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RESEARCH ARTICLE

What determines respondents' valuation uncertainty? Impact of subjective perceptions from the demand and supply sides

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Abstract

Based on a contingent valuation method survey on air quality improvement in northern China, we construct several subjective perception determinants of respondents' valuation uncertainty from both the demand and perceived supply sides. Using the individual-level uncertainty measurements initially proposed by Wang and He (2011) and their alternative transformations, we analyze how these factors of demand and perceived supply sides affect people's valuation uncertainty. Our results demonstrate the significant contribution of these determinants in explaining respondents' uncertainty. On the demand side, people who 'don't know much' about benefits-related factors have the highest level of uncertainty, and those claiming to 'know nothing' most often report the lowest level of uncertainty. On the supply side, people who either do not trust or are not satisfied with the control policies tend to be more certain of their valuation. The subsequent analyses also suggest that these results be interpreted as negative certainty, which is attributed to a lack of interest.

Keywords: contingent valuation method (CVM); demand uncertainties; determinants of valuation uncertainty; perceived supply uncertainties; subjective perceptions

JEL classification: Q51

1. Introduction

Various preference-based methods have been developed to reveal public demand for environmental goods or services where market prices are unavailable. One of the most widely used methods is the contingent valuation method (CVM), which has been accepted in both political and academic areas (Vossler and Evans, 2009; Carson *et al.*, 2014; Vossler and Holladay, 2018).

In microeconomics, consumers are assumed to have well-defined preferences for goods or services provided in the market, i.e., the assumption of completeness (Pindyck and Rubinfeld, 2005). Following this assumption, respondents in CVM studies are assumed to be capable of expressing their preferences for the proposed good as an exact monetary value. However, empirical studies provide evidence that people generally have a high level of uncertainty about their preferences, especially in the context of environmental valuation. Some researchers believe that people can provide only a range of willingness to pay (WTP) instead of an exact amount (Wang, 1997; Bateman *et al.*, 2005; Hanley *et al.*, 2009; Voltaire *et al.*, 2013). While some uncertainty can be mitigated by a better survey design, some uncertainty can never be resolved (Wang, 1997; Shaikh *et al.*, 2007).

Existing studies (e.g., Hanley *et al.*, 2009; Brouwer, 2011; Voltaire *et al.*, 2013) have identified several determinants of valuation uncertainty, including respondents' attitudes toward contributing to public programs, their knowledge of the public good to be valued, family income, and costs. However, in different studies, researchers have focused on different factors; thus, a unified theoretical model about the determination of uncertainty has not yet emerged (Brouwer, 2011), and little is known about this topic (Alberini *et al.*, 2003; Akter *et al.*, 2008).

Moreover, there is no consensus about the ways in which people's WTP uncertainty can be measured. To obtain an individual-level uncertainty measurement, most previous analyses using the dichotomous choice WTP question format are based on self-reported numerical certainty scales (NCSs), e.g., 1–10 or 0–100 per cent, or polychotomous categories (PCs), e.g., 'definitely yes', 'probably yes', 'not sure', 'probably not' and 'definitely not', elicited by follow-up questions posed after dichotomous choice valuation questions. However, this 'response uncertainty' reveals only respondent's uncertainty at a randomly proposed specific bid price, which means that these self-reported uncertainty levels lack comparability due to their dependence on the proposed bid price. An alternative uncertainty measurement that can overcome these concerns is one that follows the approach developed by Wang and He (2011), which is based on the WTP responses collected by a multiple bounded discrete choice (MBDC) elicitation format. This valuation approach can estimate the WTP mean value and variance for each respondent; in their paper, the authors propose measuring the uncertainty of an individual by the estimated standard variance in his or her individual distribution of WTP.

To better understand these issues, we first conduct a comprehensive review of the potential determining factors of valuation uncertainty that have been previously discussed in the literature. Following this, we reclassify these factors into three categories: demand-side factors, including respondents' attitudes, knowledge or past experience with related environmental goods and personal income levels; perceived supply-side factors, such as belief in the proposed environmental good and trust level toward the institution providing it; and finally, general sociodemographic determinants. By doing so, we attempt to contribute to the related literature by proposing a theoretical framework and a global approach that allow us to analyze the potential determinants of WTP uncertainty in a comprehensive way. As a second step, based on a CVM survey using an MBDC-format WTP question that was collected in 2014 in northern China, we adopt both the individual-level uncertainty measure initially proposed by Wang and He (2011) and its alternative transformations based on related discussions from the literature (e.g., Hanley *et al.*, 2009; Voltaire *et al.*, 2013) to analyze how the identified demand-side and perceived supply-side factors affect people's valuation uncertainty. To our knowledge, this is the first study in which different uncertainty measurements and one at the individual level calculated from the Wang and He (2011) approach are compared.

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The remainder of this paper is structured as follows. In section 2, we first present different determinants of valuation uncertainty previously discussed in the CVM literature, followed by the presentation of our reclassification of these determinants. Section 3 presents the different strategies for measuring respondents' valuation uncertainty currently used in CVM studies, highlighting why we prefer to adopt the approach of Wang and He (2011) in our paper. Our survey and data are introduced in section 4. In section 5, the initial and alternative measures of individuals' WTP uncertainty are introduced, followed by the development of a theoretical framework to analyze the potential determinants of valuation uncertainty. The empirical results are presented and discussed in sections 6 and 7. Conclusions and discussions are provided in section 8.

2. Literature review on identified determinants of valuation uncertainty

The CVM literature has proposed different determinants to explain often-observed respondents' valuation uncertainty.

Bid price is considered by many authors to be an important source of uncertainty identified in existing CV studies. Based on a survey of 1,600 U.S. households for Mexican Spotted Owl recovery, Loomis and Ekstrand (1998) reported a quadratic relationship between bid prices and payment certainty measured by a follow-up self-reported ten-point scale. This relationship implies that valuation uncertainty is lowest for very high and very low bids but increases when the intermediate-level bid is proposed. A similar quadratic relationship between bid prices and uncertainty was also revealed in Brouwer (2011), which presents a study on the valuation of water quality improvement in the Scheldt River basin using a self-reported percentage certainty scale. However, other studies have reported different patterns for the relationship between uncertainty and proposed bid price. For example, in a study on people's WTP for a whale conservation program, Lyssenko and Martínez-Espiñeira (2012) estimated an ordered logit model with the ten-point certainty scale as the dependent variable. They found a negative correlation only between bid price and uncertainty; more precisely, the higher the bid price is, the lower the response certainty is. A similar finding was also reported by Akter *et al.* (2009), who studied air travelers' WTP for carbon offsets with five options for verbal categories as an uncertainty measure.

Respondents' attitudes toward the good being valued are also often reported to be significantly correlated with uncertainty in valuation answers. The literature shows that respondents who are in favor of environmental protection programs (Champ and Bishop, 2001), those who believe that the environment should be protected irrespective of the costs and who have a greater sense of responsibility for contributing to mitigating climate change (Akter *et al.*, 2009) and those who have a positive attitude toward contributing to nature conservation actions (Voltaire *et al.*, 2013) are more inclined to provide more certain WTP responses. On the other hand, Samnaliev *et al.* (2006) found that respondents who object to user fees are also more certain of rejecting the proposed bid price. In a valuation study of coastal water quality improvement in Scotland, Hanley *et al.* (2009) reported that the more interesting an individual finds the interview, the greater their valuation uncertainty is.

The impacts of knowledge of or experiences with valued public goods are considered in many studies, and the findings are generally consistent. Prior knowledge was found to reduce uncertainty in Loomis and Ekstrand (1998), Hanley *et al.* (2009) and Voltaire *et al.* (2013). Champ and Bishop (2001) reported that respondents with more experience in donating money to environmental causes generally have lower levels of valuation

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uncertainty. Brouwer (2011) also found that familiarity with valuation scenarios reduces response uncertainty.

