Heat and Economic Preferences

Michelle Escobar Carías[1]
David W. Johnston
Rachel Knott
Rohan Sweeney

November 3rd, 2022

Abstract

Does temperature affect economic preferences and the likelihood of irrational behavior? Using data from Indonesia, we answer this question by estimating how risk aversion, impatience and the occurrence of a rational choice violation vary with outdoor temperatures within areas over time. Our findings show that hot weather causes more rational choice violations and increases impatience, but does not affect risk-aversion. These effects are driven by temperatures on the night prior to the survey rather than by temperatures during the day of the survey. An important mechanism behind these effects is a significant increase in sleep disturbances, leading to depleted cognition the next day, particularly math skills. These findings suggest that heat-induced night-time sleep disturbances cause stress on the brain, which then manifest in significantly lower cognitive functions that are critical for economically rational and utility-maximizing decision-making. These effects are largest for the poor, those with low electricity consumption, and people from in areas with low rates of air-conditioning ownership.

JEL Classification: Q54, D01, D81, D91, I15, I25

Keywords: Temperature, risk aversion, impatience, rational choice violations, sleep, cognition

[1] Corresponding author: michelle.escobarcarias@monash.edu. Address: 900 Dandenong Road, Centre for Health Economics Monash University, Caulfield East, 3145, Victoria, Australia.

1. Introduction

People's economic preferences influence types of behavior that are important for individual economic well-being as well as for broader social welfare. For instance, studies show that savings behavior and investments in human capital inputs, such as child immunizations and schooling, depend partly on a person's level of patience (Ashraf et al., 2006; Banerjee et al., 2010). Similarly, risky choices linked to economic development, such as opening a new business, becoming self-employed, and the optimal use of fertilizer, depend on a person's willingness to accept risks (Ekelund et al., 2005; Liu & Huang, 2013). In the neoclassical theory, these types of individual preferences are assumed to be stable across time (Stigler & Becker, 1977). However, a growing body of evidence shows that preferences change after exposure to negative shocks, such as natural disasters, violence, bereavement and financial crises, with the size and direction of effects varying substantially across studies (Cameron & Shah, 2015; Hanaoka et al., 2018; Callen et al., 2014; Callen, 2015; Kettlewell, 2019; Levin & Vidart, 2020).

In this study, we investigate whether economic preferences and rational behavior are impacted by temperature. According to the latest report from the Intergovernmental Panel on Climate Change (IPCC, 2021), human-induced climate change has already increased the level of average temperatures and the frequency of temperature extremes over land. Evidence suggests that these temperature spikes could lead to significant changes in decision making due to their negative impacts on cognition, sleep patterns and mood. For instance, Mani et al. (2013) and Schilbach et al. (2016) show that mentally taxed individuals are less likely to engage in slower, deliberative and logical thinking – what Kahneman (2011) refers to as System 2 thought processes – and these are required for making complex calculations and decisions. Schilbach et al. (2016) propose that individuals have a limited System 2 budget, and factors such as sleep deprivation and heat can reduce a person's limited mental bandwidth. This hypothesis has been broadly corroborated by a number of economic studies. Examples include high-stakes decisions by judges (Heyes & Saberian, 2019), consumer behavior and purchase decisions (Busse et al., 2015), violent interactions among incarcerated populations (Mukherjee & Sanders, 2021) and even criminal behavior in poor neighbourhoods of the United States (Heilmann et al., 2021).

We use data from Indonesia to estimate the effects of temperature on risk aversion, impatience and rational choice violations.[2] Weather data come from NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA-2). Elicited rational choice, and time and risk preference data come from the Indonesia Family Life Survey (IFLS). To identify causal effects, we use short-term variations in temperature over time within climate zones defined by the interaction of a village's province, altitude, distance to the coast, and level of urbanity. Subsequently, we estimate the effects of temperature on cognition, sleep, and mood in order to better understand the mechanisms driving the relationships between temperature and economic preferences. These three outcomes have been shown to be negatively impacted by extreme heat (Zivin et al., 2018; Garg et al., 2020; Park et al., 2020a; 2020b; Minor et al., 2020; Obradovich et al., 2017; Mukherjee & Sanders, 2021; Almås et al., 2020; Baylis, 2020) and to be associated with decision making (Benjamin et al.,2013; Nofsinger & Shank, 2019; Cueva et al., 2015).

Our findings show that higher temperatures lead to significantly increased rational choice violations and higher impatience, but do not significantly affect risk aversion. We show that these effects are mainly driven by temperatures on the night prior to the survey rather than by temperatures on the day of the survey. The estimates indicate that a 1°C increase in midnight temperature is associated with a 1 percentage point (3.2%) increase in irrational behavior and a 0.9 percentage point (1.5%) increase in impatience. Our exploration of potential mechanisms indicates that higher night-time temperatures significantly increase the likelihood of experiencing a severe sleep disturbance and of feeling poorly the next day due to poor sleep. This then leads to reduce cognitive functioning the following day - mathematical skills in particular - at a rate of 1.6%-3.6% of a standard deviation for each degree Celsius. No temperature effects were detected on mood. Based on these findings, we posit that heat-induced night-time disturbances affects sleep causing stress on parts of the brain, such as the prefrontal cortex (Miller, 2000), which manifest in significantly lower cognitive functions the next day. These functions are important for individuals to perform economically rational decision-making, and therefore high night-time heat leads to an increase in sup-optimal decision-making.

---

[2] Our measure of rational choice violation follows from individuals entirely avoiding entering a more than fair lottery. This could also be considered a non-standard preference such as individuals having a certainty premium (Callen et al., 2014) and/or regret aversion (Zeelenberg et al., 1996), which are not necessarily considered irrational. However, in our sample, cognitive abilities are highly and negatively correlated with making 'rational choice violations' but not with risk aversion, an actual preference. We therefore argue that this is more likely than not, evidence of rationality errors from which individuals obtain no positive utility.

We additionally explore non-linear temperature effects and heterogeneous treatment effects by individual and household characteristics. The former exploration shows a linear increase in rational choice violations and impatience when midnight outdoor temperatures are above 22°C. Given that 24% of our sample experienced midnight temperatures above this threshold the night prior to their survey, these findings are relevant for a large portion of the Indonesian population. With regards to heterogeneity, we find that temperature effects are larger for individuals with lower schooling, those who reside in households with lower asset wealth, and in households with low electricity expenditure. These results suggest that poorer households are less able to mitigate their exposure to extreme outdoor temperatures, and therefore are the most negatively affected by heat in terms of the quality of their decision making.

These findings contribute to a small collection of studies that investigate the effect of temperature on time and risk preferences in laboratories. Overall, these studies show little consensus. Almås, et al. (2020) studied the impact of heat on university students in Berkeley, California, and Nairobi, Kenya. They find no evidence that heat stress affects risk-taking, time preferences, cognition, or social behavior except for destructive tendencies. [3] In contrast, Wang (2017) finds that high ambient temperatures lead individuals to pursue high-risk options. A third study conducted by Cheema & Patrick (2012) finds that individuals exposed to warmer temperatures in the lab are less likely to gamble or purchase innovative products.

Our study contributes to this literature in several ways. Although the temperature variations we use are not randomized as they are in laboratory studies, we leverage a quasi-experimental design in which temperatures are as-good-as-randomly assigned (an assumption we extensively investigate). Further, we overcome some general limitations of laboratory experiments, such as small sample sizes and limited experimental subject pool. Our sample of approximately 50,000 individuals ages 15 to 90 years old is significantly larger than the highest-powered laboratory study with 2,000 observations (Almås, et al., 2020). Further, our findings are more generalizable given our use of a (nearly) nationally representative sample. This helps increase the external validity of our results for populations residing in low- and middle-income countries. Finally, in contrast to the cited experimental studies, we do not assume an immediate impact of heat on preferences. Instead, our data allow us to identify heterogeneous responses to timing and duration of heat exposure.

