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ORIGINAL ARTICLE

Hyperbolic Discounting with Environmental Outcomes across Time, Space, and Probability

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Abstract
Environmental discounting is a potentially important research area for climate change mitigation. We aimed to replicate and extend earlier work on the discounting of a negative environmental outcome. We measured ratings of concern, and willingness to act to mitigate, an outcome involving air pollution that would hypothetically affect the garden and drinking water of the participants over psychological distance represented by temporal (1 month, 6 months, and 1, 3, 5, 10, and 80 years), spatial (5, 20, 50, 100, 1000, and 5000 km), and probabilistic (95%, 90%, 50%, 30%, 10%, and 5% likelihood) dimensions. For our data from 224 first-year psychology students, of four potential models (an exponential, simple hyperbolic, and two hyperboloid functions), the Rachlin hyperboloid was the best-fitting model describing ratings of concern and action across all three dimensions. Willingness to act was discounted more steeply than concern across all dimensions. There was little difference in discounting for outcomes described as human-caused rather than natural, except that willingness to act was discounted more steeply than concern for human-caused environmental outcomes compared to natural outcomes across spatial (and, less conclusively, temporal) distance. Presenting values of the three dimensions in random or progressive order had little effect on the results. Our results reflect the often-reported attitude-behavior gap whereby people maintain concern about a negative event over dimensions of psychological distance, but their willingness to act to mitigate the event is lower and more steeply discounted.

Keywords Behavioral economics · Environmental psychology · Temporal discounting · Probability discounting · Spatial discounting

Introduction

The world's climate has changed dramatically over the last decades, as human activities drive anthropogenic climate change. Global atmospheric conditions of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) have increased markedly. These increases catalyze the occurrence of global climate hazards. It is clear that human behavior needs to change drastically, yet current trends show that behavior is not changing quickly enough (Intergovernmental Panel on Climate Change [IPCC], 2018). In consequence, it is important to understand the barriers to sustainable behavior.

As reasons for a lack of public behavior change in response to climate change are wide-ranging, multileveled, and complex (Gifford, 2011), *judgmental discounting* and *uncertainty* have been deemed especially relevant factors for behavioral psychology and were listed as one of the "dragons of inaction" or psychological barriers to climate change mitigation and adaptation (Gattig & Hendrickx, 2007). Concurrent with Gifford's (2011) proposition on factors accelerating discounting and, hence, inaction towards environmental behavior, a report of the American Psychological Association task force on the interface between psychology and climate change (Swim et al., 2009) stressed people's tendency to discount the likelihood of future and remote events. Given that environmental risks involve high levels of uncertainty, and their consequences are often delayed and occur in distant

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places (Gattig & Hendrickx, 2007), research on the way people discount outcomes over the dimensions of time, space, and probability is highly relevant to understanding their inaction on issues of climate change.

Temporal Discounting

Temporal discounting of monetary outcomes is a much-studied phenomenon and describes the way the subjective value of a commodity or a financial outcome is reduced over time (Madden & Bickel, 2010). Data consistently reveal the individual tendency to discount rewards over time (Doyle, 2012). Thus, when outcomes are delayed, their value monotonically decreases. Temporal discounting has been explained by impulsivity and a tendency for immediate gratification (Bickel, Odum, & Madden, 1999).

From a behavioral perspective, less research has dealt with temporal discounting regarding the environment and, in particular, sustainable behavior (Hirsh, Costello, & Fuqua, 2015). Environmental outcomes may be discounted in a similar way as monetary outcomes and such a finding would be useful, because it would imply that the large body of research on temporal discounting using monetary outcomes could be applied also to environmental outcomes (Hardisty & Weber, 2009). Given that monetary and environmental outcomes were discounted similarly over a period of 1 year in Hardisty and Weber's (2009) research, for example, they concluded that findings from research on monetary discounting would predict the way environmental outcomes are discounted over longer periods (Hardisty & Weber, 2009). However, the range of delays commonly used in studies of environmental temporal discounting is often too limited to allow for valid predictions of longer delays or for curvilinear modelling of the discounting (Kaplan, Reed, & McKerchar, 2014). Research on the discounting of environmental outcomes over longer time periods has not tended to use delays longer than 10 years (e.g., Meyer, 2013; Viscusi, Huber, & Bell, 2008a), although some researchers have used delays of up to 25 years (e.g., Berry et al., 2017). Berry, Nickerson, and Odum (2017) stated that there is almost no research that uses the time-frames that environmental policies are designed for. Berry, Nickerson et al.'s own research on the discounting of air quality included a delay of 75 years, but more discounting research with long time frames is needed, especially considering that "the role of time is especially salient for environmental decisions, which have consequences that unfold over decades, centuries, or millennia" (Hardisty et al., 2012, p. 684).

Probability Discounting

Any sign of uncertainty about climate change may be interpreted by an individual as a justification for inaction or postponed action towards mitigating climate change (Gifford, 2011). For example, the communication of uncertainty in the reports of the IPCC led many individuals to interpret phrases such as "likely" or "highly unlikely" as having a lower likelihood than intended (Budescu, Broomell, & Por, 2009). Moreover, both real and perceived uncertainty have reduced the frequency of proenvironmental behavior in experimental studies on resource dilemmas, where uncertainty was found to be detrimental to the collective as it induced overharvesting (Hine & Gifford, 1996). Dilemmas involving environmental outcomes may be described as situations in a shared-resource system (e.g., air, water, forests), where the individual stands to benefit from a future outcome or availability of the common-pool resource, but only at the same level as everyone else, who may or may not have personally chosen to forgo environmentally harmful behavior. Researchers have shown that people tend to discount probabilistic financial (Rachlin, Raineri, & Cross, 1991) and environmental (Kaplan et al., 2014) outcomes in a similar way as they discount those outcomes over time.

