



# A double-bounded risk-risk trade-off analysis of heatwave-related mortality risk: Evidence from India

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## Abstract

As climate variability is increasing, extreme events such as temperature fluctuations are expected to become more frequent. Low- and middle-income countries (LMICs) are especially vulnerable to heat-related variability and its ensuing impacts on mortality. Therefore, there is an urgent need to understand how citizens in LMICs trade-off climate-related mortality risks with other risks such as traffic accidents, and what values they place on reducing such risks. As populations in LMICs are income-constrained, we adopt a non-monetary, risk-risk trade-off (RRTO) valuation method instead of the standard willingness-to-pay stated preference-based approach. We estimate the resulting risk premium for heatwave-related mortality risks through an adapted double-bounded, dichotomous choice approach to establish whether, on average, people value avoiding these risks more compared to reducing traffic risks. Using a sample of over 2,300 individuals from across seven states in India, a country with one of the highest heat-related mortality globally, we estimate the heatwave risk mortality premium to be between 2.2–2.9, indicating that on average, individuals weigh reducing heatwave-related mortality risks more than two times that of reducing traffic accident mortality risks. Based on a standard benefit transfer methodology for LMICs, this premium translates to a Value of Statistical Life (VSL) of USD 0.37–2.61 million for India.

**Keywords** Climate change · Heatwaves · Context premium · Risk-risk trade-off · Value of statistical life · India

**JEL Classification** I12 · Q51 · Q54

## 1 Introduction

Climate change is significantly affecting people's lives and livelihoods and there is increasing evidence that the variability of heat and extreme weather has an impact on physical and mental health, and ultimately, premature mortality (e.g., Barreca

et al., 2016; Dell et al., 2014; IPCC, 2014). An increasing trend in temperatures in the last decades has been documented (IPCC, 2021) and the impact of climate change is expected to intensify with additional warming, putting to test the influence that temperature has on human lives. Further, there is growing consensus that it is low- and middle-income countries (LMICs) that are among the most affected by extreme weather events (IPCC, 2022).

There is then an urgent need to understand how citizens in LMICs trade-off climate-related mortality risks with other risks such as traffic accidents, and what values they place on reducing such risks. However, as a large share of the population in LMICs is income-constrained, the use of willingness to pay (WTP) to put a monetary value on the premature reduction of climate-related mortality risks might not reflect their actual WTP (Robinson & Hammitt, 2011). In this study, to estimate preferences for heatwave-related mortality risk changes in an LMIC (India), we adopt the non-monetary risk-risk trade-off (RRTO) method of Viscusi et al. (1991) that does not include money in individual choices, whilst still providing a reliable estimate of how people value avoiding increased risks (or value reducing risks). Further, we introduce a methodological innovation to non-monetary valuation that has previously only been used for estimating WTP.

The RRTO is a non-monetary, relative valuation approach that gathers information on individual choices about the trade-off of two types of risk changes. The method summarizes these choices in a ratio (also known as the context premium) that provides a measure of the strength of preference for avoiding specific risks. As respondents choose only between risks rather than risk and money, this method has been argued to reduce the degree of cognitive load for participants (Mussio et al., 2023; Nielsen et al., 2019). RRTO has been applied across a number of contexts, using predominantly Western samples, to examine the trade-offs for fatal and non-fatal risks, such as extreme weather events (Mussio et al., 2023), chronic illnesses (Magat et al., 1996; McDonald et al., 2016; Van Houtven et al., 2008; Viscusi et al., 1991), “dread” risks (Chilton et al., 2006), traffic accidents (Nielsen et al., 2019), mass shootings and terrorist attacks (Dalafave & Viscusi, 2021, 2023; Viscusi, 2009) and natural disaster deaths compared to other risks such as terrorism and traffic accidents (Viscusi, 2009). Therefore, our study contributes to the literature by shedding light on how people value mortality risk changes in a developing country context, using the RRTO framework.

Whilst Mussio et al. (2023) established the validity of the RRTO method for estimating a climate-change context premium related to extreme weather events in the UK, it used the standard approach of a one-shot question (single-bounded dichotomous choice).<sup>1</sup> Our study is novel in that it is the first one to adapt the double-bounded, dichotomous choice (DBDC) approach—first proposed for WTP estimation by Hanemann (1985) and Carson et al. (1986)—to the RRTO method. Through this approach, we elicit a second discrete response to an RRTO question, which is set based on an individual’s response to the first question, thus determining the two

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<sup>1</sup> Prior research has used single-choice approaches, dichotomous-choice approaches (with and without follow-up questions) and multiple price list formats (to elicit indifference points between risks) to estimate the RRTO context premium (Chilton et al., 2006; McDonald et al., 2016; Van Houtven et al., 2008).

response bounds. The DBDC, with the extra information that it provides through the answers to two questions instead of one, has been empirically proven to be asymptotically more efficient than the single-bounded approach (Hanemann et al., 1991).

Further, following calls for increased consideration of how behavioral insights might inform the economic valuation of policy consequences (Robinson & Hammitt, 2011), especially in the context of climate change (McDonald et al., 2015), we also analyse the determinants of the context premium. In particular, following Mussio et al. (2023) we investigate the impact of people's psychological distance to climate change on their stated trade-offs by using a validated measure of Construal Level Theory (Spence et al., 2012), which has previously been shown to be a significant driver of RRTOs. We extend that work in two respects. First, we also include the degree to which people consider the potential future outcomes of their current actions and behaviours by including a psychologically validated measure of the Consideration of Future Consequences (Strathman et al., 1994). Second, cultural factors have been shown to be important in the judgment and decision literature, including in the context of risk (Weber & Hsee, 1998) and time perception both with respect to the future (Ji et al., 2001) and the past (Ji et al., 2009). By focusing on India in the present study, we are able to offer insights from a different cultural context (to the UK, the focus of Mussio et al., 2023).

