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

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ONLINE APPENDIX

Appendix A. WTP scenario used in our survey

The WTP question in the survey concerns a municipal-level program that aims to improve air quality; it is called the New Blue Sky Project. Based on an existing project called the Blue Sky Project, this new project aims to reinforce the existing measures and propose new ones, with the following particular targets: controlling the total number of private automobile vehicles; controlling automobile vehicle emissions; increasing the coal washing ratio; mobilizing the use of clean energy; accelerating the conversion from coal to gas and from coal to electricity; upgrading the existing pollution control equipment; adding new higher efficiency equipment; and controlling the emissions from industrial and restoration sectors. Furthermore, construction emissions and dust on transportation networks should be controlled, the interior decoration of civil houses should be controlled, and the number of related potential pollution problems should be reduced.

The new project will bring about a series of significant environmental quality improvements, including the following:

		2017		2013
	Additional improvement brought about by the new project	**New project**	Current project	Status quo
Annual average of $PM_{2.5}$ concentration (ug/m^3)	**Reduce by 10 ug/m^3**	**110**	120	160
Premature deaths per year	**Reduce by 500 persons**	**2,000**	2,500	4,000
Number of outpatient cases due to air pollution per year	**Reduce by 10,000 persons**	**60,000**	70,000	100,000
Number of hospitalizations due to air pollution per year	**Reduce by 1,000 persons**	**4,000**	5,000	6,000
% of days with air quality higher than the Class-II level in a year	**Increase by 40 days**	**150 (40%)**	110 (30%)	38 (10%)

If you did not need to pay any cost for the improvements listed above, would you support the new project?

a) Absolutely yes b) Probably yes c) Not sure d) Probably not
e) Absolutely not

To implement the abovementioned 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 collecting a monthly municipal tax via the water bills of local households for 3 consecutive years (i.e., from 1 January 2015 to 31 December 2017). This fund would be collected and managed by the related governmental department. It would be solely used for the abovementioned new project, and the fund usage would be publicly reported to the local residents.

Now, suppose the residents such as you **had an opportunity** to vote for the implementation of this new air quality improvement project. If **most of the local people supported** this project, then **this project would be implemented; however,** every household would need to pay a certain fee. If the majority of the people were **against the project**, then the project **would not be implemented,** and the residents would not need to make additional payments. However, the air quality would not be further improved. The payment for the new project would also means that there would be less disposable income for other purposes.

Now, we would like to know the possibility that your household would support this project and make a certain payment each month. Please compare the amounts that you would be willing to pay with the bid prices in the following box and **choose the possibility of you paying each bid price.**

Reminder: There is no right or wrong response here; we only wish to know your honest response.

Table A1. The MBDC matrix

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

Appendix B. Estimation of individual's WTP

Suppose that an individual i's WTP for better air quality is V_i, which is a random variable with a cumulative distribution function $F(t)$. The mean value of V_i is assumed to be μ_i; thus, the WTP model can be expressed as

$$V_i = \mu_i + \varepsilon_i \tag{B1}$$

where ε_i is the random component of WTP with a mean of zero and standard variance of σ_i, which is assumed to be an intrinsic measurement of individual i's uncertainty about his or her own preferences. Theoretically, individuals have their own specific valuation distributions with various functional forms. However, in this study, we assume a normal distribution for $F(t)$ to simplify the estimation of our models, as seen in previous studies (Wang *et al.*, 2013, 2014, 2015, 2020; Suk *et al.*, 2014; He *et al.*, 2015; Wang and He, 2018; Magembe *et al.*, 2022). More information about how an individual with a normal distribution function would answer the MBDC valuation questions is provided in appendix C to help us better understand the models and the uncertainty measures presented in our study.

