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Exploring the change in the heterogeneity of public preferences for air quality improvement policies before and after the COVID-19 pandemic: comparative results from latent class model analysis

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Abstract

In addition to the deadly effects of the COVID-19 pandemic, positive changes have been made in air quality. It is important for decision-makers to know whether people's preferences change as the environment changes. This study tests the stability of public's preferences and willingness to pay (WTP) for air quality improvement before and after the COVID-19 pandemic, using a choice experiment. To explore the determinants of the public's preference heterogeneity for air quality improvement, we introduced the risk perception psychological factor and further compared the public's preference heterogeneity before and after the COVID-19 pandemic based on a latent class model. The results suggest that the characteristics of respondents' preference categories are similar in the face of a public health crisis and an uncertain future, and the heterogeneous preference of respondents for air quality improvement before the COVID-19 pandemic (2019) and after the COVID-19 pandemic (2021) which can be described in terms of three classes: "sensation preferable," "health preferable," and "price sensitive." However, the sources of influencing preference heterogeneity before and after the COVID-19 pandemic are different, which are reflected in risk perception and socio-economic characteristic variables. After the COVID-19 pandemic, females with stronger perceived risk effects and lower acceptability of air pollution will pay more attention to the health attributes of air quality improvements. The results also reveal that respondents show different WTP for air quality improvement attributes, with respondents before the COVID-19 pandemic showing higher WTP than those after. The contribution of this study is to provide theoretical insights to explore the effects of stability of public preferences in the context of public health emergencies, and to provide valuable guidance for policy makers to formulate governance measures in line with public demands.

Keywords Preference heterogeneity · Risk perception · Willingness to pay · Latent class model · COVID-19 pandemic

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1 Introduction

Due to the COVID-19 pandemic, stringent control measures were implemented globally in 2019 end (Mahato & Pal, 2022). To contain and delay the spread of the COVID-19 pandemic, various countries have taken several measures, such as canceling large public events, travel restrictions, social distancing and mandatory face masks in public places. These measures have been effective in slowing the spread of the virus among people and in controlling pollution and emissions from human activities. The data of China Statistical Yearbook from 2019 to 2021, the concentration of $PM_{2.5}$, PM_{10} and other air pollutants decreased year by year (Zeng & Bao, 2021), with the average concentration decreasing by 20% and 10%, which showed significant changes in air quality compared with before the COVID-19 pandemic (Mostafa et al., 2021). More stringent curfews have been imposed in Thailand in response to the COVID-19 pandemic, nitrogen dioxide level in 2020 declined by 9.1% and 9.8% for the whole of Thailand and Bangkok metropolitan area (Oo et al., 2021). During the COVID-19 pandemic, a nationwide lockdown was imposed in India, pollution levels in cities dropped sharply and air quality improved markedly. Concentrations of PM_{10} and $PM_{2.5}$ have witnessed a maximum reduction ($>50\%$) in comparison with the pre-lockdown phase (i.e., 2019) and the reduction about 60% and 39% (Mahato et al., 2020). The lockdown was considered an effective measure to control air pollution. It can reduce health risks from epidemics and improve air quality. The change in air quality before and after the COVID-19 lockdown has made people realize that air pollution has a large negative impact on daily life (Bang & Khadakkar, 2020), it will prompt a rethinking of past attitudes and perceptions toward improving air quality.

Recent studies have proved that individual preferences are temporally stable (De Andrés Calle et al., 2020; Hynes et al., 2021a). Wunsch et al. (2022) tested the reliability of individual preferences and welfare estimates of coastal climate change over the course of the COVID-19 pandemic and found that preferences were stable in the context of the COVID-19 pandemic. Hynes et al. (2021b) found that both preferences and WTP remained relatively stable in the face of major public health crises and economic turmoil. Sereenonchai et al. (2020) indicated that increased WTP for self-protection of urban respondents result from severe haze experience. Another research on preference stability has focused on the extent to which individuals respond differently to choice tasks within the same set of tasks. Hoeffler and Ariely (1999) investigated the impact of several dimensions of experience (effort, choice, and experience) on preference stability. The results reveal that the type of experience and its corresponding effort have a large impact on the process of preference development. Duersch et al. (2017) analyzed the stability of preferences experimentally, by repeatedly eliciting ambiguous attitudes toward multiple 3-color Ellsberg urns over a period of two months. Schaafsma et al. (2014) tests the temporal stability of stated preferences and willingness to pay values from a choice experiment in a test–retest. The results show that the estimated preference and scale parameters are different, indicating that the choice has changed between the two surveys. Few studies explore the stability of preferences for air quality improvement, especially the change in public preferences and willingness to pay for air quality improvement in the context of a major crisis. This study attempts to fill this gap and explore changes in public preference and willingness to pay for air quality improvement before and after the COVID-19 pandemic.

As air is a public good, its value cannot be directly assessed by market. The stated preference method can be used to obtain the public preference degree and assess the economic value of public goods (González et al., 2019). Previous studies on the stability

measurement of environmental goods preferences mainly focus on the conditional valuation (CV). Gregory (1986) estimated the temporal reliability of learning in the range of CVM. Skourtos et al. (2010) summarized 20 studies of temporal stability based on CVM, noting significant differences in the time periods studied (from 2 weeks to 20 years) but mostly finding support for stability within 5 years. There were also some studies using CE retest procedures to examine the temporal stability of preferences (Bliem et al., 2012), and find the stability between different researchers and samples (Lew & Wallmo, 2017). Compared to CVM, the choice experiment involves hypothetical scenarios where respondents need to make trade-offs between multiple attributes and reveal their preferences and valuations of these attributes (Birol et al., 2006). Given that air is characterized by multiple properties and levels (Tang & Zhang, 2016), it is of particular interest to study changes in public preferences for air quality improvement based on CE. Hoeffler and Ariely (1999) found that respondents construct their preferences in different contexts and adjust their decision-making behavior over time and these preferences change over time. To reflect the changing preferences of respondents, we used a choice experiment to test the stability of public air quality improvement preferences and WTP in the wake of the onslaught of a global crisis. With two choice experiment questionnaires, which reflecting changes in public air quality improvement preferences and willingness to pay, on samples from the same region, decision-makers identified the importance of public's attribute and decision-making preference motives when making decisions.

