Context-dependent preferences for climate change mitigation — the role of seasons, information, and floods[a]

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CONTEXT-DEPENDENT PREFERENCES FOR CLIMATE CHANGE MITIGATION — THE ROLE OF SEASONS, INFORMATION, AND FLOODS

Abstract. The experimental valuation literature has found that people's preferences are context-dependent. This paper examines the effects of three different contexts—weather seasons, information, and an unprecedented flooding event—on people's preference for climate change mitigation. We conducted an online choice experiment in China in both warm and cool seasons. We also explored whether providing information on climate change consequences and an unprecedented flooding event would affect this valuation. Using a mixed logit model and Poe test, we found no significant treatment effects of seasons and information for most of the attributes except for 'frequency of typhoons' and 'costs'. However, we find that when provided with information, respondents' Willingness to Pay (WTP) for climate change mitigation in general is significantly higher during the cool season than the warm season. In addition, in the warm season, providing information on climate change consequences reduces the WTP for climate change mitigation in general. However, during the cool season, providing information on climate change consequences increases respondents' WTP for reducing the duration of heatwaves and decreasing biodiversity loss. Finally, we found that the unprecedented flooding event did not change participants' valuation of climate change mitigation when provided with information on climate change consequences.

Keywords: Climate change; Context-dependent preferences; Willingness to pay; Mixed logit model

JEL classification: C90; Q51; Q54

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1. Introduction

Environmental valuation is an important field in environmental economics, offering crucial information for environmental policy design. However, controversies remain about the validity and scope of environmental valuation methods, such as the contingent valuation method (CVM), recommended by NOAA (Arrow et al., 1993) to be used in the estimation of willingness to pay (WTP) and willingness to accept (WTA) for environmental services. One main problem with environmental valuation is it can be context-dependent. The experimental valuation literature describes different contexts, such as real versus hypothetical, private versus public goods, non-dealer versus dealer or buyer versus seller, and indicates that these distinctions matter (Lusk and Shogren, 2007; Shogren and Taylor, 2008; Carlsson, 2010; Rojas and Cinner, 2020; Zhang and Qin, 2021).

Climate change is the most challenging environmental problem faced by the world today, requiring scientifically sound policies, concerted efforts, and continuous evaluation. Implementing cost-effective climate policies depends on the public's valuation of climate change mitigation and adaptation. Many studies rely on the contingent valuation method to elicit people's valuation of climate change mitigation and adaptation (Nemet and Johnson, 2010; Longo et al., 2012; Carlsson et al., 2012). However, these valuation studies frequently did not take context dependency into account, such as the effect of the weather on people's valuation of climate change mitigation. One might expect public perception of climate change to change after experiencing unseasonably cold or warm weather. Past studies have found a link between local temperature anomalies and the perception of climate change (Moore et al., 2019; Hamilton and Stampone, 2013; Zaval et al., 2014; Deryugina, 2013; Donner and McDaniels, 2013).

In addition, as many people might not be aware of the severity of climate change consequences, improved knowledge about them might also affect the valuation of climate change mitigation. Information, and its nature, have been found to affect WTP estimates (Ajzen et al., 1996; Fox et al., 2002). Finally, with more frequent natural disasters such as hurricanes and floods occurring recently, an open question is how these events alter people's support for climate change policies. However, this question has rarely been studied, presumably due to the unpredictable nature of severe natural disasters and the resulting absence of pre-event surveys.

In this paper, we ask three main questions: 1) is the WTP for climate change mitigation influenced by the weather seasons (warm seasons versus cool seasons)? 2) does providing information about the consequences of climate change affect this valuation? and 3) what is the impact on this valuation of experiencing an unprecedented flooding event that may relate to climate change? We aim to answer these questions in the context of China. As China is the largest greenhouse gas emitter, the study of these questions in China is important. We conducted a choice experiment in China to elicit people's valuation of different attributes of climate change (heat waves, floods, loss of biodiversity, and super typhoons) and mitigation cost in both warm and cool seasons (season treatment), with and without information on climate change consequences (information treatment), and before and after the flooding event (flooding treatment). We then used the ratio of the coefficients on mitigation cost and on the different attributes to calculate WTP for these climate change attributes. Most of the studies on the valuation of climate change mitigation have been conducted in U.S. and European contexts, (e.g., Berk and Fovell (1999); Berrens et al. (2004); Longo et al. (2012); Carlsson et al. (2012); Dienes (2015); Alberini et al. (2018)); with increasing literature focused on China (Carlsson et al., 2013, 2012; Yang et al., 2014; Duan et al., 2014; Li et al., 2016; Winden et al., 2018). Unlike these studies, which employ methods of contingent valuation, we used a multiple-treatment choice experiment. Choice experiments have several advantages over the contingent valuation method (Hanley et al., 1998; Holmes et al., 2017). First, a choice experiment might be more reflective of actual decision problems. Choice experiments (CEs) involve presenting respondents with a series of hypothetical scenarios and asking them to choose their preferred option, whereas contingent valuation involves asking respondents to assign a dollar value to a good or service that is not traded in the markets. Second, CEs can be used to value individual attributes of the environmental good as well as the environmental good as a whole. This may allow us to see what attributes matter most to the respondents, which is of interest to policymakers. Third, CEs avoid the problem of the tendency toward "yes-saying" found in the contingent valuation method, as respondents are not presented with "yes or no" choices but rather a choice situation involving choosing one out of several environmental alternatives. Despite the previous advantages, CEs also have their challenges. Similar to CVM, CEs are still a stated preference approach and suffer from strategic behavior and hypothetical bias (Meginnis et al., 2021). Also, the cognitive requirement is high for respondents, as they have to choose between alternatives with several attributes; this could lead to bias as respondents may use unknown decision heuristics (Holmes et al., 2017).

In the information treatments, participants were given a paragraph of text describing climate change consequences. The flooding treatment examined the effect of experiencing a major natural disaster possibly related to climate change, the 2021 Henan floods[4]. We happened to conduct warm-season treatments immediately before the floods, not expecting their occurrence. The treatments thus also became the control treatments to examine the effects of the floods. We conducted the flooding treatment immediately after the floods to see if the natural event, which caused severe damage and many casualties, changed people's valuation of climate change.

Using a mixed logit model and Poe test, we find that when provided with information, respondents' WTP for climate change mitigation, in general, is significantly higher under cool seasons compared to that under warm seasons. In addition, during warm seasons, providing information on climate change consequences reduces the WTP for climate change mitigation in general. However, during cool seasons, providing information on climate change consequences increases respondents'

[4] For a detailed account of the floods, we refer readers to https://floodlist.com/asia/china-henan-zhengzhou-floods-update-july-2021

WTP for reducing the duration of heatwaves and biodiversity loss. Finally, we find that the unprecedented flooding event did not change participants' valuation of climate change mitigation when they were provided with information on climate change consequences. This is a somewhat surprising result, which implies that the severe flooding event did not affect respondents' valuation for climate change mitigation beyond the effect of the knowledge about those consequences. One potential explanation is that Henan province has been exposed to flooding for hundreds of years. In addition, there was a major flooding event in 2020 as well.

The structure of the paper is as follows. Section 2, following a literature review, provides our hypotheses. Section 3 describes our choice experiment's design. Section 4 estimates an econometric model. Section 5 discusses our results, and we offer our conclusions in section 6.

2. Literature review and hypothesis formulation

Instead of studying the effects of temperatures on the valuation of climate mitigation, previous literature has mainly focused on either using polling data to assess the effects of temperature anomalies on the public's beliefs concerning anthropogenic climate change or on using Twitter data to determine the notability of temperature extremes. For example, using data from U.S. national public opinion polls from 1990 to 2010, Donner and McDaniels (2013) found that beliefs in climate change and U.S. mean temperature anomalies over the previous 3-12 months were significantly positively correlated. Using Gallup's Environmental Poll data, Deryugina (2013) found that people's belief in global warming was not affected by very short periods of abnormally warm or cold temperatures (1 day to 2 weeks) but was affected by longer periods of abnormal temperatures (1 month - 1 year). This result differs from several other studies which found that climate beliefs are influenced by very short-run temperature anomalies (Egan and Mullin, 2012; Hamilton and Stampone, 2013; Li et al., 2011). Alternatively, Moore et al. (2019) examined the effects of temperature anomalies on the notability of temperature extremes by drawing on over 2 billion social media posts about weather on Twitter. They found that the reference points for normal weather change over time. People tend to view the weather experienced over the last 2-8 years as normal. This implies that the public evaluates abnormal weather using recent years as a baseline, rather than weather patterns from a longer time ago.

