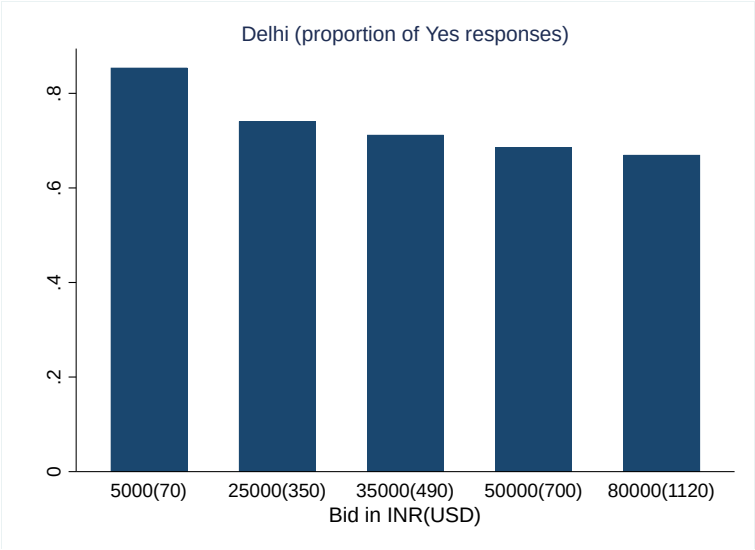
WHO. (2018). *Ambient Air Quality Database Application*. Retrieved from: https://whoairquality.shinyapps.io/AmbientAirQualityDatabase/

Wu, D., Xu, Y., & Zhang, S. (2015). Will joint regional air pollution control be more cost-effective? An empirical study of China's Beijing–Tianjin–Hebei region. *Journal of Environmental Management, 149*, 27-36.

Zhang, Q., He, K., & Huo, H. (2012). Policy: cleaning China's air. *Nature, 484*(7393), 161.