---

[3] Almås, et al. (2020) find that heat affects people's willingness to destroy other people's earnings in a game known as joy of destruction, consistent with the temperature-aggression hypothesis.

We also contribute to the mixed literature on the relationship between economic preferences and extreme natural, social and economic events as well as to the literature on the effects of poverty on economic preferences (Bartoš et al., 2021; Carvalho et al., 2016). For example, Cameron & Shah (2015) find that Indonesians who have experienced a flood or an earthquake exhibit more risk-averse tendencies, while conversely, Hanaoka et al. (2018) find that victims of the 2011 Great East Japan Earthquake became more risk-tolerant and increased gambling. In other related literature, studies have found that environmental conditions can increase the likelihood of making violations of rational choice in purchasing decisions. For example, Busse et al. (2015) find that sales of convertibles and four-wheel drive vehicles are significantly influenced by idyosincratic shocks in temperature, cloud cover and snowfall. In a similar vein, Conlin et al. (2007) find that the probability of customers returning catalog orders of cold-weather items is significantly increased when order-date temperatures drop. Both are examples of how environmental conditions may increase the propensity for rational choice violations, which are costly to the individual and potentially to society.[4]

The rest of the paper proceeds as follows. Section 2 outlines the sources of data, outcomes and treatment measures. Section 3 outlines the empirical strategy. Section 4 provides a discussion of the main findings, robustness checks and placebo tests. Section 5 provides a discussion regarding potential mechanisms behind the identified temperature effects and section 6 concludes.

2. Data

2.1 Indonesia Family Life Survey

Data on time and risk preferences, rational choice, cognition, sleep, and mood come from waves 4 and 5 of the Indonesia Family Life Survey.[5] These two survey waves spanned 2007-2008 and 2014-2015, and include over 50,000 completed surveys from respondents residing in more than 3,800 villages across 38 provinces. All IFLS outcomes used in the analyses were collected verbally in face-to-face sessions with the survey respondents. Descriptions and summary statistics of the key IFLS variables are shown in Table 1, and are further detailed in the below subsections.

---

[4] For instance, according to The Guardian (2020), about five billion pounds of returned goods in the United States ended up in landfills in 2019, which contributed 15 million metric tons of carbon dioxide to the atmosphere.
[5] The time and risk preference modules were not collected in waves 1-3 of the Indonesia Family Life Survey.

2.1.1 Risk and Time Preferences

The IFLS risk aversion module is a staircase-type instrument that includes a series of hypothetical choices between accepting a certain amount of money or accepting a risky lottery that offers a 50% probability of winning an amount 'c times smaller' 'or x times larger' than the certain value. The factors c and x are adjusted with subsequent tasks depending on previous choices (see Appendix Figure A1 for the complete sequence of potential choice tasks).

We use the first-choice task in the module to capture violations of expected utility (rational choice violations). In it, individuals are given a hypothetical choice between a certain amount or a 50% chance of winning that amount or twice that amount. The rational option is the coin flip, as per the non-satiation assumption (Perloff, 2014). Nevertheless, 32% chose the certain option and refused the gamble. We use a binary indicator of this choice as our measure of a rational choice violation.[6]

The remaining 68% of respondents choose the 'risky' option in the first-choice task and are given subsequent decisions that can be categorized into four groups: most risk averse (27.9%), second most risk averse (8.8%), third most risk averse (10.6%) and least risk averse (17.5%). The outcome variable in our regression analyses is a binary variable equalling one if the individual is in the most risk averse group, and zero if in one of the other three groups. By this definition, 37.3% of this sample is considered risk-averse.

Our measure of impatience is derived from a similar staircase-type instrument with a series of hypothetical choices beginning with earning a certain amount today or that same amount at a future date. The first value is held constant in each subsequent question, and the second value increases throughout the series to capture different discount rates (See Appendix Figure A2 for the complete sequence of potential choice tasks). We construct a binary measure for myopic preferences where respondents are assigned a value of one if their sequence of decisions categorises them in the most impatient group and zero otherwise. Approximately 62% of

---

[6] It is important to note that this lottery choice sequence was not monetarily incentivized, a relevant feature of the risk and time modules because the majority of the Indonesian population identify themselves as Muslim and gambling is forbidden in Islam. Furthermore, to account for the possibility that our 'rational choice violation' outcome might partly capture reluctance to gamble due to religious beliefs, our main regression models control for religion and religiosity. Moreover, as shown in Appendix Table C1, individuals who identify as Muslim are not statistically more likely to make rational choice violations (-1.1 percentage points, $p = 0.846$).

individuals are in the most impatient category.[7] All three main outcome variables are dichotomized to ease interpretation.

We validate these economic preference measures by estimating the associations between them and individual behaviours. Following the approach used by Falk et al. (2018) to validate the measures obtained in the Global Preference Survey (GPS), we create two groups of behavioural outcomes – accumulation decisions and risky choices – and regress these outcomes on either impatience, risk aversion, or the probability of making rational choice violations.

Economic theory relates patience with the ability of individuals to save and invest in education in order to accumulate financial and human capital. If an individual's marginal utility of consumption in the present is very high or their expectations of the future are very low (i.e. myopic or impatient), she will be less inclined to save and invest. In columns 1 and 2 of Table 2 we show that indeed, for our sample of IFLS respondents, impatience[8] is associated with a 3.3-percentage point reduction in the probability of saving and an 8.8 percentage point reduction in the probability of achieving secondary education or higher.

Similarly, we investigate whether rational choice violations[9] and risk aversion are significantly associated with risky behaviour: self-employment, planning to open a business, and using tobacco. Our findings indicate that both risk-averse individuals and people who make rational choice violations are less likely to be employed and plan to start a business (columns 3 and 4, Table 2). Conditional on smoking, both consume a significantly lower number of cigarettes (columns 5 and 6, Table 2).

2.1.2 Sleep, Cognition and Mood

Wave 5 of the IFLS contains a validated sleep disturbance instrument based on the Patient-Reported Outcomes Measurement Information System (PROMIS) developed by the USC Centre for Economic and Social Research (CESR) in the United States. The module consists of self-reported answers to ten questions that capture sleep quality and sleep deprivation using a seven-day reference period. Each item is rated by the respondent on a five-point scale (1 =

---

[7] As with risk aversion, the first decision in the time preference task captures a non-standard preference, in this case, negative time discounting. Negative time discounters form only 2% of our sample and are subsequently excluded from the analysis.

[8] In our sample, males, people with a lower likelihood of having secondary schooling and people with lower cognitive scores are more likely to be impatient as shown in Appendix Table C1.

[9] In our sample, females, unemployed individuals, people without secondary schooling and those with low cognitive scores are significantly more likely to make rational choice violations. See Appendix Table C1 for further details.

never to 5 = always). The aggregated scores can range from 10 to 50, with a higher score indicating a sleep disturbance of greater severity. Following clinical practices and guidelines, these scores are converted to T-scores[10]. For the purpose of our analyses, we create a binary indicator for sleep disturbances that is equal to 1 if the aggregated t-scores are 60 or over, indicating that the person has a moderate to severe sleep disturbance. As shown in Table 1, 16.4% of our sample had a severe sleep disturbance in IFLS5. Next, we conduct a factor analysis with the 10 sleep items to create two latent variables: poor sleep quality and sleep deprivation that leads to feeling poorly during the day. As Table 1 shows, these are standardized variables with a mean of zero and standard deviation of one.