India provides a relevant context for this study as it is one of the countries most impacted by the adverse consequences of temperature change. India's maximum temperature has increased at an average rate of 0.99 °C/100 years in the period 1901–2020 (World Bank, 2021). It has become a hotspot in the last decade, with heatwaves in 2015, 2016, 2019, 2022 and 2023. The prolonged heatwave during March–May 2022 brought in new record temperatures reaching almost 47 °C (Indian Meteorological Department, 2022) and a similar pattern is being observed in 2023. The country witnessed an increase of 55% in deaths due to extreme heat between 2000–2004 and 2017–2021, being one of the countries with the highest heat-related mortality (Romanello et al., 2021).

We report results from an online RRTO survey with a large sample of over 2,300 respondents from across seven states in India that have been previously affected by heatwaves. In the survey, respondents are asked how they trade-off heatwave-related mortality risks versus traffic accident mortality risks. We find evidence of a heatwave risk context premium of 2.2–2.9. This means that in the aggregate, individuals weigh reducing heatwave-related mortality risks more than twice as much as reducing traffic accident mortality risks. While Consideration of Future Consequences is not found to be a significant explanatory factor for the heatwave context premium, psychological closeness to climate change (as measured by the Construal Level Theory) is positively associated with the context premium. Individual experience affects the context premium, with a previous negative experience due to traffic accidents reducing it.

From a policy perspective, there would be substantial benefits from implementing health and safety policies to reduce the risk of mortality from heatwaves in LMICs. However, these risk reductions have not been monetarized. The Value of Statistical Life (VSL) is usually applied with this objective (Robinson et al.,

2019a).<sup>2</sup> Policymakers could incorporate the RRTO context premium into the VSL instead of calculating it from scratch with WTP data which tends to be a more costly option.<sup>3</sup> This process could be useful, for example, for budgetary allocations to local communities to adapt to the effects of climate change. Using benefit transfer, VSL values from different sources, and following the recommendations for benefit-cost analysis (Robinson et al., 2019a), we construct an implied range of VSLs for heatwave-related mortality risks in India of USD 0.37–2.61 million (in 2021 values).

This paper is organized as follows. In the next section, we discuss our study design and implementation. Section 3 describes the methodology. Section 4 presents the results from the RRTO estimation and VSL. Finally, Section 5 provides concluding remarks.

## 2 Design and implementation

### 2.1 Experimental and survey design

The survey is divided into three sections, as detailed in Online Appendix A. In the first section, participants are provided with information pertaining to the risks considered in the survey, specifically, the mortality risks associated with traffic accidents and heatwaves. This segment offers contextualization for these risks following by descriptions of what constitutes risk, and specifically, the nature of traffic accident and heatwave fatalities.

The definition employed for traffic accidents is comprehensive (Department for Transport, 2022) and includes motor vehicle accidents, cycling accidents, pedestrian accidents, and related health outcomes stemming from such accidents. In the case of heatwaves, the definition is aligned with the criteria used by the Indian Meteorological Department (2022) and the National Disaster Management Authority (2023). This definition provides information regarding prior heatwaves and its associated health symptoms. Additionally, respondents are informed of the baseline mortality risks associated with both traffic accidents and heatwaves, which are presented in terms of risks per 100,000 people per decade.<sup>4</sup> It has been suggested that, in a stated preference survey, a verbal probability analogy is a good supplement to numerical probabilities (Corso et al., 2001; Hammitt & Graham, 1999). Therefore, to put the

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<sup>2</sup> The VSL is defined as the aggregate current willingness to pay (WTP) for marginal reductions in the probability of premature death which, taken over the group of people affected, will reduce the expected number of deaths during the forthcoming period (Jones-Lee, 1989). It is also commonly referred to as the Value of Preventing a Statistical Fatality (VPF) in countries such as the UK.

<sup>3</sup> The context premium, which is calculated for trading off traffic accidents and heatwaves can be pegged to the original VSL (to calculate a VSL for heatwaves) when the VSL figure is calculated in the context of traffic.

<sup>4</sup> Both risk changes are set to occur in the same time period (which is fixed), so time discounting is assumed to be equal between the two.

numbers into perspective, this block also included an explanation of how these risk are expected to impact cities of varying sizes in India over the next decade.

In Section 2, we introduce the double-bounded risk-risk trade-off questions. We follow the prevailing approach in the literature, which frames the decision scenario as a choice between relocating from the respondent's current residential area to one of two distinct areas within a city (Cameron et al., 2010; Clarke et al., 1997; Nielsen et al., 2019; Van Houtven et al., 2008). These two areas differ solely in terms of the two types of mortality risks considered. The decision scenario explicitly states that other factors, such as housing quality, access to medical services, employment opportunities, and general living and working conditions, are identical in both areas of the new city. Following this RRTO approach, the decision to move is a conditional decision based on the mortality risks presented to the respondents. As the need to move is established, the only decision that needs to be made by the respondent is which area to move to. Participants make a single decision of selecting which of the two areas within the city they would prefer to move to.

Respondents are asked to assume that the baseline mortality risks for the two events were 80 deaths per 100,000 people per decade. Baseline deaths are constructed from previous traffic accident data from the Indian National Crime Records Bureau (96 deaths per 100,000 people every ten years) and the literature on heatwaves (60 deaths per 100,000 people every ten years; Zhao et al. (2021)). For ease of comparison, we averaged and rounded the two risks to provide us with the same baseline risk—80 deaths per 100,000 people per decade—for both events.<sup>5</sup> Respondents are first presented with a practice choice (Fig. 1). After this, they are presented with a randomly selected choice scenario from a set of nine scenarios. Each scenario asks the participant whether they would prefer to move to Area T (where traffic accident mortality risk increases while heatwave mortality risk remains constant) or Area H (where heatwave mortality risk increases while traffic accident mortality risk remains constant).<sup>6</sup> This initial choice is followed by a second RRTO question, the design of which is contingent on the responses provided in the first choice scenario. At the heart of this methodology lies the empirical estimation of indifference points concerning the two risk increases (Mussio et al., 2023). Therefore, we incorporate an option that allows respondents to indicate indifference between the two areas, ensuring the robustness of our analysis.<sup>7</sup>

<sup>5</sup> As the two baseline risks were similar, we decided that averaging these risks was a reasonable compromise given the problems noted in the literature on the impact of baseline risk on choices. Chilton et al. (2006) shows that alternative behaviors (to expected utility) could lead to respondents choosing the option with the lowest baseline risk regardless of other options or preferences for context. By standardizing the baseline risk, we remove this potential confound in context premium estimates and we note that India is a suitable setting for this study as the baseline mortality risks of heatwaves and traffic accidents are very close in magnitude.