Although no consistent conclusions have been revealed, the discussion about the impacts of trust-related factors on valuation uncertainty should not be neglected. Brouwer (2011) found that people who do not believe in the reasonable utilization of funds and lack trust in the organization providing environmental goods tend to be more certain about their WTP for water quality improvement. In contrast, in Akter *et al.* (2009), respondents' belief in the effectiveness of the proposed program was found to reduce the uncertainty of WTP for carbon offsets.

Basic socioeconomic and demographic characteristics are also considered to be correlated with valuation uncertainty in CVM studies, although less consistent conclusions can be drawn. Brouwer (2011) and Voltaire *et al.* (2013) suggested that the higher the income level is, the more certain the respondents are about their WTPs, while higher household income seems to increase the level of valuation uncertainty according to Hanley *et al.* (2009). Gender and age are also identified as significant determinants of uncertainty. Lyssenko and Martínez-Espiñeira (2012) reported that males tend to be less certain about their WTP responses; however, opposite conclusions were found in Mahieu *et al.* (2012) and Brouwer (2011). In Brouwer (2011), younger people were found to be more certain, while in Mahieu *et al.* (2012) and Voltaire *et al.* (2013), older people were found to be more certain.

As presented above, although various determinants of uncertainty have been considered by researchers, there is not yet a clear consensus across studies; the same factor can be found to play quite different roles in different studies. We did not find any study that has analyzed the relative importance of these factors in uncertainty determination. Although it is impossible to develop a vector that includes all the factors considered in past studies, a comprehensive analysis of potential determinants of valuation uncertainty is needed for a better understanding of this issue. In this article, we propose to classify the major determinants of uncertainty identified in the CVM literature, except for some basic demographic characteristics (e.g., gender, age, education, income), into either the demand side or the perceived supply side. Determinants of uncertainty on the demand side can be defined as the factors that affect an individual's perception of the benefits that they can obtain from the valued good, e.g., previous visiting experiences at similar sites (Hanley *et al.*, 2009) and the general belief that natural resources should be protected (Akter *et al.*, 2009). In addition, as income is an important determinant of respondents' demand for the valued good in the CVM literature, we also consider future income uncertainty to be an important determinant of valuation uncertainty on the demand side.[1] On the supply side, uncertainty determinants mainly refer to whether an individual trusts the government to supply the proposed good or believes in the promised effects. In other words, supply-related uncertainty determinants describe, from the perspective of respondents, the extent to which a valued public good is provided at its promised level. In table 1 which cites the related literature, we provide detailed information on the two sides of uncertainty determinants, as well as basic demographic characteristics identified in the existing studies.

[1] Although bid prices are also identified as a determinant of uncertainty in several studies (e.g., Loomis and Ekstrand, 1998), as mentioned above, such prices will not be considered in this article since all respondents were presented with the same bid price ladder in our survey.

Table 1. Reclassification of uncertainty determinants identified in previous studies

	Determination factors
Demand side	
Attitudes	Being in favor of environmental protection program (Champ and Bishop, 2001), the belief that natural resources/environment should be protected (Akter *et al.*, 2009), attitude toward or the sense of responsibility for contributing to public programs (Samnaliev *et al.*, 2006; Akter *et al.*, 2009; Voltaire *et al.*, 2013), being interested in the interview (Hanley *et al.*, 2009)
Knowledge or experience	Prior knowledge of the valued good (Loomis and Ekstrand, 1998; Hanley *et al.*, 2009; Voltaire *et al.*, 2013), experience of donation to environmental causes (Champ and Bishop, 2001), familiarity with valuation scenario (Brouwer, 2011)
Income	Hanley *et al.*, 2009; Brouwer, 2011; Voltaire *et al.*, 2013
Bid price	Loomis and Ekstrand, 1998; Akter *et al.*, 2009; Brouwer, 2011; Lyssenko and Martínez-Espiñeira, 2012
Supply side	Mistrust of the government (Brouwer, 2011), belief in the provision of the good to be valued (Akter *et al.*, 2009)
Basic demographic characteristics	Gender (Brouwer, 2011; Lyssenko and Martínez-Espiñeira, 2012; Mahieu *et al.*, 2012), age (Brouwer, 2011; Mahieu *et al.*, 2012; Voltaire *et al.*, 2013)

3. Literature review on measurement of uncertainty

Analyzing the determinants of valuation uncertainty necessitates a discussion of the existing measurements of uncertainty. Previous studies can be classified into two major groups according to the valuation uncertainty measures adopted.

In the first group, after the WTP questions, respondents' uncertainty is measured by a follow-up question that most often employs a self-rated certainty scale asking how certain the respondents are about their WTP answers. Such a scale can either be numerical (the NCS method) or verbal polychotomous (the PC method). A ten-point scale (expressed as 1–10, with 1 indicating very uncertain and 10 indicating very certain) is most widely used when the NCS method is adopted (Loomis and Ekstrand, 1998; Champ and Bishop, 2001; Samnaliev *et al.*, 2006; Lyssenko and Martínez-Espiñeira, 2012). Similarly, a self-reported percentage certainty scale (0–100 per cent, with 0 per cent indicating very uncertain and 100 per cent indicating very certain) has also been adopted by some researchers (Brouwer, 2011). Other researchers have used verbal categories (e.g., extremely unlikely, fairly unlikely, not sure, fairly likely, extremely likely) as uncertainty measures (Akter *et al.*, 2009). We also find studies that have adopted graphical/visual illustrations for respondents' uncertainty levels, such as Corso *et al.* (2001) and Krupnick *et al.* (2002).

For both the NCS and PC methods, two fundamental conditions must hold so that uncertainty information can be effectively collected (Loomis and Ekstrand, 1998). The first condition requires respondents to be able to accurately assess their own degree of uncertainty (scored by a specific number) in their answers to the WTP questions. We, however, believe this could be a daunting task in itself, to which respondents may well introduce additional errors of their own. The second condition requires all respondents to interpret the scales equivalently. However, there might be heterogeneity in people's understanding of these scales – i.e., certain individuals tend to be systematically low or high raters (MacKenzie, 1993; Roe *et al.*, 1996) – and such incomparability of rating responses across individuals may add more noise than signals. Although some researchers believe that the PC method employing a verbal category (e.g., extremely likely or fairly likely) may lead to less heterogeneous bias, the findings of Hanley *et al.* (2009) revealed that these verbal categories could still be interpreted differently by different respondents.

Another concern related to the follow-up self-rated uncertainty scale is that the follow-up uncertainty question is most frequently used after some close-ended dichotomous choice WTP questions, for which a respondent receives one bid price that the surveyor randomly chooses from a list of prices. Under these circumstances, the reported uncertainty of a respondent is therefore directly related to the bid price that he or she faces. For example, a systematically higher level of response uncertainty can be expected when the proposed bid is closer to an individual's real WTP, while lower uncertainties may be obtained when bid prices are much higher or lower than his or her real WTP.

Instead of viewing the individual's WTP as a specific value, several researchers have suggested that the individual's WTP be characterized as a random variable with a particular distribution considering valuation uncertainty (Wang, 1997; Evans *et al.*, 2003; Vossler *et al.*, 2003; Wang and He, 2011) or an interval (Hanley *et al.*, 2009; Mahieu *et al.*, 2012; Voltaire *et al.*, 2013); thus, they have proposed deriving respondents' uncertainty directly from their given answers for each of the bid prices proposed in a bid price ladder/payment card. More precisely, Laplante *et al.* (2004), Wang *et al.* (2004) and Wang and He (2011) proposed the use of the MBDC or stochastic payment card (SPC) elicitation technique to invite people to reveal their payment certainty as a percentage for each of the proposed prices. The series of responses obtained from the MBDC matrix for the same person are subsequently used to separately estimate that person's individual WTP distribution. This process consists of estimating the value of the mean WTP and the variance in the WTP in a respondent-by-respondent manner, where the variance in the WTP measuring the width of the individual WTP distribution is considered by Wang and He (2011) to be an intrinsic measurement of uncertainty for this person. Relatedly, Hanley *et al.* (2009) and Mahieu *et al.* (2012) proposed using a two-way payment ladder to ask respondents to identify the bids that they are definitely willing to pay and the bids that they are definitely not willing to pay. By doing so, the intermediate bids that are left empty on the payment ladder can be used to measure respondents' uncertainty; thus, more bids left empty logically signifies a higher level of uncertainty. Voltaire *et al.* (2013) presented two identical price ladders to respondents and asked them to use one ladder to point out the highest price below which they would definitely pay and use the other to point out the lowest amount above which they would definitely not pay. If the amounts pointed out on the two ladders are the same, then the individual is considered to know with certainty his or her WTP; otherwise, the individual's uncertainty can be measured by the ratio of the interval formed by these two prices to the larger number of the two.