Given a bid value t_{ij}, the probability for individual i to give a "yes" response can be expressed as

$$\begin{aligned} P_{ij} &= Prob(V_i > t_{ij}) \\ &= 1 - F(t_{ij}) \end{aligned} \tag{B2}$$

Once the probability P_{ij} 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 for their numerical likelihood information as with the SPC approach, equation (B2) can be estimated for each individual. Following Wang and He (2011), the verbal likelihood coding strategy for our analysis is 0.9999999 for "Definitely yes", 0.75 for "Probably yes", 0.50 for "Not sure", 0.25 for "Probably not", and 0.0000001 for "Definitely not". The estimation model can be constructed as

$$P_{ij} = 1 - F(t_{ij}) + \lambda_i, \tag{B3}$$

where λ_i is the error term, with a mean of 0 and a standard variance of δ_i. Several reasons motivated the inclusion of λ_i in equation (B3). First, we suspect that people may have very different perceptions of the verbal probability levels proposed in our survey. Such personal-level differences in how to interpret probability levels are unobservable to researchers and should therefore be captured by an error term in our separate estimation at the individual level. Second, as mentioned in Wang and He (2011), the adoption of the specific normal distribution as a functional form for $F(\cdot)$ is a simplification assumption. This assumption also led to the necessity of retaining the error term λ_i. Considering the potential heterogeneity of individuals in their perceptions of verbal probabilities and valuation distributions, the variance in λ_i can be different for different individuals but is constant for the same individual i with his or her intrinsic valuation distribution. t_{ij} is the independent variable that corresponds to the bid price presented in the MBDC matrix. Furthermore, P_{ij} is the dependent variable, corresponding to the verbal likelihood of favoring the new program given by respondent i at price t_{ij} by using the MBDC format. Based on our coding strategy explained previously, P_{ij} takes values ranging between 0 and 1.[1]

With the normal distribution assumption for $F_i(\cdot)$, a mean μ_i and a standard variance σ_i, we have $F(t_{ij}) = \Phi(\frac{t_{ij}-\mu_i}{\sigma_i})$. Thus, equation (B3) becomes

$$P_{ij} = 1 - \Phi\left(\frac{t_{ij}-\mu_i}{\sigma_i}\right) + \lambda_i \tag{B4}$$

Furthermore, we assume that the error term λ_i has a normal distribution, with zero mean and standard variance δ. Then, we have

$$\frac{\lambda_i}{\delta} = \frac{P_{ij}-1+\Phi(\frac{t_{ij}-\mu_i}{\sigma_i})}{\delta} \sim \mathrm{N}(0,1). \tag{B5}$$

As our estimation is conducted at the individual level, δ has no influence on the estimation as long as it is a normal distribution (Wang and He, 2011).

The log likelihood function for individual i can be developed as

$$LogL_i = \sum_{j=1}^{J} log\, \phi\left(\frac{P_{ij}-1+\Phi\left(\frac{t_{ij}-\mu_i}{\sigma_i}\right)}{\delta}\right) \tag{B6}$$

Here, $\phi(\cdot)$ is a standard normal distribution probability density function. This approach is equivalent to a least squares nonlinear estimation. With the log-likelihood function (B6), μ_i and σ_i can be estimated for each individual i at the first stage. In the second stage, Wang and He (2011) proposed regressing μ_i and σ_i on some personal variables to analyze WTP

[1] Although we only propose 18 bid prices ranging from 0 to 1,000 yuan/month, our intention was to use these values to capture the whole range of the potential WTP values that a person can have in his or her WTP distribution. This strategy is similar to the proposition of various bid prices in a dichotomous close-ended contingent valuation questions, though each person randomly encounters only one of these bid prices. In our paper, a respondent provides his or her answer for each of the bid prices. An ideal way to make such assumptions more acceptable would be to provide the bid prices in a more intensive way and directly ask the individuals for their numerical likelihood information at each of the bids, as with the SPC elicitation technique (see Wang *et al.*, 2004 or Laplante *et al.*, 2004, for examples). But such MBDC would have taken too much time and may have led to fatigue and loss of interest in our respondents. Following Wang and He (2011), we considered both the probability levels measured by the five choice options and the bid price as continuous variables, with the probabilities ranging from 0 to 1 and the bid prices ranging from 0 to 1,000; thus we adopt OLS estimation.

distribution determinants.