<sup>6</sup> For clarity, we refer to the areas throughout the paper as Area T and Area H. However, we adopted the labels Areas 1 and 2 in the survey to provide a neutral framing.

<sup>7</sup> Whilst this has been done at the individual level in Chilton et al. (2006), McDonald et al. (2016), and Nielsen et al. (2019), given the nature of the data, we follow Van Houtven et al. (2008) and estimate indifference points at the aggregate sample level. In addition, our design follows the principles first established for WTP data (Carson, 1985; Hanemann, 1985) but adapts it to RRTO data.

The place where you currently live has the following risks of death per 10 years:

	Your current Area risk of death per 10 years
Traffic accidents	80 in 100,000
Heatwaves	80 in 100,000

Please choose between Area T or Area H of the new city, or if you are equally happy with moving to any of the two Areas.

	Area T risk of death per 10 years	Area H risk of death per 10 years
Traffic accidents	<b>70</b> in 100,000	<b>90</b> in 100,000
Heatwaves	<b>70</b> in 100,000	80 in 100,000

Please indicate the option which you most prefer:

Area T
  Area H
  I am equally happy to move to either Area

Fig. 1 Risk-risk trade-off practice choice.

By varying the sizes of the mortality risks randomly across respondents, we can present choice scenarios with different Risk Difference Ratios (RDRs) between Area T and Area H. Each RDR is calculated as:

$$RDR = \frac{p_t^H - p_t^T}{p_\eta^T - p_\eta^H} \tag{1}$$

In Area T (where traffic accident mortality risk increases), the mortality risks are represented by  $p_\eta^T$  and  $p_t^T$ , where subscripts  $\eta$  and  $t$  denote heatwaves and traffic respectively, while  $p_\eta^H$  and  $p_t^H$  represent comparable mortality risks in Area H (where heatwave-related mortality risk increases). Based on how choices change with respect to the RDRs, the responses can be used to estimate the expected value of the ratio between  $VSL_t$  and  $VSL_\eta$ —the Mortality Equivalence Ratio (MER)—and calculate the  $VSL_\eta$  using  $VSL_t$  values (Van Houtven et al., 2008; see footnote 2 for a definition of  $VSL_t$ ).

The range of RDRs in the first choice scenario adheres to principles analogous to those employed in designing optimal bids for eliciting WTP using a dichotomous choice approach (Alberini, 2005) and includes a reasonably large (but plausible) proportion of mortality risk increases.<sup>8</sup> Based on the results of our pilot study, we

<sup>8</sup> Under Expected Utility Theory, marginal increases and decreases in risk are assumed to be equally weighted given the assumption that linearity holds at the margin. The proposed analysis is unaffected by the choice of risk increases or risk reductions but, in practical terms, given the relatively low baseline mortality risk in either case, we adopt risk increases as in Chilton et al. (2006), McDonald et al. (2016), and Nielsen et al. (2019). This allows for a broader range of risk changes to be included in the analysis (since risk decreases are bounded from below by 0 in 100,000 whilst risk increases are effectively unbounded).

determined five different increases in traffic accident mortality risk ( $p_t^H - p_t^T$ ) and five increases in heatwave-related event mortality risk ( $p_\eta^T - p_\eta^H$ ) for our first choice scenario. Our baseline is 80 deaths in 100,000 per decade for both traffic and heatwave-related mortality risks, and the vector of increases for the first choice scenario is (85, 90, 95, 100, 105).<sup>9</sup> Hence, our RDRs for the first question presented to the participants, which are calculated using Eq. (1) and our five increases in mortality risks, range from 5 (highest traffic accident risk increase) to 0.2 (highest heatwave risk increase) and are centred at 1, where both risk increases are low (85 per 100,000 per decade; see Table 1). Figure 2 presents an example of a choice scenario the respondent faces between Areas T and H (RDR = 5.0). Note that there is no area in any of the scenarios that is unambiguously better than the other.

The respondent's second choice scenario is contingent on the region selected by the respondent in the initial choice scenario. If the participant initially selects Area T, the subsequent scenario involves increasing traffic accident mortality risk by 5 deaths per 100,000 over 10 years (as depicted in Fig. 2), while keeping the other mortality risk constant. Similarly, if the the participant initially chooses Area H, then in the subsequent scenario we increase the heatwave mortality risk by 5 deaths per 100,000 over 10 years while keeping the other mortality risk constant. If the participant is indifferent between areas in the first choice scenario, there is no need for a second choice scenario, as we have already identified their indifference point. In such cases, the respondent proceeds directly to the socioeconomic questionnaire (Section 3). A summary of the DBDC RRTO elicitation process is provided in Fig. 3, the list of first and second choice scenarios is available in Table 1, and the model framework is described in Online Appendix C.

Section 3 of the survey includes socioeconomic questions such as age, gender, education, employment status and income, etc. It also elicits risk and time preferences using non-incentivized questions. Further, we also account for participants' psychological distance to climate change. Public engagement with climate change often suffers from low levels of participation, as individuals tend to perceive the threat of climate change as being distant in time and space (Lorenzoni & Pidgeon, 2006; Wang et al., 2019, 2021). To capture such psychological aspects associated with temporal and geographic distance, among other things, we employ a validated measure based on Construal Level Theory (Spence et al., 2012).

There are individual differences in the extent to which (temporally) distant outcomes are considered for decision-making (Strathman et al., 1994). Thus, we also consider the degree to which respondents weigh up current and future outcomes captured by the validated psychological measure of Consideration of Future Consequences (Strathman et al., 1994). The two psychological measures are complementary as temporal distance and the future consequences of climate change are related. Consideration of Future Consequences is context-dependent (Bruderer Enzler, 2015; Murphy et al., 2020) and prior research has shown that the consideration of future or distant outcomes, partially accounts for higher levels of scepticism about climate

<sup>9</sup> We vary the risk for each event independently, holding the other event risk constant at its low value (85 per 100,000 per decade). Hence, there are nine, not ten, scenarios in total.