Spatial Discounting

Environmental consequences of climate change are not only characterized by temporal delay and uncertainty, but also often occur elsewhere. Individuals may discount environmental outcomes at a higher rate if they occur in distant locations (Hannon, 1994; Hirsh et al., 2015), because they may be more concerned about, and more willing to act to mitigate, environmental events that occur in their local communities than those that occur far away. Gattig and Hendrickx (2007) stated that research about the role of space in environmental discounting is sparse. Links have been made, however, between spatially distant outcomes and decision theory (see Vlek & Keren, 1992, for an overview), and researchers in fields other than psychology have been active in the spatial-discounting domain. The not-in-my-backyard (Frey, Oberholzer-Gee, & Eichenberger, 1996) phenomenon has also sparked research interest in spatial dilemmas. Researchers in economics and other disciplines have, for example, reported that people become less willing to pay for environmental programs (Hanley, Schläpfer, & Spurgeon, 2003; Pate & Loomis, 1997), and more willing to support proposed coal or nuclear power plants (Hannon, 1994), as they become more geographically distant. Spatial discounting is a highly relevant dimension to global environmental risks (Gattig & Hendrickx, 2007), because people more directly affected by climate change might be more concerned and more willing to act than those who perceive the effects as happening elsewhere.

Human versus Natural Causes

Another issue of potential importance to people's willingness to act to mitigate climate change is the extent to which people

believe that climate change is caused by human activity or by natural factors. Although most people now believe that the climate is changing (Hartter et al., 2018), many still do not accept that the change is caused by human activity (Hartter et al., 2018). Siegrist and Sütterlin's (2014) research suggested that people are more concerned about the negative consequences of human-caused hazards than hazards that are naturally caused. Across four experiments, the same negative outcome (e.g., number of birds killed by an oil spill) was more negatively evaluated when caused by humans than when caused by nature, even though the participants received identical information (Siegrist & Sütterlin, 2014). Research claiming that climate change is a natural phenomenon caused, for example, by cosmic rays that induce low cloud cover (Ueno, Hyodo, Yang, & Katoh, 2019) may lead people to conclude that they do not need to be concerned about, or attempt to mitigate, climate change. On the other hand, if people believe that climate change is human-caused, they may be more willing to act to mitigate its effects. O'Connor, Bord, Yarnel, and Wiefek (O'Connor, Bord, Yarnal, & Wiefek, 2002) found that people who accurately identified the causes of climate change were more likely to support government initiatives to mitigate climate change and more likely to state that they would engage in actions themselves to reduce their environmental impact.

Exploring the discounting rates for environmental outcomes that are thought to be human-caused or natural likely represents a novel contribution to the discounting literature, with implications for both policy makers and future researchers.

Hyperbolic discounting

Two main models have been used to describe discounting data. Economics traditionally uses a time-consistent, exponential, discounting model (Mazur, 1987):

$$V = Ae^{-kX} \tag{1}$$

based on a rational, theoretical approach (Myerson & Green, 1995). Psychology typically uses a time-inconsistent, hyperbolic, discounting model (Mazur, 1987):

$$V = \frac{A}{1 + kX}, \tag{2}$$

based on the function that has tended to best fit empirical discounting data (Myerson & Green, 1995).

In discounting models, k is equivalent to the slope of the fitted function, describing the discount rate across X values of time, space, or (decreasing) probability. The intercept A, representing the amount of an outcome to be discounted, can be replaced with a constant (in our case, 100), which represents the undiscounted maximum dependent value (in our case of concern towards or percent of time devoted to addressing the problem). Hyperbolic discounting in general refers to the nonlinear and nonconstant tendency to prefer a smaller payoff now over a larger payoff later, which comes as the result of a biased disregard for future outcomes and events (Hardisty et al., 2012; Laibson, 1997). Values placed on rewards correspondingly decrease rapidly across short delays and then fall more slowly and level off as delays lengthen. In line with a diverse body of research on tangible (e.g., money) and nontangible outcomes (e.g., health), both exponential and hyperbolic functions have been used to model discounting rates (Hardisty et al., 2012).

Slightly more complex, two-parameter hyperbola-like functions, referred to elsewhere as hyperboloid functions (e.g., Berry, Nickerson, & Odum, 2017; Young, 2017), where an exponent, s, is added to the denominator, have also been described in relation to discounting data (Green & Myerson, 2004; Myerson & Green, 1995; Rachlin, 2006). In Myerson and Green's (1995) model:

$$V = \frac{A}{(1 + kX)^s} \tag{3}$$

the entire denominator is raised to a power, unlike in Rachlin's (2006) model:

$$V = \frac{A}{1 + kX^s}. \tag{4}$$

In these hyperboloid functions, the parameter, s, is thought to represent individual sensitivities to variations in the magnitude of the outcome.

Although the two-parameter hyperboloids (Eqs. 3 and 4) have been shown to fit the discounting of monetary outcomes better than the simple hyperbolic and exponential models (McKerchar et al., 2009; McKerchar, Green & Myerson, 2010), researchers have not, as yet, fully explored which function provides the best fit to the discounting of environmental outcomes. Evidence has been presented to support the exponential (e.g., Hannon, 1994), the hyperbolic (e.g., Kaplan et al., 2014; Viscusi, Huber, & Bell, 2008b), and hyperboloid functions (e.g., Berry, Friedel, et al., 2017; Berry, Nickerson, & Odum, 2017; McKerchar, Kaplan, Reed, Suggs, & Franck, 2019) for the discounting of environmental outcomes, but model fit *comparisons* in relation to environmental outcomes are rare. Research exploring best-fitting model functions to the data of *individuals* in environmental discounting tasks is even scarcer. Discounting functions of individuals may not resemble those of the average (or median) individual created from aggregated data (Myerson & Green, 1995), and little research has focused on model selection for discounting data at the level of the individual participant (Franck, Koffarnus, House, & Bickel, 2015).

The present study

Kaplan et al. (2014) assessed the ability of a quantitative and theoretical model, within a behavioral economic framework, to describe discounting in relation to air quality. They used a visual analogue scale to assess concern, as well as the extent to which participants would act, with respect to the environmental hazard, along the dimensions of temporal, social, and probabilistic distance. Across these dimensions, ratings of concern were higher than ratings indicating the extent to which the individual was likely to act. This finding aligns with the scientific consensus on environmental behavior, in that verbal statements, ideals, attitudes, and intentions regarding environmental issues rarely match planned or actual behavior (Gifford, 2011; Sargisson & McLean, 2015; Spence, Pidgeon, & Uzzell, 2009). Across conditions, Kaplan et al. applied Mazur's (1987) hyperbolic model (Eq. 2) to their data and fit k values (rate of subjective discounting) across participants and conditions. The hyperbolic model adequately fit the data, which was based on self-reported responses following hypothetical scenarios. As such, these findings supported, first, using self-report measures along a relevant dimension (Hirsh et al., 2015) and, second, to using choice-based methods to predict real-world behavior and outcomes (Hardisty, Thompson, Krantz, & Weber, 2013). Given the high relevance of the topic, we sought to replicate and extend Kaplan et al.'s findings. We examined the discounting of university students' ratings of concern and allocated time towards solving the environmental outcome of air pollution. Further, we fit Eqs. 1–4 to the data of individual participants to compare the model fit of these four, commonly used, discounting functions.

