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Abstract

Contingent valuation (CV) studies often adopt public programs in the scenario designs in order to increase credibility and to ensure incentive compatibility. However, such scenario designs can introduce biases in willingness-to-pay (WTP) estimations due to the potential distrusts of respondents in the governments who are responsible for implementing the public programs. In this study, a joint selection modeling strategy, which accommodates both valuation protests and WTP adjustments, is developed for identification and calibration of the potential biases in WTP estimations caused by the public distrust in government. The joint selection model of WTP with public distrust in government is applied to two CV studies conducted in China on air quality improvements. Both channels through which public distrust in government can affect WTP estimation, valuation protest and WTP adjustment, are empirically identified, and the potential biases in WTP estimation caused by the public distrust in government can be as high as 20%.

Keywords: public distrust, contingent valuation, protest, selection bias, WTP determination.

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Introduction

Contingent valuation method (CVM) has been used to value the intangible benefits of environmental goods and services in over 130 countries (Carson, 2011, Johnston et al. 2016). One major advantage of this method is its capacity to estimate the "passive use value", which stems from the public nature of environmental goods and services and cannot be revealed by people's choices in the marketplace (Krutilla, 1967; Carson 2012). As a "practical alternative when prices aren't available" (Carson, 2012), CVM results have been widely used in benefit-cost analyses.

To increase the credibility of the proposed hypothetical environmental quality change under valuation and to ensure the incentive compatibility of the required payment from all respondents, most CVM studies adopt hypothetical public programs that would induce the environmental quality change. One classic example is Carson et al. (2003), which evaluated the lost passive use value due to the damages from the Exxon Valdez oil spill via an escort ship program partially financed by a one-time household federal tax. The validity of such universal payment vehicle is based on the implicit assumption that people *should* pay if they value the change in the proposed environmental goods and services. Such assumption, however, risks being incompatible with the context of hypothetical political market when public trust in institution stays at relatively low levels.

Lindsey (1994) identifies two reasons related to low levels of trust in institutions that explain people's zero bids: "too much waste in government" or "opposed to all new taxes". He believes that although these reasons provide no information about people's true valuation of the project in question, they still convey information about respondents' general preferences for more governmental programs. Jorgenson and Syme (2000) believe that it may be "inappropriate" to consider such zero bid as protest zeros and exclude them from analysis, since such attitude can affect people's willingness to pay (WTP) downwards and its distribution among the population may be non-homogenous. From a more general point of view, Jorgenson et al. (1999) and Jorgenson and Syme (2000) also point out that people's willingness to pay for a governmental program, even not reported as zero, may also be associated with "their attitudes toward paying that reflect the fairness of the acts and equity concerns", therefore risks to be biased by people's distrust in government.

Such potential incompatibility between using hypothetical governmental programs in CVM studies and low levels of public trust in institutions may become an important methodological issue in face of the current declining trend of population's general trust observed in all key institutions: business, government, NGO and media (2017 Edelman Trust Barometer). Defined as an "implosion", this new phenomenon of public distrust is broadly observed in two-thirds of the 28 countries participating in the Edelman Trust Barometer survey and considered to take its origin in the Great Recession of 2008 (2017 Edelman Trust Barometer). Such a problem may be particularly more worrisome for developing countries, where, due to corruption, low institutional quality and governmental inefficiency, public trust in government and institution may already stay at much lower levels, and therefore may render the CVM studies even less efficient.

However, so far in the literature, the potential biases caused by public distrust in institutions in CV studies where public programs are involved have not been thoroughly studied. Although some papers provided evidences about the potential influence of the public trust on WTP estimation in CVM studies (more details are given in the next section). There is not yet systematic method proposed in the literature that allows to identify and to calibrate such biases in the CVM.

In this paper, we present a method of identification and calibration of the potential biases in WTP studies due to low public trust in institution. With this method, a series of identification questions are asked of the survey respondents with regard to their willingness-to-pay and their trust in the government, and a modeling procedure is developed to further analyze and calibrate the potential biases caused by public distrust. The method is applied to two CV studies on air quality improvement at the city level in China. One city, Xingtai, is located in northern China, where air pollution is notoriously bad and income is also low. Another city, Guiyang, is located in southwest China, where both income and air quality are relatively acceptable. Significant biases are found in both cities' studies that can be attributed to the public distrust. However, the bias found in Xingtai is much higher than that in Guiyang, where both income and air quality are better.

Beside as a case of valuation bias caused by public distrust, the Chinese case presented in this paper can also be of particular interest for the following reasons:

First, this is a particular case of public trust studies. On one hand, the cross-country Trust Barometer surveys consistently report relatively high level trust of Chinese people in their government, compared to those of other countries. On the other hand, many past studies, such as the seminal research of Fukuyama (1994), indicate that in China as in many countries in East Asia, the Confucius tradition has led to a low level of generalized trust, which he described as "a loose tray of sand", since people generally have low confidence in individuals other than family members. Ren (2009) explains such divergence in the measure of public opinion by respondent's political fear, which may push respondents to give false response to avoid possible persecution. Saich (2007) and Yang and Tang (???????) believe Chinese citizens disaggregate the state with high satisfaction for central government that falls *dramatically* as government gets closer to the people.

Second, evidences also show that such potential public distrust is reinforcing with time. Several studies (Hu, 2015; Xin and Xin 2017) report a common declining trend in the level of generalized trust in China across different periods from 1990 to 2011. Such decline trends is also expectable with China's fast dynamics in marketization process: the findings in Xin and Xin (2017) predict that the marketization rate plays as a significant predictor for such declining process in the future.

Third, although previous paper as Shi (2001) or Chen (2005) believe traditional political culture (cultural approach: Mishier and Rost, 2001) plays dominant roles in public trust level, more recent social science studies start to confirm that Chinese people's political trust in both central and local governments are more strongly affected by the institutional factors, particularly the economic and political performance of government (Wong et al.

2011; Zhong, 2014). This new tendency may further confirm the current alarming situation of public distrust in local government in China. Some survey data already reveal such trend: Zhong (2014) indicated that only 40% of the Chinese people believe they can get information about the governmental expenditure and over 60% of the people do not believe public servants serve for people's interest.

Finally, as rarely discussed in the literature, Chinese citizens' trust in environmental governance should also be expected at the relatively lower level and to follow the common decreasing trends. This is on one hand related to the persistence of a disjuncture between governmental promise and actual performance in environment-related issues (Bina, 2010). It is also expectable due to the nature of normal good of people's environmental demand: the co-existence of ever-deteriorating environmental pollution in China and fast income growth should contribute to an accelerating trend in Chinese people's demand for a better environment. Such demand, in turn, can create big contrast with the actual alarming environmental condition, therefore contributes to the decreasing trends of public trust in environmental governance.

Therefore, we expect a significant public distrust in the government-led environmental protection projects in China, which may lead to downward biases in the WTP estimations for environmental improvements based on hypothetical public projects.

1. Literature review and a model of public distrust and willingness to pay

We can classify the existing discussions in the literature about the roles of public trusts in WTP determination into the following two different channels of observation:

The first is about the protest zeros. Jones et al. (2008) used an open-ended WTP question to evaluate the environmental benefits resulting from the construction of a sewage treatment plant in Mitilini, Greece. They find that among the zero respondents, 56.8% said that it was the responsibility of the state to pay while the remaining 28.4% stated they did not regard governmental management as reliable. By using a Tobit model to derive WTP estimation, their results show that if not excluded, these public-distrust related protest answers can largely reduce the mean WTP estimate, even to the negative value (-5.20 Euro). Glenk and Fischer (2010) also find that among the sample that were not willing to contribute to the new fund for water management strategies in the context of climate change in Scotland, about 18% believe the government cannot be trusted.