In our paper, we follow the second group of authors and consider individual WTP as a random variable where uncertainty can be measured by an interval of WTP. More precisely, in the present study, we adopt the approach of Wang and He (2011) to first reproduce their uncertainty measurement, i.e., the variance in WTP. In addition, we propose two uncertainty measurement transformations inspired by the discussions of Hanley *et al.* (2009) and Voltaire *et al.* (2013) for comparison and robustness checks of our results.

4. Survey and data

This paper is based on a survey that was conducted in 2014 through face-to-face interviews to evaluate people's WTP for air quality improvement in Xingtai city, Hebei Province, China. In Xingtai, air pollution was among the worst in the country, and most residents strongly complained about serious air pollution but also desired rapid economic development.

Prior to the formal survey, several focus group discussions were organized during which the project team consulted with various local community workers, government officers and local residents. Discussions were held focusing on people's perceptions and attitudes toward the current local economic and environmental situation and about new air quality improvement programs. The questionnaires were developed and finalized after several rounds of pretests within the communities.

The final version of the questionnaire included four parts. In the first part, multiple questions were asked about respondents' knowledge of the health impacts of air pollution and the current air pollution control measures, as well as their subjective perceptions about the effectiveness of existing policies about environmental issues in their city (e.g., whether a respondent is satisfied with these policies enacted by the government). Respondents were also asked whether they trust the government with regard to implementing air pollution control measures. These questions were carefully designed and asked; an individual's demand-related and perceived supply-related uncertainty determinant indicators were constructed based on the provided answers. The second part queried respondents about their degree of exposure to air pollution in their daily life (e.g., whether their windows are often open), illness experiences caused by air pollution (e.g., whether they have chronic respiratory or cardiovascular diseases) and personal measures taken against air pollution (e.g., whether they wear masks and have air filters installed at home). Questions about whether respondents pay attention to green labels when shopping and about their experiences related to taking part in environmental protection activities were also asked. We expected the responses in this part to provide some objective information explaining the subjective perception indicators elicited in the first part.

The third part of the questionnaire included the valuation scenario and WTP questions. The local air quality situation was first described, and respondents were then asked about their familiarity with that information. Then, a new air quality improvement program was presented, and the respondents were told that the program implementation needed to be assured by a municipal tax at the household level, which would be collected through monthly water bills over the course of three years (i.e., from 1 January 2015 to 31 December 2017). We adopted a 'cheap talk' strategy to remind respondents of their budgetary constraints and the nature of the referendum applied to the final decision. This scenario was followed by the MBDC questions on WTP. More details about the valuation scenario and the MBDC matrix are provided in online appendix A. The fourth part of our questionnaire asked about people's socioeconomic and demographic characteristics. Specifically, in addition to their family income in 2013, respondents were also asked whether they had a clear picture of any potential change in their family income for the coming year.

The MBDC format was adopted for the development of valuation uncertainty measurements, in which individuals were invited to choose the possibility of voting for the implementation of the new program at each of the 18 payment levels varying from zero yuan to 1,000 yuan/month. This MBDC format has been previously used by many

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researchers, such as Welsh and Poe (1998), Alberini *et al.* (2003), Kobayashi *et al.* (2012), Wang and He (2011, 2018) and Wang *et al.* (2015). The design of bid levels in our study was enlightened by previous studies conducted in China, such as Wang *et al.* (2015) and Wang and He (2018). To help reduce the cognitive burden as much as possible, inspired by Hanley *et al.* (2009), Mahieu *et al.* (2012) and Voltaire *et al.* (2013), in the interviews, we invited respondents to first consider the maximum amount below which they would definitely pay (the lower bound) and the minimum amount above which they would definitely not pay (the upper bound); then, they were instructed to make a choice from 'Probably yes', 'Not sure' and 'Probably not' for each of the bids situated between the lower and upper bounds.

To obtain relatively good geographical and socioeconomic representativeness, three districts in Xingtai city were first randomly selected; then, we selected a total of 28 communities from districts that roughly evenly covered the urban areas. One community worker from each selected community was trained to help conduct the survey by assisting with the distribution and collection of the questionnaires from the sampled households. A total of 700 questionnaires were evenly distributed among the selected communities. Households were randomly selected from each community based on the household list provided by the community office, from which vacant households were excluded beforehand. The heads of the selected households were invited to answer the questionnaire. In general, after the survey and valuation questions were introduced to the respondents, the questionnaires were left at the selected households for their response in their spare time. The community workers came two days later to collect the completed questionnaire. The neutrality and anonymity of all survey participants were ensured to the greatest extent possible. A total of 581 completed questionnaires were ultimately obtained. The questionnaires that were not included in the sample were either those not returned due to the absence of household members on the day of questionnaire collection or those for which the series of key questions were not completely answered.

5. The uncertainty measure, model and hypotheses

5.1 The uncertainty measures

Based on the WTP responses elicited by the MBDC matrix, we adopted the approach proposed by Wang and He (2011) to estimate individual *i*'s WTP mean, μ_i, and standard variance, σ_i. The standard variance is assumed to be an intrinsic measurement of individual *i*'s uncertainty about his or her own preferences. More details about the estimation of individual *i*'s WTP distribution are provided in online appendices B and C.

Considering the possibility that the variance could be positively correlated with the mean value of a WTP distribution, we decided to use the individual WTP standard variance divided by the individual mean WTP (i.e., σ_i/μ_i) as our main uncertainty measurement to eliminate the scale effect. The choice of this 'scaled' uncertainty measure was also motivated by our observations of the close correlation of uncertainty with respect to the proposed bid price in studies employing a dichotomous choice WTP question format with follow-up uncertainty scale questions. This scaled format of uncertainty has also been used in previous studies, such as Voltaire *et al.* (2013). For comparison, we also report our analysis based on the uncertainty measurement proposed by Wang and He (2011), i.e., σ_i, the standard variance of individual WTP. Following Hanley *et al.* (2009) and Voltaire *et al.* (2013), we also adopt two other measures, i.e., $\text{Ln}(U_i - L_i)$ and $\text{Ln}((U_i - L_i)/U_i)$, where L_i is the highest price below which individual *i* would definitely pay, and U_i is the lowest amount above which he or she would definitely not pay.

Compared to the self-reported NCS/PC scale, our uncertainty measurement is estimated on the reported probability for a respondent to accept each price of a same series of bids, therefore avoiding potential biases caused by presenting different bid prices for different individuals. This measurement is also different from that proposed by Hanley *et al.* (2009) and Voltaire *et al.* (2013) since, in addition to asking respondents to identify the highest bid below which they are definitely willing and the lowest bid above which they are definitely not willing to pay, we further propose three other levels of uncertainty inside the definitely willing and unwilling (i.e., Probably yes, Not sure and Probably not), with the purpose of better capturing the potential nuances in people's uncertainty levels for different bid prices.

5.2 Model and hypotheses

Next, we use the promised air quality improvement program as the main vehicle[2] to discuss how determinants of the demand and perceived supply sides affect an individual's valuation uncertainty for better air quality. Assume that an individual i's utility function at the status quo level E_0 can be written as

$$V_{i,0} = V\{\, H_i(E_0),\ Y_{i,0}, S_i\}, \tag{1}$$

where $H_i(E_0)$ is the health status related to current air quality E_0; S_i is a vector of stable socioeconomic and demographic variables, e.g., age, education and sex; and $Y_{i,0}$ is the current family income for respondent i. All the determinants are known at the current status; thus, there is no uncertainty for individual i's utility $V_{i,0}$.