Unlike these studies, we focus on the valuation of climate change mitigation in general and also the valuation of climate change attributes, rather than beliefs in human-caused climate change. This focus allows us to more quantitatively measure the preference for climate change mitigation and to compare the relative importance of the attributes, which are of interest to policymakers. In addition, the beliefs in climate change are generally obtained from opinion polls that could be subject to hypothetical and "yay-saying" biases. The design of the choice experiment, however, can reduce these biases. Furthermore, previous studies mainly use observational data, whereas we adopt experimental methods that aim to find causal relationships. Finally, our study examines the effect of seasons (warm seasons versus cool seasons) rather than temperature anomalies on the valuation for climate change mitigation.

Intuitively, temperature anomalies could affect preference for climate change mitigation since it enhances beliefs on climate change. One might ask: How would seasons affect climate change mitigation? We believe that seasons provide an important context that will alter the preference for climate change mitigation. Seasons capture more than just temperature. Warm seasons (i.e., summers) are characterized by high temperatures, more rain, and more frequent hurricanes. On the one hand, warm seasons might give people a cue of what it would be like if climate change accelerates and thereby increase people's valuation of climate change mitigation, while cool seasons might reduce people's concern about climate change, decreasing their valuation of climate change mitigation. On the other hand, reference-dependent preference theory suggests that only changes relative to a reference point matter for valuation (Kahneman and Tversky, 1979; Thaler, 1999;

Samuelson and Zeckhauser, 1988). This implies that climate change consequences might be perceived as less severe when evaluated in warm seasons (as the distance from the reference point–the season–is smaller) compared to valuations in the cool seasons, due to adaptation. Tochihara et al. (2022) showed some biological evidence that suggests that people from warm areas are more able to tolerate heat than people from cool areas.

Therefore, our first hypothesis is:

H1: People's average WTP for climate change mitigation is the same in the cool season as in the warm season.

Past experimental studies on environmental goods have found that new information about health consequences of pollutants affected their WTP to mitigate the pollution (Zhang and Qin, 2021). Zhang and Qin (2021), for example, conducted an auction experiment in China with anti-PM2.5 face masks. They found that providing subjects with information about the health consequence of PM 2.5 pollution increased buyers' WTP for the anti-PM2.5 filter. Ellison et al. (2016) studied how information on the proposed Food Safety Modernization Act (FSMA) regulations, which aimed to prevent food contamination, affected consumers' WTP for organic grape tomatoes. They found that information affects consumers' safety perceptions, but not their WTP. Hayes et al. (1995) used experimental auctions to study people's valuation for food safety. They found that participants' valuations of food with different objective risks are relatively flat. This suggests that participants put more weight on their prior risk belief than the new information of food risk they receive. For a literature review on information provision experiments in economics, see Haaland et al. (2023).

In this study, we also test whether providing information regarding climate change consequences could impact people's WTP for mitigation measures. One might expect that this information enhances the knowledge of some participants about the climate change consequences. Thus this information should increase their WTP. Our second hypothesis is formulated as:

H2: Information about the consequences of climate change will not influence people's average WTP for climate change mitigation.

Our third hypothesis derives from the natural experiment of the 2021 Henan floods. The floods were on a historically unprecedented scale in China, generating significant media attention both domestically and abroad. On the one hand, the experiences of the floods may enhance people's understanding of climate change by making the risk more salient and familiar. On the other hand, this experience doesn't necessarily translate into heightened concern for climate change if respondents don't attribute the extreme weather events to climate change (McCright et al., 2014; Reser et al., 2014; van der Linden, 2016).

Past literature has examined the effects of extreme weather events such as hurricanes (Bergquist et al., 2019), droughts (Carlton et al., 2016; Carmichael and Brulle, 2017), flooding (Demski et al., 2017; Spence et al., 2011; Ogunbode et al., 2019), and heatwaves (Dai et al., 2015) on climate change beliefs. These studies have largely relied on observational data of perceived natural disaster experiences derived from surveys, yielding mixed evidence.

For example, Demski et al. (2017) showed that the experience of a series of floods in the UK led to increased engagement with climate change. This finding was arrived at by comparing the survey responses of individuals affected by the floods with a nationally representative sample. Similarly, Spence et al. (2011) compared the climate beliefs of respondents who self-reported flooding with those who did not, and found links between flooding experience and climate change belief and willingness to save energy to mitigate climate change. However, they admitted that their cross-sectional design could not ensure the findings were causal and called for longitudinal designs to uncover causal relationships. Ogunbode et al. (2019) also used self-reported UK flooding experience and found that the experience of floods was only associated with the perceived threat of climate change and mitigation intention for people who attributed the flooding to climate change. Carlton et al. (2016) compared the survey data on climate change belief before and after a severe drought in the U.S. and found that the effect of drought experience on the climate change beliefs on agricultural advisors was insignificant.

Unlike previous studies, we use a natural experiment to examine the causal relationship between flooding experience and the valuation of climate change mitigation. Based on the previous literature, our last hypothesis is:

H3: When provided with information on climate change consequences, the Henan floods did not affect people's WTP for climate change mitigation.

3. Methodology

3.1. *Choice experiment*

The choice experiment consisted of choice sets with different levels of climate change attributes. We asked participants to decide which one of two sets (mix of attribute levels) they prefer. After choosing, we presented them with another pair, which may have contained some of the levels of the previous sets. To reduce the cognitive burden for participants, and to reduce the total number of possible choice sets (from 125—see Table I), we used an orthogonal main effect design using the package "support.CEs" (Aizaki et al., 2014) in the statistical software R. In particular, we used a randomized rotation design, which resulted in 18 pairs of choice sets that were presented in one block to participants. Each choice set contained different levels of attributes regarding climate change. Participants had to make a selection in every choice set to advance (no default or option to skip was given). Fig 1 is a sample of a choice card.

There were five climate change attributes and each attribute had three levels associated with three scenarios regarding the consequences of climate change. These three scenarios were: an increase in global temperature of 1°C, 1.5°C, and 2°C. The attributes and levels were: a) major floods, of the kind that occurs (levels: 1 every 50 years, 1 every 40 years, 1 every 30 years); b)

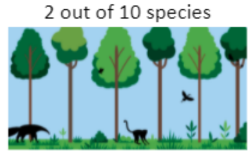
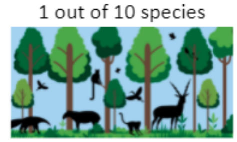
	Set 1	Set 2
Occurrence of major floods	one every 50 years	one every 40 years
Duration of heatwaves	Twelve days	Four days
Loss of biodiversity	2 out of 10 species 	1 out of 10 species 
Occurrence of super typhoons	one every 7 years	one every 3 years
Your contribution to climate change mitigation	15 yuan per month	25 yuan per month
Your Choice	☐	☐

FIGURE 1. Example choice set

heatwaves in which the temperature is above the average temperature of the warm season for (levels: 4 days, 8 days, 12 days); c) loss of biodiversity, in the form of species extinction at the rate of (levels: 1 out of 10 species, 2 out of 10 species, 3 out of 10 species); d) super typhoons, of the kind that happens (levels: once every 7 years, once every 5 years, once every 3 years); e) mitigation cost, in the form of a monetary contribution to climate change mitigation at (levels: 5 yuan (0.7 US dollar) per month, 15 yuan (2.1 US dollars) per month, 25 yuan (3.5 US dollars) per month). The attribute levels for flood frequency, heatwave duration, and super typhoon frequency were based on previous studies (Alfieri et al., 2017; Perkins-Kirkpatrick and Lewis, 2020; Ding et al., 2010; Tsuboki et al., 2015). To determine mitigation cost levels, we conducted a small nationwide study to elicit people's WTP for climate change mitigation policy. Based on this preliminary study, we chose 5 yuan, 15 yuan , and 25 yuan per month as the levels for people's contribution to climate change mitigation. These levels of WTP are less than one percent of an average household's monthly income and are consistent with previous studies of climate change valuation in China (Carlsson et al., 2013). All attributes and their levels are shown in Table I.