**Table 1** List of risk-risk trade-off scenarios

First choice scenario	Traffic accident mortality risk (in 100,000, per 10 years)	Heatwave mortality risk (in 100,000, per 10 years)	Risk Difference Ratio (RDR)	Area choice in first choice scenario	Second choice scenario	Traffic accident mortality risk (in 100,000, per 10 years)	Heatwave mortality risk (in 100,000, per 10 years)	Risk Difference Ratio (RDR)
0. Baseline	<b>80</b>	<b>80</b>						
1	105	85	5	T		110	85	6
				H		105	90	2.50
				Indifferent	No second choice scenario			
2	100	85	4	T		105	85	5
				H		100	90	2
				Indifferent	No second choice scenario			
3	95	85	3	T		100	85	4
				H		95	90	1.50
				Indifferent	No second choice scenario			
4	90	85	2	T		95	85	3
				H		90	90	1
				Indifferent	No second choice scenario			
5	85	85	1	T		90	85	2
				H		85	90	0.50
				Indifferent	No second choice scenario			
6	85	90	0.5	T		90	90	1
				H		85	95	0.33
				Indifferent	No second choice scenario			
7	85	95	0.33	T		90	95	0.67
				H		85	100	0.25
				Indifferent	No second choice scenario			
8	85	100	0.25	T		90	100	0.50
				H		85	105	0.20
				Indifferent	No second choice scenario			
9	85	105	0.2	T		90	105	0.40
				H		85	110	0.17
				Indifferent	No second choice scenario			

change (Veckalov et al., 2021). Following Dohmen et al. (2023), to avoid treating ordinal variables comprised of Likert scale responses as having cardinal significance, we transform the psychological scales into indicator variables that take value 1 if the score is above the median and 0 otherwise. Finally, we include a series of questions to explore how perceptions and experiences of heatwave and traffic accident mortality risks affect choices.

### 2.2 Survey administration

The survey was administered by Dynata, an online survey platform, during July and August 2022 and coded using Qualtrics. We collected data from the following seven Indian states: Delhi, Haryana, Punjab, Rajasthan, Uttar Pradesh in the north, and

The place where you currently live has the following risks of death per 10 years:

	Your current Area risk of death per 10 years
Traffic accidents	80 in 100,000
Heatwaves	80 in 100,000

Please choose between Area T or Area H of the new city, or if you are equally happy with moving to any of the two Areas.

	Area T risk of death per 10 years	Area H risk of death per 10 years
Traffic accidents	<b>105</b> in 100,000	80 in 100,000
Heatwaves	80 in 100,000	<b>85</b> in 100,000

Please indicate the option which you most prefer:

- Area T
  Area H
  I am equally happy to move to either Area

Fig. 2 Example of a risk-risk trade-off choice scenario, first bound, RDR = 5.

Andhra Pradesh and Tamil Nadu in the south. Our decision to conduct the study in these seven states was guided by the heatwave risks being pertinent and relatable for the study population which would make the scenarios more realistic for them since respondents will have had direct recent experience of heatwaves. This makes heatwaves a salient comparator to traffic accidents, reducing any biases that may arise from comparing two

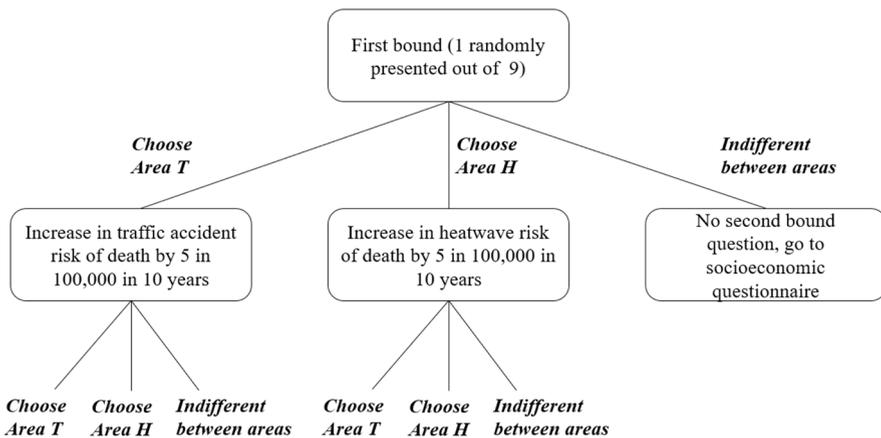


Fig. 3 RRTO double-bound elicitation process.

risks, only one of which a respondent had been exposed to. The subgroup of states was selected based on two sources. First, we chose the states which experienced the highest temperatures during the 2019 heatwave in the north and states which were affected by the heatwave in the south. Second, we used the World Bank (2022) climate data projections for India (2020–2039) to choose the most affected states.<sup>10</sup> From the overlap of the two sources, we chose a group of states that were worst affected by the 2019 heatwave and had the worst predictions for the number of very hot days.

Prior to administration, the survey was tested for comprehension with a convenience sample of 10 participants and then piloted with 200 participants on Dynata to determine the final choice scenarios for the RRTO questions. We collected responses from 2,334 participants. Participants took on average 26 min to complete the survey, and were paid a fixed fee of £4.50 (USD 5.7) for their participation. A comparison of some basic characteristics between our online sample and individual-level data for these states from the nationally representative India Human Development Survey (IHDS) of 2011–2012 shows our sample to be a little older (36 years vs. 29 years in IHDS) and with a higher proportion of females (58% vs. 50% in IHDS) but very similar in terms of share of population with income below INR 50,000 (24% vs. 25.3% in IHDS).<sup>11</sup>

### 3 Analytical strategy

#### 3.1 Maximum likelihood estimation of the DBDC RRTO

To estimate the DBDC model for our RRTO responses, we follow the approach of Lopez-Feldman (2013). In our model, we assume that our MER (also known as the context premium for heatwave mortality risk vs. traffic accident mortality risk) follows a linear function and that the error term is normally distributed:

$$MER_i(z_i, u_i) = z_i' \beta + u_i, u_i \sim N(0, \sigma^2), \quad (2)$$

where  $i$  corresponds to each participant,  $z_i$  is a vector of explanatory variables (described and summarized in Table 2) and  $u_i$  is the error term. As an objective of our analysis is to understand the impact of heatwaves on decision-making, we examine the decision to move to Area H. Under this model, we have four cases, depending on the decision to move in the first and second choice scenarios. The probability of the four cases is as follows, where, for example,  $P(A_{H1}, A_{H2})$  means that the

<sup>10</sup> For a map of the temperatures during the 2019 heatwave in India, please refer to the following Earth Observatory NASA (2019) map: <https://earthobservatory.nasa.gov/images/145167/heatwave-in-india> (last accessed July 21, 2022). The information used from the World Bank is the projected climatology of number of very hot days ( $T_{max} > 35^\circ\text{C}$ ) for 2020–2039 (SSP 1–2.6, reference period 1995–2014, last accessed May 05, 2022).