With the proposed improvement in air quality from E_0 to E_1, all else being equal, the individual's utility becomes

$$V_{i,1} = V\{\varphi_i[H_i(E_1),\ Y_{i,1}],\ S_i\}. \tag{2}$$

Although most of the socioeconomic variables (e.g., gender, age) are stable, we should consider the potential variation in future income since the project will be realized at some time in the future. Here, we assume that individual i has intrinsic uncertainty about the valuation of the promised air quality improvement, mainly due to uncertainty about his or her future health situation $H(E_1)$ and about his or her expected future income $Y_{i,1}$, which are captured by the random term $\varphi_i[H_i(E_1), Y_{i,1}]$.

The individual's WTP for this improvement can therefore be written as

$$\mathrm{WTP}_i = \mathrm{WTP}\{\ H_i(E_0),\ Y_{i,0},\ \varphi_i[\ H_i(E_1),\ Y_{i,1}],\ \ S_i\ \}. \tag{3}$$

In equation (3), $H_i(E_0)$ and $Y_{i,0}$, which represent current health status and current income respectively, are frequently discussed determinants of individuals' WTP. The uncertainty term $\varphi_i[\ H_i(E_1),\ Y_{i,1}]$ captures the influence of the main uncertainty determinants on individual i's WTP distribution. More precisely, we expect that the greater the uncertainty term is, the greater the variance in the WTP distribution of individual i will be. Equation (3) also reminds us that if the uncertainty term $\varphi_i[\ H_i(E_1),\ Y_{i,1}]$ is

[2]Although the air quality improvement program is used as the basis for explanation in this study, the choice of the particular context should not alter the direction of the discussion about the anticipated signs of the coefficients.

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not included in the WTP function, then its omission can cause estimation bias related to endogeneity problems.

Following the discussion in section 2, the function of an individual's valuation uncertainty, determined by the encompassing term $\varphi_i[H_i(E_1), Y_{i,1}]$, can be then specified as

$$\text{WTP uncertainty} = f\{\varphi_i[H_i(E_1), Y_{i,1}]\} + \epsilon_i = f(D_i, PS_i, Oth_i) + \epsilon_i. \quad (4)$$

Equation (4) assumes that people's valuation uncertainty has three categories of determinants, i.e., demand-related determinants (D), perceived supply-related determinants (PS), and other determinants (Oth), including the generally considered sociodemographic variables in the literature and extended variables concerning people's environmental attitudes and health status. $\boldsymbol{\epsilon}_i$ represents the error term.

The demand-related determinants (D) are factors that affect people's perceived benefits from better air quality. The previous literature allows us to identify four variables for this category of determinants. They are respondents' knowledge about the current air quality (*sq*), their knowledge about the existing environmental regulation (*ctrlpol*), their knowledge about the potential adverse health impacts caused by air pollution (*health_impt*) and their uncertainty about future income change (*incomf_unc*). We believe that better knowledge about the first three aspects should allow individuals to have a better understanding of the potential benefits of better air quality. This is because air quality can be viewed as an 'Experience Good', i.e., a good about which consumers are uncertain about their preferences and learn about them with each consumption event (Nelson, 1970, 1974; Stigler and Becker, 1977). Such an event can be, for example, the experience of suffering from chronic respiratory disease caused by air pollution. As discussed in section 2, the literature already provides some empirical insights into the role of knowledge and experiences in reducing individuals' uncertainty in WTP (Champ and Bishop, 2001; Hanley *et al.*, 2009; Brouwer, 2011; Voltaire *et al.*, 2013). Moreover, Czajkowski *et al.* (2014) presented additional theoretical evidence for the impacts of people's experience on their more certain preferences for environmental public goods. Using a Bayesian framework, the authors developed a theoretically consistent random utility model that captures this effect by allowing the model's scale parameter to be a function of experience; they concluded that a subject's preference certainty should increase with increasing experience.

The demand for goods and services is also affected by the expectation of future income change (Mankiw, 2006). This is especially true in hypothetical situations where purchase decisions and payments occur at some moments in the future. In addition, air quality is considered a luxury good to some extent, implying that the demand for this service can be more sensitive to income change than the demand for necessities. Although the influence of income level on valuation uncertainty has been tested in previous studies (Hanley *et al.*, 2009; Brouwer, 2011; Voltaire *et al.*, 2013), to the best of our knowledge, the impacts of future income change have still been ignored. We assume that making purchase decisions can be more difficult for individuals whose future income changes present more uncertainty. Accordingly, a higher valuation uncertainty is expected with more uncertain income changes.[3]

[3] An anonymous reviewer suggested that one can buy social health insurance to mitigate the uncertainty in disposable income change in the future. While we totally agree, we also believe the future income uncertainty that we consider in our model should go beyond people's future health uncertainty. There are many other factors that can affect people's expected future income, such as social and macroeconomic conditions

Perceived supply-related determinants (*PS*) in this paper include two variables: respondents' satisfaction with the effectiveness of existing air pollution control measures (*ctrl_stsf_trust*) and their trust in the government to thoroughly implement the proposed air quality improvement projects (*ctrl_imple_trust*). Both factors can be interpreted as public trust in the supplier of the proposed public good. The distrust in public institutions has been found to contribute to lower-level support for environmental programs (Johnson and Scicchitano, 2000). The impacts of trust-related factors on response certainty have been previously studied, but the findings are not convergent. In a study with a PC format, Akter *et al.* (2009) concluded that respondents who believe in the effectiveness of carbon emission offsetting programs have greater levels of response certainty. However, in another study with an NCS design, Brouwer (2011) found that individuals who distrust the government are more certain in their WTP responses.

Finally, for the socioeconomic variables, for the purposes of comparison, we first include only the most frequently used ones, including gender, age, education level and household income; additionally, some health and attitudinal variables were added to the estimation in an extended model.

Following the approach of Wang and He (2011), we estimate the WTP mean and variance for each individual in the first stage as shown in online appendix B. Then, in the second step, we regress the uncertainty measured by the estimated variance of the individual WTP distribution and its transformations on the assumed determinants, as proposed in equation (4). This approach allows us to obtain a more intrinsic measurement of uncertainty in people's WTP in the first step and to avoid the potential bias in the measurement of uncertainty that can be caused by the correlation between WTP and its uncertainty, as many other one-step approaches based on cross-sectional databases involving all respondents may have.[4]

In table 2, we report the descriptive statistics of the variables involved in our uncertainty determination models. The initial questions in the survey are also presented in the table.

6. Impacts of potential uncertainty determinants

Next, we analyze how the uncertainty level in valuation is dependent on the potential determinants identified in the previous section. For the valuation uncertainty level, the logarithmic transformation $\mathrm{Ln}(\sigma_i/\mu_i)$ is adopted, which describes the percentage of

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and the perspective about future that each respondent may hold. For example, a lack of trust in the government can affect the WTP distribution (Wang *et al.*, 2020), which cannot be eliminated by buying insurance. Moreover, the current situation in China leads us to believe that the coverage of health insurance, and therefore its income-smoothing role, in China is relatively limited. Furthermore, it should be noted that serious inefficiency and inequality exist in China's social health insurance. Specifically, urban and rural residents are enrolled in separate programs, with the latter enjoying limited benefits (Meng *et al.*, 2015). The health insurance programs available in rural areas are administered at a low level (e.g., county), which greatly weakens the risk sharing and portability of health insurance (Huang and Wu, 2020).

[4]It is possible that the answers given by the same person in the MBDC matrix are correlated between themselves. This concern has already been raised by some previous studies using the MBDC matrix, such as Vossler and Poe (2005). The solution that Vossler and Poe (2005) proposed is to use a random effect probit estimation to take care of the potential correlation between answers provided by the same person. We believe that the approach developed by Wang and He (2011) shares a logic similar to that of Vossler and Poe (2005), i.e., to first estimate for each person the mean and variance of his or her individual WTP distribution, then using cross-section OLS estimation in a second step to study the determinants of the estimated valuation uncertainty.