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Appendix C. More information about Wang and He's (2011) approach

By considering each individual's WTP as a continuous random variable, V_i, which follows a particular distribution, Wang and He (2011) presented individual i's valuation probability density function f(V_i) with the mean value of E(V_i) and the variance of Var(V_i). They assumed that, theoretically, individuals have their own specific valuation probability distributions with various functional forms. Many post studies have adopted a normal distribution for simplicity in empirical analysis (Wang *et al*., 2013, 2014, 2015, 2020; Suk *et al*., 2014; He *et al*., 2015; Wang and He, 2018; Magembe *et al*., 2022).

Based on the valuation probability density function, for a given bid price t, there is a certain probability that individual i will say yes (in favor of the program). The likelihood responses to given bid prices are mainly determined by the situation of the bids compared to the individual's valuation distribution. In figure C1, the Areas I, II, III, IV and V correspond to the five levels of probability from DY (definitely yes) to DN (definitely not). The location and frontiers of these areas are known by the individual, probably based on his or her tastes, personality and attitude toward risk, etc.; however, they are unknown to researchers. In figure C1, for t=t1, the whole valuation distribution curve is located on the right side of the bid; thus, the probability of the individual accepting the bid is equal to 1, i.e., Pr(WTP>t)=1; the individual will therefore choose DY as their answer since the bid falls in Area I. At the other extreme end, for t=t5, Pr(WTP>t)=0; thus, the individual answers "definitely not" since the bid falls in Area V. In more general situations, when t=t2, Pr(WTP>t) is relatively large; thus, there is a high probability for the individual to support the program. Correspondingly, t2 falls in Area II, which means that the individual will choose the "Probably yes" response. When t=t4, Pr(WTP>t) is very small, as t4 falls in Area IV, which means that the individual will choose the "Probably not" answer. Finally, for bid t3, which is a price close to the mean value of WTP E(V_i), Pr(WTP>t) is close to 0.5. In this situation, it can be difficult for an individual to answer either "yes" or "no"; thus, he or she may give a "don't know" response (Area III).

Based on this figure, Wang and He (2011) assumed that, theoretically, with a valuation distribution in mind, an individual's likelihood responses to the MBDC valuation questions would change from "Definitely yes" to "Probably yes", to "Not sure", to "Probably not", then to "Definitely not", with an increase in bid prices.