A battery of cognitive tests can also be found in the IFLS. Four cognitive tests were administered to respondents age 15 to 90 in wave 5 of the IFLS: (i) an adaptive number series test measuring fluid intelligence related to quantitative reasoning (Strauss et al., 2017); (ii) a date awareness, word recall, and subtraction test measuring 'mental intactness' (Fong, et al., 2009); (iii) the Raven's Progressive Matrices test that measures non-verbal abilities (Raven, 2000); and (iv) a test of mathematical skills with addition, subtraction, multiplication and division questions (see the Appendix D for more details on each test). We standardized the score from each test such that it has a mean of zero and a standard deviation of one. We also use a standardized composite measure of cognition by performing a principal component analysis of the four tests. In wave 4 of the IFLS, some of these tests were only asked of adults aged 15-31 years, and one item – fluid intelligence – was not included at all.

To test whether we can find a similar effect of temperature on mood as reported by Almås et al. (2020), we extract four questions from the IFLS5's Positive and Negative Affects module. This module asks individuals how angry, tired, enthusiastic or happy they felt 'yesterday', the day before the survey. As explained in Table 1, the responses 'quite a bit' and 'very' are aggregated to create binary variables. On average 31% of adults reported having felt angry, 45% felt tired, 58% felt enthusiastic, and 64% felt happy on the day before the survey.

2.2 NASA MERRA-2 Dataset

We obtain hourly and daily records of temperature, relative humidity, precipitation, wind speed, and pollution from NASA's MERRA-2 dataset. This dataset integrates both station and

---

[10] According to the APA Dictionary of Psychology, T-scores are a type of standardize score based on a score distribution that has a mean of 50 and a standard deviation of 10.

satellite data to provide localized indicators across the extensive landmass of the Indonesian territory, including areas with no proximal weather stations. Specifically, MERRA-2 provides environmental estimates for 0.5º x 0.625º cells (approximately 50 kms x 60 kms) at hourly and daily time scales from 1981 to 2021 (Rienecker, et al., 2011).[11]

MERRA-2 climate records are matched to IFLS respondents through the GPS coordinates of their villages of residence. Village level GPS coordinates were only collected in wave 1 (1993) and wave 5 (2014-2015) and so approximately 30% of wave 4 respondents (2007-2008) were omitted from the sample because they had no GPS coordinate data.[12] An additional 4.5% of respondents were omitted because their village was located at a distance greater than 50 kilometers from the closest MERRA-2 grid point. This restriction was made to reduce measurement error in the temperature variable. Figure 1 presents a map of the Indonesian territory with markers for the MERRA-2 grid points and each Indonesian village in wave 5 of the IFLS.

We use three temperature variables in the regression analyses: temperature at the beginning of the survey, maximum temperature on the survey day, and midnight temperature on the night prior to the survey. The mean maximum temperature on survey dates was 28.7ºC, with 1.4% of individuals experiencing a maximum temperature above 35ºC. The mean temperature in the first hour of the interview was 24.6ºC, and the mean midnight temperature on the night prior was 23.6ºC.

3. Empirical Strategy

3.1 Defining Climate Zones

We identify the effects of temperature on time and risk preferences by exploiting differences in temperature across time within homogenous climate zones. A key identifying assumption of this approach is that temperature variation within climate zones is exogenous. That is, we assume that individuals within the same climate zone face different temperatures only because

---

[11] Auffhammer et al. (2013) caution that the output for regions where stations are sparse or of poor quality is a model prediction, and therefore likely to be less accurate than for regions with greater coverage of weather stations. This is especially relevant when using fixed effects estimators where it can amplify statistical concerns such as attenuation bias.

[12] The majority of wave 4 respondents had GPS coordinates because they were residing in a village visited by surveyors in wave 1 or wave 5. Omitted wave 4 respondents were those living in a 'new' village.

of differences in survey dates.[13] This assumption is violated if there are significant differences in climatic conditions within the same area. For example, people living at sea-level may experience systematically hotter temperatures than those living at higher altitudes, and may also experience differences in socioeconomic and cultural environments that are associated with economic preferences. For this reason, rather than comparing differences between people living within politically-defined areas that often encompass different climatic conditions, we define our own areas.

Three key determinants of temperature within regions of a country are altitude, distance to the sea, and the level of urbanity (NASA, 2016; NOAA, 2021; EPA, 2021). Altitude, the height measured from sea level, is inversely correlated with temperature (Pielke, 2021). Costal temperatures tend to be cooler than inland temperatures, and thus distance from the sea is positively correlated with temperature. Finally, cities can cause an 'urban heat island effect', which occurs when cities replace natural land cover with dense concentrations of pavement, buildings, and other surfaces that absorb and retain heat (EPA, 2021). We therefore compare survey respondents living in the same Indonesian province and with similar altitude, distance to the sea, and level of urbanity. Specially, we create 285 climate zones by interacting: 24 province indicators, four altitude groups (<50 meters, 50-100 meters, 100-500 meters, 500+ meters)[14], three distance-to-the-coast groups (<30 km, 30-60 kms, 60+ kms), and an indicator of the village's urban or rural status.[15] The map in Figure 2 provides an example of the 19 resulting climate zones in the province of North Sumatra. Elevation is drawn in the background as shown by the grey shading, with darker areas representing higher altitude zones. The different climate zones used for the area fixed effects models are represented by different colours located at the centre point of each surveyed village. Our identification strategy implies, for instance, that we compare preferences across time of people residing in rural mountainous villages far from the coast (blue circles).

---

[13] Appendix Figure A3 shows the number of days it took to roll out the survey instrument in each climate zone with an average of 40 days.

[14] The choice of thresholds for the altitude and distance to the coast groups was based on the shape of the distribution of both variables. The placement of the cut-off points is chosen so as to create approximately equally sized bins while maintaining a large enough number of observations within each threshold. Nevertheless, our main results are not sensitive to various adjustments of these thresholds.

[15] Interacting smaller administrative units than provinces, such as districts or subdistricts, significantly reduces the temperature variation available for identification (especially when considering lagged effects, as we do). Following standard procedures, the survey was rolled-out by geographical areas, and therefore some areas were completely surveyed within days. For instance, the sub-district of Bengo in the province of South Sulawesi was 96% surveyed in 12 consecutive days in 2015.

Figure 3a plots the variation in temperatures on the day of the survey within these constructed climate zones. It demonstrates that there is sufficient temperature variation for the identification of temperature effects. Across the survey data collection period within climate zones individuals experience differences in temperature of several degrees. Finally, Figure 3b shows that the source of this temperature variation within climate zones is almost entirely due to the duration of time it took to roll-out the survey in each climate zone, rather than because of environmental or socioeconomic differences within the zones. We regress maximum temperature on the day of the survey on date of survey fixed-effects and find that 1.8% of climate zones have an R^2 between 0.66 and 0.8, 4.9% have an R^2 between 0.8 and 0.9, 14.9% have an R^2 between 0.9 and 0.95, and 78.4% have an R^2 above 0.95. These different R^2 values are represented in Figure 3b by colour (darker colours representing higher R^2 values). In a robustness test discussed in Section 4 we verify that our main results are nearly identical when using a subsample of climate zones with high R^2 values (i.e. zones in which practically all temperature variation is caused by variation in interview dates).

3.2 Main Specification

The effects of temperature on economic preferences are estimated with the following regression specification:

$$Pref_{iat} = \beta_1 temp_{at} + \beta_2 weather_{at} + \beta_3 lat_{ia} + \beta_4 X'_{iat} + \tau_t + \phi_a + \varepsilon_{iat} \qquad (1)$$

where $Pref_{iat}$ is the economic preference of individual *i*, residing in climate zone *a* in time *t*. Parameter $weather_{at}$ contains environmental variables specific to each village located in area *a*, at time *t* such as daily maximum precipitation, wind speed, and particulate matter 2.5 (pollution). We also include controls for village latitude which can cause temperatures to drop the further away from the equator. It has also been found to affect economic output (Hall & Jones, 1999), settlement patterns, and even disease environment (Mellinger et al., 2000), all of which could be linked to economic preferences, and therefore important to account for.