Table I. Climate change attributes and their levels

Attributes	Levels
Occurrence of major floods	once every 50 years once every 40 years once every 30 years
Duration of heatwaves	4 days 8 days 12 days
Loss of biodiversity	1 out of 10 species 2 out of 10 species 3 out of 10 species
Occurrence of super typhoons	once every 7 years once every 5 years once every 3 years
Contribution to climate change mitigation	5 yuan per month 15 yuan per month 25 yuan per month

3.2. *Treatments*

The treatments in our study were primarily based on two variables:seasons and information. For seasons, we conducted sessions in warm and cool seasons. The season treatments are labeled "high temperature" (HT) and "low temperature" (LT) depending on whether they were conducted in warm or cool seasons.

For information, we created a paragraph of the scientifically-based consequences of climate change for the attributes evaluated in the choice experiment (Appendix B). This paragraph was randomly assigned to half of the participants, generating two treatments; one in which people had the information (labeled as treatment "I") and another in which they did not (labeled as treatment "NI"). High temperature-no information (HT-NI) was selected as the baseline. In addition to the two-by-two treatment design, we included a fifth treatment due to an unprecedented natural event potentially related to climate change—the 2021 Henan floods—that happened after we had conducted the two treatments in the warm season. Leveraging this natural event and the treatments implemented prior to the floods, we added a new "flood information" (FI) treatment after the floods to examine the impact of experiencing this event on the WTP for climate change attributes. The "FI" treatment was conducted only in the warm season (soon after the floods) and included the information paragraph. This treatment allows us to examine the effect of flooding on the valuation of climate change mitigation, given that people already knew climate change could cause more severe floods.

The choice sets remained the same throughout the treatments. Table II shows a summary of the treatments.

The baseline treatment (warm season without information) and the warm season with information treatment were conducted on July 13$^{\text{th}}$, 2021. The survey was conducted again on August 6$^{\text{th}}$, after the floods in Central China's Henan province. The floods occurred between 17$^{\text{th}}$ and 31$^{\text{st}}$ July 2021 as a result of heavy rainfall. Information and no information treatments were repeated on October 26$^{\text{th}}$, 30$^{\text{th}}$, and December 3$^{\text{rd}}$ for the cool season treatments. The national average temperatures in the warm season (June to August) and the cool season (September to November) are 21.7 degrees Celsius and 10.6 degrees Celsius, respectively [5].

TABLE II. Experimental design

	Warm season (HT)	Cool season (LT)
No information (NI)	Control group	Treatment 2
Information (I)	Treatment 1	Treatment 3
Flood (FI)	Treatment 4	

3.3. *Hypothetical bias mitigation*

Although CE does not directly ask respondents about their WTP for environmental goods, it is still possible there is a hypothetical bias. The hypothetical bias literature recommends several ways to address it, such as cheap talk (Cummings and Taylor, 1999; List, 2001), consequentiality (Carson and Groves, 2007; Vossler et al., 2012), and solemn oath (Jacquemet et al., 2013). Cheap

5 China Climate Bulletin 2021, https://www.cma.gov.cn/zfxxgk/gknr/qxbg/202203/t20220308_4568477.html

talk scripts usually tell respondents that they tend to overstate their WTP and also remind them of the budget constraint. However, the effect of cheap talk is found to be mixed, and cheap talk script can sometimes exacerbate the hypothetical bias (Aadland and Caplan, 2006). Cheap talk is no longer recommended as an ex-ante approach to mitigate the bias (Holmes et al., 2017). The consequentiality approach shows both theoretically and empirically that when respondents view the survey as having actual policy consequences, respondents are more likely to reveal their true preferences (Carson and Groves, 2007; Vossler et al., 2012). To convince respondents that the study has consequences for policy-making, we tell them our climate change study is a project sponsored by the country's Ministry of Education in the consent form. In addition, to make the payment for climate change mitigation more realistic, we choose the electricity bill as the payment vehicle. Finally, respondents whose answers do not pass the attention test set up by the survey company are dropped. Only eligible respondents are paid for their time answering the survey. Our WTP estimates show they are similar to other studies' WTP in China about climate change mitigation.

3.4. *Subjects*

The choice experiment was conducted online through the professional survey company Wenjuanxing[6], as part of a survey. Wenjuanxing maintains a national subject pool of more than 2.6 million subjects, with a gender distribution of 48% female and 52% male. Overall, the company's subject pool is younger than the general population: around 75% are less than 30 years old and 8.3% are older than 40. The young average age of the subject pool is the result of the ways in which surveys are distributed and implemented by the company. Most are distributed through social media and these surveys are completed online using smartphones. In addition to the choice experiment, participants were asked to volunteer their socioeconomic information and answer some climate attitude questions. Socioeconomic and climate attitude questions can be found in Appendix B. To

[6] See their website https://www.wjx.cn for detail.

recruit participants, Wenjuanxing sent an invitation to their subject pool to answer the survey, with subjects self-selecting to participate. Upon completion of the survey, participants received minor monetary compensation.

4. **Econometric model**

To analyze responses to the choice experiment we used a variation of the Random Utility Model (McFadden Daniel, 1974). The model assumes that individual k's utility is the sum of the systematic (v) and random (ϵ) components (Holmes et al., 2017):

$$V_{ik} = v_{ik}(\boldsymbol{Z_i}, y_k - p_i) + \epsilon_{ik} = \boldsymbol{\beta Z_i} + \lambda(y_k - p_i) + \epsilon_{ik} \tag{1}$$

where V_{ik} is the indirect utility associated with alternative i; $\boldsymbol{Z_i}$ is a vector of attributes associated with alternative i; and y_k and p_i are income and price, respectively. The random error terms ϵ_{ik} are assumed to be independent and identically distributed (IID) following a Type 1 extreme value distribution. β is the preference parameter for non-monetary attributes and λ is the marginal utility of money. Thus, the probability that individual k chooses alternative i when facing two alternatives i and j from the choice set $\boldsymbol{C}$ is:

$$\begin{aligned} P_{ik} &= P[\boldsymbol{\beta Z_i} + \lambda(y_k - p_i) + \epsilon_{ik} > \boldsymbol{\beta Z_j} + \lambda(y_k - p_j) + \epsilon_{jk}; \forall j \in \boldsymbol{C}] \\ &= \frac{exp(\mu[\boldsymbol{\beta Z_i} + \lambda(y_k - p_i)])}{\sum_{j=1}^{N} exp(\mu[\boldsymbol{\beta Z_j} + \lambda(y_k - p_j)])} \end{aligned}$$

where μ is the scale parameter, reflecting the variance of the error term. When $\boldsymbol{\beta}$ is not allowed to vary with individuals, the model is called a conditional logit model; otherwise, it is a mixed logit model. The conditional logit model is unbiased only if the assumption of the IID structure of the error term holds. This assumption is unlikely to hold in the case of correlation in unobserved factors over multiple choices by each individual. However, the mixed logit model can accommodate a non-IID structure of the error terms. The mixed logit model also accommodates the possibility that individuals have random variations in tastes (Train, 1998).

It is possible that participants in our choice experiment might have different preferences for the attributes used. In addition, each individual makes a series of choices which might contain the same choice set; thus the error terms structure is unlikely to be IID. Therefore, we created a mixed logit model for our analysis using the statistical software STATA 14.