The second channel is through the determination of WTP. Krystallis and Chryssohoidis (2005) estimate Greek consumers' WTP for organic good and found public trust in certification to be a significant determinant for WTP. Glenk and Fischer (2010) also confirm that public trust is a significant determinant factor that contributes positively to people's WTP for the new water management strategies in Scotland. Jones et al. (2014) analyze the influence of social capital parameters on WTP via a CVM study on coastal defenses program in southeast England. Institutional trust is one of the four social trust parameters that they considered and is found to exert a positive influence on WTP along with other dimensions of social trust. Oh and Hong (2014) conclude that Korean citizens' subjective trust in either government or its capacity to complete an announced goal can largely influence their WTP for a public project administrated by government, based on their CVM study on an indoor air quality improvement project in subway stations in Seoul. Habibov et al. (2017) investigate the role of social trust on people's willingness to pay tax to improve public healthcare in 29 post-communist countries. Their conclusions also confirm that an increase in social trust, in which the institutional trust is one component, is associated with a greater willingness to pay more tax.

The studies that analyze the link between governmental trust and WTP are rare in China. The only study that we have found is Chen and Hua (2015). Based on a single bound dichotomous choice WTP question, their analysis identifies Chinese citizens' distrust of government as one of the major reasons for their protest responses in their CVM study for urban heritage trees in Guangzhou city. Among the 457 usable observations, they identified 282 respondents (62% of total sample) giving protest responses, in which 205 (73% of the total protest respondents) persons held "distrust in government" as the sole reason. Their follow-up analysis shows that regardless of the amount of WTP, protesters who distrust government and non-protesters actually share similar salient values with the urban heritage tree program, especially for their distinctive historical and cultural values. In this sense, considering the protest answer as zero would largely reduce the mean WTP.

To better understand how public distrust can affect valuation, a model of WTP associated with public trust can be developed mathematically in the following.

Trust has a definition initially developed in the social science. The definition given by Rousseau et al. (1998, p.395) regards "trust as a psychological state comprising the intention to accept vulnerability based upon positive expectations of intentions or behavior of another". Such definition provides the behavior economists with a mechanism to directly introduce trust into the choice-based utility maximization framework by interpreting the "vulnerability" as a perception of risk for the expected situation not to be realized. Following this logic, we can write the decision-making process of a utility-maximization respondent in face of a WTP question for a public environmental improvement project as following:

The utility of the respondent in face of current air quality Q_0 is $U(Q_0, Y)$, where Y is household income. The proposed hypothetical project promises an improvement of air quality to $\overline{\Delta Q}$, which means the target level to be $\overline{Q_1},\ with\ \overline{Q_1} = Q_0 + \overline{\Delta Q}$, but requires an annual payment B. For a respondent, his or her utility with the project can be written as $U(Q_1(t), Y - B)$, where Q_1 is respondent's expected level of air quality improvement and t signifies the level of trust this respondent has toward the local government, with $0 \leq t \leq 1$ and $\frac{\partial Q_1}{\partial t} > 0$. The underlying assumption is that a respondent's expected air quality with the new project Q_1 is conditional on his/her level of trust in the local government's efficiency t. We can further assume

$$Q_1(t) = Q_0 + \overline{\Delta Q} e^{(\frac{t-1}{t})}.$$

Therefore in the case of full trust (t=1), $Q_1(t) = Q_0 + \overline{\Delta Q} = \overline{Q_1}$; when a respondent totally distrusts the government (t→0), $Q_1(t) \to Q_0$, But in most of the cases, we expect people to have partial trust in the government, i.e., $0 < t < 1$;so the expected $Q_1(t) > Q_0$ and $Q_1(t) < \overline{Q_1}$.

For a respondent with a level of trust t, his decision to accept or refuse the project can be explained by following logic:

Choose to accept the project if $U(Q_0, Y) \leq U(Q_1(t), Y - B)$;
Choose to refuse the project if $U(Q_0, Y) > U(Q_1(t), Y - B)$.

Assuming that the implicit WTP is the maximal payment that equalizes the initial utility of this respondent to that after his acceptance of the project, we will have
$U(Q_0, Y) = U(Q_1(t), Y - WTP)$.

We can therefore derive the function of WTP as

$$WTP = WTP(Q_0, Q_1(t), Y)$$

The higher the level of the trust, the closer the expected air quality improvement $Q_1(t)$will be to the announced target level $\overline{Q_1}$. We therefore expect a positive correlation between WTP and people's trust in local government, since $\frac{\partial WTP}{\partial t} = \frac{\partial WTP}{\partial Q_1} \cdot \frac{\partial Q_1}{\partial t} > 0$.

We can also define $d = \frac{1}{t}$ as a measurement of distrust. In this case, since $\frac{\partial WTP}{\partial d} < 0$, the higher the level of public distrust, the lower the WTP will be.

2. Survey and Identification of Distrust

3.1 The Survey

Two surveys are conducted in order to estimate WTP of the residents in Xingtai and Guiyang respectively for better air quality. Xingtai is a city located in northern China, where air pollution is among the worst in the country, while Guiyang is located in the southwest of China, which suffers relatively less from air pollution. In 2013, the annual average concentration of $PM_{2.5}$ in Xingtai was 160 $\mu g/m^3$, three times as high as in Guiyang. There were merely 38 days in the whole year with AQI (Air Quality Index) meeting Class I or II standards in Xingtai, compared to 254 days in Guiyang.[1]

The two CV surveys were conducted between September 25 and December 16, 2014. Prior to the surveys, several focus group discussions were organized, where the project team consulted with various local community workers, government officers and local residents. Discussions were held focusing on people's perceptions and attitudes towards the current local economic and environmental situations and about the new air quality improvement projects (the impacts of the proposed air quality improvements and the payment vehicles, etc., as shown in the appendix). The questionnaires were developed and finalized after several rounds of pre-tests with the communities.

Twenty eight communities that roughly evenly cover the cities' urban areas were selected to conduct the surveys. One community worker from each of the selected communities was trained to help conduct the survey by assisting the distribution and collection of the questionnaires from the sampled households. In each city, 800 questionnaires were evenly distributed to the selected communities. Within each community, households were randomly selected based on the household list provided by the community office, from which the households that were believed to have no residents were excluded beforehand. The heads of the selected households were informed by the trained community workers of the purpose of the survey. We obtained a total of 793 completed questionnaires in Guiyang City and 781 completed questionnaires in Xingtai City. Neutrality as well as anonymity of the survey participants were ensured to the best possible. The trained community workers checked the quality of the questionnaires completed and some household heads, when feasible, had been asked to rework on the questionnaires again in case of missing/incoherent responses.

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[1] Although the air qualities in both cities have been improved dramatically, the great difference still exists. In 2017, the annual average concentration of PM2.5 was 32 µg/m3 in Guiyang and 80 µg/m3 in Xingtai, meeting Class I and Class II of National Ambient Air Quality Standards (GB3095-2012) respectively.

The final version of the questionnaire includes four parts. The first part is about environmental perceptions and attitudes, in which we make efforts to identify respondents' perceptions and attitudes toward three types of entities that all have either positive or negative contributions to the environmental pollution: government, enterprises and non-governmental organizations (NGOs). In the second part, respondent's relationship with air pollution are asked, where the degree of exposure to air pollution, health impact of air pollution, personal measures against air pollution are carefully questioned. The third part contains a series of questions around the multiple bound discrete choice (MBDC) WTP question. Finally, the questions about people's socioeconomic characteristics are included in the fourth part of the questionnaire.

The WTP questions in the survey pertain to a municipal-level program to improve air quality in the two cities. More details about the proposed air pollution control projects and supportive materials are provided in Appendix 1. The MBDC format questions on the WTP for the new air quality improvement project is based on a municipal tax at household level that would be collected through the monthly water bill for 3 years. A "cheap talk" strategy is used to remind respondents of their budget constraint and the nature of referendum applied to the final decision.

The MBDC matrix used in the survey is shown in the following table, in which people are invited to choose a possibility to accept each of the 18 payment levels varying from zero yuan to 1000 yuan/month. Such MBDC matrix has been used in the past by Welsh and Poe (1998), Alberini et al. (2003), Wang and He (2011, 2018), Wang et al. (2013a, 2013b), Wang et al (2015)， and others. To take a full usage of the two dimensions' information collected by the MBDC CV question format, we will use in this paper the approach proposed in Wang and He (2011) to carry out the WTP estimations.