Some researchers confirmed the temporal stability of preferences in CE, but they frequently ignored the role of complex psychological factors, such as environmental attitudes (Hoyos et al., 2015), psychological distance (Singh et al., 2017), and risk perceptions (Roder et al., 2019), and failed to analyze the impact of psychological factors during the COVID-19 pandemic and whether it affects the stability of individual preferences. The existing studies explore the public's risk perceptions on air pollution (Hodgson & Hitchings, 2018), and how these perceptions influence their behavior in response to the environment change (Wang & Watanabe, 2019). There are few studies to incorporate the public's risk perceptions in special cases into econometric models to explain temporal stability of preferences. Especially, people collect information about psychological factors in the environment without relying on psychometric scales in particular environmental contexts. In this study, the LCM was used to capture preference heterogeneity and its sources of individual characteristics, and the psychological factors of risk perception were incorporated into the model. Comparison of the parameter estimation results of the LCM after the COVID-19 pandemic and before the COVID-19 pandemic, and analysis of the mechanisms affecting the change in the preferences of public heterogeneous groups. Psychological factors taken into account in the COVID-19 pandemic will enrich the behavioral features of preferences, understand individual preference heterogeneity, and improve the interpretation of valuation models.

In this paper, we conduct using the same questionnaire and choice set at two different time points before and after the COVID-19 pandemic to test the change of public preferences and WTP for air quality improvement, and compare the impact of risk perception on the heterogeneity of public preferences before and after the COVID-19 pandemic by constructing a latent class model. This research enriches the non-market value evaluation and preference motivation research in the air quality, specifically include (1) explore the change of public preference heterogeneity and willingness to pay for air quality improvement under the influence of the COVID-19 pandemic; (2) explore the changes in sources of preference heterogeneity before and after the COVID-19 pandemic, especially how public's risk perceptions affect their preference for air quality improvement. Previous studies

on air quality improvement preference were limited to one-time choice experiment, without considering the impact of environmental changes on public preferences and willingness to pay. The results of this study can be incorporated into environmental protection data. By learning from current experiences, management systems and policies, policymakers consider reducing the level of air pollutants and increasing the research and development of clean energy technologies, it is of great significance to change the traditional government-led regulatory air pollution control model and promote the multi-party cooperative environmental governance system of the government. Especially, integrating time-varying environment with existing policies will help enhance public satisfaction and acceptance of air quality improvement policies in a specific period.

The rest of this paper is arranged as follows. Section 2 elaborates on the properties and levels of the choice experiment, the experimental design of CE, the generated questionnaire and data collection. Section 3 briefly introduces the Random utility model and the latent class model approach. Section 4 presents the model results, including reliability and validity tests for the risk-aware construction, preference heterogeneity analysis, and stability tests for the WTP valuation. Section 5 discusses the broader implications of the results. Section 6 presents the conclusions, policy recommendations, directions for future research and research limitations.

2 Choice experiment and data collection

2.1 Choice experiment

The fundamental purpose of the choice experiment is to elicit public preferences for diverse air quality improvement policies. To understand the preferences and support for air quality improvement policies of the respondent, the alternatives were described by five attributes: clean air days, hazy days, mortality, policy delay and annual payment. The selection of these attributes and their levels are based on previous research, consultations with scientists and government officials, and a pilot test (Mao et al., 2020a). A summary description of the above attributes and their levels is shown in Table 1.

After determining the attributes and levels used in the experiment, there are 405 ($3^4 \times 5$) alternatives combined by different attributes and their levels. It is cumbersome and cost prohibitive for respondents to compare and select from so many alternatives. The D-efficient fractional factorial principal effect design is applied to reduce the number of alternatives. A total of 15 choice sets are generated. These choice sets are then randomly allocated into five blocks, each of which is assigned three choice sets, the choice set consists of a status quo option and two alternatives presented in Table 2. Respondent will be assigned a task with three choice sets and then choose one of the three options in the given choice set as their preferred option.

2.2 Survey and data collection

This study chooses the city of Harbin, the capital of Heilongjiang province, with an area of 10,192 km^2 in northeastern China, as the study area. By the end of 2020, the city will have 5.53 M permanent urban residents. It is an important economic and cultural center in Northeast China and manufacturing base for the country. The "2020 Statistical Yearbook of Harbin" issued by the Harbin Municipal People's Government, the average

Table 1 Attributes and levels used in the CE

Attributes	Indicator description	Indicator level
Clean air days	Annual clean air days ratio	60%*
		70%
		80%
		90%
Hazy days	Annual number of haze days	40 d *
		30 d
		20 d
		10 d
Mortality	Annual decrease rate of premature deaths due to air pollution	0 *
		Decreased by 10%
		Decreased by 20%
		Decreased by 30%
Policy delay	Years of policy implementation	5 y*
		3 y
		1 y
Annual payment	The tax willingness to pay for the air pollution improvement policy per year	CNY 0*
		CNY 100
		CNY 200
		CNY 400
		CNY 600
		CNY 800

"*" Indicates the status quo level of each attribute; "d" instead of day, "y" instead of years

Table 2 Sample choice set

Scenario: Suppose options A, B and C are the ONLY ones available

	Option A	Option B	Option C
The annual percentage of days with good air quality	90%	80%	60%
Days of heavy and above pollution per year	10 d	20 d	40 d
Rate of decrease in annual premature deaths caused by air pollution	Decreased by 30%	Decreased by 0%	Decreased by 10%
The delay years of policy effects	1 y	3 y	5 y
Additional annual tax for improving air pollution	CNY 400	CNY 800	CNY 0

$PM_{2.5}$ concentration in Harbin was 53 µg/m^3, higher than the 10 µg/m^3 recommended by the World Health Organization (WHO) (http://www.harbin.gov.cn). Harbin was chosen as an empirical study area due to its representative and typical characteristics. The urban area of Harbin mainly covers 9 districts, and six urban districts located in the inner city of Harbin are selected as the research area, which contains most of the city's resident

population (i.e., Songbei District, Daoli District, Nangang District, Pingfang District, Xiangfang District and Daowai District).