**Figure 1:** Proportion of "Yes" Votes vs. Bid Amount



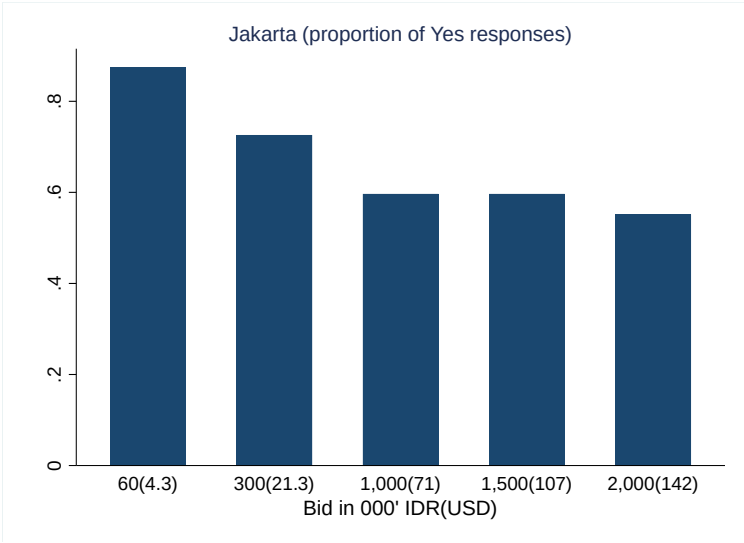
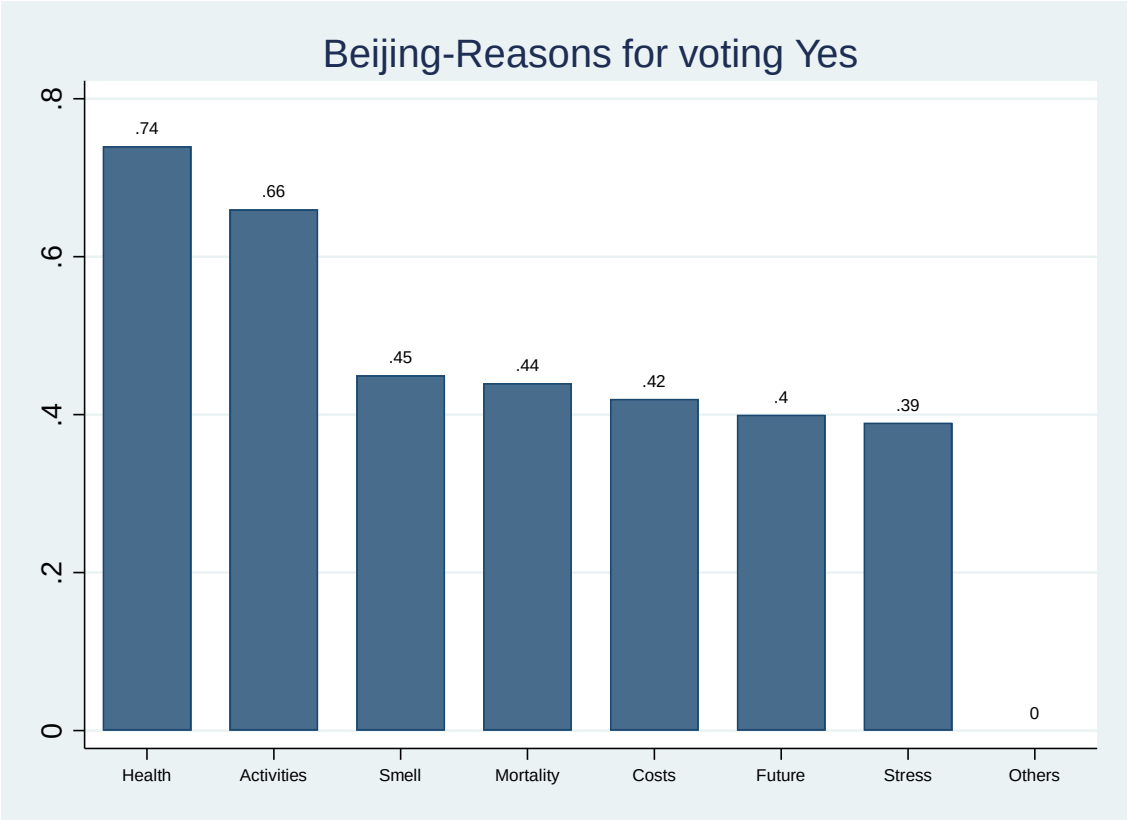