X_{iat} consists of individual and household-level time-varying covariates such as age, gender, marital status, religion, the individual's main income-generating activity, their highest level of education, a squared function of equivalized expenditure, the same demographic characteristics for the household head, number of children, and numbers of adults in the house, day of the week, and hour when the interview began. Finally, τ_t and ϕ_a are a set of month-year and climate zone (province-urban-altitude-distance to coast) fixed effects, respectively. Month-

11

year fixed effects control for potential seasonal patterns and festivities that could affect exposure to heat, cognition, sleep and economic preferences.[16]

Our treatment variable $temp$ represents maximum temperature on the day of the interview, midnight temperature the night before the interview, and the temperature at the hour when the survey began. We also consider the possibility that any potential effects could be non-linear. In a more flexible non-parametric specification, we employ bins of midnight temperature to study the shape of this relationship (<21ºC, 21-22, 22-23, 23-24, 24-25 and 26ºC >), with temperatures 14-21ºC as the reference. This reference level has been used in other studies and recognized as an ideal range for human comfort (Barreca et al., 2016; Connolly, 2013). There were no temperatures below 14ºC registered in the IFLS villages during the period of study, precluding a further split to study the effects of colder temperatures.

Analysis presented in the preceding section suggests that within climate zone variation in temperature is determined by interview date. However, we have also explored whether there is endogenous selection of village climate based on economic preferences. For the sample of people who moved villages between IFLS4 and IFLS5, we regress changes in a person's temperature between 2007-2008 and 2014-2015 on economic preferences measured in 2007-2008, and our standard set of covariates. The estimates in Appendix Table C2 show that economic preferences in 2007-2008 do not significantly predict maximum, mean and midnight temperatures in 2014-2015; supporting our identification assumptions.

4. Temperature Effects on Time and Risk Preferences

4.1 Main Results

In this section, we present the results from estimating regression equation (1). Table 3 shows estimates of the linear effects of maximum temperatures on the day of the survey (Panel A), the temperature when the survey began (Panel B), and midnight temperature the night before the survey (Panel C). The regressions in Panel D explore the relative importance of temperature on the day of the survey versus the night before.

---

[16] We cluster standard errors by village, the level of variation in our treatment variable (Abadie et al., 2017). However, our standard errors are similar if we change the level of clustering to a) the climate zone level, and b) the MERRA-2 grid level to account for smoothed averages at the grid level in weather station scarce cells

We find that temperature, regardless of when it is measured, is unrelated to reported risk aversion (column 1, Table 3). This is consistent with the results in Almås, et al. (2020) obtained in laboratory-controlled environments. In contrast, we find that temperature has a significant positive relationship with rational choice violations and impatience. A 1ºC increase in the maximum temperature of the day of the survey is estimated to increase rational choice violations and impatience by 0.3 and 0.4 percentage points, respectively. Corresponding effects for temperature at the commencement of the survey equal 0.7 and 0.4 percentage points. The largest point estimates correspond to temperature on the midnight before the survey, with a 1ºC increase in temperature increasing rational choice violations by 1 percentage point and impatience by 0.9 percentage points. These latter effects are approximately equivalent to 30% and 70% of the gender gaps in these outcomes (see Appendix Table C1). The results in Panel D provide further evidence that high night-time temperatures are more impactful on economic preferences than high day-time temperatures.[17] When day-time and night-time temperatures are simultaneously included, the day-time temperature coefficients reduce in magnitude (and become statistically insignificant), while the midnight temperatures are very similar to the values in Panel C.

To test for non-linearity, we replace the continuous midnight temperature measure with five temperature categories. The estimated effects of these categories, relative to <21ºC, on the three preference outcomes are shown in Figure 4. The estimates for rational choice violations and impatience appear roughly linear, providing support for our main regression specification. When midnight temperatures are >26ºC it is estimated that respondents are 6.8 (22%) and 6.1 (10%) percentage points more likely to make rational choice violations and impatient decisions, respectively, compared to when midnight temperatures are <21ºC.

In Table 4, we test the sensitivity of the estimates to additional covariates. Columns 1 and 4 present results from regressions that include humidity controls (from the MERRA-2 dataset). Temperature and humidity are negatively correlated, and humidity can affect people's comfort levels. Columns 2 and 5 present results from regressions that include controls for longitude, a geographic coordinate that specifies the east-west position in reference to the prime meridian. Longitude does not directly affect climate, but it is the basis of time zones within Indonesia,

[17] To avoid multicollinearity issues in Panel D, we include only maximum temperature on the day of the survey and midnight temperature, which had the lowest pairwise correlation at approximately 0.35. In Appendix Table C4 we demonstrate that even when all three temperature variables are included together, midnight temperature still appears to be the most important for economic preferences.

which affects hourly weather records. Finally, Columns 3 and 6 present results from regressions with interviewer fixed effects. This accounts for the possibility that interviewers influence the timing of the survey and decisions made in the lottery games, and that interviewers themselves could be affected by heat. Our results remain relatively stable across the three alternative specifications and the *p-values* in Panel B show that the effects of maximum and midnight temperature remain significantly different from each other in most specifications.[18]

The estimates presented thus far suggest that high nighttime temperatures are the main driver of the observed increases in rational choice violations and impatience. However, concerns regarding our approach to determine the relative importance of daytime and nighttime temperatures can arise given that these measures are highly correlated due to the tropical climate of Indonesia. In Appendix B we propose an alternative approach to further explore the nighttime temperature hypothesis. First, we create a heat matrix that captures different combinations of heat levels on the night prior to the survey and on the day of the survey (see Appendix Figure B1). In Tables B1-B2 in the Appendix we present the results of estimating equation 1 using these different combinations instead of the simultaneous inclusion of the two continuous variables as done in Panel D of Table 3. These new results corroborate that not only are hot midnights important contributors to the effects on rational choice violations and impatience, they are also a necessary condition for these effects to manifest. For example, it is not enough for temperatures on the day of the survey to be high. If temperatures in the night prior are not also in the medium to high heat categories, the estimates are both economically and statistically insignificant.

4.2 Effect Heterogeneity

Next, we explore whether the observed effects of temperature on rational choice violations and impatience vary systematically by individual characteristics such as gender, age, and socioeconomic status, as well as household level expenditure in electricity in the month prior to the survey. Figure 5 shows that temperature effects on rational choice violations and impatience are not statistically different by gender or age group, but that there are significant differences by educational attainment (*p-values* = 0.004 and 0.632), consumption (*p-values* = 0.063 and 0.033), and electricity expenditure (*p-values* = 0.001 and 0.160).[19] For each

---

[18] A full set of sensitivity checks including results using maximum temperature on the day of the survey and temperature at the start of the survey as treatment variables can be found in Appendix Table C3.

[19] Household electricity expenditure is used as a proxy for air-conditioner use at home. Households with low energy consumption are unlikely to be using an air-conditioner.

significant difference, people with lower economic status (low education, low consumption and low electricity expenditure) are those with larger temperature effects. This result suggests that people of lower socio-economic status have less means to protect themselves from the effects of high temperatures and are, as a consequence, experiencing larger deteriorations in the quality of their decision-making abilities.