Based on the feedback from a pre-survey of 100 questionnaires conducted in September 2019 and conducted extensive consultations with government officials and experts in environmental science, we corrected inaccurate statements and questions to ensure the efficiency and operation of the survey. The official survey collected data from six urban districts in Harbin in October 2019 and October 2021 to gather information on the stability of public air quality preferences before and after the COVID-19 pandemic. Different samples were randomly interviewed in the same survey area, the researchers were able to answer the respondents' questions to obtain direct information feedback and improve the effectiveness of the questionnaire.

The final questionnaire was divided into four parts: the first part includes the topic of the survey, the status and hazards of air pollution. The second part encompasses the questions related to the public's risk perception, including the degree of air pollution control (Risk controllability, RC), perceived risk effect of air pollution (Perceived risk effect, PRE), what extent he/she trust in the air quality improvement policies launched by the government (Government trust, GR) and acceptability of air pollution effect (Acceptability pollution, AP). Details of the constructions involved in the questionnaire and their measurement metrics are reported in Table 3. The third part contains three choice sets generated by the choice experiment approach to elicit individuals' preferences and WTP. The final part of the questionnaire covers the socioeconomic status of the respondents, including gender, age, education, income, number of children, number of cars, etc.

3 Methodology

3.1 Random utility model

Choice experiment, as an important method to evaluate the economic value of non-market goods or services, is based on the random utility theory (Lancaster, 1966) and consumer theory in economics. The utility that an individual obtains from a commodity or service depends on the characteristics (i.e., attributes and their levels) of the commodity or service, it will be weighed by comparing the differences among its multiple attributes, the change of any attribute level may lead to the change of individual's preference.

According to the random utility theory, the utility (U_{nij}) that individual n chooses alternative i from the choice set J can be divided into a deterministic element, V_{nij}, and a stochastic element, ε_{nij}.

$$U_{nij} = V_{nij} + \varepsilon_{nij} \tag{1}$$

For a given choice set J, the probability that respondent n chooses alternative i but not alternative j is given as follows:

$$P_{nij} = \exp^{V_{nij}} / \sum_{j=1}^{J} \exp^{V_{nij}} \tag{2}$$

Table 3 Reliability and validity tests for the measurement model

Constructs	Indicators	Mean	S.D.	Estimates	Cronbach's α	AVE	CR
Perceived risk effect (PRE)	PRE1	3.721 (3.903)	1.061 (0.989)	0.733 (0.749)	0.768 (0.793)	0.529 (0.566)	0.770 (0.795)
	PRE2	3.862 (3.913)	0.984 (1.067)	0.787 (0.796)			
	PRE3	4.193 (4.275)	0.966 (0.878)	0.648 (0.709)			
Risk controllability (RC)	RC1	3.466 (3.610)	0.940 (0.827)	0.735 (0.824)	0.826 (0.876)	0.624 (0.704)	0.832 (0.877)
	RC2	3.413 (3.639)	0.935 (0.824)	0.858 (0.882)			
	RC3	3.461 (3.637)	0.973 (0.851)	0.772 (0.810)			
Government trust (GR)	GR1	3.196 (3.540)	0.983 (0.855)	0.679 (0.752)	0.788 (0.863)	0.569 (0.684)	0.797 (0.866)
	GR2	3.368 (3.601)	0.930 (0.847)	0.843 (0.920)			
	GR3	3.518 (3.728)	0.983 (0.884)	0.733 (0.800)			
Acceptability of pollution (AP)	AP1	2.538 (2.252)	1.191 (0.953)	0.806 (0.791)	0.863 (0.846)	0.679 (0.648)	0.863 (0.847)
	AP2	2.751 (2.555)	1.056 (0.913)	0.822 (0.826)			
	AP3	2.642 (2.401)	1.158 (0.977)	0.845 (0.799)			

Outside bracket is 2019; inside bracket is 2021

3.2 Latent class model

Based on the responses from CE surveys, multiple discrete choice models can be employed to analyze public preferences. The most widely used is the conditional logit (CL) model, which offers an overview of the average preferences (Andreopoulos et al., 2015). The CL model assumes that the preferences are homogenous across respondents, and alternatives are independent and uncorrelated (Xie, 2010). This assumption has been challenged since the fact that individuals' preferences are heterogeneous, particularly in complex environmental problems (Chen & Ting Cho, 2019). To overcome the limitations of the CL model and illustrate motivations of behavior and preferences among individuals or groups, the latent class model has been developed (Greene & Hensher, 2003). In contrast to the CL model, the LCM was a semi-parametric model, it does not require the a priori selection of individual-specific characteristics (Boxall & Adamowicz, 2002). In the LCM, the sample consists of a finite number of identifiable classes. These classes differ substantially in their preference structure, each class is characterized by relatively homogeneous preferences. The LCM can estimate the probability of individual choice in each class and explain the formation mechanism of preference heterogeneity (Meldrum, 2015).

In the LCM, an individual n belongs to a latent class s. The utility function becomes:

$$U_{nij|s} = V_{nij|s} + \varepsilon_{nij|s} = \beta_s X_{nij} + \varepsilon_{nij|s} \quad s = 1, 2, \cdots, S \tag{3}$$

where X_{nij} is a vector of air quality improvement attributes. β_s is a vector of coefficient assigned to each attribute in class s. The choice probability of individual n in class s takes the following form:

$$P_{nij|s} = \frac{\exp\left(\mu_s \beta_s X_{nij}\right)}{\sum_{j=1}^{J} \exp\left(\mu_s \beta_s X_{nij}\right)} \tag{4}$$

where μ_s is the scale parameter. Respondents are classified into one of the S latent classes according to the class membership likelihood function M, which is determined by the respondent characteristics S_n. The membership likelihood function is given by:

$$M_{ns} = \lambda_s Z_n + \xi_{ns} \tag{5}$$

where λ_s ($s = 1, 2, \ldots, S$) is the vector of class-specific coefficients, Z_n represents the characteristics of individual n, including socio-economic and risk perception factors, ξ_{ns} are the error elements. The probability that an individual n is in class s is given by the following function:

$$H_{ns} = \frac{\exp\left(\lambda_s Z_n\right)}{\sum_{s=1}^{S} \exp\left(\lambda_s Z_n\right)} \tag{6}$$

Combining conditional choice Eq. (4) with membership classification Eq. (6), the unconditional probability function is given as:

$$P_{nij} = \sum_{s=1}^{S} P_{nij|s} H_{ns}$$
$$= \sum_{s=1}^{S} \left[\frac{\exp\left(\mu_s\beta_s X_{nij}\right)}{\sum_{j=1}^{J} \exp\left(\mu_s\beta_s X_{nij}\right)} \right] \times \left[\frac{\exp\left(\lambda_s Z_n\right)}{\sum_{s=1}^{S} \exp\left(\lambda_s Z_n\right)} \right] \tag{7}$$

3.3 Willingness to pay

Based on the coefficient estimated by LCM that provides useful information on the preference heterogeneity, the value of marginal WTP change in each attribute can be calculated by the ratio of the coefficients of any interest attribute k and the negative price attribute p.

$$\text{WTP}_{k|s} = -\frac{\beta_{k|s}}{\beta_{p|s}} \tag{8}$$

where $\beta_{k/s}$ and $\beta_{p/s}$ are the coefficients on air quality improvement and price attributes in class s.