We measured temporal spatial, and probability discounting using a within-participant design, as suggested by Terrell, Derenne, and Weatherly (2014). Some of Kaplan et al.'s (2014) participants completed temporal and social discounting tasks, and, separately, different participants completed the probability discounting task, producing a mixed design. Instead, all of our participants completed all three discounting tasks (temporal, spatial, and probability). Rather than including social distance (i.e., to whom the event occurred as Kaplan et al. did), we included spatial distance, which is potentially relevant to the environmental outcomes resulting from climate change. In addition, we extended the temporal delay to 80 years (from the 10 years used by Kaplan et al.), because environmental outcomes, and changes in air quality in particular, may take several decades to unfold. In line with the findings of Kaplan et al., we expected that participants would discount their concern towards, and willingness to act to mitigate, an environmental outcome over psychological distance, in a similar way as financial outcomes are discounted. We expected that ratings of concern and action, for all three dimensions of time, space, and probability, would fit a hyperbolic (or hyperboloid) discounting model. We expected the (best-fitting) functions to be shallower and higher for concern than for time devoted to action (hereafter referred to as *action*), reflecting the often-reported attitude-behavior gap (Gifford, 2011; Kaplan et al., 2014; Spence et al., 2009).

We were also interested in whether environmental discounting would change when the environmental outcome was described as being human-caused rather than natural (Dolan et al., 2012; Hardisty et al., 2013). In line with previous findings on risk and climate change perception (Siegrist & Sütterlin, 2014), we expected participants to discount concern and action towards an environmental hazard less steeply when it was reported to be caused by human activity, compared to naturally, despite identical outcomes implied by both environmental scenarios.

Kaplan et al. (2014) presented values of delay, social distance, and probability to participants in a progressive order. However, Hardisty et al. (2013) noticed strong order effects in their research and concluded that future research needs to counterbalance and investigate order effects when using within-subject discounting tasks. Therefore, we presented the values of temporal, spatial, and probabilistic distance in either progressive or random order to determine whether value order would elicit differences in participant ratings.

Method

Participants and Setting

Our initial sample was 227 participants, each enrolled in a first-year undergraduate psychology course at the University of Groningen in the Netherlands. Students participated in exchange for course credits. The sample characteristics overall closely matched those of Kaplan et al. (2014), who also used undergraduate psychology students. We excluded three participants due to missing data. The final dataset was 224 participants (M_{age} = 20.42 years, 95% CI [20.14, 20.71]). Participants (65% female) were from different national backgrounds, mainly German (41%) or Dutch (33%), but all indicated sufficient English proficiency before participating.

Design and Procedure

Data were collected by means of an online questionnaire administered through Qualtrics®. Following demographic questions on age, gender, education level, and nationality, participants were presented with a series of hypothetical scenarios each followed by two questions, to which participants responded using a Visual Analogue Scale (VAS). In Qualtrics®, a slider could be moved freely from the default

middle position to the left and right along a horizontal line, each end labeled with a descriptive anchor. Previous behavioral researchers who have used VASs in clinical studies on sexual discounting (Johnson & Bruner, 2013) and chronic pain (Carlsson, 1983; Price, McGrath, Rafii, & Buckingham, 1983) have demonstrated that this form of assessment holds adequate test–retest reliability.

At the top of each online questionnaire page, participants were presented a vignette that slightly differed depending on the task (temporal, spatial, or probability), a statement, and two questions with response sliders—all presented on the same page at the same time. Participants read the vignette and the statement and then chose a value on a VAS associated with each of the two questions (described below). Individual ratings on each VAS were quantified by Qualtrics® as soon as participants had moved the slider at least once and were recorded when participants advanced to the next page of the questionnaire.

Discounting Tasks

Participants were first randomly assigned to either the progressive- or random-order condition. Participants were then randomly assigned to either the human-caused (fossil-fuel power plant) or natural-caused (lightning strike) condition, giving four conditions; progressive-human (n = 55), progressive-natural (n = 55), random-human (n = 57), and random-natural (n = 57). Each participant completed all three discounting tasks (temporal, spatial, and probabilistic) in a random order.

In each discounting task, seven values were presented for temporal distance (1 month, 6 months, 1 year, 3 years, 5 years, 10 years, and 80 years), six for spatial distance (5, 20, 50, 100, 1000, and 5000 km) and six for probability (95%, 90%, 50%, 30%, 10%, and 5%).

Temporal discounting task In the temporal discounting condition, participants read one of two vignettes describing either a human-caused [Vignette 1] or natural [Vignette 2] hazard. Both vignettes contained the roman text, with one version of the italicized text appearing in the human-caused and the other version in the natural scenario:

> Imagine that you own a garden and pump up your own drinking water from underground water reservoirs. [Vignette 1] *A nearby fossil fuel power plant continuously burns coal. As such, this process produces a lot of air pollution, including the noxious gas sulfur dioxide (SO_2).* [Vignette 2] *One day, a stroke of lightning naturally causes a nearby forest fire. Uncontrolled forest fires produce a lot of air pollution, including the noxious gas sulfur dioxide (SO_2).* When sulfur dioxide combines with water and air, it forms sulfuric acid, which is the main component of acid rain. After a while, this pollution will settle down and also pollute the soil and groundwater. Your garden and drinking water supply is also at risk.
>
> Below the vignette was a statement:
>
> *Within **X Delay**, polluted groundwater will reach your garden and drinking water reservoirs. When that happens, you will not be able to eat vegetables from your garden or drink your own water for a long time.*

Delay values (X) were presented either randomly or in progression from shortest to longest.

Spatial discounting task in the spatial discounting condition, participants read one of the same two vignettes used in the temporal-discounting task, however, with spatial distance incorporated into the vignette ("A fossil fuel power plant X distance away. . . ." or ". . . a forest fire X distance away.") Spatial distance values were presented to participants either randomly, or progressively from smallest to largest.