Monthly payment over 3 years	Definitely yes	Probably yes	Not sure	Probably not	Definitely not
Free (0 Yuan)					
3 Yuan					
5 Yuan					
10 Yuan					
15 Yuan					
20 Yuan					
30 Yuan					
40 Yuan					
50 Yuan					
80 Yuan					
100 Yuan					
150 Yuan					
200 Yuan					
300 Yuan					
500 Yuan					
700 Yuan					
800 Yuan					
1000 Yuan					

3.2 Identification of distrust

After introducing the new air quality improvement project and before the WTP question, we ask a filter question, which invites respondents to announce whether they would like to support this new project if it requires no payment from their households. We use this question as our first identification for the potential protest respondents who chose either "not sure", "probably not" or "definitively not" options.[2] Based on the responses given to this question, we therefore firstly identify 91 potentially protest responses in Guiyang sample and 150 in Xingtai sample (c.f. Table 1).[3]

In addition, after the WTP question, two follow-up questions are included. The first question is regarding the reasons to refuse supporting the project even at zero bid proposed in the MBDC matrix ("not sure", "probably not" or "definitively not" options were chosen), in which both protest answers (don't trust government, government/entreprises should pay, don't believe the project can reach its objective, don't understand the scenario) and real zero answers (don't have enough money, don't need a new project, the improvement

[2] The other two options are "definitively yes" and "probably yes" for this question.
[3] These responses are further verified based on the answers given to the first WTP follow-up question asking why a respondent is not willing to support the project even at zero cost.

proposed in new project is not big enough and current air quality is good enough) are proposed as choice options. The answers given by the respondents to this question allow us to distinguish the true zero (13 for Guiyang and 31 for Xingtai according to Table 1) answers from the potential protest answers. As shown in Table 1, further data cleaning on the responses given to WTP question allows us to identify some other protest respondents, including those starting with negative answer at zero bid (5 in Guiyang and 6 in Xingtai).

We further identify some positive answers (probably yes, definitively yes or not sure) even at the highest bid (32 in Guiyang and 36 in Xingtai). The second follow-up question of WTP inquires about the reasons why one would be ready to pay the highest bid listed in the MBDC matrix[4]. We find most of the answers provided by the respondents reveal "warm glow" effect. Grammatikopoulou and Olsen (2013) also study these positive answers for very high bid as cases of selection to warm glow. They find that removal of these warm glow bidders does not significantly distort WTP. We therefore decide to exclude these observations, as well as those observations having disordered (31) or missing (30) answers, in order to focalize on analyzing the protest observations in this study.

The data cleaning work finally identifies in total 93 protest answers in Guiyang and 127 protest responses in Xingtai. After excluding those with true zero bids, with warm glow answers, and having missing or disordered answers, 626 observations in Guiyang and 551 observations in Xingtai (c.f. Table 1) can be used to estimate individual valuation distributions with the Wang and He (2011) approach, which can still be affected by people's distrust in the government.

3. **The Models**

4.1 WTP Model

[4]Respondents understand that the payments listed in the card are only for easy expressing of WTP information for everyone and are not necessary reasonable WTP values.

To take a full advantage of the two-dimensional development provided by MBDC CV questions, we use the two-stage approach proposed by Wang and He (2011) to carry out our WTP estimations. This method considers an individual's WTP as a random variable with a cumulative distribution function. An MBDC WTP question can help reveal individual-specific WTP distribution because this CV question format invites respondents to express their probability of accepting each of the given bid prices. By assigning numerical values to verbal probability responses (ranging from "Definitely Yes" to "Definitely Not") given by each respondent, we can directly estimate individual-specific cumulative distribution function for WTP by using all their probability answers associated with the corresponding bid prices. The estimated cumulative distribution function reports a mean WTP value and a standard variance, both of which can then be used in the second stage, where they are regressed on their potential determinants, among which public distrusts can be included. A more detailed description of the Wang- He modeling approach is provided in Appendix 5.

4.2 A Joint Selection Model for WTP Estimation with Distrust

As public trust in government can affect WTP estimation both through respondents' providing protest zero and via lowering the WTP value as suggested in the model presented in section 2, we need to develop a joint model in which the process of decision-making of a respondent is a joint one that involves both whether or not to participate in valuation and if yes, whether or not to reveal truthfully the results of his/her valuation.

The first stage estimation of Wang-He approach allows us to obtain individual mean WTPs for all respondents who decided to answer the WTP question (participants). For the protest respondents, we can simply denote their mean WTP as non-observable. In this way, we can follow the traditional Heckman two-step model (Heckman, 1979) to develop a joint selection model for WTP estimation with distrust, in the following.

Let S_i denote the dichotomous choice that takes value of 1 if the individual decides to reveal his/her WTP (participants), and 0 if not (protests). We, therefore, have,

$$S_i = \begin{cases} 1\ if\ z_i'\gamma + \epsilon_i \geq 0 \\ 0\ if\ z_i'\gamma + \epsilon_{i,} < 0 \end{cases}$$

For the respondents having $S_i = 1$, we can use Y_i^* to denote his/her mean WTP that the individual has. This means,

$$Y_i^* = x_i'\beta + \varepsilon_i,\ \varepsilon \sim N[0, \sigma_\varepsilon{}^2]$$

Where x_i' is the vector of sociodemographic characteristics of the individual i which can explain the value of his or her mean WTP. We need x_i' to be different from z_i' to ensure the model identification. The joint distribution of $(\epsilon_i, \varepsilon_i)$ can be assumed to be bivariate normal with mean equal to 0 and variance equal to 1, and the correlation denoted as ρ. If ρ=0, the two decisions can be considered as independent and the parameters of the two equations can be estimated separately. If ρ>0, it signifies the participants have higher WTP than the protest ones. In this case, focusing only on participants leads to upward bias of sample mean WTP. If ρ<0, it means that the participants have lower WTP than the protest ones. Then, focusing only on participants leads to downwards bias of sample mean WTP. Grammatikopoulou and Olsen (2013) reported a negative and significant ρ but Strazzera et al. (2003) instead reported a positive ρ.

We can also assume that the standard variance of individual WTP distribution $\sigma_i^*$is also dependent on the characteristics of the respondents and their decision to protest or not. Then we have,

$$\sigma_i^* = y_i'\delta + u_i,\ u \sim N[0, \sigma_u{}^2]$$

Where y_i' is the vector of sociodemographic characteristics of the individual i which can explain the value of his or her variance of individual WTP distribution. We know that y_i' to be different from z_i' to ensure the model identification. The joint distribution of (ϵ_i, u_i) is assumed to be bivariate normal with mean equals to 0 and variance equals to 1 and the correlation denoted as θ. If θ=0, the two decisions can be considered as independent and the parameters of the two equations can be estimated separately. If θ>0, it signifies the participants have wider WTP variance than the protest ones, which can be considered as the participants face higher uncertainty in their WTP valuation process. If θ <0, it signifies the participants have more narrow WTP variance than the protest ones, which can be considered as the participants face less uncertainty in their WTP valuation process than the non-participants.

The joint selection model can be described as the following equation:

$$E(lnY_i^*|S_i = 1) = x_i'\beta + \rho\sigma\lambda(z_i'\gamma),$$
$$E(ln\sigma_i^*|S_i = 1) = y_i'\delta + \theta\sigma\lambda(z_i'\gamma),$$

Where $\lambda(z_i'\gamma) = \frac{\phi(z_i'\gamma),}{\Phi(z_i'\gamma),}$ is the inverse of the Mills ratio.