4 Results

4.1 Descriptive statistics

The formal survey was administered twice in October 2019 and October 2021 using a same choice experimental questionnaire and face-to-face interviews survey. The samples of both surveys are residents living in the six main districts of Harbin, and involved a total of 380 (2019) and 350 (2021) respondents. After screening the incomplete and non-effective questionnaires, a total of 372 (2019) and 335 (2021) questionnaires with 1116 (372 questionnaires × 3 choice sets) and 1005 (335 questionnaires × 3 choice sets) valid observations are used for further analysis.

Table 4 shows the socio-economic demographics of the two samples. The degree of similarity between the sociodemographic characteristics across both surveys can be formally tested by the Chi-square test. The last column in Table 4 shows the results of the Chi-square test: gender, age, education, children, cars and income distributions are not significantly different between the two samples. The social and economic characteristics of both samples are similar to the population in Harbin. The gender of respondents is close to the average, with about 57% (2019) and 56% (2021) women, 43% (2019) and 44% (2021) men in the sample. The largest share of respondents in both surveys had an age structure between 18 and 40 years, the age category ">60" years and "<18" years is lower. In the interview survey, the response rate of older and children is generally low based on a lack of understanding of the questionnaire and the ability to complete the questionnaire independently. The majority of respondents in both surveys have advanced education (College & above), with 65% (2019) and 68% (2021), respectively. Most respondents had a child or none, about 56% (2019) and 57% (2021) of respondents own a car. The largest share of respondents in both surveys has a monthly personal income between 2000 and 5000 CNY, with 43% (2019) and 45% (2021) income of less than 2000 CNY.

Table 4 Descriptive statistics on socio-economic characteristics of respondents

	Sample 2019 (n=372)	(%)	Sample 2021 (n=335)	(%)	Chi-square (Significance level)
Gender					$x^2 = 0.073$; ($\rho = 0.787$)
Male	167	42.60%	147	43.80%	
Female	205	57.30%	188	56.10%	
Age					$x^2 = 2.274$; ($\rho = 0.810$)
Less than 18 years	14	3.80%	10	3.00%	
18–25 years	195	52.50%	185	55.20%	
26–40 years	118	31.80%	110	32.80%	
41–50 years	35	9.40%	23	6.90%	
51–60 years	7	2.00%	6	1.80%	
More than 61 years	2	0.50%	1	0.30%	
Education					$x^2 = 0.885$; ($\rho = 0.829$)
Less than primary	12	3.40%	10	3.00%	
High school	37	9.90%	31	9.30%	
College	244	65.50%	230	68.70%	
Bachelor & above	79	21.10%	63	18.80%	
Children					$x^2 = 0.649$; ($\rho = 0.885$)
0	196	52.80%	185	55.60%	
1	144	38.70%	122	36.40%	
2	25	6.60%	20	6.00%	
3 & above	7	2.00%	7	2.00%	
Cars					$x^2 = 0.528$; ($\rho = 0.913$)
0	98	26.30%	91	27.30%	
1	209	56.30%	191	57.30%	
2	50	13.50%	39	11.60%	
3 & above	15	4.00%	13	3.90%	
Income					$x^2 = 0.880$; ($\rho = 0.927$)
Less than 2000 CNY	160	43.00%	150	44.80%	
2000–5000 CNY	77	20.60%	70	21.40%	
5000–8000 CNY	69	18.60%	62	18.50%	
8000–15000 CNY	41	10.90%	33	9.90%	
More than 15000 CNY	25	6.80%	18	5.40%	

4.2 Risk perception measurement

4.2.1 Construct validity and confirmatory factor analysis

Risk perception was first used in the field of psychology. It is the embodiment of the public's understanding, recognition and assessment of risk, including a judgment of the probability of risk occurring at a particular time and place and the possible consequences (Slovic et al., 1987). It is difficult to directly characterize and measure public perception of risk, because risk perception reflects the psychological changes that occur in the face of a risky

event, it is a process by which the public experiences, understands, and reacts to a risky event. Many scholars have used psychometric models to measure people's judgments about the riskiness of diverse hazards (Wachinger et al., 2013). Previous studies divided risk perception into several dimensions and used a five-point Likert scale to scientifically analyze how risk is perceived (Wang & Watanabe, 2019) and what factors affect the public's perception of risk (Yan et al., 2019). Based on previous studies, this study divided the psychological scale of air pollution risk perception into four structures. Perceived risk effect of air pollution indicates that people's perceptions of air pollution consequences (Mao et al., 2020b). Risk controllability indicates that the degree to risk events from air pollution is controlled (Li et al., 2022). Government trust is the public's confidence in the government to reduce the risks posed by air pollution (Pu et al., 2019). Acceptability of pollution means the public's ability to withstand the damage caused by air pollution (Fischhoff, 1978). The estimation results are reported in Table S1.

The Cronbach's α coefficients of latent variables show that the measured items have good internal consistency. The values for Kaiser–Meyer–Olkin (KMO) are greater than 0.7 and Bartlett's test of sphericity ($p = 0.000 < 0.01$) shows suitability for the confirmatory factor analysis (CFA). The KMO and Bartlett's test of sphericity results as seen in Table S2.

The average variance extracted (AVE) for each factor was assessed for the convergent validity. Before and after the COVID-19 pandemic, AVE values of the constructs all exceed 0.5, the marginal value suggested by Fornell and Larcker (1981). Composite reliability (CR), another indicator of convergent validity, are all higher than 0.7 for all reflective constructs. These results suggest an acceptable convergence validity. The AVE values for any two constructions are compared with the correlations calculated between these two constructions. Table 5 shows strong evidence of the effectiveness of the discriminant.