4.3 Cumulative Effects

In Table 5, we explore whether repeated nights of high temperatures could be having a cumulative effect leading to a larger change in economic preferences than a single hot night. We test this by regressing our main outcomes of interest on the number of nights above 25ºC in the past 7 days. The choice of this threshold is based on the results in Figure 4 that show significant positive effects above this value. This choice is also supported by the findings of Minor et al. (2020) that night-time minimum temperatures above 25ºC significantly increase the probability of getting less than 7 hours of sleep. We also interact a dummy for temperatures above 25ºC on the night prior to the survey and the number of hot nights in the past seven days. This allows last night's temperature to have a different effect depending upon the number of nights in the past week that were also hot.

The estimates in column 1 of Table 5 suggest that having a hot night directly before the survey and the number of hot nights during the week prior both increase rational choice violations. We observe a similar effect for impatience (column 2). The estimated coefficient for a hot night yesterday becomes statistically insignificant, but each hot night in the past week significantly increases impatience by 0.5 percentage points. The coefficient on the interaction term is negative in both regressions, indicating that the positive effect of a hot night before the survey is smaller if it follows a hot week; however, these coefficients are imprecisely estimated.

4.4 Robustness Checks and Tests

We estimate several additional regressions to determine whether our main results are robust to alternative specifications and sample exclusions. First, we include covariates indicating whether individuals were surveyed during Ramadan. During this period, those who observe the custom normally change their eating and sleeping patterns, and these changes could impact economic preferences. Only 1.6% of our sample was surveyed during Ramadan, and so this is unlikely to be a major driver of our results. Nevertheless, we test for this possibility and the results show that the additional controls have no effect on the magnitude or significance of our

original estimates (see Appendix Table C4). The coefficient on the Ramadan term is close to zero and negative for rational choice violations but large and positive for impatience. However, it is statistically insignificant in both cases. This indicates that either the period of time when the custom is observed has no incidence on the occurrence of rational choice violations and impatience, or that our main specification already accounts for its effects.

Second, we exclude survey respondents who were visited more than once to complete the survey. Multiple visits could be (partly) caused by temperature – for instance, if interviewees suspend the interview until a cooler, more comfortable time – and incidence of multiple visits may be associated with individual characteristics associated with economic preferences. Results in Appendix Table C4 indicate that our main estimates are robust to the exclusion of the 19% of the sample with more than one visit.

Third, we exclude all observations in climate zones where less than 90% of the variation in temperature is explained by date of survey fixed-effects (see discussion in Section 3.1 and associated Figure 3B). In these climate zones, part of the variation in temperature may be caused by differences in environmental and geographical factors, which may not be exogenous in our regressions. In Appendix Table C5, we demonstrate that excluding these climate zones has very little effect on the estimated coefficients.

Next, we perform a placebo test using future temperatures. In Appendix Table C6, we add the maximum temperature of the same day-of-the-week, but two weeks later. Being in the future, this variable should have no statistically or economically significant effect on any of our preference outcomes, so long as the current temperature and the temperature in two weeks is not highly correlated. Results indicate that the estimates for midnight temperatures are unchanged and the effects of future temperature on rational choice violations and impatience are close to zero and statistically insignificant. Finally, we perform a second placebo test by regressing individual and household characteristics that should not be affected by weather on our main measures of temperature. Appendix Table C7 shows, as expected, that midnight temperature on the night prior to the survey and temperature on the day of the survey do not significantly affect the respondent's age, gender, marital status or even household equivalised expenditure in the past month.

Finally, in Appendix E we adjust for the fact that we are testing multiple hypotheses in several sections of this study by computing Westfall-Young stepdown adjusted p-values which also

control the familywise error rate and allow for dependence amongst p-values. The adjusted p-values are computed for all treatments and outcomes in each panel of Tables (E) 2 – 6.

5. Potential Mechanisms

The findings discussed in Section 4 indicate that high nighttime temperature is largely responsible for the deterioration in decision making abilities experienced by our sample. If nighttime heat is indeed the main driver, we would also expect to observe a significant deterioration in people's sleep quantity, quality and/or how tired or functional they are after a night of poor sleep. In this section we use detailed sleep disturbance indicators measured in wave 5 of the IFLS to test whether these effects are present after hot nights. If such effects exist, people's cognitive abilities and mood could also be affected after a night of poor sleep. Therefore, we explore these two additional potential mediators using data collected through a battery of cognitive tests and a positive/negative affects module.

5.1 Sleep

Previous researchers have identified a potential link between sleep and economic preferences. For example, better sleep quality is associated with lower discount rates, less present bias, and less loss aversion (Nofsinger & Shank, 2019). Conversely, lack of sleep has been shown to increase financial risk taking (McKenna, et al., 2007; Killgore, 2007; Killgore et al., 2012). At the same time, there is a growing body of literature showing that sleep is negatively affected by high nighttime temperatures. For example, Minor et al. (2020) show that rising night-time temperatures shorten sleep duration by delaying its onset, and increase the probability of insufficient sleep. Similarly, Obradovich et al. (2017) show that higher nighttime temperatures increase self-reported nights of insufficient sleep, such that a 1°C night-time temperature anomaly produces an increase of 3 nights of insufficient sleep per 100 individuals per month.[20]

In Table 6 we provide some suggestive evidence that this relationship can also be found in our sample of respondents. Given the seven-day reference period of our sleep disturbance outcomes, we now regress our sleep disturbance indicator and the two latent indicators of sleep quality and sleep deprivation on the number of nights above 25°C in the past week. Column 2 also shows this relationship using a binary indicator that equals 1 is 5-7 nights in the past week were above 25°C. These results corroborate our expectations. That is, every hot night in the

---

[20] In Obradovich et al. (2017) an anomaly is the 30-day average of daily minimum temperature deviations from their normal daily values (1981-2010) over the same 30-day period when respondents report insufficient sleep.

past week increases the probability of having a sleep disturbance by 0.4 percentage points (3% relative to the mean). If all nights in the past week were hot, this increases to 2.4 percentage points (15% relative to the mean). In Panel B we also observe that while respondents are not more likely to report a decline in sleep quality due to hot nights, high nighttime temperatures due increase their symptoms of chronic sleep deprivation which manifest in feeling poorly the next day.

In Appendix Table C8 we show that these deleterious effects of temperature on the likelihood of experiencing a sleep disturbance are largest for people in the bottom half of the consumption distribution and for people living in districts where air-conditioning ownership rates are below the national average (5%). Similarly, respondents are feeling more poorly the next day after a hot night if they have low electricity expenditure and if they live in districts with low air-conditioning rates. This is remarkably consistent with the findings in section 4.2 where we explored the heterogeneous effects of temperature on preferences and rationality.

5.2 Cognition

Several studies have studied the links between cognition and economic preferences with mixed results. For instance, Benjamin et al. (2013) find that students with high math test scores demonstrate low risk aversion in small-stakes gambles and less short-run discounting. Similarly, Falk et al. (2018) find that math skills are "uniformly positively linked to patience, risk taking, and social preferences" (p. 1647). In contrast, Andersson et al. (2016) find that cognitive ability is related to errors in decision making but not to risk preferences. At the same time, a growing body of evidence shows that high temperatures have the potential to impair cognition (Zivin et al., 2018; Garg et al., 2020; Park et al., 2020a; 2020b). Together, this evidence suggests that high temperatures deplete cognitive function, which then in turn, affects economic preferences.