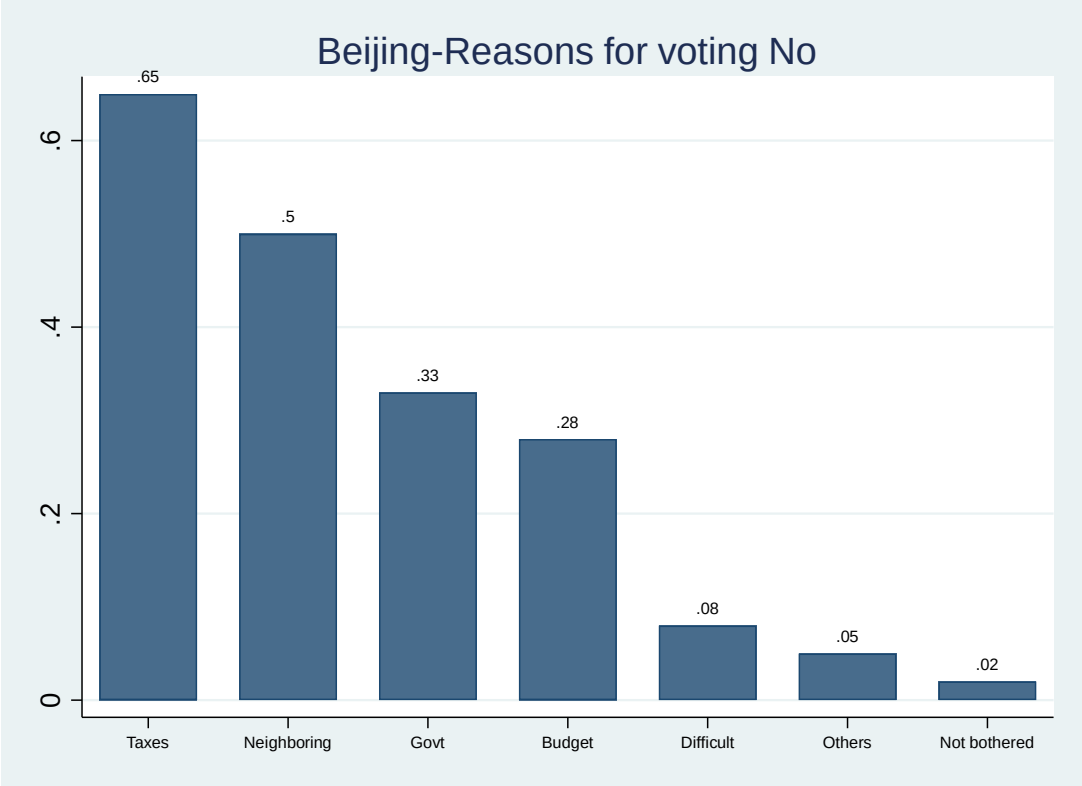
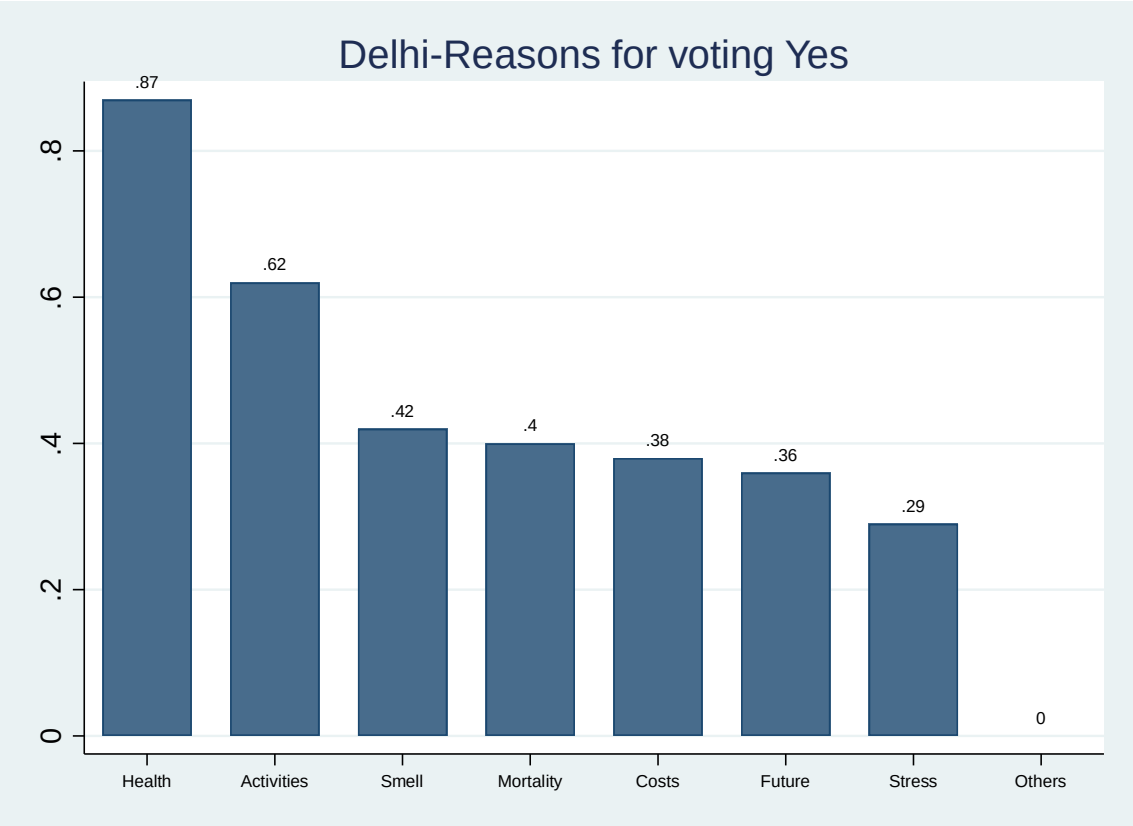
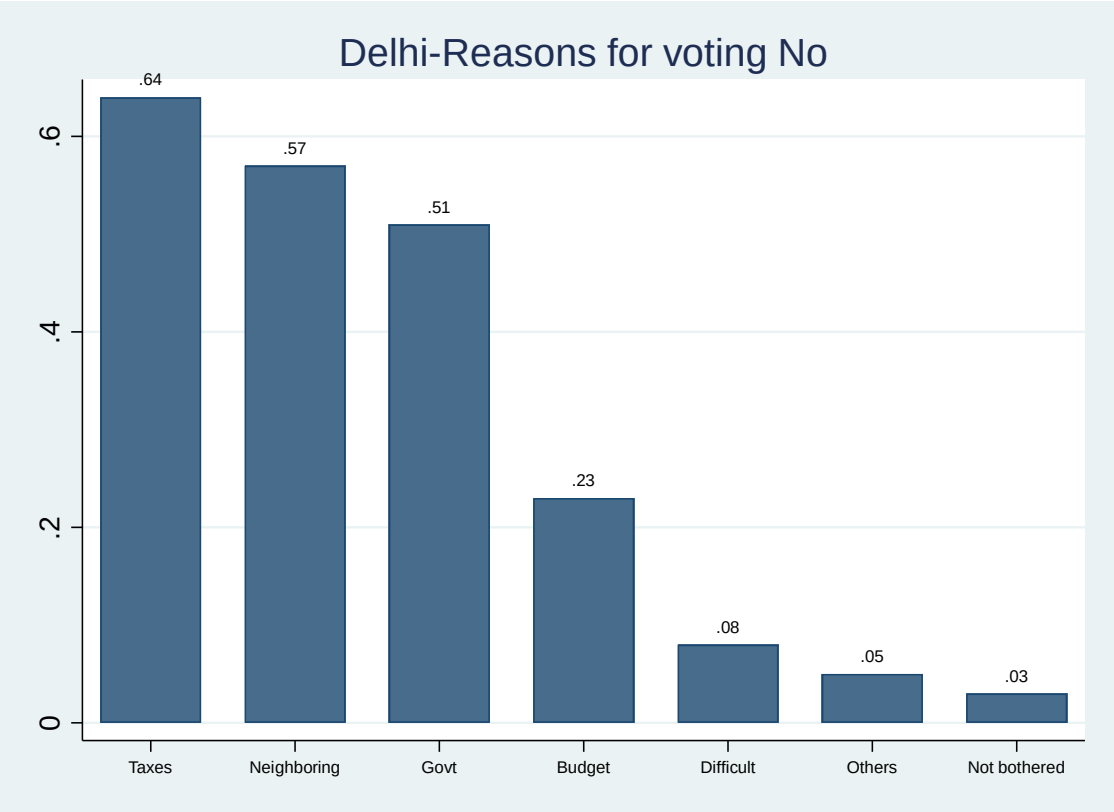