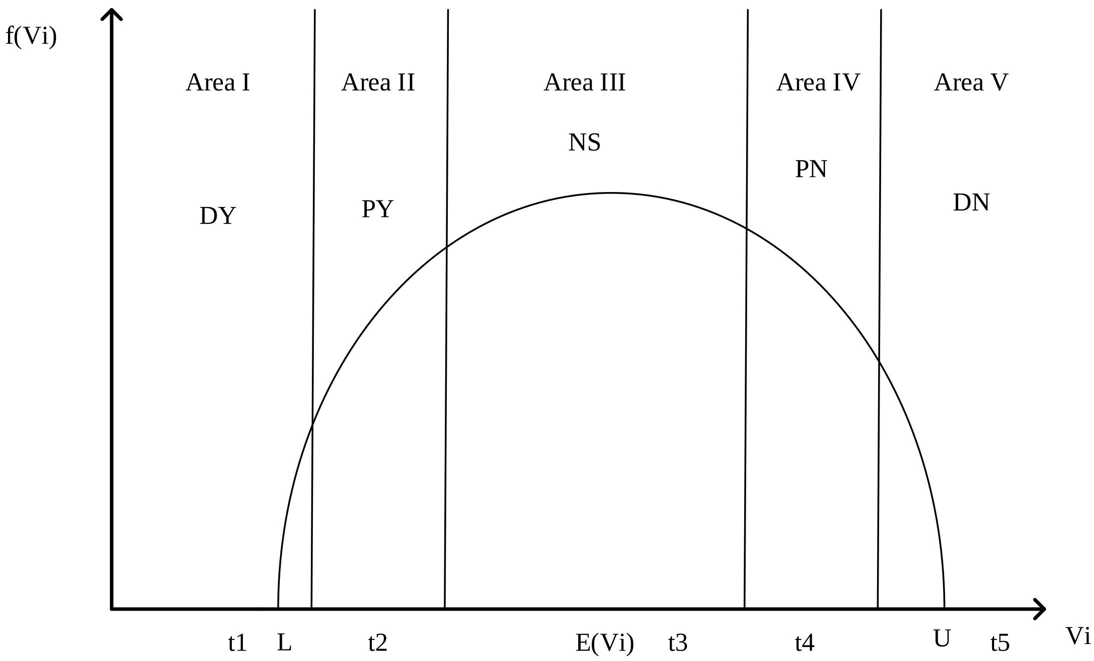

Figure C1. Individual's valuation distribution and likelihood responses.

The mean value of individual i's WTP is assumed to be μ_i, and the standard variance is σ_i. t_{ij} is the j^{th} bid price on the MBDC matrix. P_{ij} is the probability of individual i favoring the new program at bid t_{ij}, which is approximately revealed by the answers given by respondent i in the MBDC matrix. Following Wang and He (2011), we encode verbal likelihood as follows: 0.9999999 for "Definitely yes", 0.75 for "Probably yes", 0.50 for "Not sure", 0.25 for "Probably not", and 0.0000001 for "Definitely not".[2] Then, for individual i, each bid t_{ij} is accompanied by a numerical probability P_{ij}. We can therefore base this on the log likelihood function for individual i , which is presented in Eq. (6), to estimate the individual mean WTP μ_i and variance σ_i since we have 18 pairs of P_{ij} and t_{ij} for each individual i.

We believe that 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 evidenced by many other one-step approaches that are based on a whole database involving all respondents.

[2] Sensitivity analyses are conducted on the coding strategy by Wang and He (2011), who conclude that the differences in the results are insignificant as long as the coding strategies are symmetrical.

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Appendix D. Complete estimation results corresponding to table 4

Table D1. Impacts of benefits-related factors (status quo of air quality)

	Model (1) $\mathrm{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (2)** $\mathrm{Ln}(\sigma_i)$	**Model (3)** $Ln(U_i - L_i)$	**Model (4)** $Ln(\frac{U_i - L_i}{U_i})$	**Model (5)** $\mathrm{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (6)** $\mathrm{Ln}(\sigma_i)$	**Model (7)** $Ln(U_i - L_i)$	**Model (8)** $Ln(\frac{U_i - L_i}{U_i})$
sq_know	0.846	1.277	0.806	0.302	0.653	1.074	0.710	0.224
	(0.316)	(0.576)	(0.449)	(0.0942)	(0.318)	(0.603)	(0.474)	(0.095)
sq_DKmuch	1.114	1.087	0.614	0.348	1.028	0.930	0.522	0.327
	(0.179)	(0.237)	(0.187)	(0.0590)	(0.175)	(0.252)	(0.203)	(0.056)
age	0.0113	0.0162	0.0102	0.0030	0.012	0.018	0.011	0.003
	(0.0052)	(0.0095)	(0.0075)	(0.0014)	(0.005)	(0.009)	(0.007)	(0.001)
male	0.209	0.344	0.301	0.0949	0.205	0.329	0.300	0.082
	(0.120)	(0.203)	(0.163)	(0.0328)	(0.122)	(0.210)	(0.172)	(0.033)
university_above	0.254	0.794	0.610	0.0561	0.252	0.756	0.589	0.055
	(0.126)	(0.224)	(0.183)	(0.0316)	(0.126)	(0.224)	(0.185)	(0.032)
child	-0.119	0.130	0.176	-0.103	-0.053	0.134	0.180	-0.081
	(0.152)	(0.318)	(0.256)	(0.0379)	(0.150)	(0.321)	(0.262)	(0.040)
logincomf	0.116	0.978	0.763	-0.0642	0.131	0.997	0.774	-0.061
	(0.0872)	(0.149)	(0.129)	(0.0231)	(0.086)	(0.148)	(0.130)	(0.023)
label					0.363	0.588	0.369	0.088
					(0.089)	(0.157)	(0.131)	(0.024)
Activity					-0.149	-0.104	-0.056	-0.073
					(0.106)	(0.195)	(0.163)	(0.031)
ill_self					-0.407	-0.411	-0.313	-0.062
					(0.121)	(0.235)	(0.197)	(0.033)
ill_fmly					0.312	0.083	0.045	0.099
					(0.117)	(0.233)	(0.200)	(0.032)
constant	-2.559	-1.668	0.899	-0.503	-3.093	-2.458	0.389	-0.607
	(0.349)	(0.617)	(0.507)	(0.0977)	(0.390)	(0.678)	(0.556)	(0.112)
N	426	426	426	426	426	426	426	426
R^2	0.1636	0.1851	0.1536	0.2113	0.2108	0.2175	0.1755	0.2513