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Table 2. Questions and statistics of uncertainty-related variables

	Questions and the codes	Mean (Std. dev.)
Uncertainty determinants on demand side		
Indicators of uncertain benefits		
sq	**To what extent do you know the situation of local air quality?**	
sq_know	Know a lot = 1; otherwise = 0	0.0305 (0.1722)
sq_dKmuch	Don't know much = 1; otherwise = 0	0.7793 (0.4152)
sq_knowno	Know nothing = 1; otherwise = 0	0.1901 (0.3929)
ctrlpol	**To what extent do you know local policies of air pollution control?**	
ctrlpol_know	Know a lot = 1; otherwise = 0	0.0751 (0.2639)
ctrlpol_dKmuch	Don't know much = 1; otherwise = 0	0.6432 (0.4796)
ctrlpol_knowno	Know nothing = 1; otherwise = 0	0.2817 (0.4504)
health_impt	**To what extent do you know the impacts of air pollution on health?**	
health_impt_know	Know a lot = 1; otherwise = 0	0.2653 (0.4420)
health_impt_dKmuch	Don't know much = 1; otherwise = 0	0.6502 (0.4775)
health_impt_knowno	Know nothing = 1; otherwise = 0	0.0845 (0.2785)
	Uncertain income change	
incomf_unc	Do you, generally, have a clear picture about the change of your family income in the following year? Know nothing = 1; Know something = 0	0.0822 (0.2749)
Uncertainty determinants on supply side		
Indicators of perceived supply quality		
ctrl_imple_trust	Do you, generally, believe the government would thoroughly implement air quality improvement policies? Believe = 1; otherwise = 0	0.6808 (0.4667)
ctrl_stsf_trust	Are you, generally, satisfied with current environmental regulation and protection measures established by your municipality? Satisfied = 1; otherwise = 0	0.4343 (0.4962)

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Table 2. *Continued.*

	Questions and the codes	Mean (Std. dev.)
Basic social-economic, demographic variables		
age	Years of age	44.1482 (11.4801)
gender	Male = 1; female = 0	0.6204 (0.4859)
university_above	Bachelor's degree or above = 1; otherwise = 0	0.3310 (0.4711)
child	Are there children under 15 years old in your family? Yes = 1; no = 0	0.8981 (0.3028)
lnincomf	Ln(family income) (10,000 Yuan/year)	1.4641 (0.6258)
Additional attitudinal and health related variables		
label	Do you pay attention to the green label when shopping? Never = 1; sometimes = 2; often = 3	1.7418 (0.6317)
activity	Have you ever taken part in environmental protection activities during the past half year? Have taken part in = 1; haven't = 0	0.5469 (0.4984)
ill_self	Have you suffered from chronic respiratory or cardiovascular diseases? Have = 1; haven't = 0	0.3568 (0.4796)
ill_fmly	Have your family suffered from chronic respiratory or cardiovascular diseases? Have = 1; haven't = 0	0.3333 (0.4720)

WTP variance with respect to the mean value of an individual's WTP.[5] For comparison, we also present the results with a simple $\mathrm{Ln}(\sigma_i)$, which is the initial uncertainty measure proposed by Wang and He (2011). The measurements $\mathrm{Ln}(U_i - L_i)$ and $\mathrm{Ln}((U_i - L_i)/U_i)$ developed by Hanley *et al.* (2009) and Voltaire *et al.* (2013) are also used in our analysis as robustness checks. After excluding potential protesters, the respondents who gave negative answers at the zero bid, positive answers at the highest bid, or missing or disordered answers, we retain 426 observations for the following analysis.[6]

[5]The uncertainty measure introduced in our paper and the coefficient of variation are expressed in a similar format, i.e., the ratio of the standard variance to the mean value. We thank an anonymous reviewer for reminding us of this similarity. However, the estimation and comparison of this ratio in our paper is at the individual level, while that for the coefficient of variation is conducted for two groups of observations.

[6]① Protesters are identified according to a filter question, which is asked after the new air quality improvement project is introduced but before the payment vehicles and the MBDC matrix are shown. The question is as follows: If this project were totally free, meaning that you do not need to pay anything for it, would you be willing to support this new project? (1) definitely yes, (2) probably yes, (3) not sure, (4) probably not, (5) definitely not. Respondents who answered either 'not sure', 'probably not' or 'definitely not' are defined as refusing the project based on this filter question. The real zero bids are then identified

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Table 3 first reports the OLS estimations of the determination of valuation uncertainty, with only the most conventional sociodemographic variables included in the first four columns (Models 1–4), and both the conventional and extended sociodemographic variables (i.e., some attitudinal and health-related variables) included in the 5th to 8th columns (Models 5–8). Our results show that most of the socioeconomic and demographic characteristics included in our estimations are significant. Male respondents are found to have a significantly higher level of valuation uncertainty than women. This result can be explained by psychological studies suggesting that females tend to adopt more inclusive or rational decision modes (Blais and Weber, 2001) and to process information in a more complex and systematic way than men (Weber *et al.*, 2000; Mahieu, 2010). These behavioral differences may lead to differences in uncertainty between males and females when assessing their WTP scenarios. We also find that older respondents have a significantly higher level of uncertainty. This can be explained by Ye *et al.* (2010), who assumed that older people may have less access to environmental protection publicity in China. The positive impacts of education on valuation uncertainty revealed in this study are inconsistent with the findings of several past studies, such as Fischer and Hanley (2007), who found that more educated respondents more easily choose the cognitively controlled decision-making styles, which can contribute to reducing their level of uncertainty. We find only that respondents with children under 15 years old in their family have a significantly lower uncertainty degree in the models with $\mathrm{Ln}((U_i - L_i)/U_i)$ as the uncertainty measure; the coefficients of this variable in the other models are not different from zero. Family income is found to significantly affect people's valuation uncertainty; however, the direction of its effect on uncertainty changes between models with different uncertainty measures. A positive impact is found when uncertainty is measured by $\mathrm{Ln}(\sigma_i/\mu_i)$, $\mathrm{Ln}(\sigma_i)$ or $\mathrm{Ln}(U_i - L_i)$, which is similar to the conclusions drawn in Hanley *et al.* (2009), while a negative impact is found with the uncertainty measure $\mathrm{Ln}((U_i - L_i)/U_i)$, which is consistent with the findings of Voltaire *et al.* (2013). The further inclusion of variables capturing people's attitudes toward environmental protection and two variables measuring people's health increases the explanatory power of our model (cf. R^2 values). Respondents declaring that they pay attention to green labels while shopping were found to have significantly higher valuation uncertainty. Having health problems themselves was found to reduce the level of valuation uncertainty (only significant for the measure $\mathrm{Ln}(\sigma_i/\mu_i)$), while having sick family members was found to increase the level of valuation uncertainty (only significant for $\mathrm{Ln}(\sigma_i/\mu_i)$ and $\mathrm{Ln}((U_i - L_i)/U_i)$).

Based on the estimations shown in table 3, we further add the demand-side and perceived supply-side determinants to our estimation. These new results are reported in table 4. Considering the potentially strong correlation between the demand-side and perceived supply-side determinants, which are all subjective-perception-based, we include the identified uncertainty determinants separately in six different estimations to avoid multilinearity. Therefore, the purpose of these estimations is to explore whether it is necessary to include these subjective-perception-based determinants in the uncertainty

from potential protesters by a follow-up question placed after the MBDC question, which asks the respondent why they do not want to pay a fee for the project. We identify a person as providing a real zero bid and keep them in the analysis only if he or she chooses one of the following four response options: 'I do not have enough money', 'The current air quality improvement project is good enough', 'The improvement proposed in the new project is not big enough', or 'The improvement of the air quality has few impacts on me'. ② Negative responses at zero bid are 'not sure, probably not, definitively not'. ③ Positive answers at the highest price (1,000 yuan per month) are 'definitively yes', 'probably yes' and 'not sure'.