The unconditional probability of choosing alternative i for individual k now can be expressed as

$$P_{ik|\boldsymbol{\theta}} = \int \frac{exp(\boldsymbol{\beta} Z_i)}{\sum_{j=1}^{N} exp(\boldsymbol{\beta} Z_k)} f(\boldsymbol{\beta}|\boldsymbol{\theta}) d\boldsymbol{\beta} \tag{2}$$

where $\boldsymbol{\theta}$ is a vector of the underlying parameters of the taste distribution, and $f(\boldsymbol{\beta}|\boldsymbol{\theta})$ is the density distribution of the coefficient vector $\boldsymbol{\beta}$. In our setting, we assume that all attribute coefficients follow a jointly normal distribution. The price coefficient is treated as fixed to avoid a number of severe issues that arise when it is treated as random (Meijer and Rouwendal, 2006; Olsen, 2009). We also do not constrain the price parameter to be non-positive, as the literature reveals that a not-insignificant share of individuals made choices implying positive price parameters (Svenningsen and Thorsen, 2020). One explanation is that respondents try to signal commitment to the issues.

The coefficients $\boldsymbol{\beta}$ can be estimated using the user-written Stata command "mixlogit", which uses Halton draws to simulate the likelihood function (Hole, 2007). We use 100 Halton draws instead of the commonly used 1,000 draws to reduce the computational burden. The literature shows that using 100 draws can have performance close to or even superior to that of using 1,000 draws (Bhat, 2001; Train, 2009)

5. **Results and Discussion**

5.1. *Sample and summary statistics*

The survey was sent by the professional survey firm Wenjuanxing to a national pool of 3944 subjects. In total, 1,653 participants took the survey. The participation rate is high as subjects answer surveys for money. The sample was 47.4% male and 52.3% female. 18.7% of the participants were younger than 25 years old and 60.7% of the participants were between the ages of 25 and 35; the survey was distributed through the most popular social media app in China, WeChat, whose users are relatively young. Subjects had diverse occupations, including students, technicians, managers, college graduates, etc. Most of the participants belonged to households of 3 or 4 people, which is representative of China's average household size. In terms of education level, 73.5% of the participants held a bachelor's degree. The participants' household monthly income was diverse, ranging from less than 4,000 yuan (588 US dollars) to more than 24,000 yuan (3,529 US dollars). Only 20% of the participants stated that they had a political affiliation. The summary statistics of the socioeconomic characteristics for the control and treatment groups are reported in table III. We find the gender and occupation composition are balanced across treatments using a chi-square test, but there are significant differences for age, household size, education, and household monthly income among some treatments (see table VIII in the appendix). We will discuss controlling for these differences in the socio-demograhics characteristics in our regressions below.

We summarize participants' climate attitudes in table IX. For ease of exposition, we classified the choice of somewhat disagree to strongly disagree as negative, and the choice of somewhat agree to strongly agree as positive. Most respondents agree that climate change is a serious threat to the world and to China. Most of them agree that climate change is caused by human activities such as the burning of fossil fuels and that we need to take action to mitigate climate change. Regarding the impact of climate change, most respondents agree that climate change will increase

Table III. Summary statistics

	All	HTNI (%)	HTI (%)	HTFI (%)	LTNI (%)	LTI (%)
Sex						
Male	47.4	45.2	45.9	42.1	52.0	48.2
Female	52.3	54.4	53.7	57.9	47.6	51.6
Other	0.3	0.4	0.4	0.0	0.4	0.2
Age composition						
Age<25	18.6	19.3	19.2	28.9	13.7	16.2
25=<Age<35	60.7	56.0	54.7	49.1	64.4	70.5
35=<Age<45	14.6	16.6	19.2	13.6	16.7	9.5
Age>=45	6.1	8.1	6.9	8.4	5.1	3.8
Occupation						
Student	11.9	12.0	13.0	19.4	9.1	9.2
Other worker	60.6	61.7	60.5	59.7	58.9	62.4
Technician/RD	12.7	11.2	11.0	9.2	13.2	16.2
Manager	14.8	15.1	15.5	11.7	18.8	12.2
Household size						
1	1.0	1.9	0.0	1.1	0.9	1.1
2	5.3	8.9	4.1	5.1	4.9	4.5
3	48.5	48.3	57.3	44.3	47.1	47.5
4	29.3	29.7	23.6	29.3	29.7	31.8
5 or more	15.9	11.2	15.0	20.2	17.4	15.1
Education						
1 (lowest)	1.0	0.8	2.0	0.7	0.2	1.6
2	3.9	6.2	4.5	5.5	2.6	2.5
3	13.6	14.3	12.6	18.3	10.2	14.0
4	73.5	69.1	72.8	68.9	80.7	72.3
5	8.1	9.7	8.1	6.6	6.3	9.7
Household monthly income						
Low (<8,000 yuan)	21.3	20.1	21.2	29.3	17.9	20.3
Middle (8,000 to 16,000 yuan)	45.2	46.7	43.9	45.4	46.5	43.9
High (>16,000 yuan)	33.5	33.2	34.9	25.3	35.6	35.8
Party member						
1 (Yes)	20.0	19.7	24.0	16.1	22.3	18.0
2 (No)	80.0	80.3	76.0	83.9	77.7	82.0
Number of respondents	1653	259	246	273	431	444

the frequency of droughts and raise the sea level. However, they are divided on the frequency of floods and the duration of heatwaves. Respondents indicate a strong WTP to mitigate climate change. On the subject of the inter-generational equity of climate change, respondents agree that climate change will affect future generations' health and welfare and that the current generation should take action to protect the environment. They agree that inter-generational equity is an important concern for policymaking. They are willing to pay to mitigate climate change so that future generations will not be hurt. Our results show that the climate attitudes across treatments are also relatively homogeneous; we confirmed this using a t-test.

5.2. *Preference on attributes*

We first examined the results from a mixed logit model for each treatment separately, gaining insights into how respondents value attributes in each treatment. Due to the possibility of scalar parameter differences across treatments, we then estimated a generalized multinomial logit (GMNL) model to examine the effects of different treatments on respondents' utility/dis-utility derived from changes in each attribute. Lastly, we formally compared the effect of different treatments on the respondents' WTP for each attribute.

Table IV illustrates the results of the mixed logit estimation for all treatments. The mixed logit model does not control for the socio-demographic characteristics as the attribute levels are predetermined and thus are not affected by these socio-demographic factors. Columns (1) and (2) show the results when there is no information, and columns (3) and (4) show the results when there is information, for cool and warm seasons respectively. Column (5) shows the result of the flood information treatment. The cost coefficients are significantly negative in all treatments, except in the scenario of warm season with no information; this suggests that most participants react negatively to payment increases for climate change mitigation. In the case of warm season with no information, however, participants are not affected by payment increases. In the past, similar results have been attributed to non-rational behavior associated with answering climate change questions possessing significant moral consequences (Svenningsen and Thorsen, 2021, 2020). Therefore, it is possible that participants were indifferent to the range of mitigation costs presented in the choice experiment. Another explanation is related to reference points: in warm season, people might be less sensitive to mitigation costs if they perceive worse situations with climate change, making them more inclined to avoid that outcome despite the cost. To explain why participants react negatively to costs under warm seasons with information, we can think of information about climate change consequences as an equalizer, reducing overly pessimistic expectations due to high temperature; this would generate the expected negative reaction to cost increases.

The negative signs on all attributes across all treatments indicate that when compared to the baseline scenario of a frequency of flooding of once in 50 years, hurricane of once in 7 years, heatwave length of 4 days, and a loss of 10% of species, all other attributes generate significant dis-utility for respondents. In addition, a flooding frequency of once in 30 years generates significantly more dis-utility for respondents than that of once in 40 years (Wald test, p=0.000 for all models); a hurricane frequency of once in 3 years generates significantly more dis-utility for respondents than that of once in 5 years (Wald test, p=0.002, 0.118, 0.000, 0.000, 0.000 for models (1) to (5)). Also, respondents significantly dislike a heatwave of 12-day length compared to a heatwave of 8-day duration (Wald test, p=0.000 for all models). Finally, they more significantly dislike a situation with 30% species loss than that of 20% (Wald test, p=0.000 for all models). These results indicate that worse levels of climate change attribute generate higher levels of dis-utility. Most of the standard deviations of those coefficients are significantly different from zero, suggesting that the mixed logit model is more appropriate than the conditional logit model. For a robustness check, we also estimate a mixed logit model that includes an alternative specific constant (ASC), to control for people who might tend to choose the first/last alternative systematically. However, the resulting coefficients and their significance are very similar to those without the ASC.