The goodness-of-fit metric used to consider model validity shows an acceptable fit to the measured model. The acceptable values of GFI, CFI and NFI should be greater than 0.9. REMSA is acceptable between 0.03 and 0.08, and the χ^2/df value at or less than 5 is considered a better fit (Fornell & Larcker, 1981). The results of the fit to the measured model as seen in Table S3.

4.2.2 Respondents' risk perception scores

We construct the weights of the risk perception evaluation metrics from the above evaluation results in Table 3. To explore the hypothesized effect of risk perception, the

Table 5 Correlations of the constructs

	2019				2021			
	PRE	RC	GR	AP	PRE	RC	GR	AP
Perceived risk effect (PRE)	0.727				0.752			
Risk controllability (RC)	0.241	0.790			0.105	0.839		
Government trust (GR)	0.072	0.283	0.754		0.059	0.470	0.827	
Acceptability of pollution (AP)	− 0.124	0.099	0.116	0.824	− 0.179	− 0.003	0.060	0.805

The diagonal value is the square root of AVE. The non-diagonal number is the correlation coefficient between constructs

scores of these four constructions are assigned to values of 1, 2, and 3, representing high, medium, and low levels, on a tertiary level. Sequentially, these scores are used in the next analysis of preference heterogeneity. The estimation results are presented in Table 6.

4.3 Preference heterogeneity

To further analyze the characteristics of preference heterogeneity among different groups and to compare with the results before the COVID-19 pandemic, this study estimated the LCM based on data from 2019 to 2021, and compared the information criteria statistics including the Bayesian information criterion (BIC), the Akaike information criterion (AIC) and the AIC with a penalty factor of 3 (AIC3) of the models with different segmentation. The results of three information criteria under different class numbers of the model as seen in Table 7. The AIC decreases as more classes are added, and the marginal reduction diminishes after the three classes are included. The BIC decreases until two classes are included, then increases as more classes are added to the model, AIC3 is minimized with the 3-class model. Of all the models, the 3-class model is suggested for our analysis.

Figure 1a shows the relative importance of attributes in the three-class model in 2019. Of the respondents, 50.47% are assigned class 1, 29.16% belong to class 2, and 20.37% belong to class 3, as indicated by the size of the circle. Class 1 contains the majority of respondents who list clean air days as their preferred attribute, with other attributes having a much smaller relative importance. Respondents from this class pay more attention to the intuitive sensation of air quality and labelled as "sensation preferable." Class 3 members have a high preference for mortality attributes and are labeled as "health preferable." Class 2 members have a high preference for the price attribute, while having a low preference for other air quality improvement attributes, thus the Class 2 are called "price sensitive," and consider payment as the most important determinant.

Figure 1b shows the relative importance of attributes in the three-class model in 2021. Of the respondents, 66.70% are assigned to class 1, 27.57% to class 2 and 5.73% to class 3, as indicated by the size of the circle. As in 2019, class 1 contains the majority of respondents who regard clean air days as the preferred attributes, with other attributes

**Table 6** Weights of indictors of risk perception

Constructs	Indicators	Weights	
		2019	2021
Perceived risk effect (PRE)	PRE1	0.322	0.324
	PRE2	0.319	0.329
	PRE3	0.358	0.346
Risk controllability (RC)	RC1	0.315	0.327
	RC2	0.352	0.344
	RC3	0.332	0.328
Government trust (GR)	GR1	0.307	0.320
	GR2	0.360	0.352
	GR3	0.331	0.326
Acceptability of pollution (AP)	AP1	0.327	0.326
	AP2	0.336	0.337
	AP3	0.336	0.335

Table 7 LCM classification

classes	Number of parameters	2019-LCM Model				2021-LCM Model			
		LL	BIC(LL)	AIC(LL)	AIC3(LL)	LL	BIC(LL)	AIC(LL)	AIC3(LL)
1	5	−1379.5240	2789.6822	2769.0479	2774.0479	−1940.2902	3913.1168	3890.5804	3895.5804
2	21	−1226.9353	2745.3111	2523.8706	2558.8706	−1824.0441	3784.7410	3690.0882	3711.0882
3	37	−1173.7134	2668.6734	2477.4269	2527.4269	−1722.9544	3686.6780	3619.9087	3656.9087
4	53	−1138.0995	2858.2516	2466.1990	2561.1990	−1646.3262	3737.5382	3398.6525	3751.6525
5	69	−1076.2509	2918.3604	2402.5017	2542.5017	−1615.4583	3692.8256	3381.8234	3850.8234
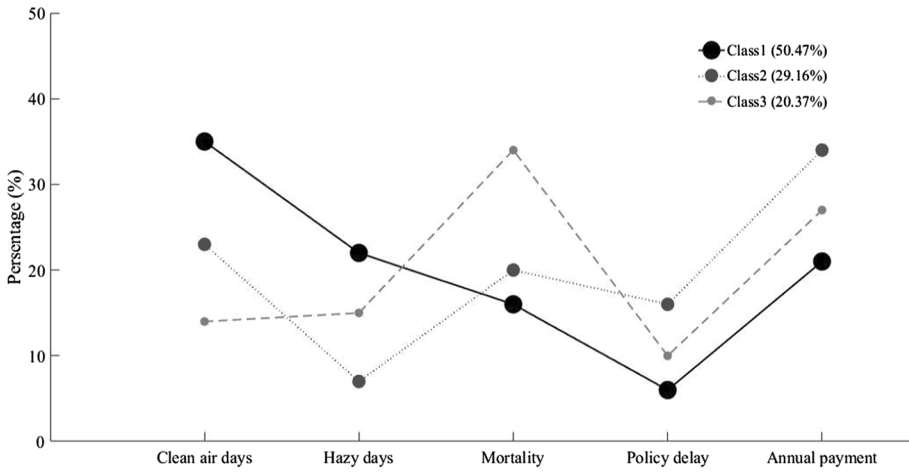
(a) The relative importance of the attributes in 3-class LCM
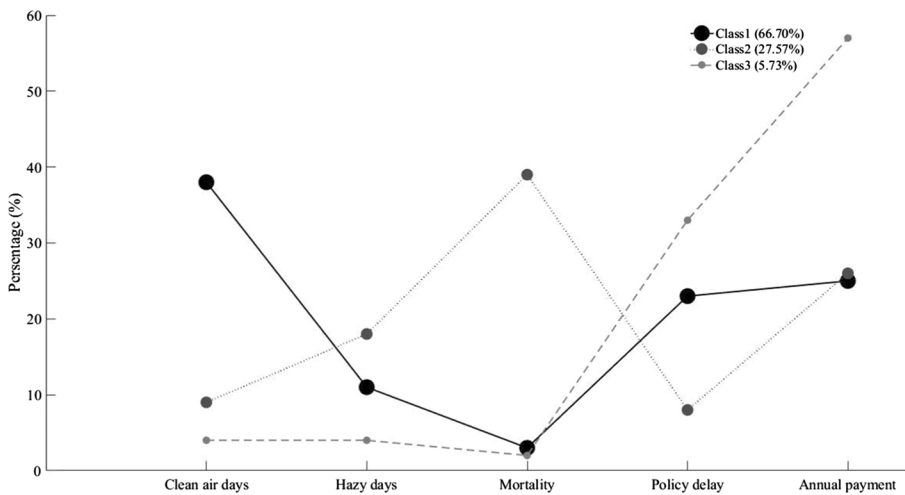
(b) The relative importance of the attributes in 3-class LCM