In Panel A of Table 7 we study the effects of night-time temperature on cognitive functioning. Results are presented separately for waves 4 and 5 because of the differences in the ages of respondents tested (15-31 in wave 4; 15-90 in wave 5). The top row contains results for the predicted factor from a principal component analysis of all available cognitive tests. The second row contains results for the standardized score from the math test, which is included because past studies have emphasized the importance of math skills for economic preferences. The estimates show that a 1°C increase in midnight temperature on the night before the tests

decreases overall cognition by 3.6% of a standard deviation and 1.3% of a standard deviation for individuals aged 15-31 in IFLS4 and individuals aged 15-90 in IFLS5, respectively.[21] Results are similar for the standardized math score: a 1℃ increase reduces scores by 3.9% and 1.3% of a standard deviation.[22]

In light of these results, we have also explored the association between cognitive functioning and economic preferences. Interestingly, we find that a one standard deviation increase in overall cognition is not associated with risk aversion (0.7 percentage points), but is strongly associated with reduced rational choice violations (5.3 percentage points) and impatience (5.5 percentage points); conditional on age, sex, educational attainment, household demographics, and household expenditure (see Appendix Table C1). Though these estimates cannot be interpreted causally, the fact that temperature affects cognition, rational choice violations and impatience (but not risk aversion), and that cognition is associated with rational choice violations and impatience (but not risk aversion), is highly suggestive of cognition being an important pathway for the temperature effects shown in Table 3. Consistent with the results in Figure 4, Appendix Figure A4 shows that there is a nearly monotonic (decreasing) relationship between night-time temperatures and cognition in both IFLS waves.

5.3 Mood

The final potential mechanism we investigate is mood. The empirical evidence shows that temperature can significantly influence our mood. For example, a number of studies have documented that exposure to high temperatures can cause extreme responses such as violent acts of aggression in multiple settings and agents, from American football and baseball players (Craig et al., 2016; Krenzer & Splan, 2018), to prison inmates (Mukherjee & Sanders, 2021), and university students (Almås et al., 2020). Others have studied different emotions such as revealed happiness and found that individuals living through a very hot day can experience a decrease in happiness similar to a happiness drop from a Sunday to a Monday (Baylis, 2020). These findings are relevant to our study because mood can significantly influence economic preferences. For example, aggression is positively associated with risk-taking behavior (Cueva

---

[21] In Appendix Table C9, we re-estimate the cognition effects for respondents aged 15-31 in IFLS5 so that we can compare effect sizes across waves. The estimates indicate much larger (more negative) temperature effects in wave 4 than in wave 5. These findings could suggest that our sample is increasingly adapting to high temperatures, for example by acquiring air-conditioning units.

[22] For wave 4, temperature also significantly decreased scores on the date awareness and word recall test (3.3%). For wave 5, temperature also significantly decreased the fluid intelligence score (1.6%) and the Raven's Progressive Matrices test score (2.0%).

et al., 2015; Deffenbacher et al., 2003; Arnett et al., 1997), while a happy mood is associated with significant reductions in impatience over money (Ifcher & Zarghamee, 2011). The relationship between happiness and risk preferences is mixed with some studies finding that positive mood leads to risk seeking behavior (Campos-Vasquez & Cuilty, 2014), and others finding that positive mood leads to more risk-averse behavior (Kliger & Levy, 2003). However, support has more often been found for the former (Lane, 2017).

We explore the effects of temperature on mood in panel B of Table 7 and find that midnight temperatures prior to the survey have no significant effect on the likelihood of feeling anger, tiredness, happiness, or enthusiasm. These findings suggest that increased sleep disturbances leading to depleted cognition and not mood, are the most likely channels through which high night-time temperatures are affecting rational choices and impatience.

6. Discussion

Using Indonesian data eliciting economic preferences in combination with climate records from NASA's MERRA-2 dataset, we estimate the causal impacts of temperature on time and risk preferences, and rational choice. Identification is based on comparing survey responses between people living in the same climate zone, who experienced different temperatures because of the allocation of different survey dates. Through this approach we add to the small literature on the causal effects of temperatures on economic preferences, which mostly contains evidence from laboratory experiments.

Results show that higher temperatures on the day of the survey and the night prior to the survey significantly increase the likelihood of making rational choice violations and making impatient choices. Night-time temperatures are especially important, with a 1°C increase in midnight temperature associated with a 3.2% (relative to the sample mean) increase in irrational behavior and a 1.5% increase in impatience. Results also indicate a model of cumulative heat effects, such that multiple nights of high temperatures in the preceding week add to the effect from the night before the survey. Finally, increased sleep disturbances and reduced cognitive functioning seem the most likely drivers of these results. High night-time temperatures lead to sleep deprivation, making people feel poorly the next day which manifests in significantly reduce cognitive functions, with mathematical skills particular affected, while mood is unaffected.

Altogether, these findings indicate that heat-induced night-time disturbances appear to cause stress on the brain, leading to significantly lower math skills the following day. These lower cognitive skills in turn, prevent individuals from engaging their system 2 thought processes to perform economically rational decision-making. As Cheema & Patrick (2012) suggest, it appears as though the physical and psychological stress that heat imposes upon individuals, leads them to rely more often on intuition and lower-level processing, also known as system 1 thinking. This, in turn, is reflected in a substantial increase in sub-optimal economic decision making as individuals default towards the certain option and the earlier albeit smaller reward.

Importantly, a decomposition of temperature effects by individual characteristics shows that the effects are larger for poorer households, likely due to their lower ability to adapt, such as by acquiring air-conditioning units. This indicates that the effects of a rise in the intensity and frequency of extreme heat will be spread unevenly. Effects will likely differ between low- and high-income households within countries, and between developed and developing countries. Greater macroeconomic and household wealth mean that air-conditioning coverage across the developed world is becoming widespread in homes, office spaces, and public transport, such that individuals in wealthier nations can mostly protect themselves from the deleterious impacts of heat. This is evidenced in the 75% decline in heat-induced fatalities in the United States since the 1960's; almost entirely due to residential air-conditioning (Barreca et al., 2016).

Across the developing world, the financial and infrastructural capacity to deal with high temperatures is significantly lower. Dwellings need to be connected to a power grid, yet 13% of the world does not have access to electricity (World Bank, 2021), and households need to have the income to acquire air-conditioning units and pay the associated electricity bills. Furthermore, low-cost dwellings tend to be built with materials that store heat rather than insulate their inhabitants from it (Naicker et al., 2017). Overall, further attention and research is needed on how the poor make investment and risky decisions, and whether or not these are systematically less optimal in regions of the world where temperatures are getting closer to the upper threshold of human adaptability.

References

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. (2017). When should you adjust standard errors for clustering. *NBER Working Paper Series, WP 24003*. doi:10.3386/w24003

Almås, I., Auffhammer, M., Bold, T., Bolliger, I., Bembo, A., Hsiang, S. M., . . . Pickmans, R. (2020, December). Destructive behavior, judgement, and economic decision-making under thermal stress. *NBER Working Paper Series*. doi:10.3386/w25785

Andersson, O., Holm, H. J., Tyran, J.-R., & Wengström, E. (2016). Risk aversion relates to cognitive ability: Preferences or Noise. *Journal of the European Economic Association*, 1129-1154

Arnett, J. J., Offer, D., & Fine, M. A. (1997). Reckless driving in adolescence: 'State' and 'trait' factors. *Accident Analysis & Precention, 29*(1), 57-63. doi:https://doi.org/10.1016/S0001-4575(97)87007-8

Ashraf, N., Karlan, D., & Yin, W. (2006). Tying Odysseus to the Mast: Evidence From a Commitment Savings Product in the Philippines. *Quarterly Journal of Economics, 121*(2), 635–672. doi:https://doi.org/10.1162/qjec.2006.121.2.635

Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy, 7*(2), 181-198. doi:https://doi.org/10.1093/reep/ret016

Banerjee, A. V., Duflo, E., Glennerster, R., & Kothari, D. (2010). Improving immunisation coverage in rural India: clustered randomised controlled evaluation of immunisation campaigns with and without incentives. *BMJ, 340*(c2220). doi:doi:10.1136/bmj.c2220