<sup>11</sup> Note that the seven study states account for 38% of the Indian population as per the 2011 Indian Census. Our sample is not representative of the seven study states given the mode of the data collection using online surveys. This critique holds true for most studies globally that use online surveys and such online surveys are now increasingly used in economics. Nevertheless, we believe that the findings are valuable in informing policy.

individual chooses Area H in the first question and Area H in the second question and  $RDR_1$  and  $RDR_2$  are the RDRs from the first-choice scenario and the second-choice scenario respectively:

$$P(A_{H1}, A_{H2}) = P(MER < RDR_2), \tag{3}$$

$$P(A_{H1}, A_{T2}) = P(RDR_2 \leq MER < RDR_1), \tag{4}$$

$$P(A_{T1}, A_{H2}) = P(RDR_1 \leq MER < RDR_2), \tag{5}$$

$$P(A_{T1}, A_{T2}) = P(MER > RDR_2). \tag{6}$$

In order to estimate the parameters in this model ( $\hat{\beta}$  and  $\hat{\sigma}$ ), we construct a four-part likelihood function that must be maximized:

$$\sum_{i=1}^N \left[ d_i^{HH} \ln \left( \Phi \left( z_i' \frac{\beta}{\sigma} - \frac{RDR_2}{\sigma} \right) \right) + d_i^{HT} \ln \left( \Phi \left( z_i' \frac{\beta}{\sigma} - \frac{RDR_2}{\sigma} \right) - \Phi \left( z_i' \frac{\beta}{\sigma} - \frac{RDR_1}{\sigma} \right) \right) + d_i^{TH} \ln \left( \Phi \left( z_i' \frac{\beta}{\sigma} - \frac{RDR_1}{\sigma} \right) - \Phi \left( z_i' \frac{\beta}{\sigma} - \frac{RDR_2}{\sigma} \right) \right) + d_i^{TT} \ln \left( 1 - \Phi \left( z_i' \frac{\beta}{\sigma} - \frac{RDR_2}{\sigma} \right) \right) \right], \tag{7}$$

where  $d_i^{HH}, d_i^{HT}, d_i^{TH}, d_i^{TT}$  are indicator variables that take the value of one or zero depending on the choices made by each participant. For example, if  $d_i^{HH} = 1$  and  $d_i^{HT}, d_i^{TH}, d_i^{TT}$  are 0, this means that the participant chose Area H in the first choice scenario and Area H in the second choice scenario. By using this approach and maximizing the likelihood function, we can estimate  $\hat{\beta}$  and  $\hat{\sigma}$  and directly estimate the MER. For this estimation, we use data from participants who chose an area (either Area T or Area H) for the first choice scenario (i.e., non-indifferent). More specifically, we use as inputs of the model the participant responses to each of the two choice scenarios as well as the associated RDR for the two choices presented ( $RDR_1$  and  $RDR_2$ ).

As an example, consider the following specification with just one explanatory variable,  $z_1$ :

$$MER_i(z_i, u_i) = \beta_0 + \beta_1 z_{1i} + u_i. \tag{8}$$

Using this example specification, the aggregate “univariate MER” can be directly derived as:

$$MER_{UNI} = \beta_0. \tag{9}$$

## 4 Results

### 4.1 Descriptive statistics

Descriptions and summary statistics for the variables used in the analysis are provided in Table 2. Column 1 presents the summary statistics for the full sample of 2,334 participants. 42% of the participants are male and the average age is 36 years. 89% of the sample has at least a bachelor's degree and 85% is currently employed. 24% are classified as low-income, i.e., those earning an income of less than INR 50,000 per month. 94% own some form of air cooling technology at home (either an air cooler or an air conditioner). Approximately 82% report having ever experienced traffic accident-related injuries or suffering from heatwave-related health consequences.

A participant is coded as being *risk averse* if their response is above the sample median of the responses to “How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please choose a value on the scale, where the value 0 means not at all willing to take risks and the value 10 means very willing to take risks.” The variable *patient* is equal to 1 if the participant response is above the sample median of the responses to the question “Are you generally an impatient person, or someone who always shows great patience? Please tick a box on the scale, where the value 0 means very impatient and the value 10 means very patient.” Accordingly, 48% of our sample is categorized as risk averse and 39% as patient.

The Construal Level Theory measure is calculated as a composite scale following Spence et al. (2012) (Cronbach's alpha 0.89), incorporating 14 questions on geographical distance, social distance, temporal distance, uncertainty, concern about climate change and preparedness to act. Based on this measure, we then create a binary variable *Psychological Distance to Climate Change* that equals 1 for those whose values exceed the sample median value. Based on this classification, half of our sample can be classified as psychologically close to climate change. For Consideration of Future Consequences, the scale is composed of 12 questions with answers ranging from 1 (“extremely uncharacteristic”) to 5 (“extremely characteristic”). Following Strathman et al. (1994) and Bruderer Enzler (2015), the scale averages the 12 answers (after reverse-coding a subset of questions), where higher values indicate a higher concern for future outcomes (Cronbach's alpha 0.94). Based on the Consideration of Future Consequences measure, we create a binary variable *Future Consequences* that equals 1 for those whose values exceed the sample median value. According to this, 44% of our sample would prioritize the future consequences of their actions.