Notes: Robust standard errors in parentheses. This is the same in the following tables. 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.

Table D2. Impacts of benefits-related factors (air pollution control policies)

	Model (1) $\mathrm{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (2)** $\mathrm{Ln}(\sigma_i)$	**Model (3)** $Ln(U_i - L_i)$	**Model (4)** $Ln(\frac{U_i - L_i}{U_i})$	**Model (5)** $\mathrm{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (6)** $\mathrm{Ln}(\sigma_i)$	**Model (7)** $Ln(U_i - L_i)$	**Model (8)** $Ln(\frac{U_i - L_i}{U_i})$
ctrl_know	-0.0713	0.358	0.374	-0.0357	-0.274	0.111	0.232	-0.086
	(0.229)	(0.455)	(0.385)	(0.0651)	(0.232)	(0.458)	(0.386)	(0.064)
ctrl_DKmuch	0.358	0.880	0.637	0.0560	0.242	0.749	0.569	0.027
	(0.140)	(0.204)	(0.165)	(0.0435)	(0.136)	(0.220)	(0.184)	(0.041)
age	0.0131	0.0193	0.0122	0.0035	0.013	0.020	0.013	0.003
	(0.0052)	(0.00946)	(0.0075)	(0.0013)	(0.005)	(0.009)	(0.007)	(0.001)
male	0.308	0.485	0.391	0.123	0.276	0.422	0.361	0.102
	(0.130)	(0.204)	(0.162)	(0.0373)	(0.128)	(0.210)	(0.171)	(0.036)
university_above	0.469	1.027	0.740	0.120	0.433	0.963	0.709	0.107
	(0.133)	(0.217)	(0.180)	(0.0359)	(0.129)	(0.219)	(0.183)	(0.035)
child	-0.237	-0.0307	0.0701	-0.135	-0.164	0.006	0.097	-0.114
	(0.157)	(0.308)	(0.247)	(0.0386)	(0.154)	(0.315)	(0.256)	(0.041)
logincomf	0.122	0.978	0.758	-0.0601	0.142	0.999	0.771	-0.056
	(0.0826)	(0.146)	(0.128)	(0.0216)	(0.080)	(0.146)	(0.130)	(0.021)
label					0.482	0.645	0.383	0.130
					(0.092)	(0.152)	(0.127)	(0.027)
activity					-0.086	-0.162	-0.120	-0.044
					(0.112)	(0.204)	(0.172)	(0.032)
ill_self					-0.347	-0.350	-0.276	-0.041
					(0.120)	(0.231)	(0.195)	(0.034)
ill_fmly					0.326	0.095	0.050	0.107
					(0.113)	(0.228)	(0.197)	(0.032)
constant	-2.005	-1.528	0.876	-0.289	-2.759	-2.388	0.375	-0.480
	(0.312)	(0.610)	(0.503)	(0.0824)	(0.367)	(0.669)	(0.551)	(0.104)
N	426	426	426	426	426	426	426	426
R^2	0.0679	0.1802	0.1609	0.0798	0.1345	0.2163	0.1827	0.1451

Notes: 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.