Probability discounting task In the probability discounting condition, participants read one of the same two vignettes used in the temporal-discounting task. Below the vignette was a statement similar to the one for the temporal task, except that instead of stating "within X delay. . .", the statements began "There is a X% chance that. . . ." Again, values (X) were presented either randomly, or began with 95% and then progressively decreased to 90%, 50%, 30%, 10%, and 5%.

Measures

We included two dependent measures, concern and action, by way of two response sliders positioned on the same page as each vignette.

Concern As in Kaplan et al.'s (2014) study, participants were first asked "How concerned are you about the effects of the pollution to your garden and groundwater? Shift the slider below to indicate how concerned you are." Anchors on each side of the VAS read "Not concerned at all" to "Extremely concerned." Responses were recorded as 0 = not concerned at all to 100 = extremely concerned.

Action Second, we asked participants "What percentage of your time will you spend to fix the problem? Shift the slider below to indicate what percentage of time you will spend to fix the problem." Anchors on the left and right for this question read "0%" and "100%."

Data Analysis

To explore which of four models provided the best-fitting function to the data, we used Gilroy, Franck, and Hantula's (2017) open-source software to fit Eqs. 1–4 to the raw scores of each individual participant for each of the three discounting dimensions (time, space, and probability). We also adopt Gilroy et al.'s labels for the four equations, whereby Eqs. 1–4 are referred to as the exponential, the (simple) hyperbolic, Myerson and Green, and Rachlin models. Gilroy et al.'s model selection software uses the Bayesian Information Criterion (BIC), which approximates the log of the Bayes factor (Kass & Raftery, 1995), to estimate the posterior probability of each model being true given the data (Gilroy et al., 2017, p. 390). Lower BIC values indicate better models in terms of the balance of predictive ability and complexity (Franck et al., 2015). We preferred the BIC over R^2 as a measure of fit because Johnson and Bickel (2008) demonstrated that R^2 is a biased fit measure for discounting data due to the fact that the discount rate, k, is positively correlated with R^2. Rachlin (2006) also argued that it is not possible to distinguish between Eqs. 3 and 4 on the basis of R^2. In addition, R^2 will naturally be higher for a two-parameter function compared to a one-parameter function. The BIC, however, includes a penalty for each parameter such that two-parameter models are appropriately penalized relative to one-parameter models (Franck et al., 2015; Gilroy et al., 2017), providing a fairer comparison of model fit than R^2. Using the BIC for each individual fit, we calculated how often (on what percentage of occasions) each model provided the best fit (lowest BIC value) for each task type (fits for concern and action using random and progressive order for human-caused and natural outcomes across time, space, probability, giving 2 x 2 x 2 x 3 = 24 conditions).

To compare discounting rates across conditions, we fit the best-fitting function found using the BIC comparison to median VAS ratings of concern and action for each task. Given that, in general, discounting data includes extreme scores and nonnormal distributions, median scores were considered to be the most appropriate measure of central tendency (Hart, 2001). Functions shown in all figures were fit and graphed using Sigmplot 13.0®.

Following Kaplan et al. (2014), a different expression was used for probabilistic distance, in that the percent chance of the outcome's occurrence was converted to the odds against its occurrence, $\Theta = (1 - p)/p$, where Θ is the odds against and p is the percent chance, so it could then be treated as X. Probability values of 95%, 90%, 50%, 30%, 10%, and 5% were converted to .053, .111, 1, 2, 2.33, 9, and 19.

On an individual level, ratings of concern and action were used to estimate each participant's discount rate k for all three dimensions. We used k as calculated using the hyperbolic model (Eq. 2), so that our results were comparable with Kaplan et al.'s (2014), as well as k from the best-fitting function (Rachlin model; Eq. 4). We ran three separate mixed analyses of variance (ANOVA) in SPSS 25® to test for effects of the within-subject variable of *rating type* (concern vs. action) and the between-subject variables of *condition* (human vs. natural) and *order* (random vs. progressive) on the k values separately for temporal, spatial, and probabilistic distance. (Note that the data for two participants were removed prior to running the ANOVA on k values from Eq. 4 as their k values were extremely high ($k > 35$).) Separate ANOVA were run rather than running a multivariate ANOVA including all three dimensions because k values for each task differed due to the varying range of values used with each distance, and were therefore noncomparable. The Greenhouse-Geisser correction was applied for all within-subject comparisons to account for violations of the assumption of sphericity.

Results

We fit all four functions to individual data for each condition using Gilroy et al.'s (2017) program, and extracted the BIC values. Across all 24 conditions, the Rachlin model (Eq. 4) most frequently provided the best fit to the individual data (in 21 cases), with the Myerson and Green model (Eq. 3) more frequently providing the best fits in two cases (human/random/concern fits for time and space), and Eqs. 3 and 4 providing the best fit equally often in one case (nature/progressive/concern for time). The exponential (Eq. 1) was the worst-fitting model in 13 of 24 cases, the Myerson and Green model (Eq. 3) in 8, the hyperbolic (Eq. 2) in 6, and the Rachlin (Eq. 4) in 0 of 24 cases (note that the number of times a model was identified as the worst fit is greater than 24 due to ties). Equation 3 was identified as the worst model exclusively for the probability discounting dimension (all eight cases were for this dimension), whereas Eq. 1 fared particularly badly for the spatial dimension. Figure 1 summarizes the patterns of model fits for each of the discounting dimensions.

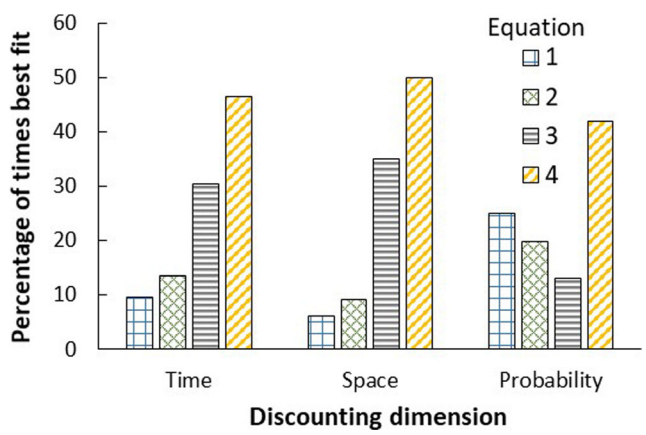

Fig. 1. The percentage of times each model was the best fitting model for individual participants across each discounting dimension.