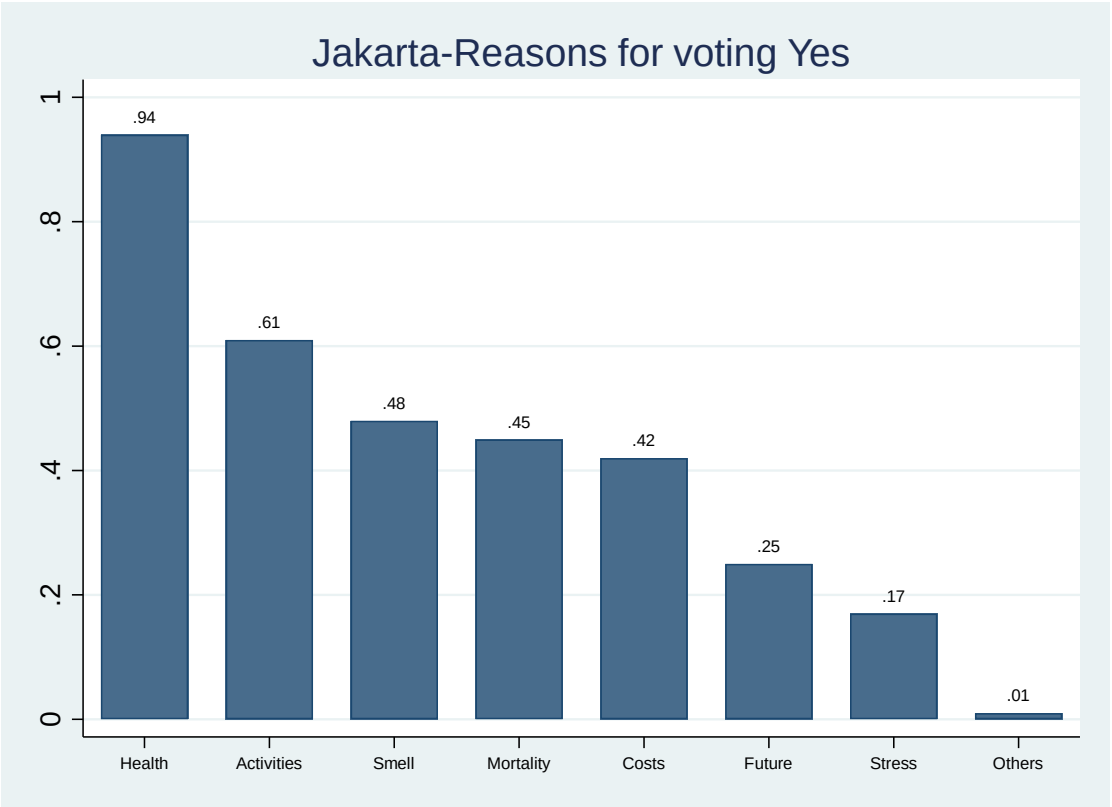
**Figure 2:** Reasons for Voting "Yes" or "No"