Fig. 1 **a** Relative importance of the attributes in 3-class LCM. **b** The relative importance of the attributes in 3-class LCM

having a smaller relative importance. Respondents from this class pay more attention to the intuitive sensation of air quality and labeled as "sensation preferable." Class 2 members have an especially high preference for mortality attributes. This class is called "health preferable." Class 3 members have a high preference for the price attribute contra a low preference for other air quality improvement attributes "price sensitive," the most important determinant for class 3 is the payment.

Next, we further analyze and compare the results of respondents' preference heterogeneous for air quality improvement under the context of different air quality

levels before and after the COVID-19 pandemic. The parameter estimation results of the LCM are reported in Table 8.

The first part of Table 8 shows the utility coefficients of the attributes associated with the air quality improvement policy, which reveal heterogeneity in the preferences for the air quality improvement policy. All parameters in class 1 are statistically significant in 2019 and 2021, and consistent with the expected signs, indicating that the utility of respondents will increase with the decrease in the hazy days, mortality, length of policy delay, and annual payment, the increase in the clean air days. In class 2, the utility coefficients for all but the annual payment attribute are not significant in 2019, indicating that respondents receive low utility from air quality improvements. The coefficient of the annual payment is negative, indicating that decreasing the paid price can increase the probability of this type of respondents to choose the air quality improvement plan. The coefficient of mortality is higher than other attributes in 2021, indicating that individuals or households who are more concerned about the health effects of air pollution fall into this group. In class 3, all coefficients of 2019 are significant, with mortality and policy delay being higher than the other attributes. The annual payment attribute coefficients for 2021 are significant; while, the other attributes are not. The results of the 2019 and 2021 by LCM indicate a clear heterogeneity in the preferences of different classes of respondents for these attributes when faced with various air pollution control options.

The second part of Table 8 shows the parameter estimation of the classification members, which reveals the source of individual preference heterogeneity.

(1) For the "sensation preferable," the gender coefficient is negative; while, the education, number of children, perceived risk effect and government trust coefficients are positive in 2019. In 2021, the gender and age coefficients are negative; while, the education and government trust coefficients are positive. As a result of the COVID-19 lockdown and the shutdown of factories and enterprises, air quality has improved and people's perceived risk effect has decreased. Youngsters have a significant willingness to improve air quality after the COVID-19 pandemic. Females with higher levels of education and stronger trust in the government have a direct sensation related to air quality, regardless of whether they have experienced the COVID-19 pandemic.

(2) For the "price sensitive," the number of children, income, and acceptability of pollution coefficients are positive; while, the education, number of cars and perceived risk effect coefficients are negative in 2019. The coefficients of gender and age are positive; while, the coefficients of education, income, government trust and risk controllability for 2021 are negative. Respondents are more willing to spend less to support air quality improvement policies due to social issues such as employment and income instability caused by the COVID-19 pandemic.

(3) For the "health preferable," the perceived risk effect and risk controllability coefficients are positive; while, the gender, number of cars and acceptability pollution coefficients are negative in 2019. The coefficients for the number of children, income and risk controllability are positive; while, the coefficients for gender, age and acceptability of pollution for 2021 are negative. This may be because the COVID-19 pandemic has made people more aware of the importance of health, so respondents made health a top priority.

Table 8 Parameter estimation results of the LCM

	LCM Model (2019)						LCM Model (2021)					
	Class 1 (Sensation preferable)		Class 2 (Price sensitive)		Class 3 (Health preferable)		Class 1 (Sensation preferable)		Class 2 (Health preferable)		Class 3 (Price sensitive)	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Utility function												
Clean air days	0.04***	5.99	0.30	1.37	0.32***	2.79	0.09***	8.77	0.15***	4.54	0.06	0.64
Haze days	−0.02***	−2.83	−0.11	−0.31	−0.23***	−3.72	−0.02***	−2.67	−0.22***	−5.01	−0.03	−0.59
Mortality	0.03***	3.49	0.19	1.17	0.37***	7.54	0.08	0.65	0.75***	5.21	0.03	0.27
Policy delay	−0.17***	−4.89	−0.34	−0.54	−0.65*	−1.70	−0.21***	−6.32	−0.31***	−4.29	1.29	1.24
Annual payment	−0.06***	−3.15	−0.03**	−2.79	−0.05*	−1.68	−0.01***	−6.33	−0.01***	−5.72	−0.01*	−1.69
Class membership function												
Intercept	2.19*	1.89	−0.52	−0.33	−1.68	−1.10	−1.57	−1.39	0.60	0.47	0.99	0.59
Gender	−0.16*	−1.85	0.32	1.25	−0.61**	−2.27	−0.25*	1.49	−0.53***	2.91	0.77***	−2.84
Age	−0.19	−1.48	−0.01	−0.07	0.21	1.26	−0.26***	−3.55	−0.57*	−1.84	0.83*	1.69
Education	0.29**	2.67	−0.30*	−1.78	0.08	0.45	0.65***	2.90	−0.15	−0.59	−0.50*	−1.65
Number of children	0.21**	2.26	0.28**	1.98	0.07	0.31	−0.02	0.14	0.16*	1.39	−0.17	−0.99
Number of cars	0.01	0.07	−0.90**	−2.57	−0.62*	−1.81	−0.08	0.05	0.05	0.44	0.03	0.14
Income	0.31*	1.65	−0.02*	1.67	0.13	0.75	0.04	0.70	0.59***	2.98	−0.09**	−2.09
Perceived risk effect (PRE)	0.63**	2.52	−0.40**	−1.91	0.43**	2.42	−0.01	−0.11	−0.07	−0.64	0.08	0.51
Risk controllability (RC)	0.03	0.18	−0.06	−0.29	0.03*	1.64	0.17	1.44	0.26*	1.90	−0.43***	−2.20
Government trust (GR)	0.67***	2.68	0.16	0.47	0.15	0.46	0.12*	1.70	0.13	1.21	−0.25*	−1.64
Acceptability of pollution (AP)	0.04	0.17	0.82**	2.37	0.19**	−2.41	0.05	0.59	−0.02*	−0.16	−0.04	−0.25
Log likelihood	−1173.7134						−1722.9544					
Pseudo-R²	0.4053						0.4472					