5.3. *Treatment effects on preferences for attributes*

To assess the average treatment effects on respondents' utility/dis-utility derived from changes in each attribute, we estimated five model specifications. Each included pooled samples from a different pair of the five treatments respectively. We created five dummy variables: $D_{LTNI \rightarrow HTNI}$, $D_{LTI \rightarrow HTI}$, $D_{LTNI \rightarrow LTI}$, $D_{LTNI \rightarrow HTI}$, and $D_{HTI \rightarrow HTFI}$, with each dummy being 1 if the respondents were in the treatment after the arrow sign and zero if the respondents were in the treatment

Table IV. Mixed logit estimation results

	(1) LTNI	(2) HTNI	(3) LTI	(4) HTI	(5) HTFI
Mean					
Cost	-0.00843***	-0.00368	-0.00399**	-0.0182***	-0.0118***
	(-4.76)	(-1.57)	(-2.27)	(-7.45)	(-5.22)
D_Flood 40_years	-0.205***	-0.194***	-0.196***	-0.242***	-0.115***
	(-5.85)	(-4.17)	(-5.63)	(-5.07)	(-2.59)
D_Flood 30_years	-0.408***	-0.414***	-0.360***	-0.483***	-0.379***
	(-9.15)	(-7.53)	(-8.43)	(-7.87)	(-6.59)
D_Typhoon 5_years	-0.146***	-0.123***	-0.0551	-0.112**	-0.144***
	(-4.16)	(-2.64)	(-1.58)	(-2.33)	(-3.21)
D_Typhoon 3_years	-0.268***	-0.199***	-0.205***	-0.358***	-0.351***
	(-7.01)	(-4.03)	(-5.66)	(-6.53)	(-7.43)
D_Heatwaves 8_days	-0.211***	-0.256***	-0.229***	-0.258***	-0.212***
	(-5.99)	(-5.51)	(-6.56)	(-5.39)	(-4.75)
D_Heatwaves 12_days	-0.378***	-0.534***	-0.397***	-0.473***	-0.427***
	(-10.16)	(-9.34)	(-9.69)	(-8.25)	(-8.58)
D_Biodiversity 3_10_species	-0.690***	-0.912***	-0.763***	-0.832***	-0.866***
	(-13.11)	(-12.06)	(-13.68)	(-11.26)	(-13.17)
D_Biodiversity 2_10_species	-0.362***	-0.467***	-0.360***	-0.429***	-0.411***
	(-10.41)	(-10.10)	(-10.44)	(-9.00)	(-9.28)
SD					
D_Flood 40_years	-0.00116	-0.000975	-0.00885	0.00272	0.00156
	(-0.02)	(-0.01)	(-0.11)	(0.03)	(0.01)
D_Flood 30_years	0.539***	0.431***	0.487***	0.554***	0.565***
	(10.69)	(6.01)	(9.41)	(8.16)	(8.90)
D_Typhoon 5_years	-0.00130	0.00853	0.00879	-0.00760	-0.0111
	(-0.02)	(0.14)	(0.18)	(-0.13)	(-0.15)
D_Typhoon 3_years	0.280***	0.240***	0.169*	0.389***	0.200**
	(4.41)	(2.65)	(1.90)	(5.26)	(2.00)
D_Heatwaves 8_days	-0.00636	0.0283	0.0384	0.00155	-0.00753
	(-0.13)	(0.31)	(0.46)	(0.02)	(-0.11)
D_Heatwaves 12_days	0.188**	0.482***	0.412***	0.441***	0.301***
	(2.07)	(7.05)	(7.72)	(6.13)	(3.97)
D_Biodiversity 3_10_species	0.775***	0.920***	0.867***	0.828***	0.732***
	(14.22)	(11.56)	(15.37)	(10.85)	(10.61)
D_Biodiversity 2_10_species	-0.0175	0.0129	-0.0131	-0.0263	-0.0389
	(-0.32)	(0.11)	(-0.18)	(-0.38)	(-0.51)
Observations	15516	9324	15984	8856	9828
AIC	9991.3	5853.2	10241.7	5570.6	6227.4
BIC	10121.4	5974.6	10372.3	5691.1	6349.7
ll	-4978.7	-2909.6	-5103.9	-2768.3	-3096.7

Notes: Standard errors are in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). LTNI: Low temperature and no information; HTNI: High temperature and no information; LTI: Low temperature and information; HTI: High temperature and information; HTFI: High temperature and flood information.

before the arrow sign. To evaluate treatment differences, we interacted these dummies with each attribute. In these specifications, we also do not control for the influence of socio-demographic factors. Indeed, the summary statistics indicate that several of these factors are correlated with the treatments. Yet since we have an unlabeled choice experiment (i.e., the alternatives are unlabeled), alternatives themselves (besides the attribute levels) convey no information to respondents. It is reasonable to think that the choices among alternatives would not be correlated with the socio-demographic factors.

Logit models are not completely identified because the coefficients are normalized by the variance (or scale) of the error term. In our setting, if there are scale/variance differences across treatments, we cannot know whether any differences in the estimated coefficients are due to differences in actual coefficients, due to scale differences, or both. To address the identification problems, we allowed the variance of the error term to vary across treatments by introducing a new parameter, σ^{treat}, which indicates the relative scale of the residual variance across treatments within the pair. Stata command "gmnl" is readily available to estimate a pooled mixed logit model accommodating the scale differences (Gu et al., 2013)[7].

Table V displays the results. Each column represents a different pair of treatments. The table shows the interaction between cost and the dummies to be statistically significant for the pair $LTI \rightarrow HTI$ and $LTNI \rightarrow HTI$, suggesting that mitigation cost does vary across treatments—and can be context-dependent. The table also shows that the effect of seasons on the marginal utility of cost depends on the presence of information, and the effect of information on the marginal utility of cost depends on seasons. Model (1) shows that respondents are less cost-sensitive under warm seasons (without information) compared to under cool seasons (without information), although

[7] When running the "gmnl" command in Stata, we constrain the parameter "τ" to be zero. This is because we want to capture subgroup level difference in scale factor, i.e., the difference between treatment and control groups, not the individual heterogeneity in scale factor. In addition, we constrain the parameter "τ" to be zero so as to prevent gmnl from estimating this parameter, because it is not identified in the model.

the effect is not significant at 5%. When presented with information, however, model (2) shows that respondents are significantly more cost-sensitive under warm seasons compared to under cool seasons. The latter result may be due to reference-dependent preferences. The relative change in temperature due to climate change is smaller in the warm season treatment compared to the cool season treatment, which in turn leads to higher valuation for climate mitigation in the cool season treatment. Intuitively, people living under high temperatures could be more adaptive to heat than people living under low temperatures (Tochihara et al., 2022).

Since being less (more) sensitive to mitigation cost can be interpreted as higher (lower) WTP for climate change mitigation in general, the above result implies that when provided with information, respondents' WTP for climate change mitigation is significantly higher in the cool season than in the warm season.

Model (3) shows that in the cool season treatment, respondents with climate change information are less cost-sensitive than those without information, although the effect is not significant at 5%. However, in the warm season treatment, as shown in model (4), respondents with climate change information are significantly more cost-sensitive compared to those without. Again, this result implies that for people in the warm season, providing information on climate change consequences reduces the WTP for climate change mitigation in general.