Delhi-Reasons for voting Yes
.87
.62
.42
.4
.38
.36
.29
0
0
.2
.4
.6
.8
Health
Activities
Smell
Mortality
Costs
Future
Stress
Others


Delhi-Reasons for voting No
.64
.57
.51
.23
.08
.05
.03
0
.2
.4
.6
Taxes
Neighboring
Govt
Budget
Difficult
Others
Not bothered


Jakarta-Reasons for voting Yes
0
.2
.4
.6
.8
1
.94
.61
.48
.45
.42
.25
.17
.01
Health
Activities
Smell
Mortality
Costs
Future
Stress
Others

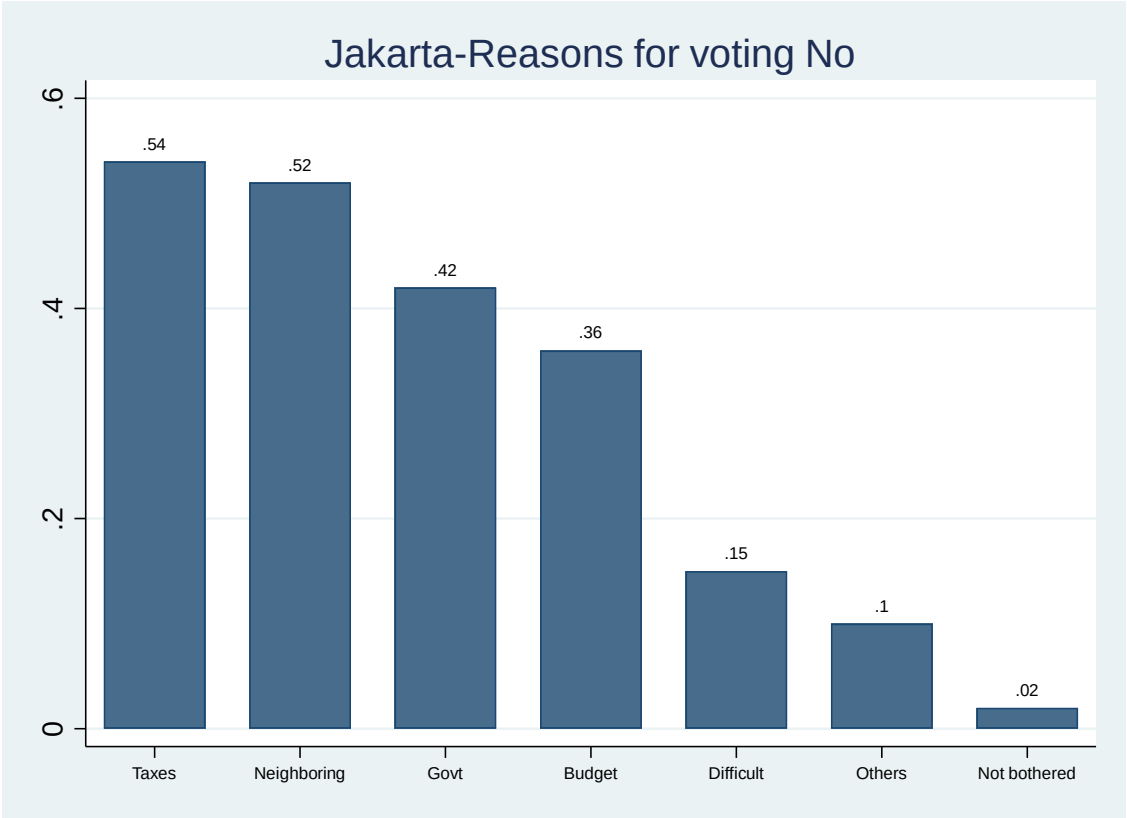
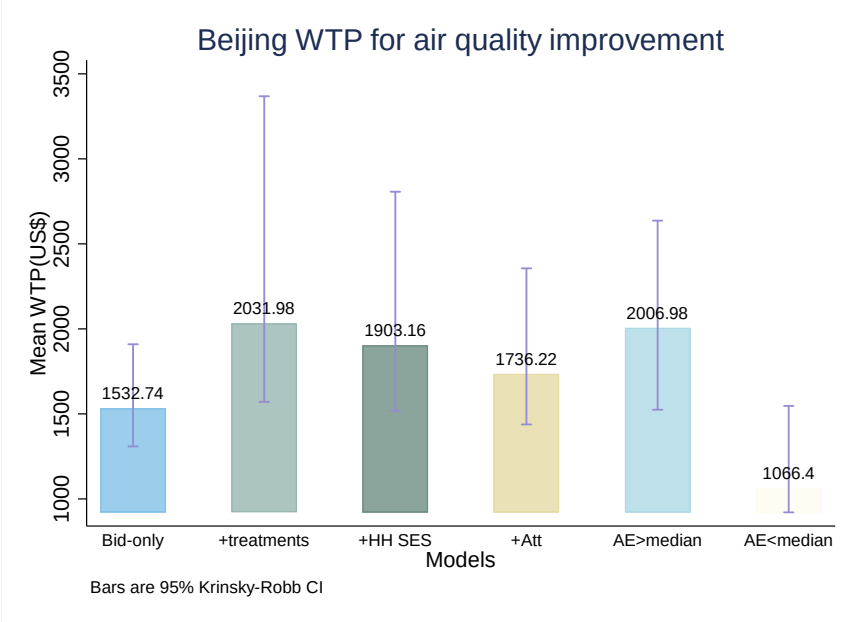
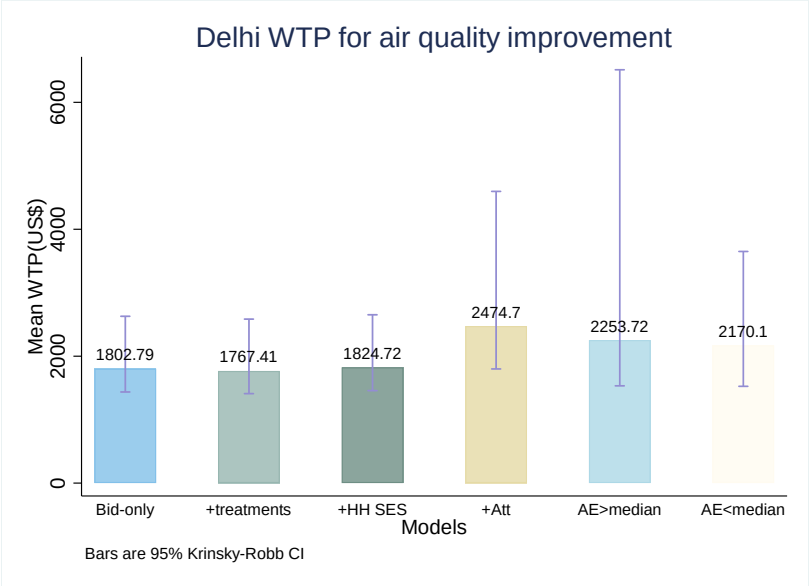