Of the total sample, 1,883 participants (i.e., 81%) are not indifferent and chose to move to either Area T or Area H in the first-choice scenario and were presented with a second-choice scenario (see Table 3). Only these participants are used for the DBDC estimation of the MER. The summary statistics of this sample are reported in column 2 of Table 2 and appear similar to those reported for the full sample in column 1. Around 26% of these 1,883 respondents switch from Area T to Area H and vice versa, and this percentage increases to 35% if we account for the switches from Area T or Area H to indifference. This degree of switching is consistent with

**Table 2** Summary Statistics

Variable	Description	(1) Full sample	(2) Two choice scenario (double- bounded) sample	(3) Indifferent first choice scenario sample
Male	= 1 if participant is male	0.42 (-0.49)	0.41 (-0.49)	0.47 (-0.50)
Log (Age)	= logarithm of age	3.54 (-0.29)	3.54 (-0.29)	3.55 (-0.30)
Low income	= 1 if participant has an income < INR 50,000 per month	0.24 (-0.43)	0.23 (-0.42)	0.29 (-0.45)
Bachelor's degree	= 1 if participant has at least a bachelor's degree	0.89 (-0.31)	0.89 (-0.31)	0.87 (-0.33)
Employed	= 1 if participant is employed	0.85 (-0.35)	0.86 (-0.35)	0.84 (-0.37)
Risk averse	= 1 if participant is risk averse	0.48 (-0.50)	0.47 (-0.50)	0.52 (-0.50)
Patient	= 1 if participant is patient	0.39 (-0.49)	0.38 (-0.49)	0.43 (-0.5)
Air cooling	= 1 if participant owns an air cooler or an air conditioner	0.94 (-0.24)	0.95 (-0.23)	0.91 (-0.29)
Traffic accident injury	= 1 if participant has suffered any injuries from a traffic accident	0.82 (-0.38)	0.84 (-0.36)	0.74 (-0.44)
Heatwave health consequences	= 1 if participant has suffered any health issues due to heatwaves	0.82 (-0.39)	0.84 (-0.37)	0.72 (-0.45)
Psychological Distance to Climate Change	= 1 if participant is psychologically close to climate change	0.50 (-0.50)	0.50 (-0.50)	0.49 (-0.50)
Future Consequences	= 1 if participant prioritizes the future implications of their current actions	0.44 (-0.50)	0.45 (-0.50)	0.42 (-0.49)
Andhra Pradesh	= 1 if participant currently lives in Andhra Pradesh	0.07 (-0.26)	0.07 (-0.25)	0.07 (-0.26)
Delhi	= 1 if participant currently lives in Delhi	0.46 (-0.50)	0.47 (-0.50)	0.41 (-0.49)
Haryana	= 1 if participant currently lives in Haryana	0.04 (-0.20)	0.04 (-0.20)	0.05 (-0.22)
Punjab	= 1 if participant currently lives in Punjab	0.04 (-0.19)	0.04 (-0.20)	0.02 (-0.15)
Rajasthan	= 1 if participant currently lives in Rajasthan	0.05 (-0.22)	0.05 (-0.23)	0.04 (-0.21)
Tamil Nadu	= 1 if participant currently lives in Tamil Nadu	0.18 (-0.38)	0.17 (-0.38)	0.21 (-0.41)
Uttar Pradesh	= 1 if participant currently lives in Uttar Pradesh	0.16 (-0.37)	0.16 (-0.36)	0.18 (-0.39)
N	Number of observations	2,334	1,883	451

*Note:* The sample size of the variable Employed is 449 for those indifferent in the first bound sample and 1874 for those answering both bound questions.

**Table 3** First and second choice scenario response sequence, by area

	Percentage of second choice scenario responses (%)	N
AT <sub>1</sub> -AT <sub>2</sub>	33.56	632
AT <sub>1</sub> -AH <sub>2</sub>	12.53	236
AH <sub>1</sub> -AT <sub>2</sub>	13.33	251
AH <sub>1</sub> -AH <sub>2</sub>	31.28	589
AT <sub>1</sub> -Indifferent <sub>2</sub>	2.87	54
AH <sub>1</sub> -Indifferent <sub>2</sub>	6.43	121
Total second choice scenario		1883
Indifferent in first choice scenario		451
Total participants		2334

*Note:* The subscript 1 means that the choice was made in the first choice scenario of the DBDC. The subscript 2 means that the choice was made in the second choice scenario of the DBDC. AT Area T, AH Area H.

the percentage of switches in the prior literature on WTP for environmental issues in Southeast Asia (Akter, 2020; Islam et al., 2019; Paparrizos et al., 2021).

As participants were presented with a first question that was randomly selected from among nine choice scenarios, we also examine whether the participants' socio-demographic characteristics are balanced. Table B1 in the Online Appendix B shows that the sample is balanced across the nine first choice scenarios, with the exception of share of respondents with at least a college degree ( $p$ -value = 0.088).

## 4.2 Results of the DBDC RRTO estimation and robustness checks

Based on the empirical framework in Section 3.1, the main input variables for the estimation of the univariate MER (our context premium) are the decision to move to Area H in the first and second choice scenarios and the RDRs of the first and second choice scenarios. Results of this estimation, with and without covariates, are presented in Table 4.

The most parsimonious specification (with only state controls) is presented in column 1 of Table 4. Our maximum likelihood estimation translates into a univariate MER of 2.26. This means that in aggregate, individuals in our sample weigh reducing heatwave-related mortality risks at 2.26 times that of reducing traffic accident mortality risks.

Specifications accounting for systematic heterogeneity are reported in columns 2 and 3 of Table 4. In column 2, we include socioeconomic variables (age, gender, education, income and employment status), risk aversion and patience, ownership of heatwave-related assets (air cooler or air conditioner), and prior experiences with consequences of traffic accidents and heatwaves. In column 3, we also include the two variables *Psychological Distance to Climate Change* and *Future Consequences*. Results show that across the 3 columns, the univariate MER varies between 2.26–2.94.