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Table 3. Results of models with only sociodemographic variables

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
	Ln (σ_i/μ_i)	Ln(σ_i)	Ln $(U_i - L_i)$	Ln $((U_i - L_i)/U_i)$	Ln (σ_i/μ_i)	Ln(σ_i)	Ln $(U_i - L_i)$	Ln $((U_i - L_i)/U_i)$
Age	0.0120 (0.00512)	0.0171 (0.00951)	0.0107 (0.00755)	0.00328 (0.00132)	0.013 (0.005)	0.018 (0.009)	0.012 (0.007)	0.003 (0.001)
Male	0.285 (0.131)	0.427 (0.205)	0.349 (0.162)	0.119 (0.0369)	0.266 (0.128)	0.389 (0.210)	0.335 (0.170)	0.102 (0.036)
University_ above	0.421 (0.134)	0.968 (0.224)	0.711 (0.182)	0.109 (0.0359)	0.371 (0.131)	0.874 (0.224)	0.658 (0.184)	0.094 (0.035)
Child	−0.216 (0.151)	0.0411 (0.318)	0.127 (0.257)	−0.133 (0.0364)	−0.165 (0.149)	0.042 (0.318)	0.130 (0.261)	−0.116 (0.040)
Logincomf	0.127 (0.0819)	1.000 (0.146)	0.777 (0.127)	−0.0600 (0.0214)	0.141 (0.080)	1.017 (0.145)	0.789 (0.129)	−0.058 (0.021)
Label					0.492 (0.089)	0.715 (0.148)	0.442 (0.123)	0.129 (0.026)
Activity					−0.038 (0.116)	−0.012 (0.197)	−0.007 (0.162)	−0.038 (0.034)
Ill_self					−0.335 (0.118)	−0.335 (0.231)	−0.267 (0.194)	−0.039 (0.034)
Ill_fmly					0.333 (0.113)	0.124 (0.226)	0.074 (0.194)	0.107 (0.032)
Constant	−1.728 (0.302)	−0.879 (0.611)	1.340 (0.499)	−0.245 (0.0767)	−2.617 (0.368)	−2.067 (0.686)	0.600 (0.562)	−0.457 (0.103)
N	426	426	426	426	426	426	426	426
R^2	0.0477	0.1468	0.1342	0.0721	0.1195	0.1921	0.1627	0.1383

Note: Robust standard errors in parentheses.

determination function but not to confirm the exact impact of each specific determinant. To save space, in table 4, we report only the coefficients of the included demand-side or perceived supply-side determinants. The coefficients of the other conventional or extended socioeconomic variables are not reported, since their value and significance remain stable in most cases. The complete estimation results can be found in online appendix D.

A comparison of the coefficients obtained for the same demand-side or perceived supply-side variable across different models reveals in general good stability; the choice of uncertainty measures and the presence of conventional or extended socioeconomic variables do not affect the stability of the results. For the role of the determinants as demand-side factors, i.e., people's knowledge about the status quo of air quality (section 1), about air pollution control policies (section 2) and about the negative health impacts of air pollution (section 3), we use the respondents who answered 'know nothing' as the reference group. Our estimations suggest that people's knowledge is a very important factor affecting valuation uncertainty. The results in sections 1 and 3 of table 4 show that people who do not know much about the status quo level of air quality or about air pollution's health impacts have the highest level of uncertainty in most of our models,

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Table 4. Models with socioeconomic variables and uncertainty determinants

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
	$\text{Ln}(\sigma_i/\mu_i)$	$\text{Ln}(\sigma_i)$	$\text{Ln}(U_i - L_i)$	$\text{Ln}((U_i - L_i)/U_i)$	$\text{Ln}(\sigma_i/\mu_i)$	$\text{Ln}(\sigma_i)$	$\text{Ln}(U_i - L_i)$	$\text{Ln}((U_i - L_i)/U_i)$
Simple model with only socioeconomic variables (table 3)								
Socio-eco var	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.0477	0.1468	0.1342	0.0721	0.1195	0.1921	0.1627	0.1383
Demand-side determinants added								
1. People's knowledge about status quo of air quality								
sq_know[2]	0.846 (0.316)	1.277 (0.576)	0.806 (0.449)	0.302 (0.0942)	0.653 (0.318)	1.074 (0.603)	0.710 (0.474)	0.224 (0.095)
sq_DKmuch	1.114 (0.179)	1.087 (0.237)	0.614 (0.187)	0.348 (0.0590)	1.028 (0.175)	0.930 (0.252)	0.522 (0.203)	0.327 (0.056)
Socio-eco var	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.1636	0.1851	0.1536	0.2113	0.2108	0.2175	0.1755	0.2513
2. People's knowledge about existing air pollution control measures								
ctrl_know[3]	−0.0713 (0.229)	0.358 (0.455)	0.374 (0.385)	−0.0357 (0.0651)	−0.274 (0.232)	0.111 (0.458)	0.232 (0.386)	−0.086 (0.064)
ctrl_DKknow	0.358 (0.140)	0.880 (0.204)	0.637 (0.165)	0.0560 (0.0435)	0.242 (0.136)	0.749 (0.220)	0.569 (0.184)	0.027 (0.041)
Socio-eco var	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.0679	0.1802	0.1609	0.0798	0.1345	0.2163	0.1827	0.1451

Table 4. *Continued.*

	Model (1) $\mathrm{Ln}(\sigma_i/\mu_i)$	Model (2) $\mathrm{Ln}(\sigma_i)$	Model (3) $\mathrm{Ln}(U_i - L_i)$	Model (4) $\mathrm{Ln}((U_i - L_i)/U_i)$	Model (5) $\mathrm{Ln}(\sigma_i/\mu_i)$	Model (6) $\mathrm{Ln}(\sigma_i)$	Model (7) $\mathrm{Ln}(U_i - L_i)$	Model (8) $\mathrm{Ln}((U_i - L_i)/U_i)$
3. People's knowledge about the health impacts of air pollution								
health_impt_know[4]	0.813 (0.304)	1.071 (0.358)	0.771 (0.268)	0.314 (0.0982)	0.713 (0.298)	0.944 (0.373)	0.728 (0.293)	0.281 (0.097)
health_impt_DKmuch	0.982 (0.299)	1.117 (0.318)	0.755 (0.232)	0.326 (0.0974)	0.889 (0.288)	1.009 (0.332)	0.714 (0.254)	0.302 (0.095)
Socio-eco var	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.0939	0.1672	0.1492	0.1352	0.1545	0.2071	0.1748	0.1869
4. People's knowledge about their future income changes								
Income_unc[5]	−1.105 (0.213)	−0.714 (0.369)	−0.328 (0.287)	−0.365 (0.0591)	−1.028 (0.262)	−0.599 (0.378)	−0.261 (0.301)	−0.344 (0.088)
Socio-eco var	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.1053	0.1550	0.1368	0.1497	0.1676	0.1977	0.1643	0.2048
Perceived supply-side determinants added								
5. Trust in government to implement air quality policies								
ctrl_imple_trust[6]	0.394 (0.124)	0.705 (0.192)	0.546 (0.155)	0.0619 (0.0381)	0.213 (0.130)	0.493 (0.197)	0.427 (0.162)	0.006 (0.040)
Socio-eco var	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.0690	0.1700	0.1559	0.0786	0.1252	0.2026	0.1749	0.1384

Table 4. *Continued.*

	Model (1) $\text{Ln}(\sigma_i/\mu_i)$	Model (2) $\text{Ln}(\sigma_i)$	Model (3) $\text{Ln}(U_i - L_i)$	Model (4) $\text{Ln}((U_i - L_i)/U_i)$	Model (5) $\text{Ln}(\sigma_i/\mu_i)$	Model (6) $\text{Ln}(\sigma_i)$	Model (7) $\text{Ln}(U_i - L_i)$	Model (8) $\text{Ln}((U_i - L_i)/U_i)$
6. Satisfaction in current environmental regulation and protection measures								
ctrl_stsf_trust[7]	0.436 (0.121)	0.776 (0.199)	0.567 (0.160)	0.0777 (0.0333)	0.338 (0.119)	0.641 (0.208)	0.483 (0.169)	0.062 (0.032)
Socio-eco var	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.0771	0.1785	0.1607	0.0836	0.1359	0.2123	0.1805	0.1451