As our attention is on how the level of distrust to local government and other organizations (enterprises, NGO) affects people's mean WTP and their variance, we introduce the level of respondent i's distrust, D_i, as independent variables in both vectors z_i and x_i. We expect an individual who has lower trust may have higher probability to protest the WTP question, and therefore be less often to participate. In such case, we cannot observe their true WTP values (protests). At the meantime, even if this individual decides to answer the WTP question (participants), in the second step, his/her distrust in institution may also lead to a decrease in the observable WTP value.

The final impact of distrust on WTP will therefore depend on the results of three elements. The first is the coefficient of D_i in the selection model which is expected to be negative, $\gamma_D < 0$. The second one is the coefficient of D_i in the WTP determination function, which is expected also to be negative, so $\beta_D < 0$. And finally the correlation coefficient ρ, which may be either positive or negative, based on the existing literature. If ρ comes out to be negative, we can safely conclude that distrust in local government leads to a downwards bias in WTP estimation, since on the one hand, distrust will increase the rate of protest and lead to a lower WTP sample mean, and on the other hand, the participants have in general lower WTP; therefore the three forces work in the same direction. If ρ comes out to be positive, although distrust still increase rate of protest and lower the WTP sample mean, but since participating respondents have significantly higher WTP than the non-participated one, the final impact of the distrust on WTP estimation will depend on the contrast of the three forces. A similar discussion on the expected results can also be applied to the estimation of the variance of WTP, σ_i.

4. The Results

5.1 descriptive statistics

Table 2 shows all the explanatory variables used in our model specifications. Summary statistics of each of the two cities are presented for both the participant and protest subsamples, and the comparison between the two subsamples are provided via the student test. Clearly, in both cities, protest respondents' socio-demographic profiles differ from those participants, with the difference in Xingtai city generally bigger than that in Guiyang (c.f. the significance of the Student test). The level of distrust to different institutions, in particular that to local government and to enterprises, are found to be statistically different between the protest and participant respondents. In both cities, we observe significantly higher level of distrust among the protest respondents. These observations provide the first clues about the potential necessity to adopt a selection model instead of simply remove the protest respondents from our analysis.

Although not directly compared, the difference between Guiyang and Xingtai cities can also be found by looking into the mean values of different subsamples (c.f. Table 2). First of all, the respondents in Xingtai city seems to be much less satisfied with their city's air quality. Over 80% of respondents in Xingtai mentioned air pollution as the most serious environmental problem (*envprob_air*) vs. lower than 30% in Guiyang city. At the same time, a much lower percentage (around 20%) of respondents are satisfied with the air quality (*satisfy_yes*) in Xingtai, compared to around 70% in Guiyang. Moreover, a higher percentage of respondents in Xingtai (over 30%) believe the air quality in their city is worse than 5 years ago (*Year5_worst*), while the percentage in Guiyang is only 17%. In addition, among the Xingtai respondents, a much higher percentage (around 45%) have bought protection mask (*mask_yes*) against air pollution, compared to Guiyang of a much lower percentage (around 15%).

Secondly, Table 2 also reveals that the respondents from Guiyang seem to have higher pro-environmental attitude. This is not only shown by the higher percentage of respondents preferring air quality improvement to economic growth (*air_prefer_yes*, around 70% in Guiyang vs. around 50% in Xingtai), by the higher percentage (around 75% in Guiyang vs. 50% in Xingtai) of respondents paying attention to environmental labels while shopping (*label_yes*), and also by the relatively higher percentage (higher than 37%) of respondents in Guiyang declaring knowing the current air pollution situation versus lower than 20% in Xingtai (*current_status_know*). More important for our paper, we observe very big differences in people's opinion toward the different institutions between the two cities. Firstly, a higher percentage of respondents in Xingtai declared to be dissatisfied with the existing governmental air pollution control measures (over 45% in Xingtai versus around 20% in Guiyang). Secondly, a very high percentage of Xingtai respondents (around 90%) reported to believe firms behaving negatively in terms of environmental protection, while the percentage in Guiyang is only about 45%. Finally, we can also distinguish a significantly higher level of trust on NGO in Guiyang city among the protest respondents, while the difference in Xingtai is not statistically significant. We therefore expect these differences between the two cities in their trust towards different institutions to affect the role of distrust in WTP for the new air quality improvement project.

5.2 Estimation results

Before discussing about how the distrust in different institutions can affect people's valuation process, we first report the results of the first-stage WTP estimation in table 3. This first-stage consists of using the information obtained from each participant respondent's MBDC matrix to estimate individual WTP distribution. In Table 3, we report the sample mean, median, minimal and maximal values of the individual mean WTP and its variance for each of the two cities. Although it seems to have a relatively good coherence between the two cities for these different values, it is easy to see that the variances of the individual WTP distribution among Guiyang respondents are obviously larger than those of the Xingtai respondents. We observe some big numbers at the higher end of the individual WTP and its variance, which leads to a large difference between the mean and median value of the sample. We therefore use a ln(WTP) and ln(variance) as dependent variable in the second stage determination analyses.

We report in Table 4 the binary Probit model results to explain the probability for a respondent to participate to answer the WTP questions. Depending on the cities, socio-economic characteristics such as age, gender, income (in natural log), long-term residents in the city are found to significantly affect the protest behaviors. In Guiyang, male respondents and those who lives in the city for less than 5 years, seem to have less likelihood to participate, while in Xingtai, older and richer respondents are found to have higher probability to participate. Respondents' probability to participate seems to increase significantly with their exposure time to air pollution in Xingtai, but the same situation is not observed in Guiyang. People's environmental perception is found to be important determinant in their selection process. In both cities, those who prefer air quality to economic growth have more probability to participate. In Guiyang, people believing that air quality is worse than 5 years ago have higher probability to participate. In Xingtai, respondents knowing more about current air pollution situation and buying mask to protect themselves from pollution have higher probability to participate. But also in Xingtai, respondents who have installed the air filter equipment in their houses seem to have a significantly lower probability to participate, an evidence that private measures evict the desire to support public measures.

Coming to the role of distrust in institutions in protest selection, all related variables are listed in the bottom part of the Table 4. To test the different dimension of respondents' distrust, we include variables that measure people's distrust/trust on three kinds of institution: government (*Distrust_gov*), firms (*Distrust_ent*) and NGO (*Trust_NGO*). In both Guiyang and Xingtai, as expected, not being satisfied with governmental measures for air pollution control leads to a significantly lower probability to participate. The other two dimensions of distrust are found significant only for Guiyang, where we can confirm that believing that firms act negatively to environment and NGOs have positive impacts on environmental protection all lead to a lower probability of participation.

Table 5 reports the modeling results of WTP determinants. For each city, we first report in the columns to the left of the table the simple OLS model where the protest respondents are excluded from the analyses. As we expected, we find the individual mean WTP to increase with household income, education level. We also found the house owners and people living in the city for more than 5 years to have in general higher WTP (only significant in Xingtai). People's perception on environmental issues is also important WTP determinants. We find people knowing current status of air pollution problems (*current_status_know*, only significant in Xingtai), paying attention to environmental label while shopping (*label_yes*, only significant in Xingtai) have in general higher WTP. In Xingtai, feeling air pollution as the most serious environmental problem is found to motivate significantly higher WTP, and in Guiyang, people believing air quality to be important for self and family also report higher WTP. In addition, people's private measures to protect themselves from pollution, such as installing air filters (*filter_d*) and choose to leave the city during very polluted days (*leave_yes*) are found to be positive determinants in WTP. Finally, we only find people's distrust towards the government to have statistical impact on their WTP in Guiyang, but not in Xingtai. In general, people's trust on enterprises and that on environment-related NGO does not impact people's WTP for the new air quality improvement project, which can be considered as reasonable since the hypothetical project is supposed to be realized by the local government.

The second columns for the two cities in Table 5 show results obtained with the joint selection model. As we can see, including the selection items in the WTP determination function do not affect stability of the coefficients of other WTP determinants. Lumda (λ) capture the coefficients before the inverse of the Mills ratio, this coefficient actually measure how being selected as participant leads to the changes in WTP. For the case of Guiyang, we find a negative but insignificant coefficient, which can be considered as evidence that WTP of the participants and protest respondents are not significantly different. For the case of Xingtai, the results report a negative and significant coefficient (-

0.458, significant at 90%), which confirms our initial expectation that participants have significantly lower WTP than the protest, all else being equal.