Barreca, A., Clay, K., Deschenes, O., Greenstone, O., & Shapiro, J. S. (2016). Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. *Journal of Political Economy, 124*(1). doi:https://doi.org/10.1086/684582

Bartoš, V., Bauer, M., Chytilová, J., & Levely, I. (2021). Pshycological effects of poverty on time preferences. *Economic Journal, 131*(638), 2357-2382. doi:https://doi.org/10.1093/ej/ueab007

Baylis, P. (2020). Temperature and temperament: Evidence from Twitter. *Journal of Public Economics, 184*(104161). doi:https://doi.org/10.1016/j.jpubeco.2020.104161

Benjamin, D. J., Brown, S. A., & Shapiro, J. M. (2013). Who is 'Behavioral'? Cognitive Ability and Anomalous Preferences. *Journal of the European Economic Association, 11*(6), 1231–1255. doi:https://doi.org/10.1111/jeea.12055

Bessone, P., Rao, G., Schilbach, F., Schofield, H., & Toma, M. (2021, April). The Economic Consequences of Increasing Sleep Among the Urban Poor. *NBER Working Paper Series, NBER Working Paper 26746*. doi:10.3386/w26746

Busse, M. R., Pope, D. G., Pope, J. C., & Silva-Risso, J. (2015). The Psychological Effect of Weather on Car Purchases. *Quarterly Journal of Economics, 130*(1), 371–414. doi:https://doi.org/10.1093/qje/qju033

Callen, M. (2015). Catastrophes and time preference: Evidence from the Indian Ocean Earthquake. *Journal of Economic Behavior & Organization, 118*, 199-214. doi:http://dx.doi.org/10.1016/j.jebo.2015.02.019

Callen, M., Isaqzadeh, M., Long, J. D., & Sprenger, C. (2014). Violence and risk preference: Experimental Evidence from Afghanistan. *American Economic Review, 104*(1), 123-148. doi:http://dx.doi.org/10.1257/aer.104.1.123

Cameron, L., & Shah, M. (2015). Risk-taking behavior in the wake of natural disasters. *Journal of Human Resources, 50*(2), 484-515. doi:10.3368/jhr.50.2.484

Campos-Vasquez, R. M., & Cuilty, E. (2014). The role of emotions on risk aversion: A Prospect Theory experiment. *Journal of Behavioral and Experimental Economics, 50*, 1-9. doi:https://doi.org/10.1016/j.socec.2014.01.001

Carvalho, L. S., Meier, S., & Wang, S. W. (2016). Poverty and Economic Decision-Making: Evidence from Changes in Financial Resources at Payday. *American Economic Review, 106*(2), 260-284. doi:http://dx.doi.org/10.1257/aer.20140481

Cheema, A., & Patrick, V. M. (2012). Influence of Warm Versus Cool Temperatures on Consumer Choice: A Resource Depletion Account. *Journal of Marketing Research, 49*(6), 984-995. doi:https://doi.org/10.1509/jmr.08.0205

Conlin, M., O'Donoghue, T., & Vogelsang, T. J. (2007). Projection bias in catalog orders. *American Economic Review, 97*(4), 1217-1249. doi:10.1257/aer.97.4.1217

Connolly, M. (2013). Some like it mild and not too wet: The influence of weather on subjective well-being. *Journal of Happiness Studies, 14*(2), 457-476. doi:https://doi.org/10.1007/s10902-012-9338-2

Craig, C., Overbeek, R. W., Condon, M. V., & Rinaldo, S. B. (2016, June). A relationship between temperature and aggression in NFL football penalties. *Journal of Sport and Health Science, 5*(2), 205-210. doi:https://doi.org/10.1016/j.jshs.2015.01.001

Cueva, C., Roberts, R. E., Spencer, T., Rani, N., Tempest, M., Tobler, N. P., . . . Rustichini, A. (2015). Cortisol and testosterone increase financial risk taking and may destabilize markets. *Nature Scientific Reports, 5*(11206). doi:10.1038/srep11206

Deffenbacher, J. L., Deffenbacher, D. M., Lynch, R. S., & Richards, T. L. (2003). Anger, aggression, and risky behavior: a comparison of high and low anger drivers. *Behavior Research and Therapy, 41*, 701-718. doi:10.1016/S0005-7967(02)00046-3

Ekelund, J., Johansson, E., Marjo-Riitta, J., & Dirk, L. (2005). Self-employment and risk aversion—evidence from psychological test data. *Labour Economics, 12*, 649 – 659. doi:10.1016/j.labeco.2004.02.009

EPA. (2021). *Reduce Urban Heat Island Effect*. Retrieved August 08, 2021, from United States Environmental Protection Agency: https://www.epa.gov/green-infrastructure/reduce-urban-heat-island-effect

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., & Sunde, U. (2018). Global Evidence on Economic Preferences. *Quarterly Journal of Economics, 133*(4), 1645-1692. doi:10.1093/qje/qjy013

Fong, T. G., Fearing, M. A., Jones, R. N., Shi, P., Marcantonio, E. R., Rudolph, J. L., . . . Inuoye, S. K. (2009). The Telephone Interview for Cognitive Status: Creating a crosswalk with the Mini-Mental State Exam. *Alzheimers Dement., 5*(6), 492-497. doi:10.1016/j.jalz.2009.02.007

Garg, T., Jagnani, M., & Taraz, V. (2020). Temperature and Human Capital in India. *Journal of the Association of Environmental and Resource Economists, 7*(6), 1113-1150. doi:https://doi.org/10.1086/710066

Hall, R. E., & Jones, C. I. (1999). Why do Some Countries Produce So Much More Output Per Worker than Others? *Quarterly Journal of Economics, 114*(1), 83–116. doi:https://doi.org/10.1162/003355399555954

Hanaoka, C., Shigeoka, H., & Watanabe, Y. (2018). Do risk preferences change? Evidence from the Great East Japan earthquake. *American Economic Journal: Applied Economics, 10*(2), 298-330. doi:https://doi.org/10.1257/app.20170048

Heilmann, K., Kahn, M. E., & Tang, C. K. (2021). The urban crime and heat gradient in high and low poverty areas. *Journal of Public Economics*, 1-25. doi:https://doi.org/10.1016/j.jpubeco.2021.104408

Heyes, A., & Saberian, S. (2019). Temperature and Decisions: Evidence from 207,000 Court Cases. *American Economic Journal: Applied Economic, 11*(2), 238-265. doi:10.1257/app.20170223

Ifcher, J., & Zarghamee, H. (2011). Happiness and Time Preference: The Effect of Positive Affect in a Random-Assignment Experiment. *American Economic Review, 101*(7), 3109-3129. doi:10.1257/aer.101.7.3109

IPCC. (2021). *Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press. Retrieved February 28, 2022, from https://www.ipcc.ch/report/ar6/wg1/#SPM

Kahneman, D. (2011). *Thinking Fast and Slow.* New York: Farrar, Straus and Giroux.