Notes: Robust standard errors in parentheses.
1. For presentation convenience, in this table, we only reported the coefficients and their robust standard errors of the separately included demand or perceived supply side uncertainty determinants. The complete estimation models always include the conventional socioeconomic variable (Models 1–4) and attitudinal and health related variables (Models 5–8). The corresponding complete estimation results can be found in online appendix D.
2. sq_know = 1: Respondents declaring 'know a lot' about the status quo of air quality, sq_DKmuch = 1: respondents declaring 'don't know much' about the status quo of air quality. The reference group is the respondents declaring 'know nothing' about the status quo of air quality.
3. ctrl_know = 1: Respondents declaring 'know a lot' about air pollution control policies, ctrl_DKmuch = 1: respondents declaring 'don't know much' about air pollution control policies. The reference group is the respondents declaring 'know nothing' about air pollution control policies.
4. health_impt_know = 1: Respondents declaring 'know a lot' about health impact of air pollution, health_impt_DKmuch = 1: respondents declaring 'don't know much' about health impact of air pollution. The reference group is the respondents declaring 'know nothing' about health impact of air pollution.
5. income_unc = 1: If the individuals know nothing about the change of their family income in the following year; = 0, otherwise.
6. ctrl_imple_trust = 1: If the individuals believe the government would thoroughly implement air quality improvement polices; = 0, otherwise.
ctrl_stsf_trust = 1: If the individuals are satisfied with current environmental regulation and protection measures established by the municipality; = 0, otherwise.

followed by those who 'know a lot'. Regarding knowledge about the existing control policies, as presented in section 2 of table 4, although individuals who do not know much also have the highest valuation uncertainty, there are no significant differences in the uncertainty level between people who declare that they 'know a lot' and those who declare that they 'know nothing'.

The identification of respondents who reported 'don't know much' as having higher levels of valuation uncertainty than those who reported 'know nothing', although somewhat unexpected, can be explained by the following logic: people can have an opinion about their potential uncertainty regarding an issue only when they know something about it. For those who declared that they know nothing, their low level of uncertainty could be related to their low level of interest in air quality-related issues. If this is the case, we should expect these respondents to have relatively lower individual mean WTP values. To test this hypothesis, in table 5, we report the means of μ_i for the three groups of respondents who declared different levels of knowledge. Although the student's t tests confirm the statistical significance of the difference between groups for two of the three aspects of knowledge, the group means of individual WTP μ_i values demonstrate quite similar patterns in differences between groups, with people who reported knowing nothing having the lowest values, followed by people who reported not knowing much and finally those knowing a lot. The co-presence of the similarly low value of uncertainty σ_i for the group that reported knowing nothing and the one that reported knowing a lot and their mean WTP μ_i values standing at two extreme ends signifies the necessity of interpreting the uncertainty measures with the true intention of the respondents to either support or not support the project. Logically, these higher certainty levels reported by people who know nothing should be interpreted as negative certainty about not supporting the project. This finding echoes, to some extent, that of Hanley *et al.* (2009), who showed that people with more interest but who are less informed tend to be more uncertain about their valuation than respondents with no interest.

Section 4 of table 4 reveals the role of future income change uncertainty, which is another potential demand-side determinant in valuation uncertainty determination. More specifically, compared to people who know something about their future income changes (*income_unc* = 0), those who declare that they know nothing (*income_unc* = 1) are reported to have a lower level of valuation uncertainty. The result remains significant in five of the eight estimations. A comparison of the mean WTP μ_i, variance σ_i and ratio σ_i/μ_i between the groups in table 5 reveals no significant differences between the groups. For those who indicated that they 'know something' about their future income changes, we also asked in the questionnaire about its potential trends, i.e., increases, decreases or remaining constant. The answers from the respondents show that the valuation uncertainties between people with predictions of increases, decreases and remaining constant are not significantly different but are all significantly larger than those of people who indicate that they 'know nothing' of their future income changes. More discussion about these results is provided in the next section.

For the supply-related determinants (cf. sections 5 and 6 of table 4), both trust in the governmental implementation of current environmental policies and the level of satisfaction with the results of the existing air pollution control measures are found to be positively correlated with the level of uncertainty in valuation.[7] This result echoes the findings reported in Brouwer (2011). One potential explanation is that people who do

[7]The result of Model (4) with $Ln((U_i - L_i)/U_i)$ as an uncertainty measure seems to be an exception, in which those trusting in implementation are found to be insignificantly different from the reference group.

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Table 5. Student's t test for comparison of individual mean WTP and variance between groups

	Demand-side determinants											Perceived supply-side determinants			
	Status quo of air quality			Existing pollution control policies			Health impacts of air pollution			Future income changes		Trust in government		Satisfied with existing environmental measures	
	Know nothing	Don't know much	Know a lot	Know nothing	Don't know much	Know a lot	Know nothing	Don't know much	Know a lot	Know nothing	Know	Not trust	Trust	Not satisfied	Satisfied
μ_i	39.180	52.196 (1.217)	73.261 (1.534)	37.211	54.684 (1.860)	62.705 (1.836)	29.008	47.471 (1.352)	64.261 (1.958)	69.400	48.660 (−1.369)	44.959	52.899 (−0.889)	46.558	55.322 (−1.043)
σ_i	26.066	59.577 (2.367)	54.526 (1.191)	32.145	61.700 (2.351)	57.385 (1.479)	18.948	52.047 (1.827)	66.375 (2.010)	55.279	52.851 (−0.121)	41.426	58.502 (−1.450)	46.781	61.219 (−1.303)
σ_i/μ_i	0.405	0.868 (2.458)	0.587 (1.232)	0.595	0.874 (1.634)	0.556 (−0.361)	0.543	0.846 (1.009)	0.663 (0.800)	0.431	0.802 (1.395)	0.572	0.865 (−1.875)	0.715	0.845 (−0.886)

Note: T-values in parentheses.

not believe in the promised implementation or who are unsatisfied with the existing policies are more certain of refusing to pay for air quality improvement. Evidence for this explanation can be found in Wang *et al.* (2020), who concluded that the persistence of disjuncture between governmental promises and actual performance in environmental governance has contributed to a decrease in the level of public trust and a decrease in people's WTP for new environmental regulation measures. The validity of this explanation is supported by table 5, which shows that the mean values of μ_i and σ_i for people who declared that they do not trust in governmental implementation or are unsatisfied with existing environmental measures are much smaller than those of their counterparts. However, the differences were not confirmed by student's t tests.

A comparison of the results reported in table 4 shows that including demand-side and supply-side determinants in most cases greatly exacerbates the explanatory power of the models of valuation uncertainty determination, thereby demonstrating the necessity of including them in the determination function of valuation uncertainty. Although the increase in the R^2 value seems to be sometimes greater in the models containing demand-side factors, this difference should be at least partially explained by the fact that the knowledge-related variables are captured by two dummies, while both supply-side factors are captured by only one dummy.

7. Characteristics of the respondents providing strong negative certainty

One of the common findings of table 4 is the significantly higher level of certainty found for respondents who declared that they 'know nothing' about benefit-related factors or their future income changes and those who do not trust or are not satisfied with the implementation of existing air pollution control measures.

To obtain a better understanding of these respondents, in table 6, we provide comparisons of the mean values of the extended list of sociodemographic characteristics between groups.

First, the differences in most of the conventional socioeconomic variables between groups are relatively less significant. We find significant group differences only for education and income. People who declare that they 'know nothing' about air quality-related knowledge are found to be significantly less educated than those who declare that they know at least something. Those who declare that they know nothing about their future income changes are also found to be less educated, and this finding is significant at the 90 per cent level. We also find that respondents who do not trust the implementation of existing air pollution control measures are also less educated than their counterparts; this outcome is also significant at the 90 per cent level. –

The extended socioeconomic variables – more precisely, the variables revealing people's attitudes toward the environment and their health conditions – seem to present more significant differences between groups. The respondents who reported knowing nothing about air pollution-related knowledge or about their future income changes, and who did not trust in or were not satisfied with the existing air quality improvement measures, are systematically found to be those who pay the least amount of attention to the green labels of goods and services that they purchase, those who participate the least in environmental protection activities, and those who systematically suffer less from health problems themselves and have the least level of concern about the health situation of their family members, all of which can be considered additional evidence about their relatively low level of interest.