Combining the results of the selection model and WTP determination model and their correlation parameters, we can say that for Xingtai city, respondents' distrust in institutions (in particularly in local government) affect the WTP estimation via the selection. More precisely, a person having lower level of trust in local government have significantly lower probability (-0.372) to participate. Since the protesting respondents are found to have higher mean WTP, an increase in people's distrust in local government actually lead a downward bias in valuation of the new air quality improvement project. The channel through which public distrust affect the WTP value is different in Guiyang city, although we do find evidence that people's distrust (in both local government and firms) decreases the probability to participate, our results do not report significant difference in mean WTP between protesting and participating respondents. However, the simple OLS model with the protest respondents excluded confirms the negative and significant contribution of people's distrust in local government on WTP. We therefore conclude that for the case of Guiyang, public distrust seems to affect downwards the WTP in a direct way via the WTP determination function.

The results of the determination function of the variance of WTP are reported in Table 6. The statistical significance of the results is less satisfactory than that of the mean WTP estimation. For both Xingtai and Guiyang, we do not identify significant coefficient for Lumda (λ). This signifies the variance of the individual WTP distribution is not significantly different between participant and protest respondents. The simple OLS estimation without selection, however, still reports the distrust of people to local government to play a negative role on variance of individual WTP distribution (only significant in Xingtai) but the trust to the NGO plays a positive one (only in Xingtai). As the variance of the individual WTP distribution can be interpreted as a measurement of respondents' uncertainty, we can therefore believe the distrust to the local government reduces people's uncertainty, but the trust to NGO increases it.

We report in Table 7 the mean and the confidence intervals of the WTP for both cities, followed by the simulated mean WTP of the whole sample with the same respondents but the three dimensions of distrust recovered to the situation of trust, i.e. respondents reporting distrust to one or several of the three institutions have their dummies modified to be trust. By doing so, we obtain simulated mean WTP for a same sample of respondents who are not affected by the public distrust; these numbers are reported in the second columns for each of the cities. As we can see, the results obtained from the survey conducted in Xingtai city seem to suffer more from public distrust, which leads to an important downward bias in the reported mean WTP (9.68 Yuan/month vs. 12.18 Yuan/month, equal to a 20% bias). The public distrust in Guiyang city, however, is found to exert much smaller influence on WTP, with a slight bias from 10.70 Yuan/month to 10.28 Yuan/month, signifying a reduction less than 4% in the mean WTP.

5. Conclusion and discussion

In this study, we analyze how public distrust in government affects WTP estimations with the contingent valuation method when public programs are involved. With distrust, people may either refuse to participate in valuation, or offer lower WTP values. Identification questions can be developed to help determine the levels of distrust among the survey respondents, and the answers to the identification questions can be employed to analyze the protest models, the WTP models, as well as the joint models. A joint selection model of WTP with distrust is developed in this study, which can help correct the potential biases caused by excluding the protest respondents in WTP modeling, as usually did in CV studies, and can be used to calibrate the potential biases caused by public distrust in government.

Two contingent valuation studies are conducted to estimate people's WTP for the implementation of a new air quality improvement program at the municipality level respectively in Guiyang and Xingtai of China, with the strategy developed for identifying and calibrating potential biases caused in public distrust in government. Our results suggest that distrust in government can lead to statistically significant downward bias in WTP estimation in China. The two possible channels through which the distrust in the local government affects WTP are both empirically demonstrated. For the case of Xingtai, a poor city with worst air pollution in China, people with distrust in the local government are statistically significantly less likely to participate in the air quality valuation and the protesters have higher latent WTP in general. In total, the WTP estimation bias can be 20% downwards caused by the distrust in Xingtai. For the case of Guiyang, where both income and air quality are merely acceptable, there is no significant difference found in WTP values between the protesting and participating respondents. The distrust in government leads a slightly lower WTP estimation of 3.9%, which directly comes from the WTP function.

An interesting issue is regarding why the distrust in government plays different roles in influencing WTP in the two different cities. As mentioned before, Xingtai is a northern city suffering for years from heavy air pollution problems. Respondents from Xingtai do report very high level of dissatisfaction towards the local government's air pollution control measures (55% for protest respondents and 40% for valuation participants) and employed more frequently private protection measures (air filters, masks). Such dissatisfaction towards current status of air pollution is also found to be associated with a higher level of dissatisfaction with the existing governmental air pollution control measures and with the bad environmental behaviors of firms. The protests from these individuals who actually need more urgently better air quality result in an important downwards bias of WTP estimation if the selection bias is not taken into account.

The situation is different in Guiyang city. As a southern city suffering less from air pollution problems, people's perception about the air quality and governmental capacity to control the pollution actually stay at relatively high level (c.f. Table 2); the dissatisfaction with local government's air pollution control measures are 27% for protest respondents and 12% for valuation participants. This may explain why there is no significant difference between people protesting and people accepting to reveal their WTP. Under this circumstance, we obtain only a quite marginal influence of public distrust on the WTP, directly via the WTP determination function.

Therefore, the ways how public distrust in local government affects the contingent valuation study results should be location specific. Both channels of participation and conservative responding to the WTP questions can be in effect and can even be in effect simultaneously. Modeling approaches, such as the one developed in this study, which take into consideration both the protest bias and the WTP modeling bias and allow direct calibration of the role of the public distrust in both bias, are needed.

Table 1. Protest Identification

	Guiyang	Xingtai
Total numbers of questionnaires returned	**793**	**781**
Potential Protests	**106**	**158**
Refuse at the filter question[1]	*91*	*150*
Negative answers at zero bid[2]	*6*	*6*
Always not sure	*9*	*2*
Zero WTP identified from potential protest answers[3]	**13**	**31**
Total protests identified	**93**	**127**
Further excluded in the WTP modeling process	**61**	**72**
No MBDC answers	*5*	*25*
Positive answers at the highest bid price[4]	*34*	*38*
Disordered MBDC answers	*22*	*9*
Total observations used for modeling	719	678
For protests modeling	93	127
For WTP modeling	626	551

Note: 1.The filter question is asked after the new air quality improvement project is introduced but before the payment vehicles and the MBDC matrix are given. The question is: If this project came out to be totally free, that means you do not need to pay any cost for it, are you willing to support this new project? 1) definitvely yes, 2) probably yes, 3) not sure, 4) probably not, 5) definitely not. We identify respondents giving “not sure, probably not and definitively not” as refusing the project at this filter question. 2. Negative answers at zero are “not sure, probably not, definitively not”. 3. The real zeros are identified by the follow-up questions after the MBDC question, which questions the reason why the respondent does not want to pay any fee for the project: we identify a person as providing real zero if he/she only chose one of the four response options: “do not have enough money; current air quality improvement project is good enough; the improvement proposed in the new project is not big enough; or the improvement of air quality have few impact on me”. 4. Positive answers at highest price (1000 Yuan per month) are “definitively yes, probably yes and not sure”.