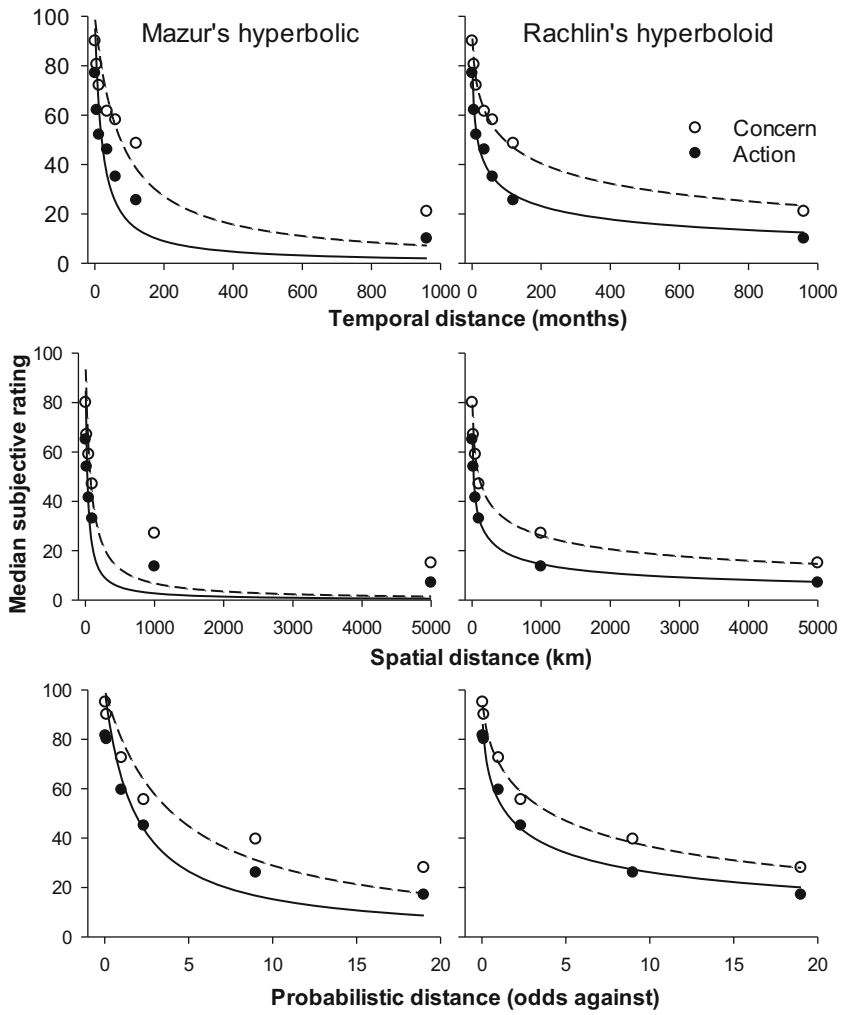

Fig. 2. Median subjective ratings of concern (open circles; dashed lines) and action (filled circles; solid lines) in relation to an environmental event as a function of temporal (top panel), spatial (middle panel), and probabilistic distance (bottom panel). Curves in the left panel are hyperbolic functions fitted according to Eq. 2, and in the right panel are Rachlin hyperboloid functions fitted according to Eq. 4 using median VAS ratings.

To explore the difference in ratings for concern and action, median ratings of concern and action were plotted for temporal, spatial, and probabilistic distance, and both hyperbolic (Eq. 2) and Rachlin models (Eq. 4) were fit to the data (Fig. 2). The k and R^2 values for the fits shown in Fig. 2 are given in Table 1. Table 1 and Fig. 2 show that ratings of concern and action decreased with increasing time, space, and odds against. Median scores and discount values of k for concern were higher for all three dimensions than for action, and the Rachlin model (Eq. 4) fit the data better than simple hyperbolic functions (Eq. 2).

Table 1. *Values of k and R^2 for Fits in Fig. 2*

		Equation 2		Equation 4	
Dimension	Rating type	k	R^2	k	R^2
Temporal	Concern	.013	.76	.099	.99
	Action	.051	.65	.266	.98
Spatial	Concern	.014	.69	.128	1.00
	Action	.036	.72	.230	1.00
Probabilistic	Concern	.247	.90	.417	1.00
	Action	.556	.83	.811	.99

As shown in Table 2, for all three dimensions (time, space, and probability), there was a significant effect of rating type (concern vs. action) on k values (as estimated using Eq. 2), where the mean k value for action was consistently higher than for concern, showing that discounting functions for concern were shallower and higher (given that all discounting functions shared the same intercept fixed at 100) than for action. We found an identical pattern of results we ran the analyses with the k values from Eq. 4.

To explore the effect of the between-subject manipulation whereby participants were led to believe that the environmental event had human or natural causes, we fitted the Rachlin model to median ratings of concern and action for the three discounting tasks separated by human-caused and natural conditions (see Fig. 3). The k and R^2 values for the plots in Fig. 3 (Eq. 4), as well as for the hyperbolic model (Eq. 2) are in Table 3.

As shown in Fig. 3, for all three dimensions, median ratings of concern were higher (shown by smaller k values in Table 3)

Table 2. *Means, 95% CI, and Main Effects of Rating Type on k Values from Eq. 2*

Dimension	Rating type	Mean *k*	95% CI	*F*	Df	*p*	*r*
Temporal distance	Concern	.11	.04, .18	11.80	1, 220	.001	.23
	Action	.25	.18, .31				
Spatial distance	Concern	.08	.04, .12	11.74	1, 220	.001	.23
	Action	.18	.13, .23				
Probabilistic distance	Concern	1.76	.59, 2.94	6.45	1, 220	.01	.17
	Action	3.60	2.46, 4.73				

when the environmental event was believed to be human caused rather than natural. The difference between human and natural scores was less pronounced for ratings of action, where human-caused events resulted in slightly higher median ratings for temporal and spatial distance, but not for probabilistic distance. However, there was no significant effect of condition (human vs. natural cause) on *k* values (from Eq. 2) for any dimension (time: $F(1, 220) = .26$, $p = .61$, $r = .03$; space: $F(1, 220) = 1.74$, $p = .19$, $r = .09$, probability: $F(1, 220) = .08$, $p = .78$, $r = 0$). The same pattern of results was produced using *k* values from Eq. 4.