4.4 Marginal WTP values

The marginal WTP estimator provides the implied benefits of various changes in attribute levels and captures their differences under air quality improvement scenarios of 2019 and 2021 (Hoyos et al., 2015). Table 9 presents the marginal WTP for the attributes related to the air quality improvement policy and gives an estimate of the marginal WTP value.

In the 2019 LCM, respondents are willing to pay 170.20 CNY per year for a shorter policy delay. Respondents are willing to pay 48.81 CNY per year to increase the number of clean air days by 1% and 36.03 CNY per year to reduce the mortality by 1%, respondents are willing to pay 27.26 CNY per year to decrease the number of haze days. In the 2021 LCM, the marginal WTP of the attributes is consistent with the 2019 order. Compare with the weight WTP value of 2019, the marginal WTP of policy delay decreased by 45.81 CNY per year, the clean air days increased by 5.21 CNY per year, the mortality decreased by 18.21 CNY per year, and the haze days decreased by 12.62 CNY per year. Comparison of results based on marginal WTP for 2019 and 2021 suggests that the WTP of respondents will decrease after the COVID-19 pandemic as air quality improves to some extent.

5 Discussion

The COVID-19 pandemic has a huge economic (Zambrano-Monserrate et al., 2020), political (Luan et al., 2021) and health (Singh & Mishra, 2021) impact on a global scale and has seriously affected human development. In addition to its adverse effects on life and health, it has positive environmental implications and could become a reflection on the future of human behavior toward nature (Singh & Mishra, 2021). In the COVID-19 pandemic early stages, governments took drastic measures such as lockdowns, suspension of public transport operations and self-restraint orders to control the spread of the virus, leading to global reductions in pollutant emissions and marked improvements in air quality. Mandal et al. (2021) indicated that the cessation of vehicular traffic and industrial shutdowns have a significant environmental impact, short-term lockdowns can be effective in freshening the air in these mega-cities. This large-scale global outbreak has brought additional information to policymakers on the importance of air pollution management. It is worth noting that public perceptions of changes in air quality should be considered alongside government capacity and priorities, the role that trust in government may play an incentive to achieve results.

Research on whether preferences change over time is important when they are used to inform decision-making (Wunsch et al., 2022). The existing literature showed that preferences are not affected by the valuation environment and preferences do not change over time (Czajkowski et al., 2016), especially during periods of uncertainty such as the COVID-19 pandemic (Wunsch et al., 2022). People will face insecure employment opportunities and income prospects in uncertain times, which better reflects people's preference and willingness to pay for air quality improvement policies in different backgrounds compared with safe times. This study is comparable between the two surveys in terms of choice levels and willingness to pay for air quality improvement options, as well as socio-economic characteristics. Due to the sufficiently long times

Table 9 Marginal WTP estimations

Attribute	2019				2021			
	Class 1 (Sensation preferable)	Class 2 (Price sensitive)	Class 3 (Health preferable)	Weighted WTP	Class 1 (Sensation preferable)	Class 2 (Health preferable)	Class 3 (Price sensitive)	Weighted WTP
An increase in clean air days (unit: %)	71.17	–	63.18	48.81	75.66	12.89	–	54.02
A decrease in haze days (unit: day)	36.17	–	44.25	27.26	14.33	18.41	–	14.64
A decrease in mortality (unit: %)	42.50	–	71.56	36.03	–	64.65	–	17.82
A decrease in policy delay (unit: year)	285.67	–	127.75	170.20	175.67	26.20	–	124.39

'–' indicates that the marginal WTP for attributes is insignificant at the 10% level of statistical significance

interval, the presented results are consistent with the desired target outcome. It is clear from the respondents' responses to the questions that changes in perceptions of air quality and individual economic status and perceived risk in the face of a major public health event have an impact on the results of the study.

This research found that the category characteristics of public preference for air quality improvement are similar. The sources of influencing preference heterogeneity before and after the COVID-19 pandemic are different, mainly reflected in risk perception and socio-economic characteristic variables. To further examine the origin of preference heterogeneity, the inclusion of risk perceptions in the latent class model better explains the significant heterogeneity in the preferences of individuals' choice behavior toward air pollution management policies. This is also supported by the results of previous studies (Meldrum, 2015). The reasons for the change in perceived risk effects of the "Sensation preferable" group after experiencing the COVID-19 pandemic may include: First, during the COVID-19 pandemic, the youngsters went out more frequently, paid more attention to air quality and the degree of government control of the epidemic (Strommer et al., 2022), and believed the government could improve air quality as well as control the epidemic after the COVID-19 pandemic (Völker & Lienhoop, 2016). The results are similar to those found by Singh and Mishra (2021). They suggested that the lockdown experience may have affected the public's perception of the fragility of nature and increased public awareness of environmental protection. Second, female age and personal status, especially those related to family and work, showed a higher risk sensitivity due to their experience of lockdown during COVID-19 pandemic (Giordani et al., 2021). The health preference group experienced a significant change in their perceived risk impact and acceptability of pollution after the COVID-19 pandemic, the high transmission and mortality rates of the COVID-19 pandemic, which made people aware of the importance of health (Connor et al., 2020). Singhal (2020) found that in the face of a major public health crisis and future uncertainty, the public has a new understanding of the value of health and life, and people realize the necessity and urgency of improving air quality. Severe air pollution can cause a variety of diseases that threaten people's health, such as lung and respiratory diseases. After people suffering from the health hazards of air pollution, more attention is paid to reducing the health risks. Price sensitive groups experienced changes in perceived risk effect, risk controllability, government trust and pollution acceptability after the COVID-19 pandemic. The low-income people can't afford expensive governance solutions, they pay more attention to price. The impact of the pandemic lockdown, factory shutdowns and increased unemployment has caused people who are concerned about spending on necessities to not consider additional spending (Schnitzler et al., 2021).