Table 2. Description of variables and summary statistics

Variable name	description	Guiyang city			Xingtai city		
		Not-protested	Protest	Student test	Not-protested	Protest	Student test
age	Respondent's age	45.30	42.53	2.07**	44.43	42.76	1.44
male	Male respondent=1, female=0	0.36	0.49	2.49**	0.59	0.50	1.97**
logincome	Ln(Family income) (1000 yuan/month)	10.71	10.91	-2.37**	10.78	10.58	3.69***
houseowner	Houseowner=1, other=0	0.62	0.49	2.34**	0.59	0.68	-1.96**
university_d	Education level higher or equal to university level=1, lower=0	0.35	0.43	1.50	0.28	0.21	1.65*
live5years	Respondent has lived in the city for over 5 years =1, other=0	0.82	0.54	6.42***	0.72	0.76	-0.77
envprob_air	Identify air pollution as most serious env problem=1, other=0	0.31	0.23	1.57	0.87	0.80	2.02**
Year5_worse	Air quality is worst than 5 years ago=1, other=0	0.17	0.17	0.03	0.38	0.29	1.82*
Air_quality_important	Air quality is important for me and my family=1, other=0	0.97	0.90	2.86***	0.94	0.78	5.61***
Label_yes	Pay attention to green label while shopping=1, other=0	0.81	0.74	1.45	0.54	0.46	1.60
Air_prefer_yes	Prefer air quality to economic growth=1, other=0	0.78	0.63	3.16***	0.59	0.19	8.48***
travel_time_wd	Travel time during weekday (minutes)	204.57	165.75	1.39	113.19	52.38	3.46***
travel_time_wkn	Travel time during weekend (minutes)	41.30	31.02	1.91*	32.18	17.08	3.40***
ngo_know	Know NGOs working on environmental protection in the city=1, other=0	0.08	0.13	-2.65***	0.07	0.04	1.03
satisfy_no	Not satisfied with the air quality of the past year=1, other=0	0.20	0.22	-0.27	0.73	0.72	0.26
Current_status_know	Know about the current status of air quality=1, other=0	0.39	0.37	0.53	0.25	0.06	4.70***
Filter	Buy air filter=1, other=0	0.07	0.08	-0.23	0.07	0.15	-2.70***
Mask	Buy masks=1, other=0	0.12	0.16	-1.18	0.52	0.39	2.68***
leave	Leave the city during very polluted days=1, other=0	0.06	0.14	-2.87***	0.11	0.09	0.62
Participation_6 months	Participated in the NGO's activity in last 6 months=1, other=0	0.71	0.62	1.78*	0.65	0.37	5.98***
PP_satisfy_yes	Satisfied with public participation in env. Issues=1, other=0	0.64	0.52	2.38**	0.35	0.34	0.29
Distrust_gov	Dissatisfied with government's air pollution control measures=1, other=0	0.12	0.27	-3.79***	0.40	0.55	-2.98***
Distrust_ent	Enterprises behave negatively in terms of environment=1, other=0	0.54	0.68	-2.58***	0.85	0.94	-2.91***
Trust_NGO	Impact of NGO on environmental protection is positive=1, other=0	0.24	0.38	-2.80***	0.19	0.13	1.50

Table 3. WTP estimates with Wang-He Approach

	Guiyang City		Xingtai City	
	Mean WTP	Variance	Mean WTP	Variance
Mean	31.23	16.87	30.12	4.83
Median	9.25	1.82	9.16	1.29
Min	0.03	0.72	1.03	1.03
Max	529.57	898.64	502.14	364.87

Table 4. Binary probit model results for participation

	Guiyang	Xingtai
age	0.00621	0.0152***
	(0.00564)	(0.00560)
male	-0.323**	0.0602
	(0.134)	(0.137)
logincome	-0.183**	0.328***
	(0.0909)	(0.125)
houseowner	0.193	0.0920
	(0.140)	(0.151)
live>5year	0.653***	-0.124
	(0.145)	(0.172)
year5_worse	0.337*	-0.0592
	(0.189)	(0.150)
Current_status_know	-0.0213	0.510**
	(0.151)	(0.210)
filter	0.407	-0.518**
	(0.283)	(0.219)
mask	-0.0566	0.305**
	(0.202)	(0.142)
leave	-0.485**	-0.328
	(0.245)	(0.232)
air_prefer_yes	0.335**	0.954***
	(0.150)	(0.147)
travel_time_wd	9.53e-05	0.00174***
	(0.000286)	(0.000557)
travel_time_wkn	0.00155	0.00475**
	(0.00151)	(0.00216)
ngo_know????????	0.167	-0.422**
	(0.290)	(0.205)
pp_satisfy_yes	0.121	-0.305**
	(0.162)	(0.151)
Participation NGO_ 6 months	-0.0356	0.508***
	(0.159)	(0.140)
Distrust_gov	-0.354**	-0.372***
	(0.180)	(0.140)
Distrust_ent	-0.280*	-0.380
	(0.158)	(0.246)
Trust_NGO	-0.467***	0.114
	(0.157)	(0.204)
Constant	2.367**	-3.653**
	(1.068)	(1.428)
Observations	719	678
Pseudo R2	0.1541	0.2675
Chi2	85.33	174.92
Correctly predicted[1]	87.48%	85.10%

* p<0.10, ** p<0.05 and ***p<0.01.

[1] Percentage point of the correctly predicted answered based on the estimation results.

Table 5. WTP Models with Sample Selection

	Guiyang		Xingtai	
	OLS no_selection	OLS selection (Heckman)	OLS no_selection	OLS selection (Heckman)
WTP mean value estimation				
Logincome	0.307***	0.328***	0.497***	0.457***
	(0.0877)	(0.0901)	(0.108)	(0.109)
university_d	0.0104	0.0148	0.522***	0.503***
	(0.132)	(0.127)	(0.135)	(0.134)
Houseowner	0.387***	0.363***	0.341**	0.360***
	(0.125)	(0.131)	(0.138)	(0.130)
live>5year	0.200	0.0959	0.497***	0.492***
	(0.151)	(0.224)	(0.152)	(0.150)
current_status_know	0.115	0.113	0.349**	0.268*
	(0.126)	(0.129)	(0.142)	(0.144)
filter	0.556**	0.507**	0.224	0.295
	(0.243)	(0.248)	(0.228)	(0.220)
leave	0.729***	0.795***	0.402**	0.415**
	(0.271)	(0.274)	(0.187)	(0.188)
label	-0.0418	-0.0367	0.287**	0.296***
	(0.141)	(0.156)	(0.115)	(0.114)
envprob_air	-0.126	-0.127	0.859***	0.850***
	(0.127)	(0.127)	(0.170)	(0.172)
satisfy_no	-0.342**	-0.350**	0.137	0.132
	(0.155)	(0.163)	(0.155)	(0.153)
air_quality_important	0.615*	0.558*	-0.125	-0.190
	(0.317)	(0.337)	(0.194)	(0.238)
pp_satisfy_yes	0.468***	0.452***	-0.00191	-0.00256
	(0.144)	(0.147)	(0.128)	(0.123)
version_a	0.256**	0.255**	0.115	0.112
	(0.117)	(0.116)	(0.113)	(0.111)
Distrust_gov	-0.337*	-0.270	-0.0269	0.00956
	(0.179)	(0.219)	(0.125)	(0.123)
Distrust_ent	-0.100	-0.0742	0.00588	0.0411
	(0.133)	(0.142)	(0.188)	(0.183)
Trust-NGO	-0.0875	-0.0277	0.261	0.257
	(0.155)	(0.171)	(0.183)	(0.163)
λ		-0.448		-0.453*
		(0.693)		(0.266)
Constant	-2.235**	-2.246**	-4.890***	-4.320***
	(1.058)	(0.979)	(1.230)	(1.251)
Observations	626	719	551	678
R-squared	0.136		0.247	
Rho		-0.311		-0.352
Sigmal		1.44		1.29

* p<0.10, ** p<0.05 and ***p<0.01.

[1]. The H0 of the LR test is the two equation (WTP determination and selection model) are independent between them.