Table D3. Impacts of benefits-related factors (health impacts)

	Model (1) $\text{Ln}(\frac{\sigma_i}{\mu_i})$	Model (2) $\text{Ln}(\sigma_i)$	Model (3) $Ln(U_i - L_i)$	Model (4) $Ln(\frac{U_i - L_i}{U_i})$	Model (5) $\text{Ln}(\frac{\sigma_i}{\mu_i})$	Model (6) $\text{Ln}(\sigma_i)$	Model (7) $Ln(U_i - L_i)$	Model (8) $Ln(\frac{U_i - L_i}{U_i})$
health_impt_know	0.813	1.071	0.771	0.314	0.713	0.944	0.728	0.281
	(0.304)	(0.358)	(0.268)	(0.0982)	(0.298)	(0.373)	(0.293)	(0.097)
health_impt_ DKmuch	0.982	1.117	0.755	0.326	0.889	1.009	0.714	0.302
	(0.299)	(0.318)	(0.232)	(0.0974)	(0.288)	(0.332)	(0.254)	(0.095)
age	0.0129	0.0177	0.0110	0.0035	0.013	0.019	0.012	0.003
	(0.0052)	(0.0095)	(0.0076)	(0.0013)	(0.005)	(0.009)	(0.007)	(0.001)
male	0.278	0.405	0.330	0.113	0.253	0.366	0.315	0.095
	(0.126)	(0.205)	(0.163)	(0.0352)	(0.124)	(0.209)	(0.170)	(0.034)
university_above	0.397	0.920	0.672	0.0951	0.364	0.850	0.633	0.0865
	(0.131)	(0.227)	(0.186)	(0.0342)	(0.129)	(0.226)	(0.187)	(0.033)
child	-0.237	0.0313	0.125	-0.136	-0.183	0.038	0.135	-0.118
	(0.154)	(0.314)	(0.252)	(0.0392)	(0.149)	(0.314)	(0.257)	(0.041)
logincomf	0.127	1.007	0.783	-0.0580	0.137	1.020	0.793	-0.057
	(0.0821)	(0.145)	(0.127)	(0.0210)	(0.081)	(0.145)	(0.130)	(0.021)
label					0.452	0.661	0.401	0.113
					(0.087)	(0.149)	(0.125)	(0.026)
activity					-0.141	-0.126	-0.086	-0.072
					(0.107)	(0.202)	(0.170)	(0.031)
ill_self					-0.362	-0.386	-0.313	-0.054
					(0.116)	(0.231)	(0.195)	(0.033)
ill_fmly					0.263	0.052	0.026	0.085
					(0.113)	(0.229)	(0.196)	(0.031)
constant	-2.590	-1.889	0.648	-0.540	-3.221	-2.774	0.089	-0.668
	(0.401)	(0.634)	(0.509)	(0.118)	(0.444)	(0.690)	(0.552)	(0.129)
N	426	426	426	426	426	426	426	426
R^2	0.0939	0.1672	0.1492	0.1352	0.1545	0.2071	0.1748	0.1869

Notes: 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.