Jakarta-Reasons for voting No
0
.2
.4
.6
.54
.52
.42
.36
.15
.1
.02
Taxes
Neighboring
Govt
Budget
Difficult
Others
Not bothered

**Figure 3:** Willingness-to-Pay for Air Quality Improvements

Panel A




Panel B



Panel C

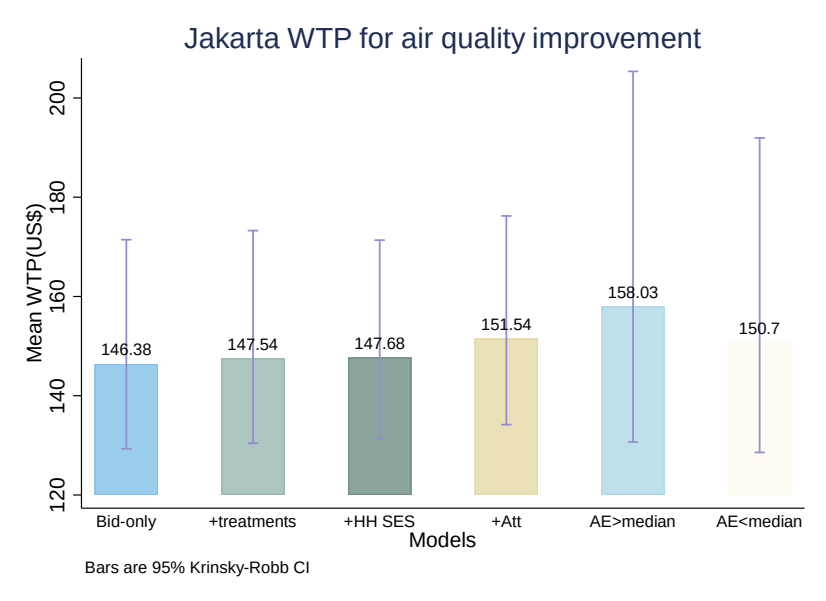

Jakarta WTP for air quality improvement
Mean WTP(US$)
120
140
160
180
200
146.38
147.54
147.68
151.54
158.03
150.7
Bid-only
+treatments
+HH SES
+Att
AE>median
AE<median
Models
Bars are 95% Krinsky-Robb CI

**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 | 18577.63 |
| 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 ≥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) | | 355.37 | 865.55 | 0 | 21370.57 |
| Income bracket (monthy 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 ≥12 in household | | 1.05 | 0.87 | 0 | 6 |
| Number of health symptoms identified | | 4.75 | 2.83 | 1 | 13 |
| Averting expenditures (USD) | | 479.45 | 1053.01 | 0 | 16121.98 |
| 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 Vote Responses