Table 6. Variance Equations with sample selection models

	Guiyang		Xingtai	
	OLS no_selection	OLS selection (Heckman)	OLS no_selection	OLS selection (Heckman)
WTP standard variance estimation				
Logincome	-0.0670	-0.0832	0.00611	0.000524
	(0.0808)	(0.0715)	(0.0766)	(0.0682)
university_d	0.133	0.130	0.152	0.149*
	(0.107)	(0.101)	(0.102)	(0.0851)
Houseowner	0.0918	0.109	0.00500	0.00773
	(0.105)	(0.104)	(0.0976)	(0.0820)
live>5year	0.118	0.196	0.0460	0.0452
	(0.124)	(0.178)	(0.107)	(0.0945)
current_status_know	0.0347	0.0361	0.0455	0.0340
	(0.0938)	(0.102)	(0.0937)	(0.0905)
filter	-0.0236	0.0141	0.107	0.117
	(0.125)	(0.197)	(0.139)	(0.138)
leave	-0.0556	-0.106	0.00339	0.00526
	(0.163)	(0.218)	(0.116)	(0.118)
label	-0.0855	-0.0894	0.209***	0.210***
	(0.129)	(0.124)	(0.0807)	(0.0723)
envprob_air	-0.0351	-0.0343	0.118	0.117
	(0.103)	(0.101)	(0.127)	(0.109)
satisfy_no	0.151	0.157	0.0281	0.0274
	(0.154)	(0.129)	(0.0982)	(0.0968)
Air_quality_important	0.506***	0.549**	-0.0399	-0.0492
	(0.145)	(0.268)	(0.130)	(0.152)
pp_satisfy_yes	0.0595	0.0721	0.0834	0.0833
	(0.0978)	(0.116)	(0.0871)	(0.0772)
version_a	-0.00310	-0.00190	0.0475	0.0471
	(0.0919)	(0.0921)	(0.0734)	(0.0704)
Distrust_gov	-0.155	-0.205	-0.240***	-0.235***
	(0.144)	(0.174)	(0.0714)	(0.0771)
Distrust_ent	-0.0519	-0.0714	-0.0405	-0.0355
	(0.0967)	(0.112)	(0.138)	(0.115)
Trust-NGO	-0.0533	-0.0985	0.284**	0.284***
	(0.117)	(0.135)	(0.140)	(0.103)
λ		0.338		-0.0644
		(0.550)		(0.169)
Constant	1.015	1.023	0.316	0.397
	(0.878)	(0.777)	(0.829)	(0.786)
Observations	626	719	551	678
R-squared	0.020		0.085	
Rho		0.296		-0.089
Sigmal		1.142		0.804

* p<0.10, ** p<0.05 and ***p<0.01.

[1]. The H0 of the LR test is the two equation (WTP determination and selection model) are independent between them.

Table 7. Estimation and simulations of WTP

	Guiyang		Xingtai	
	With Distrust respondents	Distrust become trust	With Distrust respondents	Distrust become trust
	Ln(WTP)			
OLS no selection	2.33	2.37	2.25	2.47
	[1.17, 3.40]		[1.11, 3.88]	
OLS selection (Heckman)	2.35	2.39	2.27	2.50
	[1.13, 3.40]		[1.09, 3.90]	
	WTP (Yuan/month)			
OLS no selection	10.28	10.70	9.48	11.82
	[3.22 29.96]		[1.11 48.82]	
OLS selection (Heckman)	10.48	10.91	9.68	12.18
	[3.09 29.96]		[2.97 49.40]	

Reference

Arrow, K., R. Solow, P. Portney, E. Leamer, R. Radner and J. Schuman (1993). Report of the NOAA panel on Contingent Valuation. Federal Register, January 15, 58(10): 4601-4614.

Bina, O. (2010). Environmental governance in China: Weakness and potential from an environmental policy integration perspective. *The China Review*, 19(1): 207-240.

Carson, R. T., C. Robert, W. Mitchell, M. Hanemann, R. J. Kopp, S. Presser and P. A. Rund. (2003). Contingent valuation and lost passive use: Damages from the Exxon Valdez Oil Spill. Environmental and Resource Economics, 25(2): 257-286.

Carson, R. T. (2011). Contingent valuation: A comprehensive bibliography and history. Northampton, MA: Edward Edgar.

Carson, R. T. (2012). Contingent valuation: A practical alternative when price aren't available. *Journal of Economic Perspective*. 26(4): 27-42.

Chen, J. (2004). *Popular Political Support in Urban China.* Stanford: Woodrow Wilson Center Press and Stanford University Press.

Chen, W. Y. and J. Hua (2015). Citizens' distrust of government and their protest responses in a contingent valuation study of urban heritage trees in Guangzhou, China. Journal of Environmental Management, 155(2015): 40-48.

Edelman Trust Barameter (2017). 2017 Executive Summary. Edelman Trust Barameter 2017: annual Global study.

Fukuyama, F. (1995) *Trust: The Social Virtues and the Creation of Prosperity*. Free Press, New York City, NY.

Glenk, K. and A. Fischer (2010). Insurance, prevention or just wait and see? Public preferences for water management strategies in the context of climate change. *Ecological Economics*, 69(2010): 2279-2291.

Grammatikoupoulou, I. and S. B. Olsen (2013). Accounting protesting and warm glow bidding in contingent valuation surveys considering the management of environmental goods: An empirical case study assessing the value of protecting a Natura 2000 wetland area in Greece. *Journal of Environmental Management*, 130(2013): 232-241.

Habibov. N., A. Cheung, A. Auchynnikava (2017). Does social trust increase willingness to pay taxes to improve public healthcare? Cross-sectional cross-country instrumental variable analysis. *Social Science & Medicine*, 189(2017): 25-34.

Heckman, J. (1979). Sample selection bias as a specification error. Econometrica 47: 153–161.

Hu, Anning (2015). A loosening stray of sand? Age, period, and cohort effects on generalized trust in reform-era China, 1990-2007. *Social Science & Medicine*, 51(2015): 233-246.

Jones, N., C. M. Sophoulis, and C. Malesios (2008). Economic valuation of coastal water quality and protest responses: A case study in Mitilini, Greece. *The Journal of Socio-Economics*, 37(2008): 2478-2491.

Jorgensen, B. S. , G. J. Syme, B. J. Bishop and B. E. Nancarrow (1999). Protest responses in contingent valuation. *Environmental and Resource Economics*. 14(1999): 131-150.

Jorgensen, B.S. and G. J. Syme (2000). Protest responses and willingness to pay: attitude toward paying for stormwater pollution abatement. *Ecological Economics*, 33(2000): 251-265.

Kahneman, D. and A. Tversky (1979). Prospect Theory: An Analysis of Decision under Risk, Econometrica, 47 (1979): 363-391.

Krutilla, J. V. (1967). Conservation reconsidered. American Economic Review. 57(4): 777-786.

Krystallis, A. and G. Chryssohoidis (2005). Consumers' willingness to pay for organic good: Factors that affect it and variation per organic product type. *British Food Journal*, 107(5): 320-343.

Lindsey, G. (1994). Market models, protest bids, and outliers in contingent valuation. Journal of Water Resources Planning and Management, 120(1): 121-129.

Mishler, W. and R. Rose (2001). What Are the Origins of Political Trust? Testing Institutional and Cultural Theories in Post-communist societies. Comparative Political Studies, 34(1): 30-62.

Oh, H. and J. H. Hong, (2014). Citizens' distrust in government and project implementation in the public sector. The Korean Economic Review, 2014(1): 25-40.

Saich, T. (2007). Citizens' perceptions of governance in rural and urban China. Journal of Chinese Political science. 12(1): 1-28.

Shi, T. (2001). Cultural Values and Political Trust: A Comparison of the People's Republic of China and Taiwan." *Comparative Politics* 33, no. 4: 401–19.

Strazzera, E., M. Genius, R. Scarpa and G. Hutchinson (2003). The effect of protest votes on the estimates of WTP for use value of recreational sites. *Environmental and Resource Economics*, 25: 461-476.

Wang, H. and J. He. (2011). Willingness-to-Pay Estimation with Multiple Bounded Discrete Choice Data, Applied Economics, 43(19-21): 2641-2656.

Wang, Hua and Jie He (2018). "Implicit individual discount rate in China: A contingent valuation study," *Journal of Environmental Management*, 210 (2018) 51-70.

Wang, Hua, Yuyan Shi, Yoonhee Kim, Takuya Kamata. (2013a) "Valuing water quality improvement in China: a case study of lake Puzhehei in Yunnan province," *Ecological Economics,* 2013.