Table D4. Impacts of uncertain income change

	Model (1) $\mathrm{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (2)** $\mathrm{Ln}(\sigma_i)$	**Model (3)** $Ln(U_i - L_i)$	**Model (4)** $Ln(\frac{U_i - L_i}{U_i})$	**Model (5)** $\mathrm{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (6)** $\mathrm{Ln}(\sigma_i)$	**Model (7)** $Ln(U_i - L_i)$	**Model (8)** $Ln(\frac{U_i - L_i}{U_i})$
Income_unc	-1.105	-0.714	-0.328	-0.365	-1.028	-0.599	-0.261	-0.344
	(0.213)	(0.369)	(0.287)	(0.0591)	(0.262)	(0.378)	(0.301)	(0.088)
age	0.0110	0.0164	0.0104	0.0030	0.012	0.018	0.012	0.003
	(0.0055)	(0.0096)	(0.0073)	(0.0015)	(0.005)	(0.009)	(0.007)	(0.001)
male	0.319	0.448	0.359	0.130	0.292	0.404	0.342	0.110
	(0.121)	(0.204)	(0.162)	(0.0335)	(0.123)	(0.208)	(0.170)	(0.034)
university_above	0.349	0.922	0.690	0.0857	0.314	0.841	0.643	0.074
	(0.134)	(0.222)	(0.180)	(0.0372)	(0.129)	(0.222)	(0.184)	(0.034)
child	-0.277	0.0020	0.109	-0.153	-0.218	0.0113	0.117	-0.134
	(0.192)	(0.321)	(0.258)	(0.0533)	(0.163)	(0.321)	(0.261)	(0.045)
logincomf	0.164	1.024	0.788	-0.0475	0.174	1.037	0.797	-0.047
	(0.0953)	(0.146)	(0.128)	(0.0265)	(0.079)	(0.145)	(0.129)	(0.021)
label					0.459	0.696	0.434	0.118
					(0.086)	(0.147)	(0.123)	(0.025)
Activity					-0.109	-0.054	-0.025	-0.062
					(0.111)	(0.202)	(0.167)	(0.032)
ill_self					-0.356	-0.347	-0.273	-0.046
					(0.117)	(0.231)	(0.195)	(0.033)
ill_fmly					0.286	0.0967	0.062	0.091
					(0.114)	(0.228)	(0.195)	(0.031)
constant	-1.593	-0.792	1.380	-0.200	-2.364	-1.920	0.664	-0.372
	(0.362)	(0.620)	(0.488)	(0.101)	(0.386)	(0.694)	(0.565)	(0.108)
N	426	426	426	426	426	426	426	426
R^2	0.1053	0.1550	0.1368	0.1497	0.1676	0.1977	0.1643	0.2048

Note: income_unc=1 if the individuals know nothing about the change of their family income in the following year; =0, otherwise.

Table D5. Impacts of supply-related factors: trust in implementation

	Model (1) $\text{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (2)** $\text{Ln}(\sigma_i)$	**Model (3)** $Ln(U_i - L_i)$	**Model (4)** $Ln(\frac{U_i - L_i}{U_i})$	**Model (5)** $\text{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (6)** $\text{Ln}(\sigma_i)$	**Model (7)** $Ln(U_i - L_i)$	**Model (8)** $Ln(\frac{U_i - L_i}{U_i})$
ctrl_imple_trust	0.394	0.705	0.546	0.0619	0.213	0.493	0.427	0.006
	(0.124)	(0.192)	(0.155)	(0.0381)	(0.130)	(0.197)	(0.162)	(0.040)
age	0.0118	0.0168	0.0105	0.0033	0.013	0.018	0.012	0.002
	(0.0051)	(0.0094)	(0.0075)	(0.0013)	(0.005)	(0.009)	(0.007)	(0.001)
male	0.302	0.458	0.373	0.122	0.280	0.420	0.362	0.102
	(0.129)	(0.202)	(0.161)	(0.0370)	(0.128)	(0.210)	(0.171)	(0.036)
university_above	0.390	0.913	0.668	0.105	0.360	0.848	0.635	0.093
	(0.134)	(0.222)	(0.180)	(0.0359)	(0.131)	(0.223)	(0.183)	(0.035)
child	-0.230	0.0158	0.107	-0.135	-0.176	0.0167	0.108	-0.117
	(0.155)	(0.316)	(0.255)	(0.0378)	(0.150)	(0.317)	(0.260)	(0.040)
logincomf	0.113	0.976	0.758	-0.0621	0.133	0.998	0.772	-0.058
	(0.0827)	(0.149)	(0.129)	(0.0216)	(0.080)	(0.147)	(0.130)	(0.021)
Label					0.451	0.619	0.360	0.128
					(0.093)	(0.149)	(0.127)	(0.028)
activity					-0.035	-0.006	-0.001	-0.038
					(0.116)	(0.196)	(0.161)	(0.034)
ill_self					-0.324	-0.308	-0.244	-0.038
					(0.117)	(0.230)	(0.194)	(0.034)
ill_fmly					0.304	0.058	0.016	0.106
					(0.113)	(0.227)	(0.194)	(0.032)
constant	-1.957	-1.289	1.023	-0.281	-2.667	-2.183	0.499	-0.458
	(0.316)	(0.634)	(0.519)	(0.0832)	(0.372)	(0.698)	(0.571)	(0.103)
N	426	426	426	426	426	426	426	426
R^2	0.0690	0.1700	0.1559	0.0786	0.1252	0.2026	0.1749	0.1384