It is possible that seasons anchor the expectation about climate change consequences. In the warm season, information made climate change consequences better than expected, hence it decreased WTP for mitigation. Whereas in the cool season, the information makes climate change worse than expected, and therefore, it increases their WTP for mitigation.

Most of the treatment effects for the other attributes of climate change are not statistically significant, except for the frequency of typhoons. Specifically, compared to the cool season with information (LTI) treatment, the warm season with information (HTI) treatment generates significantly more dis-utility for respondents when increasing the frequency of typhoon from once in 7 years to once in 3 years. In addition, compared to the warm season without information (HTNI) treatment, the warm season with information (HTI) treatment leads to significantly more dis-utility when increasing the frequency of typhoon from once in 7 years to once in 3 years. As for the flood information treatment, model (5) indicates it does not seem to affect respondents' preferences for changes in each attribute when compared to the information treatment. This result suggests that when people knew the consequences of climate change, the flooding event alone did not affect their preferences for climate change mitigation.

5.4. *Treatment effects on welfare measures*

As our previous results seem to show that the context influences preferences for mitigation, we now analyze how different contexts affect the implicit prices for changes in each attribute. We achieve this by comparing the WTP for each attribute change across treatments. When calculating the WTP, the scale parameters cancel out, which allows us to directly compare the WTP across treatments. The assumption of the normality of the denominator causes the estimates for WTP to have infinite moment. As a result, the standard deviation and mean of the WTP are not defined, and we cannot obtain a confidence interval. However, the median of the WTP distribution is finite (Bliemer and Rose, 2013). We thus calculated the median of WTP using the Krinsky-Robb procedure. The results are shown in table VI, where the confidence interval of the median was calculated using the median WTP and the standard deviation calculated based on the median WTP.

We further tested the difference of WTP between treatments using the convolutions approach — i.e., the Poe test (Poe et al., 1994, 2005). The Poe test does not test for mean differences in WTP estimates. It is a complete combinatorial approach that can be used to test the difference of two different distributions even if the mean is not defined (or the moment is infinite). The general idea of the Poe test is to simulate WTPs from two treatments and calculate how many WTP cases

Table V. Average treatment effects derived by generalized multinomial logit model

	(1) LTNI→HTNI	(2) LTI→HTI	(3) LTNI→LTI	(4) HTNI→HTI	(5) HTI→HTFI
Mean					
Cost	-0.00850***	-0.00400**	-0.00853***	-0.00359	-0.018***
	(-4.79)	(-2.27)	(-4.80)	(-1.53)	(-7.41)
Cost * Dummy	0.00592*	-0.0139***	0.00521*	-0.0145***	0.004
	(1.87)	(-4.64)	(1.95)	(-4.31)	(1.17)
D_Flood 40_years * Dummy	0.0391	-0.0405	0.0278	-0.0488	0.095
	(0.62)	(-0.67)	(0.52)	(-0.72)	(1.5)
D_Flood 30_years * Dummy	0.0406	-0.114	0.0839	-0.0690	0.034
	(0.50)	(-1.49)	(1.21)	(-0.80)	(0.41)
D_Heatwaves 8_days * Dummy	-0.0257	-0.0221	-0.00416	0.00283	0.015
	(-0.41)	(-0.36)	(-0.08)	(0.04)	(0.24)
D_Heatwaves 12_days * Dummy	-0.109	-0.0665	0.00904	0.0753	-0.024
	(-1.48)	(-0.89)	(0.14)	(0.84)	(-0.31)
D_Biodiversity 2_species * Dummy	-0.0640	-0.0564	0.0285	0.0447	-0.04
	(-0.95)	(-0.87)	(0.50)	(0.58)	(-0.59)
D_Biodiversity 3_species * Dummy	-0.151	-0.0185	-0.0275	0.120	-0.142
	(-1.42)	(-0.17)	(-0.30)	(0.96)	(-1.34)
D_Typhoon 5_years * Dummy	0.0426	-0.0581	0.105**	0.00729	-0.044
	(0.69)	(-0.98)	(1.99)	(0.11)	(-0.71)
D_Typhoon 3_years * Dummy	0.102	-0.144**	0.0846	-0.159**	-0.038
	(1.48)	(-2.22)	(1.48)	(-2.14)	(-0.53)
D_Flood 40_years	-0.207***	-0.198***	-0.208***	-0.194***	-0.24***
	(-5.90)	(-5.66)	(-5.92)	(-4.16)	(-5.04)
D_Flood 30_years	-0.411***	-0.361***	-0.416***	-0.420***	-0.476***
	(-9.56)	(-8.32)	(-9.50)	(-7.34)	(-7.62)
D_Typhoon 5_years	-0.148***	-0.0553	-0.149***	-0.121***	-0.113**
	(-4.19)	(-1.58)	(-4.21)	(-2.60)	(-2.36)
D_Typhoon 3_years	-0.268***	-0.206***	-0.270***	-0.197***	-0.354***
	(-7.09)	(-5.49)	(-7.22)	(-3.84)	(-6.68)
D_Heatwaves 8_days	-0.209***	-0.230***	-0.211***	-0.259***	-0.258***
	(-5.96)	(-6.58)	(-5.99)	(-5.56)	(-5.41)
D_Heatwaves 12_days	-0.380***	-0.399***	-0.381***	-0.537***	-0.468***
	(-9.68)	(-9.64)	(-9.65)	(-9.50)	(-8.37)
D_Biodiversity 3_species	-0.703***	-0.788***	-0.704***	-0.938***	-0.817***
	(-13.18)	(-14.28)	(-13.15)	(-12.59)	(-11.04)
D_Biodiversity 2_species	-0.362***	-0.363***	-0.364***	-0.471***	-0.427***
	(-10.42)	(-10.51)	(-10.44)	(-10.23)	(-8.99)
Scalar parameter					
σ^{treat}	0.105	0.0123	0.0707	-0.00329	-0.132
	(1.13)	(0.13)	(0.88)	(-0.03)	(-1.27)
Observations	24840	24840	31500	18180	18684
AIC	15833.0	15811.1	20221.2	11403.8	11784.5
BIC	16052.2	16030.3	20446.9	11614.6	11996.1
Log-likelihood	-7889.5	-7878.5	-10083.6	-5674.9	-5865.3

Notes: t-values are in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).
In the GMNL model, parameters τ and γ are constrained to be zero and are not shown in the table. The "Dummy" variable in the table represent the five dummies ($D_{LTNI \to HTNI}$, $D_{LTI \to HTI}$, $D_{LTNI \to LTI}$, $D_{LTNI \to HTI}$, and $D_{HTI \to HTFI}$), depending on the column. LTNI: Low temperature and no information; HTNI: High temperature and no information; LTI: Low temperature and information; HTI: High temperature and information; HTFI: High temperature and flood information.

from one treatment are larger than those of the other treatment. Table VII shows the p-values of the pair-wise comparisons. Columns (1) and (4) indicate that WTP for changes in all attributes are not significantly different at 5% for pairwise comparisons involving HTNI treatment.

Column (2) indicates that WTP is significantly higher under cool seasons with information, compared to warm seasons with information, for nearly all attribute changes. Again, this can be explained by reference-dependence preferences. People living under warm seasons may be more adaptive to heat than people living under cool seasons, and consequently care less about climate change (Tochihara et al., 2022). Because the warm season is also the season in which most of the floods, heatwaves, and typhoons occur, it might not be surprising that the WTP is lower for changes in all these attributes.

In addition, column (3) indicates that WTP is significantly higher for people with information (cool seasons) than without information (cool seasons), for reducing the duration of heatwaves from 12 days to 4 days and for decreasing biodiversity loss from 30% to 10%. This result, combined with the result from column (2), suggests that WTP for duration of heatwaves and loss of biodiversity is especially sensitive to changes in information and weather seasons.

To explain the results in column (3), it may simply be the case that information allows the subjects to realize the severity of climate change consequences, thereby leading to higher valuations than are found in the case without information.