Wang, Hua, Jie He, Yoonhee Kim, and Takuya Kamata. (2013b) "Willingness-to-pay for Water Quality Improvements in Chinese Rivers: An Empirical Test on the Ordering Effects of Multiple-Bounded Discrete Choices," *Journal of Environmental Management,* 2013.

Wang, Hua, Ke Fang, Yuyan Shi (2011) "Benefit-Cost Analysis with Local Residents' Stated Preference Information: A Study of Non-Motorized Transport Investment in Pune, India," *Journal of Benefit-Cost Analysis*, 2011.

Wong, T. K., P. Wan and H. M. Hsiao (2011) The base of political trust in six Asian societies: institutional and cultural explanations compared. International Political Science Review, 32(3): 263-281.

Xin, Z. and S. Xin (2017). Marketization process predicts trust decline in China. Journal of Economic Psychology. 62(2017): 120-129.

Yang, Q. and Tang, W. (????). Exloring the sources of institutional trust in China: Culture, Mobilization or performance? Asian Politics and Policy. 2(3): 415-436.

Zhong, Y. (2014). Do Chinese people trust their local government and why? An empirical study on political trust in urban China. Problems of Post-Communism, 61(3): 31-44.

Appendix 1. Description of the proposed project, its expected results, and related visual supports used in the survey

The WTP question in the survey concerns a municipal level program to improve air quality called New Blue Sky project. This is a continuation and improvement of the currently existing Blue Sky project. This new project aims to reinforce the existing measures and supplement the existing measures with the new ones, with the following particular targets: control the total volume of private automobile vehicles; strictly control the automobile vehicle emissions; increase the coal washing ratio; mobilize the use of clean energy; accelerate the conversion from coal to gas and from coal to electricity; upgrade the existing pollution control equipment; and add new higher efficiency equipment; control the emission from industrial and restoration sectors. Further, control construction emission and dust on transportation networks, at the same time to control the interior decoration of civil house and reduce the potential pollution problems.

The new project will bring a series of significant environmental quality improvement, including:

Guiyang	2017			2013
	Variation brought by the new project	New project	Current project	Status quo
PM2.5 annual concentration (μg/m^3)	Reduce by 5 μg/m^3	45	50	53
Annual premature death	Reduce 50 persons	390	440	460
Annual outpatient due to air pollution	Reduce 5000 persons	15000	20000	30000
Annual hospitalisation due to air pollution	Reduce 300 persons	1200	1500	2500
% of days whose air quality to be better than the Class II level in a year	Increase 20 days	330 (90%)	310 (85%)	278 (76%)

Xingtai	2017			2013
	Variation brought by the new project	New project	Current project	Status quo
PM2.5 annual concentration (μg/m^3)	Reduce by 10 μg/m^3	110	120	160
Annual premature death	Reduce 500 persons	2000	2500	4000
Annual outpatient due to air pollution	Reduce 10000 persons	60000	70000	100000
Annual hospitalisation due to air pollution	Reduce 1000 persons	4000	5000	6000

% of days whose air quality to be better than the Class II level in a year	Increase 40 days	150 (40%)	110 (30%)	38 (10%)

In order to implement the above-mentioned project, the municipal government is exploring various financing channels. However, based on the current situation, unless they receive financial support from local residents like you, the project might not be financially feasible.

Currently, the municipal government is considering to collect a monthly municipal tax via water bill of the local households for 3 years consecutively. This fund will be collected and managed by the related governmental department. It will be solely used for the above-mentioned new project and the fund usage will be publicly reported to the local residents.

Now, suppose the residents like you **had an opportunity** to vote for the implementation of this new air quality improvement project. If **most of the local people supported** this, **this project would be implemented;** every household would need to pay a certain fee. If majority of the people were **against the project**, the project **would not be implemented** and the residents would not need to make additional payment. However, the air quality would not be further improved.

Now, I would like to know the possibility that your household will support for this project and make a certain payment each month. Please compare the amount you are willing to pay with the bid prices in the following box and **choose the possibility of your willingness to pay for each bid price.**

A reminder: there is no right or wrong response here; we only wish to know your honest response.

Monthly payment over 3 years	Definitely yes	Probably yes	Not sure	Probably not	Definitely not
Free (0 Yuan)					
3 Yuan					
5 Yuan					
10 Yuan					
15 Yuan					
20 Yuan					
30 Yuan					
40 Yuan					
50 Yuan					
80 Yuan					
100 Yuan					
150 Yuan					
200 Yuan					
300 Yuan					
500 Yuan					
700 Yuan					
800 Yuan					
1000 Yuan					

Appendix 2. The two-stage approach proposed by Wang and He (2011)

Suppose an individual i's WTP is V_i, which is a random variable with a cumulative distribution function F (t). The mean value of V_i is μ_i and the standard variance is σ_i. The WTP model can be formulated as follows:

$$V_i=\mu_i+\varepsilon_i \tag{1}$$

Here ε_i is a random term with a mean of zero. Individual i knows his valuation distribution. When given a price t_{ij}, the probability for the person to say "yes" to the offer t_{ij} will be as follows:

$$P_{ij} = \text{Prob.}\ (Vi > t_{ij}) =1\text{-}F\ (t_{ij}) \tag{2}$$

Once P_{ij}, the probabilities for individual i to agree to the price t_{ij}, is known to a researcher, either by assigning numerical values to the verbal MBDC data or by directly asking individuals to mark their likelihood information numerically as done in the SPC approach, equation (2) can be estimated for each individual. The estimation model can be constructed as follows:

$$P_{ij} = 1\text{-}\ F\ (t_{ij}) + \lambda i \tag{3}$$

Here, λ_i is an error term with a mean of 0 and a standard variance of δ^2. δ can be constant for a respondent i, but will be different for different respondents. P_{ij} is a dependent variable, which is an answer indicating uncertainty given by a respondent i at price j. P_{ij} takes values between 0 and 1, and can be viewed as a continuous variable. Further, t_{ij} is an independent variable, which corresponds to the bid price proposed in the questionnaire; t_{ij} is also a continuous variable.

Assume a specific functional form for F_i (•), such as of a normal distribution, with a mean μ_i and a standard variance σ_i, i.e., F (t_{ij}) = $\Phi(\frac{t_{ij}-\mu_i}{\sigma_i})$, then the model (3) becomes:

$$P_{ij} = 1-\Phi(\frac{t_{ij}-\mu_i}{\sigma_i})+\lambda_i \tag{4}$$

The main purpose is to estimate and analyze μ_i, the mean value of V_i for each respondent, which is the function of personal information such as personal characteristics, uncertainties, and so on.

We will use the two-stage approach proposed by Wang and He (forthcoming) to estimate the equation (4)[5].

[5] In contrast to the estimation model presented in Wang and Whittington (2005), the equation (4) adds to the probability model an error term that reflects the consideration that probability values given by respondents may have deviations from their valuation distributions.

Stage 1: Estimate equation (4) for each individual i

Assume λ_i has a normal distribution. Then,

$$\frac{Pij - 1 + \Phi(\frac{tij - \mu i}{\sigma i})}{\delta} \sim N(0, 1).$$

Then, the log likelihood function is as follows:

$$\text{Log Li} = \sum_{j=1}^{J} \log \phi\left(\frac{Pij - 1 + \Phi(\frac{tij - \mu i}{\sigma i})}{\delta}\right) \qquad (5)$$

Here, ϕ (.) is a standard normal distribution probability density function. This is equivalent to a least square nonlinear estimation; δ has no influence on the estimation, as long as it is a normal distribution. With the log likelihood function (5), μ_i can be estimated for each individual i.

Stage 2: Analyze determinants of μ_i

Once μ_i is estimated for each individual, models can be constructed and estimated to analyze their determinants. One simple example is the following linear functional form:

$$\mu_i = \beta 0 + xi'\beta + e \qquad (6)$$

Here, x represents personal specific variables such as personal characteristics, uncertainties, and so on. $\beta 0$ and β are coefficients to be estimated; e is random error, which reflects uncertainties that a researcher faces and can be homogeneous.