| VARIABLES | (1) Beijing bid only | (2) Beijing +treatment | (3) Beijing +SES | (4) Beijing +SES | (5) Beijing AB>M | (6) Beijing AB<M |
|---|---|---|---|---|---|---|
| Bid amount (‘000) | -0.049*** | -0.031*** | -0.037*** | -0.049*** | -0.061*** | -0.051*** |
| | (0.007) | (0.008) | (0.008) | (0.009) | (0.012) | (0.011) |
| AE module before CV module | | -0.016 | -0.051 | 0.052 | 0.049 | 0.119 |
| | | (0.107) | (0.109) | (0.120) | (0.109) | (0.099) |
| Information treatment | | -0.092 | -0.100 | -0.128* | -0.164 | -0.060 |
| | | (0.068) | (0.070) | (0.074) | (0.108) | (0.100) |
| AE amount larger than bid | | 0.484*** | 0.352*** | 0.185 | | |
| | | (0.100) | (0.107) | (0.146) | | |
| Interaction of "AE before" and "AE amout larger" | | 0.085 | 0.134 | 0.057 | | |
| | | (0.139) | (0.142) | (0.153) | | |
| Age | | | -0.079*** | -0.065*** | -0.070** | -0.111*** |
| | | | (0.021) | (0.022) | (0.033) | (0.030) |
| Age-squared | | | 0.001*** | 0.001*** | 0.001** | 0.001*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Marital status | | | 0.394*** | 0.378*** | 0.349* | 0.547*** |
| | | | (0.131) | (0.139) | (0.187) | (0.208) |
| Sex | | | -0.003 | 0.001 | -0.039 | 0.044 |
| | | | (0.072) | (0.077) | (0.111) | (0.105) |
| Income (‘000) | | | 0.012*** | 0.011*** | 0.010** | 0.017*** |
| | | | (0.003) | (0.003) | (0.004) | (0.005) |
| College education | | | 0.248** | 0.308** | 0.454** | 0.078 |
| | | | (0.111) | (0.121) | (0.217) | (0.148) |
| Household size | | | 0.063 | 0.042 | -0.002 | 0.111 |
| | | | (0.048) | (0.051) | (0.073) | (0.070) |
| No. of children $\leq$ 12 | | | 0.004 | 0.003 | 0.046 | -0.067 |
| | | | (0.078) | (0.082) | (0.119) | (0.120) |
| No. of elderly $\geq$ 60 | | | 0.026 | 0.025 | 0.115 | -0.041 |
| | | | (0.058) | (0.061) | (0.089) | (0.084) |
| Satisfied with current AQ | | | | -0.293*** | -0.242*** | -0.335*** |
| | | | | (0.045) | (0.063) | (0.062) |
| Feels its possible to improve AQ | | | | -0.118* | -0.095 | -0.126 |
| | | | | (0.065) | (0.093) | (0.081) |
| Symptoms identified | | | | -0.114*** | -0.092*** | -0.122*** |
| | | | | (0.018) | (0.025) | (0.025) |
| Frequency of checking AQ | | | | 0.017 | -0.067 | 0.059 |
| | | | | (0.042) | (0.060) | (0.056) |
| Citizens are responsible | | | | -0.031 | 0.299*** | -0.358*** |
| | | | | (0.079) | (0.113) | (0.108) |
| log(averting expenditure) | | | | 0.100*** | | |
| | | | | (0.034) | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Constant | 0.746*** | 0.354*** | 0.694 | 1.486*** | 2.444*** | 3.081*** |
| | (0.063) | (0.107) | (0.468) | (0.549) | (0.746) | (0.729) |
| Observations | 1,503 | 1,503 | 1,503 | 1,447 | 750 | 749 |

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

**Table 2:** (Panel B): Probit Estimation of Vote Responses

| VARIABLES | (1) Delhi bid only | (2) Delhi +treatment | (3) Delhi +SES | (4) Delhi +SES | (5) Delhi AB>M | (6) Delhi AB<M |
|---|---|---|---|---|---|---|
| Bid amount (‘000) | -0.050*** | -0.052*** | -0.053*** | -0.045*** | -0.043*** | -0.063*** |
| | (0.010) | (0.010) | (0.011) | (0.012) | (0.016) | (0.017) |
| AE module before CV module | | 0.055 | 0.063 | 0.101 | -0.300*** | 0.257** |
| | | (0.081) | (0.084) | (0.093) | (0.109) | (0.121) |
| Information treatment | | -0.049 | -0.040 | -0.015 | -0.029 | -0.020 |
| | | (0.070) | (0.073) | (0.080) | (0.109) | (0.121) |
| AE amount larger than bid | | 0.186 | 0.177 | 0.520*** | | |
| | | (0.120) | (0.125) | (0.153) | | |
| Interaction of "AE before" and "AE amout larger" | | -0.393** | -0.430** | -0.562*** | | |
| | | (0.163) | (0.168) | (0.182) | | |
| Age | | | -0.081*** | -0.077*** | -0.055 | -0.105*** |
| | | | (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 | | | 0.404*** | 0.285** | 0.168 | 0.514*** |
| | | | (0.110) | (0.123) | (0.162) | (0.196) |
| Sex | | | -0.147** | 0.064 | 0.028 | 0.085 |
| | | | (0.075) | (0.084) | (0.114) | (0.129) |
| Income (‘000) | | | 0.050*** | 0.033** | 0.026 | 0.042* |
| | | | (0.014) | (0.016) | (0.023) | (0.023) |
| College education | | | -0.501*** | -0.215 | 0.123 | -0.587* |
| | | | (0.178) | (0.202) | (0.284) | (0.313) |
| Household size | | | -0.002 | 0.068** | 0.057 | 0.092* |
| | | | (0.030) | (0.033) | (0.049) | (0.047) |
| No. of children $\leq$ 12 | | | 0.206*** | 0.097* | 0.078 | 0.074 |
| | | | (0.054) | (0.059) | (0.080) | (0.091) |
| No. of elderly $\geq$ 60 | | | 0.134*** | 0.022 | -0.033 | 0.098 |
| | | | (0.049) | (0.055) | (0.072) | (0.088) |
| Satisfied with current AQ | | | | -0.314*** | -0.263*** | -0.383*** |
| | | | | (0.034) | (0.048) | (0.051) |
| Feels its possible to improve AQ | | | | -0.043 | -0.064 | -0.011 |
| | | | | (0.047) | (0.068) | (0.069) |
| Symptoms identified | | | | -0.019 | -0.001 | -0.034 |
| | | | | (0.017) | (0.023) | (0.025) |
| Frequency of checking AQ | | | | -0.251*** | -0.271*** | -0.206*** |
| | | | | (0.037) | (0.051) | (0.055) |
| Citizens are responsible | | | | -0.301*** | -0.210* | -0.387*** |
| | | | | (0.086) | (0.116) | (0.132) |
| log(averting expenditure) | | | | -0.025** | | |
| | | | | (0.012) | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Constant | 0.906*** | 0.917*** | 2.778*** | 4.126*** | 3.798*** | 4.642*** |
| | (0.067) | (0.095) | (0.464) | (0.530) | (0.755) | (0.841) |
| Observations | 1,501 | 1,501 | 1,501 | 1,501 | 746 | 747 |