Finally, column (5) indicates that during warm seasons, the experience of the recent, unprecedented floods combined with information on climate change consequence increases the WTP for reducing biodiversity loss from 30% to 10%, compared to the treatment with information only. The information treatment does not, however, affect the WTP for changes in other attributes. In an alternative regression focused on the sample from Henan province where the floods occurred, we found that the effects of the floods are similarly insignificant. This is a somewhat surprising finding. It may be because in the information treatment, the information already conveyed the message that the impact of climate changes will be severe, and thus the reminder of the recent unprecedented floods may not carry additional weight. In addition, Henan has always been exposed to serious floods. People there might be adapt to it to a certain degree.

Reading from table V, we see that the difference in WTP for climate change attributes across treatments as shown from table VII is mainly due to differing preferences for mitigation costs rather than for attributes. Treatments don't directly influence the preference for each climate change attribute per se.

In response to our hypotheses, we find that the effect of weather seasons on the WTP for climate change mitigation depends on the presence of information and vice verse. Specifically, our main results are:

Result 1. We reject the hypothesis that people's average WTP for climate change mitigation is the same in the cool season and the warm season. When presented with information about climate change consequences, warm seasons reduce respondents' WTP for climate change mitigation in general. In addition, warm seasons reduces their WTP for the improvement of the climate change attributes of heatwave duration, biodiversity loss, flooding and typhoon frequency.

Result 2. We reject the hypothesis that information about the consequences of climate change will not change people's average WTP for climate change mitigation. During warm seasons, providing information on climate change consequences reduces the WTP for climate change mitigation in general. In addition, during cool seasons, information on climate change consequences increases participants' WTP for the improvement of the climate change attributes of heatwave duration and biodiversity loss.

Result 3. We cannot reject the hypothesis that the Henan floods did not affect people's WTP for climate change mitigation, when presented with information on climate change consequences. Furtherthe unprecedented flooding event did not affect participants' WTP for the improvement of most of the climate change attributes when they know the consequences of climate change.

TABLE VI. Median WTP

	(1) LTNI	(2) HTNI	(3) LTI	(4) HTI	(5) HTFI
Flood probability					
1 in 50 → 1 in 40	24.31	39.77	45.75	13.26	9.64
	(24.06, 24.56)	(38.95, 40.70)	(44.92, 46.65)	(13.13, 13.41)	(9.47, 9.76)
1 in 50 → 1 in 30	48.37	81.29	83.24	26.72	31.81
	(47.93, 48.92)	(79.46, 83.37)	(81.52, 84.84)	(26.41, 27.07)	(31.42, 32.18)
Duration of heatwaves					
4 days → 8 days	24.87	50.46	52.73	14.27	17.92
	(24.58, 25.16)	(49.1, 51.83)	(51.63, 53.94)	(14.1, 14.47)	(17.64, 18.17)
4 days → 12 days	44.96	106.86	92.12	26.13	36.12
	(44.49, 45.47)	(104.35, 109.4)	(90.36, 93.78)	(25.73, 26.54)	(35.69, 36.51)
Loss of biodiversity					
-10% → -30%	81.73	180.75	177.3	45.99	73.03
	(80.82, 82.52)	(176.2, 186.47)	(173.18, 181.61)	(45.4, 46.5)	(72.22, 73.8)
-10% → -20%	43.15	92.12	83.2	23.6	34.79
	(42.72, 42.53)	(89.44, 94.67)	(81.4, 84.77)	(23.32, 23.87)	(34.36, 35.25)
Occurrence of super typhoons					
1 in 7 → 1 in 5	17.39	23.64	11.79	6.13	12.38
	(17.11, 17.6)	(22.97, 24.32)	(11.32, 12.12)	(6.01, 6.25)	(12.19, 12.54)
1 in 7 → 1 in 3	31.8	39.3	47.5	19.67	29.59
	(31.44, 32.11)	(38.1, 40.37)	(46.5, 48.6)	(19.37, 19.94)	(29.27, 29.92)

Notes: The 95% confidence intervals are in the parentheses.
LTNI: Low temperature and no information; HTNI: High temperature and no information; LTI: Low temperature and information; HTI: High temperature and information; HTFI: High temperature and flood information.

6. **Conclusion**

Climate change significantly affects people's daily lives and results in increased occurrences of summer heatwaves, more frequent and severe floods, loss of biodiversity, and more frequent and powerful typhoons. Understanding people's preferences about climate change is important for policymakers trying to make better decisions. This paper used a choice experiment to study the effect of weather seasons and information about climate change consequences on people's preferences for climate change mitigation. Leveraging the natural experiment of an unprecedented flooding event in China, we also examined the effects of experiencing this event on people's preference for climate change mitigation. Our results show a significant treatment effect of weather seasons and

Table VII. Poe test for differences of each pair-wise treatment

	(1) LTNI-HTNI	(2) LTI-HTI	(3) LTNI-LTI	(4) HTNI-HTI	(5) HTI-HTFI
Flood probability					
1 in 50 → 1 in 40	.349	.628	.4	.631	.061
1 in 50 → 1 in 30	.88	.014	.899	.056	.733
Duration of heatwaves					
4 days → 8 days	.911	.014	.948	.056	.75
4 days → 12 days	.936	014	.953	.056	.893
Loss of biodiversity					
-10% → -20%	.926	.014	.941	.056	.932
-10% → -30%	.931	.014	.963	.056	.971
Occurrence of super typhoons					
1 in 7 → 1 in 5	.746	.213	.358	.074	.878
1 in 7 → 1 in 3	.746	.024	.822	.092	.92

Notes: The p-value is for the difference between the WTP of the first treatment being less than the WTP of the second treatment in each pair of treatments.
LTNI: Low temperature and no information; HTNI: High temperature and no information; LTI: Low temperature and information; HTI: High temperature and information; HTFI: High temperature and flood information.

information on preferences for WTP for climate change mitigation in general as well as improvement of climate change attributes. In particular, and when provided with information, respondents' WTP for climate change mitigation in general is significantly higher during cool seasons compared to that under warm seasons. This is also the case for the WTP for nearly all attribute changes.

In addition, for warm season treatments, providing information on climate change consequences reduces the WTP for climate change mitigation in general. But during cool seasons, providing information on climate change consequences increases respondents' WTP for reducing both the duration of heatwaves and biodiversity loss. Finally, when respondents were presented with information, the unprecedented flooding event that occurred in China in 2021 did not affect participants' WTP for climate change mitigation in general and the improvement of nearly all climate change attributes.

Our results suggest that promoting information on climate change consequences, as many of the advertisements and education campaigns do nowadays, might not necessarily enhance people's preference for climate change mitigation, particularly if seasonality is not taken into account. In addition, the recently more frequent occurrence of severe natural disasters, possibly due to climate change, might not change preferences for climate change mitigation among people who are already aware of the severity of climate change consequences.

Finally, it could be expected that as future temperatures increase–due to climate change–people might become more willing to support policies to mitigate climate change. But our results suggest the opposite may be the case due to habituation effects. People experiencing high temperatures might adapt to them, becoming less willing to support expenditures for climate change mitigation.

An important caveat in our study relates to the homogeneity of participants' climate change attitudes. Future studies should explore the robustness of the results using more heterogeneous sampling, as well as investigating alternative explanations for the seasonal effects found. One, perhaps counter-intuitive, result that might require further research is the low sensitivity to mitigation costs during warm seasons with no information provided.

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Appendix A. Tables and figures

Table VIII. Chi-square test results

	HTNI vs HTI	HTNI vs LTNI	LTI vs HTI	LTNI-LTI	HTI vs HTFI
Gender	0.984	0.287	0.447	0.501	0.377
Age	0.864	0.061	0.000	0.008	0.033
Occupation	0.383	0.231	0.457	0.061	0.783
Household size	0.006	0.05	0.05	0.882	0.028
Education	0.564	0.007	0.591	0.017	0.258
Income	0.849	0.098	0.843	0.044	0.043
Party member	0.243	0.422	0.061	0.116	0.025

Notes: The results in the table are p-values of the Chi-square test.