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Table 6. Comparison of the sociodemographic variables between groups of respondents (student's *t* test)

	Demand-side determinants											Perceived supply-side determinants			
	Status quo of air quality			Existing pollution control policies			Health impacts of air pollution			Future income changes		Trust in government		Satisfied with existing environmental measures	
	Know nothing	Don't know much	Know a lot	Know nothing	Don't know much	Know a lot	Know nothing	Don't know much	Know a lot	Know nothing	Know	Not trust	Trust	Not satisfied	Satisfied
Age	45.185	44.039	43.308	45.483	43.920	42.25	45.778	43.816	44.770	44.086	44.248	44.713	44.010	44.046	44.481
		(−0.808)	(−0.626)		(−1.263)	(−1.409)		(−1.019)	(−0.436)		(0.08)		(0.588)		(−0.389)
Male	0.531	0.639	0.769	0.683	0.595	0.625	0.556	0.592	0.717	0.686	0.616	0.654	0.607	0.631	0.611
		(1.791)	(1.614)		(−1.668)	(−0.621)		(0.417)	(1.811)		(−0.809)		(0.942)		(0.412)
University_ above	0.148	0.364	0.538	0.308	0.299	0.656	0.194	0.307	0.425	0.200	0.340	0.272	0.355	0.353	0.297
		(3.791)	(3.416)		(−0.180)	(3.739)		(1.393)	(2.531)		(1.693)		(−1.704)		(1.206)
Child	0.938	0.886	0.923	0.867	0.905	0.938	0.889	0.910	0.867	0.829	0.903	0.890	0.9	0.888	0.908
		(−1.393)	(−0.206)		(1.137)	(1.099)		(0.405)	(−0.337)		(1.383)		(−0.325)		(−0.676)
lnincomf	1.393	1.469	1.789	1.406	1.470	1.638	1.472	1.481	1.421	1.603	1.452	1.409	1.490	1.520	1.391
		(0.987)	(2.386)		(0.917)	(2.089)		(0.087)	(−0.393)		(−1.361)		(−1.239)		(2.112)
Label	1.395	1.813	2.077	1.533	1.803	2	1.361	1.744	1.858	1.514	1.762	1.5	1.855	1.656	1.854
		(5.517)	(4.116)		(3.889)	(3.914)		(3.715)	(3.764)		(2.234)		(−5.600)		(−3.250)
Activity	0.407	0.587	0.385	0.342	0.631	0.594	0.222	0.603	0.513	0.314	0.568	0.522	0.559	0.465	0.654
		(2.943)	(−0.154)		(5.500)	(2.634)		(4.449)	(3.141)		(2.908)		(−0.706)		(−3.953)
Ill_self	0.210	0.377	0.769	0.342	0.365	0.344	0.083	0.339	0.487	0.229	0.368	0.331	0.369	0.407	0.292
		(2.852)	(4.526)		(0.443)	(0.022)		(3.165)	(4.591)		(1.654)		(−0.764)		(2.462)
Ill_fmly	0.235	0.340	0.769	0.308	0.347	0.313	0.083	0.350	0.372	0.2	0.345	0.257	0.369	0.349	0.314
		(1.834)	(4.181)		(0.742)	(0.045)		(3.275)	(3.384)		(1.749)		(−2.287)		(0.759)

Note: T-values in parentheses.

8. Discussion and conclusion

In this study, the potential determinants of valuation uncertainty on the demand side (including benefit-related factors and income change) and supply side are defined and analyzed. To do so, we use both the initial valuation uncertainty measure proposed by Wang and He (2011) and its transformation σ_i/μ_i, along with two other valuation uncertainty measures developed in previous studies for comparison and robustness checks. Empirical analyses based on a CVM survey of the value of air quality improvement in Xingtai city, China, are conducted to test the impacts of these potential determinants on people's valuation uncertainty.

In general, there is a good level of coherence in the identified roles for these uncertainty determinants in our models, and the choice of measurements does not affect our principal conclusion. For the determinants on the demand side, our results show that individuals who 'don't know much' about the status quo of air quality, about the existing control policies or about air pollution' health impacts have the highest uncertainty level in most of the models, followed by the group who declare that they 'know a lot' about these benefit-related factors; however, those people who declare that they know nothing tend to be the most certain in their valuation answers.

The generally observed higher R^2 values for models with either demand-side or perceived supply-side determinants of uncertainty indicate that more attention should be given to these determinants when analyzing valuation uncertainty in CVM studies. Our results reveal that respondents' air pollution-related knowledge, their anticipation of future income changes, their trust in government and their level of satisfaction with existing air quality-related policies are all significant determinants of valuation uncertainty.

Another finding of our empirical analysis is that contrary to expectations, a declaration of 'know nothing' about, 'don't trust' or 'not satisfied' with air quality-related issues and policies significantly reduces people's level of uncertainty about their WTP. A comparison between groups for mean WTP and for the extended list of socioeconomic characteristics seems to indicate that such a high level of certainty should be essentially related to a lower level of interest. Although one may believe that these respondents should have been identified by the series of questions for protest screening, our results show that simply asking people whether they would not support the project even at zero cost cannot efficiently identify those persons with a low level of interest since their lower level of interest does not mean that they do not have any interest in the project.

This comparison also reminds us that the determinants of uncertainty are relatively less strongly associated with conventional socioeconomic variables (e.g., age, gender, education, income) but more related to some less systematically inquired about factors in surveys, such as people's attitudes and health status. Our estimations also demonstrate that even if these extended socioeconomic factors are added to help explain people's level of uncertainty, they are not capable of replacing the explanatory role of the identified uncertainty determinants. In summary, asking more questions about people's knowledge, attitudes and opinions about related environmental issues is necessary when studying the determinants of people's valuation uncertainty.

Based on the MBDC WTP question matrix and the approach developed by Wang and He (2011), all four different measurements of individual-level respondent uncertainty, i.e., σ_i, σ_i/μ_i, $U_i - L_i$, and $(U_i - L_i)/U_i$, follow the assumption that an individual's WTP should be seen as a distribution instead of a single and exact number. Compared to the initially proposed measurement σ_i by Wang and He (2011), the transformation σ_i/μ_i

can avoid to a certain extent the dispersion of the uncertainty measurement caused by the scale effect related to the magnitude of μ_i. This transformation is also superior to the measures proposed by Hanley *et al.* (2009) and Voltaire *et al.* (2013), i.e., $U_i - L_i$ and $(U_i - L_i)/U_i$. This is because in the latter two measurements, the upper-bound U_i and the lower-bound L_i correspond to the bid price levels from which respondent i changes his or her uncertainty level. This makes these two measurements conditional on the choice of uncertainty level, e.g., Probably yes, Not sure or Probably not. The measurement σ_i/μ_i, however, is estimated directly from all the responses provided by individual i in the WTP MBDC matrix, which allows us to cover the whole range of his or her WTP distribution.

However, the approach of Wang and He (2011) does not allow us to distinguish positive certainty to support the project from negative certainty to not support it. Although using σ_i/μ_i helps scale negative certainty upward by the smaller average μ_i and positive certainty downward by the larger average μ_i (cf. the comparisons between groups for the ratio σ_i/μ_i shown in table 5) to a certain extent, such scaling cannot categorically distinguish positive from negative certainty.

In general, identifying determinants of valuation uncertainty is complicated since much of this uncertainty can be caused by subjective perceptions that are difficult to observe and measure. This complication may have resulted in the lack of studies on this particular issue. Our paper provides several examples of questions that researchers can ask in their future surveys, with the purpose of constructing proxies for these subjective perceptions that contribute to the formation of people's uncertainty. More research should be devoted to studying these determinants in different contexts and countries with other WTP elicitation methods. Future research should identify other potential determinants and collect related information through CVM surveys. Finally, we believe that exploring other intrinsic uncertainty measurements is necessary for a better understanding of the determination of respondents' uncertainty in CVM surveys.

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