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

Table 2: (Panel C): Probit Estimation of Vote Responses

| VARIABLES | (1) Jakarta bid only | (2) Jakarta +treatment | (3) Jakarta +SES | (4) Jakarta +SES | (5) Jakarta AB>M | (6) Jakarta AB<M |
|---|---|---|---|---|---|---|
| Bid amount (‘000) | -0.593*** | -0.585*** | -0.619*** | -0.658*** | -0.621*** | -0.696*** |
| | (0.067) | (0.067) | (0.069) | (0.073) | (0.103) | (0.106) |
| AE module before CV module | | 0.086 | 0.153 | 0.153 | -0.013 | 0.171 |
| | | (0.116) | (0.119) | (0.126) | (0.103) | (0.106) |
| Information treatment | | -0.057 | -0.032 | 0.002 | -0.063 | 0.101 |
| | | (0.068) | (0.070) | (0.073) | (0.103) | (0.107) |
| AE amount larger than bid | | 0.121 | 0.077 | 0.242 | | |
| | | (0.100) | (0.104) | (0.175) | | |
| Interaction of "AE before" and "AE amout larger" | | -0.063 | -0.159 | -0.125 | | |
| | | (0.143) | (0.147) | (0.155) | | |
| Age | | | -0.111*** | -0.108*** | -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 | | | 0.136 | -0.021 | -0.031 | 0.029 |
| | | | (0.099) | (0.102) | (0.149) | (0.144) |
| Sex | | | -0.248*** | -0.231*** | 0.027 | -0.482*** |
| | | | (0.073) | (0.077) | (0.108) | (0.113) |
| Household income | | | -0.000 | -0.000 | 0.000 | -0.000 |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Income (‘000) | | | 0.035*** | 0.029*** | 0.034*** | 0.031** |
| | | | (0.006) | (0.007) | (0.009) | (0.013) |
| College education | | | 0.095 | -0.007 | -0.080 | -0.023 |
| | | | (0.086) | (0.090) | (0.136) | (0.124) |
| Household size | | | -0.096*** | -0.083*** | -0.139*** | -0.045 |
| | | | (0.030) | (0.032) | (0.050) | (0.043) |
| No. of children $\leq$ 12 | | | 0.084 | 0.048 | 0.078 | 0.018 |
| | | | (0.052) | (0.053) | (0.077) | (0.075) |
| No. of elderly $\geq$ 60 | | | 0.124** | 0.053 | 0.113 | 0.016 |
| | | | (0.053) | (0.055) | (0.075) | (0.084) |
| Satisfied with current AQ | | | | -0.144*** | -0.151*** | -0.094* |
| | | | | (0.040) | (0.058) | (0.057) |
| Feels its possible to improve AQ | | | | -0.216*** | -0.258*** | -0.130* |
| | | | | (0.052) | (0.074) | (0.078) |
| Symptoms identified | | | | -0.018 | -0.016 | -0.020 |
| | | | | (0.014) | (0.019) | (0.022) |
| Frequency of checking AQ | | | | -0.315*** | -0.210*** | -0.448*** |
| | | | | (0.038) | (0.052) | (0.061) |
| Citizens are responsible | | | | 0.146 | 0.266* | 0.085 |
| | | | | (0.095) | (0.146) | (0.129) |

| | | | | | | |
|---|---|---|---|---|---|---|
| log(averting expenditure) | | | | -0.008 | | |
| | | | | (0.020) | | |
| Constant | 0.867*** | 0.789*** | 2.955*** | 4.717*** | 4.836*** | 5.051*** |
| | (0.060) | (0.103) | (0.457) | (0.513) | (0.746) | (0.746) |
| Observations | 1,506 | 1,506 | 1,506 | 1,506 | 751 | 750 |

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