**Table 4** Analysis of risk-risk trade-offs: maximum likelihood results

Outcome: Choice of Area H	(1)	(2)	(3)
Male		-0.05 (0.17)	0.08 (0.18)
Log (age)		-0.14 (0.30)	-0.24 (0.30)
Low Income		0.19 (0.20)	0.24 (0.20)
Bachelor's degree		0.16 (0.26)	0.19 (0.26)
Employed		-0.03 (0.24)	-0.09 (0.24)
Air cooling		-0.37 (0.34)	-0.37 (0.35)
Traffic accident injury		-0.38* (0.22)	-0.44* (0.22)
Heatwave health consequences		0.05 (0.22)	-0.04 (0.22)
Risk averse		-0.29 (0.18)	-0.02 (0.19)
Patient		0.86*** (0.18)	0.75*** (0.18)
Psychological Distance to Climate Change			0.86*** (0.21)
Future Consequences			0.22 (0.17)
<b>Univariate MER (Constant)</b>	<b>2.26***</b> <b>(0.12)</b>	<b>2.94**</b> <b>(1.14)</b>	<b>2.77**</b> <b>(1.14)</b>
Sigma	-2.89*** (0.09)	-2.85*** (0.09)	-2.83*** (0.09)
State controls	Yes	Yes	Yes
Observations	1883	1874	1874

*Note:* The analysis is performed on the sample of non-indifferent respondents (i.e., those presented with the first and second choice scenarios). Robust standard errors are reported in parentheses. Univariate MERs are calculated based on Eqs. (2)–(7) and are presented in bold. Beta coefficients are parameter estimates from Eq. (2), and sigma is the estimated standard deviation of the error distribution from the same model. Variable descriptions available in Table 2. \* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

In terms of explanatory variables, and regarding prior experience with the relevant risks, having experienced injuries resulting from traffic accidents is also negatively associated with the choice of moving to Area H. Focusing on the psychological variables, we find that the *Psychological Distance to Climate Change* is significantly positively correlated with the choice of moving to Area H. On the

other hand, we do not find the *Future Consequences* to be statistically significant. Although the Consideration of Future Consequences measure is complementary to the Construal Level Theory measure (particularly on temporal distance) and has been validated by the literature on climate change (Beiser-McGrath & Huber, 2018; Corral-Verdugo et al., 2009; Joireman et al., 2009; Veckalov et al., 2021), it is a general psychological scale, while the Construal Level Theory measure is designed to directly target the psychological distance of climate change. It is therefore likely that the Construal Level Theory measure, as it evaluates this specific context, could be capturing the full effect of psychological measures. Although we do not elicit information to calculate individual discount factors, we find that being patient is positively related with the choice of Area H and increases the context premium.<sup>12</sup>

As a first robustness check, we compare the MER estimated from the sample that was presented with two choice scenarios ( $N=1,883$ ) with the MER for the subgroup of participants who stated being indifferent between Areas T and H in the first-choice scenario and were not presented with a second choice scenario ( $N=451$ ). The latter set of participants have directly indicated their RRTO indifference points. Therefore, we do not have to estimate their MER, as it is the RDR of the choice scenario posed to them. The average RDR value for these participants is 1.83 (s.e. 1.73). Moreover, estimating a model that has no additional variables or state controls from the sample of 1,883 participants who were presented with two choice scenarios, we get a univariate MER equal to 1.85 (s.d. 0.25). Hence, the MER values from these two subsamples (single-bound and double-bounded) are statistically similar (a test for equality of values yields a  $p$ -value = 0.63).

For a second robustness check, although we are unable to comment on the point estimation biases, we examine whether there is an increase in the efficiency of our DBDC estimates compared to a single-bound dichotomous choice (SBDC) method (i.e., only asking a single question instead of two), as also demonstrated by Hanemann et al. (1991). To estimate a SBDC model with our data, we take the responses for our first choice scenario and use them as if they represented a single choice scenario response. Results for this sample are in Table B2 in Online Appendix B. We also run the same model restricting the sample to the participants who answered both choice scenarios (Table B3 in Online Appendix B). We can then compare the standard errors of the MERs in Table 4 (using DBDC) and see that these are much lower than those using the SBDC. Tests for standard error differences reject equality between the standard errors in Table 4, B2 and B3 in Online Appendix B ( $p$ -values < 0.001 for all pairwise comparisons between the double-bounded and the single-bounded standard errors).

<sup>12</sup> Self-reported levels of patience also have a lower time distance (to climate change) component of the Construal Level Theory scale, which given the way the question is constructed could be used as a proxy for discounting climate change. Patient individuals in our sample state that the effects of climate change in India will be felt closer in time compared to those who are impatient—which could be approximated as having a higher discount rate for climate change compared to the impatient sub-sample (Kolmogorov-Smirnov distribution test  $p$ -value = 0.079; for distribution of time distance question based on patience dummy, see Fig. B1 in Online Appendix).

### 4.3 Value of Statistical Life

Until now, our focus has been on estimating the context premium (MER), examining its determinants and establishing its robustness. However, we take this a step further and illustrate how our heatwaves context premium could be combined with an existing (or calculated) VSL for traffic mortality risk ( $VSL_t$ ) to calculate an implied VSL for India for heatwave mortality risks ( $VSL_h$ ). In principle, this monetary value could then be used by policymakers in making decisions with respect to climate-related health risks. Since there is no official government-approved  $VSL_t$  for India, we apply a benefit transfer methodology to estimate one. The typical approach when no official VSL figures exist is to extrapolate values from wealthier countries, adjust for income differences, and conduct a sensitivity analysis to assess the extent to which conclusions might depend on these estimates (Robinson et al., 2019b). Although the benefit transfer approach has its caveats, it remains the most appropriate one until country-specific VSL estimates are available (Robinson et al., 2019b; Viscusi & Masterman, 2017). Partly in view of these caveats<sup>13</sup> and partly because our primary purpose is not to estimate a definitive heatwave risk VSL for policymaking, we choose instead to provide a range of  $VSL_t$  and associated  $VSL_h$  in Table 5 below, which might be considered as a plausible range within which a heatwave mortality risk VSL might fall.