Note: ctrl_imple_trust=1 if the individuals believe the government would thoroughly implement air quality improvement polices; =0, otherwise.

Table D6. Impacts of supply-related factors: satisfaction with the control measures

	Model (1) $\mathrm{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (2)** $\mathrm{Ln}(\sigma_i)$	**Model (3)** $Ln(U_i - L_i)$	**Model (4)** $Ln(\frac{U_i - L_i}{U_i})$	**Model (5)** $\mathrm{Ln}(\frac{\sigma_i}{\mu_i})$	**Model (6)** $\mathrm{Ln}(\sigma_i)$	**Model (7)** $Ln(U_i - L_i)$	**Model (8)** $Ln(\frac{U_i - L_i}{U_i})$
ctrl_stsf_trust	0.436	0.776	0.567	0.0777	0.338	0.641	0.483	0.062
	(0.121)	(0.199)	(0.160)	(0.0333)	(0.119)	(0.208)	(0.169)	(0.032)
age	0.0122	0.0173	0.0109	0.0033	0.012	0.018	0.011	0.003
	(0.0051)	(0.0094)	(0.0075)	(0.0013)	(0.005)	(0.009)	(0.007)	(0.001)
male	0.297	0.448	0.365	0.121	0.262	0.382	0.329	0.101
	(0.130)	(0.203)	(0.161)	(0.0369)	(0.127)	(0.208)	(0.170)	(0.036)
university_above	0.441	1.004	0.737	0.113	0.391	0.911	0.685	0.097
	(0.133)	(0.221)	(0.180)	(0.0363)	(0.131)	(0.223)	(0.183)	(0.035)
child	-0.232	0.0126	0.106	-0.136	-0.175	0.023	0.116	-0.118
	(0.157)	(0.317)	(0.255)	(0.0388)	(0.155)	(0.321)	(0.262)	(0.042)
logincomf	0.159	1.058	0.819	-0.0541	0.163	1.060	0.821	-0.054
	(0.0838)	(0.150)	(0.132)	(0.0216)	(0.082)	(0.149)	(0.133)	(0.021)
Label					0.453	0.640	0.386	0.122
					(0.087)	(0.148)	(0.124)	(0.026)
activity					-0.095	-0.120	-0.088	-0.049
					(0.113)	(0.199)	(0.165)	(0.034)
ill_self					-0.283	-0.235	-0.192	-0.029
					(0.122)	(0.230)	(0.194)	(0.035)
ill_fmly					0.316	0.091	0.049	0.104
					(0.112)	(0.223)	(0.194)	(0.032)
constant	-1.972	-1.313	1.023	-0.288	-2.686	-2.199	0.501	-0.470
	(0.318)	(0.643)	(0.525)	(0.0828)	(0.379)	(0.704)	(0.577)	(0.106)
N	426	426	426	426	426	426	426	426
R^2	0.0771	0.1785	0.1607	0.0836	0.1359	0.2123	0.1805	0.1451

Note: ctrl_stsf_trust=1 if the individuals are satisfied with current environmental regulation and protection measures established by the municipality; =0, otherwise.