Likewise, to explore the effect of the order of presentation of values (random or progressive), we fitted the Rachlin model (Eq. 4) to median scores for concern and action for all three discounting tasks (Fig. 4) for data obtained from random or progressive value presentation orders. The *k* and R^2 values for the plots in Fig. 4 (Eq. 4), as well as for the hyperbolic model (Eq. 2) are in Table 4.

Figure 4 shows a potential order effect in three of the six cases, namely for ratings of concern for temporal and spatial distance and for ratings of action for temporal distance. Where a difference was shown, there was a tendency for participants to discount the environmental hazard more steeply when values were presented in progressive order. However, there was no significant effect of order (random vs. progressive) on *k* values (from Eq. 2) for any dimension (time: $F(1, 220)$

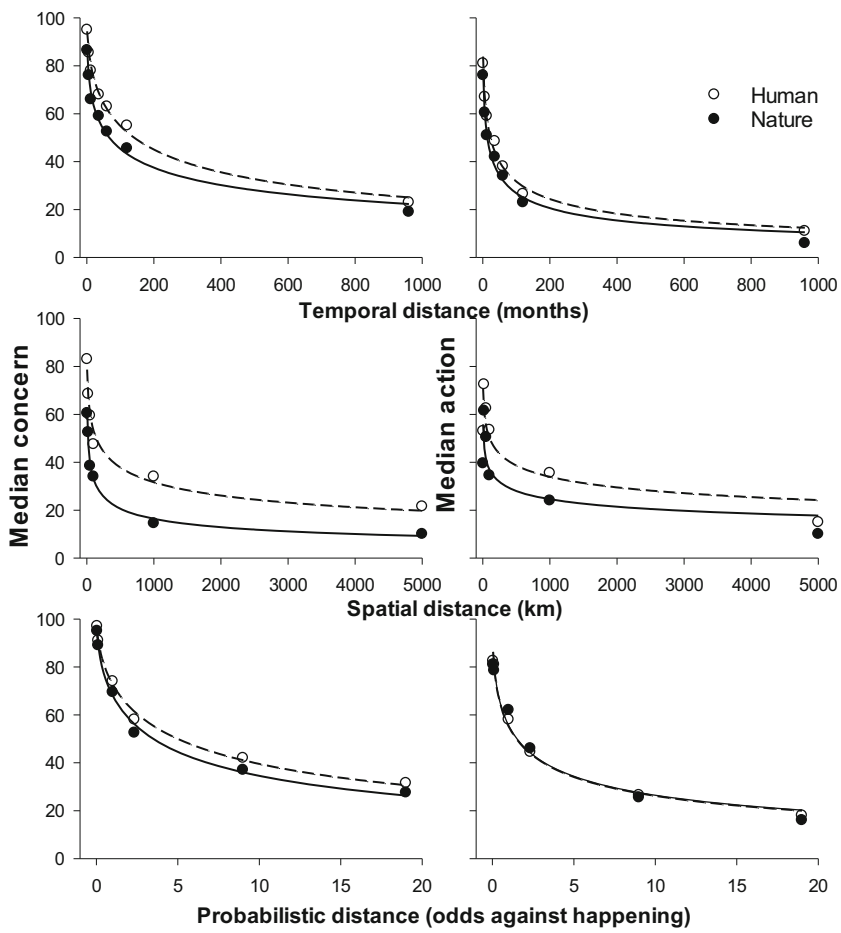

Fig. 3. Median ratings of concern (left panel) and action (right panel) for temporal (top), spatial (middle), and probabilistic (bottom) distance in relation to human-caused (open circles; dashed lines) and natural-caused (filled circles; solid lines) environmental events. Curves are Rachlin hyperboloid functions fitted according to Eq. 4 using median VAS ratings.

Table 3. *k and R^2 (in Brackets) for Fits Using Eqs. 2 and 4 for Human and Natural Causes*

		Human		Natural	
Dimension	Equation	Concern	Action	Concern	Action
Temporal	2	.009 (.84)	.004 (.78)	.017 (.66)	.006 (.71)
Spatial		.001 (.46)	.001 (.32)	.004 (.51)	.003 (.75)
Probability		.021 (.89)	.057 (.83)	.029 (.89)	.053 (.82)
Temporal	4	.059 (.99)	.192 (.99)	.140 (.99)	.269 (.98)
Spatial		.144 (.98)	.255 (.72)	.309 (.99)	.524 (.63)
Probability		.375 (.99)	.808 (.99)	.469 (.99)	.800 (.97)

Table 4. *k and R^2 (in Brackets) for Fits Using Eqs. 2 and 4 for Random and Progressive Orders*

		Random		Progressive	
Dimension	Equation	Concern	Action	Concern	Action
Temporal	2	.007 (.68)	.034 (.63)	.022 (.80)	.073 (.74)
Spatial		.008 (.12)	.023 (.64)	.020 (.79)	.039 (.76)
Probability		.233 (.91)	.570 (.92)	.245 (.85)	.503 (.68)
Temporal	4	.066 (.99)	.212 (.98)	.130 (.99)	.298 (.99)
Spatial		.136 (.97)	.245 (.99)	.142 (.99)	.218 (.99)
Probability		.378 (.99)	.749 (1.0)	.452 (.99)	.825 (.96)

= 2.65, p = .11, r = .11; space: $F(1, 220)$ = 2.24, p = .14, r = .10, probability: $F(1, 220)$ = .92, p = .34, r = .06). The same pattern of results was produced using k values from Eq. 4.