Table IX. Climate Attitude

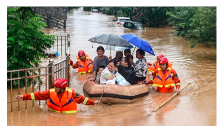
Questions	HTNI	HTI	HTFI	LTNI	LTI
Q1: Climate change is a significant threat to the world					
Negative or indifferent	3.5	3.3	2.6	3	2.9
Positive	96.5	96.7	97.4	97	97.1
Q2: Climate change is a significant threat to China					
Negative or indifferent	5.8	6.5	5.9	4.4	4.5
Positive	94.2	93.5	94.1	95.6	95.5
Q3: Climate change is due to human activities such as burning of fossil fuels					
Negative or indifferent	13.1	12.2	9.5	10.4	10.8
Positive	86.9	87.8	90.5	89.6	89.2
Q4: Taking action to mitigate climate change is not important					
Negative or indifferent	90.7	87.8	89	87.5	84.2
Positive	9.3	12.2	11	12.5	15.8
Q5: Climate change will decrease the frequency of flooding					
Negative or indifferent	60.2	62.6	59	59.4	63.7
Positive	39.8	37.4	41	40.6	36.3
Q6:Climate change will increase the frequency of drought					
Negative or indifferent	8.9	10.6	10.3	9.3	8.1
Positive	91.1	89.4	89.7	90.7	91.9
Q7: Climate change will lead to shorter heatwaves					
Negative or indifferent	42.1	43.1	43.6	44.3	41.2
Positive	57.9	56.9	56.4	55.7	58.8
Q8: Climate change will raise the sea level					
Negative or indifferent	9.3	7.7	8.1	6.5	5.9
Positive	90.7	92.3	91.9	93.5	94.1
Q9: I am willing to pay, or to reduce consumption, to reduce climate change					
Negative or indifferent	6.6	6.9	8.1	6	8.6
Positive	93.4	93.1	91.9	94	91.4
Q10: Climate change will hurt future generations' health and welfare					
Negative or indifferent	7	7.7	9.5	5.1	5
Positive	93	92.3	90.5	94.9	95
Q11: The current generation should not worry about protecting the environment; future generations should					
Negative or indifferent	87.3	80.9	86.8	81.2	82.9
Positive	12.7	19.1	13.2	18.8	17.1
Q12: Intergenerational equity should be an important consideration for climate change policy					
Negative or indifferent	22.4	17.1	15.4	15.6	17.3
Positive	77.6	82.9	84.6	84.4	82.7
Q13: I would financially contribute to actions that aim to mitigate climate change even if the benefits are to be received by future generation					
Negative or indifferent	9.3	11	10.3	10.7	11.3
Positive	90.7	89	89.7	89.3	88.7
Q14: I prefer enjoying the present and don't spend a lot of time worrying about the future					
Negative or indifferent	83	82.9	83.5	82.8	84.5
Positive	17	17.1	16.5	17.2	15.5

Appendix B. Experiment instructions (translated from Chinese)

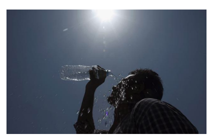
For the seasons' treatments, the instructions are as follows.

Thank you for participating in this study. This study consists of two parts. In the first part you will be presented with a series (18) of two choice sets from which you will have to select one. You should pick whichever set you prefer. Each set consists of five (5) different attributes/characteristics, which are linked to climate change. The attributes are:

Occurrence of major floods. This will be measured in terms of the frequency of major floods. Major floods are the kind that are supposed to happen rarely (twice a century) and can cause material damage and even human losses. For example, the 2020 flood (illustrated below) caused 219 deaths and 178.9 billion yuan in economic losses.

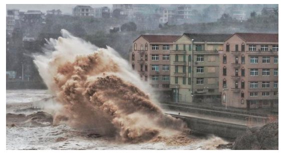


Duration of heatwaves. This will be measured as the number of consecutive days in which the daily temperature surpasses the usual summer temperature by 5 degrees Celsius or more. Heatwaves can cause fainting, dehydration, and even deaths.



Loss of Biodiversity. This will be measured as the number of species (including plants and animals) that might lose half or more of their presence in ecosystems. Coral reefs and polar bears might even disappear completely due to high temperatures resulting from climate change.

Occurrence of super typhoons. This will be measured as the frequency of super typhoons (the strongest of typhoons). For example, the super typhoon Limaki that landed in Zhejiang in 2019 had a maximum wind force of level 16 near the center. "Limaki" caused disasters such as urban and rural flooding, small and medium-sized river floods, mountain torrents, and landslides to varying degrees in Zhejiang, Anhui, Jiangsu, Shandong and other places. More than 5.358 million people were affected by the disaster, 32 people died, and 16 people remain missing.



Your contribution to climate change mitigation. This will be measured in yuan per month, and it represents a payment you would be willing to make to mitigate carbon emissions and therefore mitigate and adapt to climate change.

To pick the set you prefer, you must click the corresponding square at the bottom of the set where it says “Your Choice” and then click continue. After choosing a set and clicking continue, you will be presented with two new sets from which you again have to pick one. This process will occur 18 times. You might get similar attributes in a pair of sets but they will never be entirely the same for both sets. A set could be repeated between pairs.

After finishing with the first part of the study you will be asked to answer some questions regarding your decisions and some socioeconomic questions. You will receive monetary compensation only if you reach the end of the second part.

Climate change can cause flooding, heatwaves, biodiversity loss, and super typhoons. However, we can adopt measures to mitigate and adapt to climate change. For example, we can pay money to build dams to avoid flooding. These measures, however, entail some cost to the public in the form of tax payments. Depending on the extent of these payments to mitigate and adapt to the climate change, we will have varying degrees of those harmful consequences of climate change.

Please choose your preferred option. Then 18 choice sets such as figure 2 will follow.

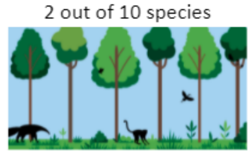
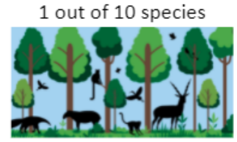
	Set 1	Set 2
Occurrence of major floods	one every 50 years	one every 40 years
Duration of heatwaves	Twelve days	Four days
Loss of biodiversity	2 out of 10 species 	1 out of 10 species 
Occurrence of super typhoons	one every 7 years	one every 3 years
Your contribution to climate change mitigation	15 yuan per month	25 yuan per month
Your Choice	☐	☐

Figure 2. Example choice set

For the information treatments, we added the following additional paragraph immediately before showing the participants the choice sets:

Before you begin, please read the following information. The climate seems as though it will continue to change throughout the world as global temperatures are expected to rise in the coming decades. The increase in temperatures will have various effects on the world and its people, with extreme weather events (such as typhoons, draughts, blizzards, etc.), rising seas, and shifting wildlife populations and habitats being the most prominent. In the coming decades, extreme weather events in China are expected to happen more often, be more severe, and last longer. As extreme weather events become more severe and widespread throughout China, it is expected that their impact on nature and society will be larger; they will potentially damage the environment, the economy, and people's wealth. The costs of protecting against climate change, adapting to new conditions, or restoring the affected areas, society and the economy are also expected to increase.

For the flooding information treatment, we added the following paragraph instead of the one above:

Before you begin, please read the following information. The climate seems as though it will continue to change throughout the world as global temperatures are expected to rise in the coming decades. The increase in temperatures will have various effects on the world and its people, with extreme weather events (such as typhoons, draughts, blizzards, etc.), rising seas, and shifting wildlife populations and habitats being the most prominent. For example, the extreme storm that struck Henan province on July 20^{th} led to 302 deaths and 50 missing people. The economic loss from the storm is 114.269 billion Chinese yuan (Xinhua News and Henan Daily). In the coming decades, extreme weather events in China are expected to happen more often, be more severe, and last longer. As extreme weather events become more severe and widespread throughout China, it is expected that their impact on nature and society will be larger; they will potentially damage the environment, the economy, and people's wealth. The costs of protecting against climate change, adapting to new conditions, or restoring the affected areas, society and the economy are also expected to increase.