As a first step, to calculate VSL estimates for India, we use the three benefit transfer approaches suggested by the Benefit-Costs Analysis guidelines (Robinson et al., 2019a) but use the  $VSL_t$  for the UK (VPF) of £2.14 million as this (in contrast to the US VSL) is specifically estimated for traffic accident mortality risks (Department for Transport Analysis Guidance DataBook, 2022).<sup>14</sup> In addition, we use a VSL of \$150,000 US Dollars (in 2005 values) for traffic accidents in India estimated directly in a stated preference survey ( $VSL_t$ , Bhattacharya et al., 2007).

The  $VSL_t$  for each of these four options is in column 1 of Table 5. In addition, we also compare the four  $VSL_t$ 's with the VSL for India derived in Viscusi and Masterman (2017) using a base US VSL coupled with adjustments for differences in income between the US and India. The VSL in that study was \$275,000 US Dollars (in 2015 values) or \$334,000 US Dollars (in 2021 values). Although their VSL estimate was calculated using labour market estimates (i.e., not in the context of traffic), it is reassuring that it lies in the mid-range of our  $VSL_t$  estimates provided in Table 5.

Second, to apply our findings at an aggregate (policy) level, we use an indirect approach (Chilton et al., 2002; McDonald et al., 2016) and 'peg' the estimated context premium—effectively our MER—for reducing heatwave mortality risks to the extrapolated  $VSL_t$  from the first step. This provides us with a range of estimates for

<sup>13</sup> In particular, those with respect to income. Whilst our sample is quite similar to the population of the seven states in terms of share with low income (see Section 2.2), this in and of itself does not deal with the caveats concerned with the difficulties in incorporating any differences in prevailing income distribution, both across comparator samples, countries or across time.

<sup>14</sup> Further main inputs for these calculations come from the following sources: Gross National Income per capita in PPP \$ (India: \$7,220; United Kingdom: \$49,420); World Bank DataBank (2022).

**Table 5**  $VSL_t$  and  $VSL_\eta$  calculations (millions of US Dollars, 2021)

	(1) $VSL_t$	(2) $VSL_\eta$
<b>FROM BENEFIT COST ANALYSIS GUIDELINES</b>		
VSL extrapolated from a US VSL of and US GNI per capita (a VSL-to-GNI per capita ratio of 160), using an income elasticity of 1.5. If this approach yields a target country value of less than 20 times GNI per capita, then 20 times GNI per capita should be used instead	0.16	0.37
VSL extrapolated from an OECD VSL-to-GNI per capita ratio of 100 to the target country	0.72	1.63
VSL extrapolated from a US VSL-to-GNI per capita ratio of 160 to the target country using an income elasticity of 1.0; i.e., $VSL = 160 * \text{GNI per capita in the target country}$	1.16	2.61
<b>OTHER SOURCES</b>		
VSL from Bhattacharya et al. (2007) for traffic accident mortality risk in India	0.21	0.47

*Note:* Calculations are performed based on the Univariate MER from specification (1) in Table 4.

the VSL for heatwave mortality risks ( $VSL_\eta$ ) for India (in column 2 of Table 5). For these calculations, we use the context premium estimated in column 1 of Table 4 and apply equation (C9) from our RRTO model described in Online Appendix C to reach a  $VSL_\eta$  (in 2021 US Dollar values). Column 2 of Table 5 presents the range of values for  $VSL_\eta$  for India ranging from \$0.37 to \$2.61 million (in 2021 values).

It is worth noting at this stage that any  $VSL_t$  used as a “peg” comes with some analytical caveats as one can only be empirically confident that the  $VSL_t$  reflects actual preferences over traffic risks if the survey scenarios are identical. In addition, although the  $VSL_t$  for the UK is based on traffic risks and continues to underpin Treasury guidance (HM Treasury Green Book, 2022), it is not a new estimate as the survey was conducted in 1996, and might not reflect the current best practices for conducting stated-preference research (Robinson & Hammit, 2011). In addition, it is important to emphasise that the premium in our study is estimated based on a sample of seven states in India. To “peg” the heatwaves context premium to a country-specific VSL for national policymaking, would require a premium that was representative for India as a whole.

## 5 Conclusion

In light of increasing climate variability and extreme weather events, there is an urgent need to understand individual preferences with respect to climate change, especially in developing countries. Further, for policy-making purposes, we also need to quantify the economic benefits from allocating resources to avoid increasing—or even decreasing—the mortality risk associated with climate change. But valuing changes in mortality risks is not without its challenges, particularly with respect to

the use of standard economic methods in income-constrained populations. This paper provides a promising alternative to a conventional monetary approach by allowing such populations to express any preferences they may have over different risks in a non-budget constrained scenario. We do so by focusing on heatwave mortality risks in India.

Using the RRTO method in a large-scale online survey conducted across seven states in India, our results indicate that, on average, individuals in our sample weigh reducing heatwave-related mortality risks approximately 2.2–2.9 times that of reducing traffic accident mortality risks. In line with the prior literature, individuals in our sample who are psychologically close to climate change weigh reducing heatwave-related mortality risks significantly more than that of reducing traffic accident mortality risks. Reducing psychological distance has been shown to increase public engagement with climate change (Jones et al., 2017; Spence et al., 2012), modifying perceptions regarding climate risks and the temporal distance of climate change. This implies that a change in communication that decreases psychological distance to climate change could be a fruitful avenue to change behaviors.

In addition, we calculate a VSL in the range of USD 0.37–2.61 million (in 2021 values) for reducing heatwave-related mortality risks using benefit transfer, suggesting that allocating resources towards avoiding heatwave-related mortality risk increases—or indeed reducing them—would be economically beneficial. Although we do not propose that our VSLs should be used directly for policy-making purposes, given the limitations of the benefit transfer methodology as deployed here, we do believe that the evidence is strong enough to argue that a VSL for traffic accident mortality risks should not be applied for heatwave-related climate policies in a discretionary manner. Instead, we believe more research is needed to validate whether such premium in resource allocation should be applied more generally in India and other LMICs going forward, on the grounds that it would, at least in part, reflect the prevailing preferences of those people whose lives are most affected by heatwave risks.

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**Data availability** Data is available upon request (for replication and reuse) by emailing the corresponding author.

## Declarations

**Competing interests** The authors declare that there are no competing interests from the authors with regards to this manuscript.

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