There were almost no significant interaction effects. Using the k values generated by Eq. 2, the only significant interaction was between rating type (concern vs. action) and condition (human vs. natural) for spatial distance, $F(1, 220)$ = 6.75, p = .01, r = .17, such that k values were more similar for concern (M = .09, 95% CI [.03, .16]) and action (M = .12, 95% CI [.05, .18]) for natural events than for human-caused events (concern: M = .07, 95% CI [.00, .13], action: M = .24, 95% CI [.17, .31]). In other words, it appeared that participants discounted concern and action for natural environmental events at similar rates, but when the event was caused by humans, action was discounted faster than concern over spatial distance. When we used the k values generated by Eq. 4, we found the same interaction between rating type and condition for the spatial dimension. In addition, there were two other significant interactions for the *time* dimension. The first matched the interaction seen between rating type and condition for the spatial dimension, $F(1, 216)$ = 7.20, p = .008, r = .18, such that k values for the time dimension were more similar for concern

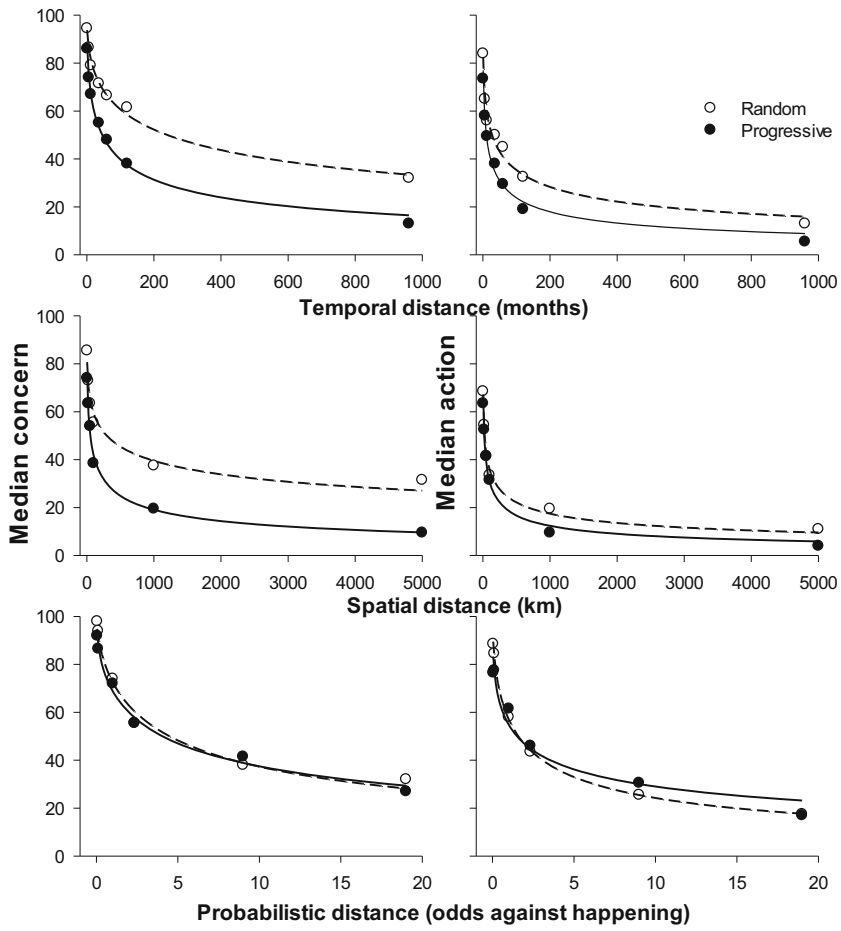

Fig. 4. Median ratings of concern (left panel) and action (right panel) for temporal (top), spatial (middle), and probabilistic (bottom) distance for random (open circles; dashed lines) and progressive (filled circles; solid lines) orders of presentation of distance values. Curves are Rachlin hyperboloid functions fitted according to Eq. 4 using median VAS ratings.

(M = .43, 95% CI [.30, .55]) and action (M = .42, 95% CI [.27, .57]) for natural events than for human-caused events, where action was discounted faster (M = .44, 95% CI [.039, .70]) than concern (M = .22, 95% CI [.10, .35]). The second significant interaction for the time dimension was between rating type and order, $F(1, 216) = 8.16$, $p = .005$, $r = .19$, such that k values for concern (M = .34, 95% CI [.22, .47]) and action (M = .33, 95% CI [.17, .48]) did not differ when the values were presented in a random order, but when presented in progressive order, k values were higher for action (M = .64, 95% CI [.249, .79]) than for concern (M = .31, 95% CI [.18, .43]).

Discussion

Our findings support and extend environmental discounting research in several ways. In line with previous research, temporal (e.g., Berry, Friedel, et al., 2017; Berry, Nickerson, & Odum, 2017; Hardisty & Weber, 2009; Kaplan et al., 2014; Meyer, 2013; Viscusi et al., 2008b), spatial (e.g., Hanley et al., 2003; Hannon, 1994; Pate & Loomis, 1997) and probabilistic (Kaplan et al., 2014) distance were found to be relevant contextual factors in the discounting of an environmental outcome, as also proposed by the construal level theory of psychological distance (Trope & Liberman, 2010). As temporal, spatial, and probabilistic distance encompass an individual's perception of *when, where*, and *whether* an event occurs, our findings further demonstrate that people prioritize outcomes that occur to them *now, here*, and *for certain* (Gattig & Hendrickx, 2007). Due to the fact that it was possible to replicate these findings in the current study design, there is support for the use of a within-subjects design when comparing discounting along dimensions of psychological distance (Hardisty et al., 2013).

In line with Young's (2017) findings, the Rachlin model fit our data better in a greater number of instances than Myerson and Green model, and both hyperboloids fit better than the hyperbolic, which fit better than the exponential for the temporal and spatial dimensions. That the hyperboloid and hyperbolic models provided better fits to the data demonstrates that the rate at which the subjective value of an outcome declines is not constant (Blackburn & El-Deredy, 2013; Hirsh et al., 2015; Kaplan et al., 2014). Whenever outcomes move along the dimensions of time, space, or probability, humans seemingly neglect these outcomes in a time-inconsistent trend. In particular, and contrary to what would be expected from an exponential model fit, the subjective value declines more rapidly initially, with the rate of change slowing as the values increase.

The Rachlin model was the best-fitting for all three discounting dimensions. The Myerson and Green model was the second-best for time and space, but the worst for probability, where the exponential function was the second-best—an unexpected finding given that Rachlin et al. (1991) found that exponential functions provided poorer fits to their probability discounting data than the simple one-parameter hyperbolic function. It may be that probabilistic discounting reflects a different process than delay discounting, evidenced by the fact that these measures often do not correlate highly (Green & Myerson, 2010) and are affected differently by experimental manipulations, such as outcome (or reward) size (McKerchar, Green, & Myerson, 2010). Discounting data were also consistently underestimated by the simple hyperbolic model fit to participants' aggregated discounting data, with median ratings of concern and action across all three discounting tasks being reliably higher than predicted (Fig. 2). As such, the subjective value of an environmental outcome may decline less rapidly than suggested by simple hyperbolic model fits.