Acquiring the average marginal WTP for various attributes can provide important insights for policymakers to design scientific and reasonable air pollution treatment projects. In terms of the marginal WTP, there is a statistical difference between the coefficients of the two groups for the health risks associated with the COVID-19 pandemic and the uncertainty of future income concerns. With the exception of the clean air day attribute, the marginal WTPs for the other air quality improvement attributes are higher in 2019 than 2021 in "Sensation preferable" and "Health preferable." Respondents prefer improving current air quality conditions over maintaining the status quo and are willing to pay a certain amount for air pollution treatment. According to the marginal WTP estimates for the attributes, respondents are more willing to pay a certain amount to increase the number of "clean air days" before and after the COVID-19 pandemic. The closure of many businesses and factories, the significant reduction in the concentration of air pollutants (Adams, 2020), the change in air quality evident to respondents, and the increase in the number of clean air

days, making the public feel the comfort of clean air gas, prompting them to give more to achieve better goals. The willingness to pay for the attributes "Hazy days," "Mortality" and "Policy delay" are lower after the COVID-19 pandemic. Respondents fell that heavy pollution is less of a threat to their daily lives than before the COVID-19 pandemic, a fact that is consistent with previous results showing reduced concerns about heavy pollution. Sekar et al. (2022) indicated that pollutant levels decrease after lockdown and that public perception is highly dependent on actual air quality. The immediate threat to human life posed by the COVID-19, there will be concerns about the impact of the pandemic on life and health, with respondents prioritizing the reduction of hazard and less concerned about mortality due to air pollution (Becchetti et al., 2022). Having learned how the government responds to the COVID-19 pandemic, respondents have adjusted their level of confidence in the government's ability to use its tax contributions responsibly to achieve the changes assumed in the survey, which means that the speed and effectiveness of policy implementation determine the amount of public funding support for air quality improvements. The COVID-19 pandemic has changed the marginal WTP of the public for air quality improvement, which supports policy makers in prioritizing different air quality improvement objectives related to these attributes, the need for policy makers to tailor air quality improvement policies to public demand preferences in return for greater public support.

6 Conclusions and policy recommendations

This paper used a choice experiment to test the stability of public air quality improvement preferences and WTP following the onslaught of a global crisis. The results suggested that the category characteristics of public preference for air quality improvement are similar in the face of a major public health crisis and an uncertain future. The sources of influencing preference heterogeneity before and after the COVID-19 pandemic are different, mainly reflected in risk perception and socio-economic characteristic variables. During the COVID-19 pandemic, the marginal WTP is lower than before. Most previous studies have only focused on the public preference heterogeneity and motivation sources under the same background, and there are few studies on the impact of environmental changes on public preference and willingness to pay, as no research has been able to test this stability during such a large global shock, previous studies of air quality improvement preferences are limited to one-time choice experiment surveys that do not take into account the effects of environmental changes on public preferences and willingness to pay. This study attempts to fill this gap to probe into the public's preferences temporal stability for air quality improvement, and the preferences heterogeneity for air quality improvement policies and the impact of WTP in the context of the COVID-19 pandemic.

This study findings have important implications for both theory and policy making. Theoretically, no previous work has been able to test the change in preferences during large global shocks. This study explores the change in the COVID-19 pandemic on public preferences and willingness to pay, as well as the impact of public risk perception on preference heterogeneity, through a choice experiment that enriches the study of air quality value assessment and provides a new theoretical perspective on environmental protection. In terms of policy making, by comparing the changes in air quality before and after the COVID-19 pandemic, the impact on the heterogeneity of public preferences will provide policy makers with more accurate and effective public information on improving air quality and provide reference for policy formulation, better link air quality improvement with

public participation. The adoption of low-energy technologies in the traditional industries of the future, while developing renewable energy sources and increasing the use of clean energy. Secondly, the government should actively develop clean energy vehicles, reduce the purchase tax of new energy vehicles and introduce subsidy policies, increase public transportation (such as shared bicycles, subways, and buses). Thirdly, the government should guide the public to separate waste and improve waste disposal techniques to minimize waste generation and maximize raw materials. Finally, strengthen education on air quality improvement in the context of normal virus prevention and control, publicize and report the harm of the novel coronavirus and the widespread impact of air pollution, solve unexpected public health in a timely manner or environmental pollution incidents to reduce the threat to people's health.

Turning to future research, this study selected only residents of the Harbin area as a sample for the survey and assessed their preferences for air quality improvement and factors influencing their willingness to pay. With the different radiation ranges in the polluted areas around Harbin, the public will be exposed to different levels of pollution, and their preferences and willingness to pay for air quality improvement will also be different. Future research will compare preferences and willingness to pay for air quality improvements among residents around Harbin to better inform and assist policy making and to increase the applicability of our research conclusions in different regions. This study analyzed the impact of latent variables of risk perception on the public's preference for air quality improvement and willingness to pay; while, the psychosocial drivers of individual behavior are complex. It will be very meaningful to further explore the socio-economic or other potential psychological sources (such as psychological distance) that give rise to this heterogeneity in follow-up studies, which will help environmental managers to develop corresponding air quality improvement measures according to the preferences of groups with different socio-economic or psychological characteristics.

Data availability The data that support the findings of this study are available on request from the corresponding author.

Declarations

Conflict of interest The authors declare that they have no known competing financial interest or personal relationships that could have appeared to influence the work reported in this paper.

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