Our results support those of Kaplan et al. (2014) that ratings of concern were higher than ratings for action for temporal and probabilistic dimensions. In addition, our results showed this to be true for spatial distance. The slopes of hyperbolic and hyperboloid functions fitted to ratings of concern were shallower and higher than the slopes for ratings of action. Therefore, participants were less willing to act than their respective ratings of concern indicated. This finding reflects a common yet unfortunate finding: reported ideals, attitudes, and intentions rarely match planned or actual behavior (Gifford, 2011; Sargisson & McLean, 2015; Spence et al., 2009). Evidence that, at least for the spatial dimension, and, less conclusively, for the time dimension, action discounted faster in response to a human-caused event than for a natural event, despite high levels of reported concern, suggest that the attitude-behavior gap may be even larger for human-caused events than for natural events. However, it may be that the rapid discounting of willingness to act is an artifact of the generality of the question. People may want to dedicate time to resolving environmental problems, but lack knowledge about actions that are available to them (Hines, Hungerford, & Tomera, 1987). Related to this, and consistent with the low-cost hypothesis (Diekmann & Preissendörfer, 2003), is that a person who is concerned about the environment might be willing to spend time engaging in a less effortful action but not to spend the same amount of time on a more effortful action. Thus, future researchers could manipulate the specificity of the question measuring willingness to act to determine whether willingness to act discounts less rapidly when specific actions are suggested and when those actions are comparatively more or less easy to perform.

Although Fig. 3 showed generally higher ratings of concern and action in most dimensions when the event was believed to be caused by humans rather than naturally, there was no significant effect of condition on discount rates. Given that the intercept is fixed in all functions at 100, higher ratings of concern or action across increasing psychological distance should be reflected in shallower slopes, and smaller discount

rates, *k*. Therefore, although there is evidence of a difference in Fig. 3, we cannot conclude that participants showed a higher degree of concern or willingness to act when the event was caused by human action. However, the significant interactions between rating type and concern for the temporal and spatial dimensions suggests that concern and action may discount at different rates depending on the perceived cause of the event, at least for spatial, and possibly temporal, distance. The interactions suggested that participants remained *more* concerned over increasing time and space, but became rapidly *less* prepared to act, when they thought the event was caused by a fossil-fuel power plant than by a lightning strike. When they were told that the outcome was the result of a natural event, there was no difference between the discounting rates for concern and action. So, in line with the findings of Siegrist and Sütterlin (2014), participants were overall more concerned about a human-caused negative environmental event, but—and this was unexpected—their reported willingness to act to mitigate a human-caused event discounted more rapidly than for a natural event. This result may be due, at least in part, to the wording of the human-caused scenario, which attributes the air pollution to a fossil-fuel power plant. Participants may have attributed responsibility for mitigation of the effects of the pollution to the plant operators, rather than taking individual responsibility to act. More research is needed to determine whether discounting rates differ as a function of the perceived cause of the outcome.

Finally, although Fig. 4 provided some evidence of order effects for the temporal and spatial dimensions, there was no significant main effect of order (random vs. progressive) on *k* values. We did, however, find a significant interaction for the time dimension using *k* values derived from Eq. 4. In this case, presenting time values in a progressive order appeared to increase *k* values for action relative to concern—an effect that was not present when the values were presented in random order. It is possible that a progressive presentation of values accelerates discounting, at least for temporal distance, because the values ascendingly build up psychological distance between participants and the outcome. This possibility requires confirmation, however. It can be argued that this is a methodological issue, because real-life decisions seldom present as discounting tasks but rather as single-value decisions. Notwithstanding, we suggest that experimental design and interpretation must proceed with care when using choice-based method and within-subject analyses (Hardisty et al., 2013), especially when experimental conditions follow each other quickly (Rachlin, 2006).

Kaplan et al. (2014) used a catastrophic scenario where air, soil, and groundwater would be polluted by uncontrolled forest fires. Given that climate hazards will likely become reality (Siegrist & Sütterlin, 2014), we intended to accommodate Kaplan et al.'s suggestion to use more relevant environmental outcomes. Our scenarios, however, were also somewhat catastrophic. Whereas the noxious gas sulfur dioxide (SO_2) contributes significantly to anthropogenic air pollution (Olivier, Schure, & Peters, 2017), this outcome may not be one that our participants will encounter. Future researchers could use other scenarios and outcomes that may be more relevant to participants, such as the general increase of CO_2 emissions and global temperature.

Furthermore, we did not compare environmental outcomes with monetary outcomes (Hardisty & Weber, 2009). Such research efforts are important to ascertain whether the extensive existing research on discounting in relation to financial outcomes could also be applied to environmental outcomes. To compare monetary and environmental outcomes, visual analogue measures may not be sufficient. Instead, different approaches such as titration (psychophysical-like) procedures may be beneficial, as they could inform future environmental research by determining individuals' indifference points regarding environmental losses and gains, for example (Kaplan et al., 2014).

Finally, research on social orientation and its consequences for choices in social dilemmas has highlighted its relevance for sustainability (Hirsh et al., 2015; Kaplan et al., 2014). Environmental choices determine communal, rather than individual, futures. The long-term consequences of proenvironmental behavior are often marked by uncertainty and demand a compromise of hedonic interest or pleasure (e.g., choosing public transportation over the car) thereby elevating the position of communal futures. Thus, it is possible that individuals' discounting of an environmental outcome is affected by social and cultural factors. Du, Green, and Myerson (2002) found, for example, that American participants discounted monetary probabilistic rewards more steeply than Chinese participants did. Cultural factors and social orientation, along with discounting over social distance, would be relevant factors to examine in the context of environmental discounting.

In conclusion, research efforts such as ours may help to bridge the gap between environmental psychology and behavioral economics (Dolan et al., 2012; Kaplan et al., 2014) and eventually provide insight for public policy efforts aimed at addressing people's involuntary disregard for delayed, distanced, and uncertain outcomes that come with the urgent and complex issue of climate change and sustainability.

Compliance with Ethical Standards The research was approved by the Ethics Committee of Psychology (ECP) of the University of Groningen. Participants gave informed consent prior to participation.

Conflicts of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Availability of Data and Materials Raw anonymized data and materials are available from the corresponding author by request.

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