Kettlewell, N. (2019). Risk preference dynamics around life events. *Journal of Economic Behavior & Organization, 162*, 66-84. doi:https://doi.org/10.1016/j.jebo.2019.04.018

Killgore, W. D. (2007). Effects of Sleep Deprivation and Morningness-Eveningness Traits on Risk-Taking. *Psychological Reports, 100*(2), 613-626. doi:https://doi.org/10.2466/pr0.100.2.613-626

Killgore, W. D., Grugle, N. L., & Balkin, T. J. (2012). Gambling When Sleep Deprived: Don't Bet on Stimulants. *Chronobiology International, 29*(1), 43-54. doi:https://doi.org/10.3109/07420528.2011.635230

Kliger, D., & Levy, O. (2003). Mood-induced variation in risk preferences. *Journal of Economic Behavior & Organization, 52*(4), 573-584. doi:https://doi.org/10.1016/S0167-2681(03)00069-6

Krenzer, W. L., & Splan, E. D. (2018). Evaluating the heat-aggression hypothesis: The role of temporal and social factors in predicting baseball related aggression. *Aggressive Behavior, 44*, 83-88. doi:10.1002/ab.21726

Lane, T. (2017). How does happiness relate to economic behaviour? A review of the literature. *Journal of Behavioral and Experimental Economics, 68*, 62-78. doi:https://doi.org/10.1016/j.socec.2017.04.001

Lauderdale, D. S., Knutson, K. L., Yan, L. L., Liu, K., & Rathouz, P. J. (2008). Sleep duration: how well do self-reports reflect objective measures? The CARDIA Sleep Study. *Epidemiology, 19*(6), 838–845. doi:https://doi.org/10.1097/EDE.0b013e318187a7b0

Levin, R., & Vidart, D. (2020). Adaptive risk taking: Theory and evidence from developing countries. *Working Paper*, 1-78.

Liu, E. M., & Huang, J. (2013, July). Risk preferences and pesticide use by cotton farmers in China. *Journal of Development Economics, 103*, 202-215. doi:https://doi.org/10.1016/j.jdeveco.2012.12.005

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013). Poverty Impedes Cognitive Function. *Science, 341*(6149), 976-980. doi:10.1126/science.1238041

McKenna, B. S., Dickinson, D. L., Orff, H. J., & Drummond, S. P. (2007). The effects of one night of sleep deprivation on known-risk and ambiguous-risk decisions. *Journal of Sleep Research, 16*(3), 245–252. doi:https://doi.org/10.1111/j.1365-2869.2007.00591.x

Mellinger, A. D., Sachs, J. D., & Gallup, J. L. (2000). In G. L. Clark, M. P. Feldman, & M. S. Gertler (Eds.), *The Oxford Handbook of Economic Geography.* Oxford, England ; New York: Oxford University Press.

Miller, E. K. (2000). The prefrontal cortex and cognitive control. *Nature Reviews Neuroscience, 1*(1), 59-65. doi:https://doi.org/10.1038/35036228

Minor, K., Bjerre-Nielsen, A., Jonasdottir, S. S., Lehmann, S., & Obradovich, N. (2020). Ambient heat and human sleep. *Working Paper*. doi:arxiv-2011.07161

Mukherjee, A., & Sanders, N. J. (2021). The Causal Effect of Heat on Violence: Social Implications of unmitigated heat among the incarcerated. *NBER Working Paper Series, Working Paper 28987*. Retrieved from https://www.nber.org/papers/w28987

Naicker, N., Teare, J., Balakrishna, Y., Wright, C. Y., & Mathee, A. (2017). Indoor temperatures in low-cost housing in Johannesburg, South Africa. *Environmental Research and Public Health, 14*(1410), 1-18. doi:https://doi.org/10.3390/ijerph14111410

NASA. (2016, November 8). *Why Does Temperature Vary?* Retrieved from Climate Science Investigations: http://www.ces.fau.edu/nasa/module-3/why-does-temperature-vary/

Ng, J. (2013). Risk and Time Preferences in Indonesia: The Role of Demographics, Cognition, and Interviewers. *Unpublished Manuscript - University of Southern California Job Market Paper*. Retrieved August 14, 2020, from https://www.semanticscholar.org/paper/Risk-and-Time-Preferences-in-Indonesia%3A-The-Role-of-Ng/030ed65a5784598af46c59596d394802eba97948

NOAA. (2021). *How does the ocean affect climate and weather on land?* Retrieved from NOAA Ocean Exploration: https://oceanexplorer.noaa.gov/facts/climate.html

Nofsinger, J. R., & Shank, C. A. (2019). DEEP sleep: The impact of sleep on financial risk taking. *Review of Financial Economics, 37*(1), 92-105. doi:https://doi.org/10.1002/rfe.1034

Obradovich, N., Migliorini, R., Mednick, S. C., & Fowler, J. H. (2017). Nighttime temperature and human sleep loss in a changing climate. *Science Advances, 3*(5). doi:https://doi.org/10.1126/sciadv.1601555

Park, R. J., Behrer, A. P., & Goodman, J. (2020). Learning is inhibited by heat exposure, both internationally and within the United States. *Nature Human Behaviour*. doi:https://doi.org/10.1038/s41562-020-00959-9

Park, R. J., Goodman, J., Hurwitz, M., & Smith, J. (2020). Heat and Learning. *American Economic Journal: Economic Policy, 12*(2), 306-339. doi:https://doi.org/10.1257/pol.20180612

Perloff, J. M. (2014). *Microeconomics* (5 ed.). Frenchs Forest, NSW: Pearson Australia.

Pielke, R. A. (2021, January 11). *Atmosphere*. Retrieved from Encyclopedia Britannica: https://www.britannica.com/science/atmosphere

Raven, J. (2000). The Raven's Progressive Matrices: Change and Stability over Culture and Time. *Cognitive Psychology, 41*(1), 1-48. doi:https://doi.org/10.1006/cogp.1999.0735

Renwick, D. (2020, January 3). The hidden environmental cost of your free holiday returns. *The Guardian*. Retrieved December 2, 2021, from https://www.theguardian.com/environment/2020/jan/02/as-americans-send-back-millions-of-holiday-gifts-theres-a-hidden-environmental-cost

Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., & Wollen, J. (2011). MERRA: NASA's modern-era retrospective analysis for research and applications. *Journal of Climate, 24*(14), 3624–3648. doi:https://doi.org/10.1175/JCLI-D-11-00015.1

Schilbach, F., Schofield, H., & Mullainathan, S. (2016). The psychological lives of the poor. *American Econonmic Review: Papers & Proceedings, 106*(5), 435-440. doi:http://dx.doi.org/10.1257/aer.p20161101

Schokman, A., Bin, Y. S., Simonelli, G., Pye, J., Morris, R., Sumathipala, A., . . . Glozier, N. (2018). Agreement between subjective and objective measures of sleep duration in a low-middle income country setting. *Sleep Health, 4*(6), 543–550. doi:https://doi.org/10.1016/j.sleh.2018.08.008

Stigler, G. J., & Becker, G. S. (1977). De Gustibus Non Est Disputandum. *American Economic Review, 67*(2), 76-90. doi:http://www.jstor.org/stable/1807222

Strauss, J., Witoelar, F., Meng, Q., Chen, X., Zhao, Y., Sikoki, B., & Wang, Y. (2017). Cognition and SES Relationships Among the Mid-aged and Elderly: A Comparison of China and Indonesia. *Working Paper*, 6-9.

Wang, X. (2017). An Empirical Study of the Impacts of Ambient Temperature on Risk Taking. *Psychology, 8*(7), 1053-1062. doi:10.4236/psych.2017.87069

World Bank. (2021, July 30). *World Development Indicators*. Retrieved from https://ourworldindata.org/energy-access#access-to-electricity

Zeelenberg, M., Beattie, J., van der Pligt, J., & de Vries, N. K. (1996). Consequences of Regret Aversion: Effects of Expected Feedback on Risky Decision Making. *Organizational Behavior and Human Decision Processes, 65*(2), 148-158. doi:https://doi.org/10.1006/obhd.1996.0013

Zivin, J. G., Hsiang, S. M., & Neidell, M. (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists, 5*(1), 77-105. doi:https://doi.org/10.1086/694177

Figures

Figure 1. IFLS5 villages and MERRA-2 grids
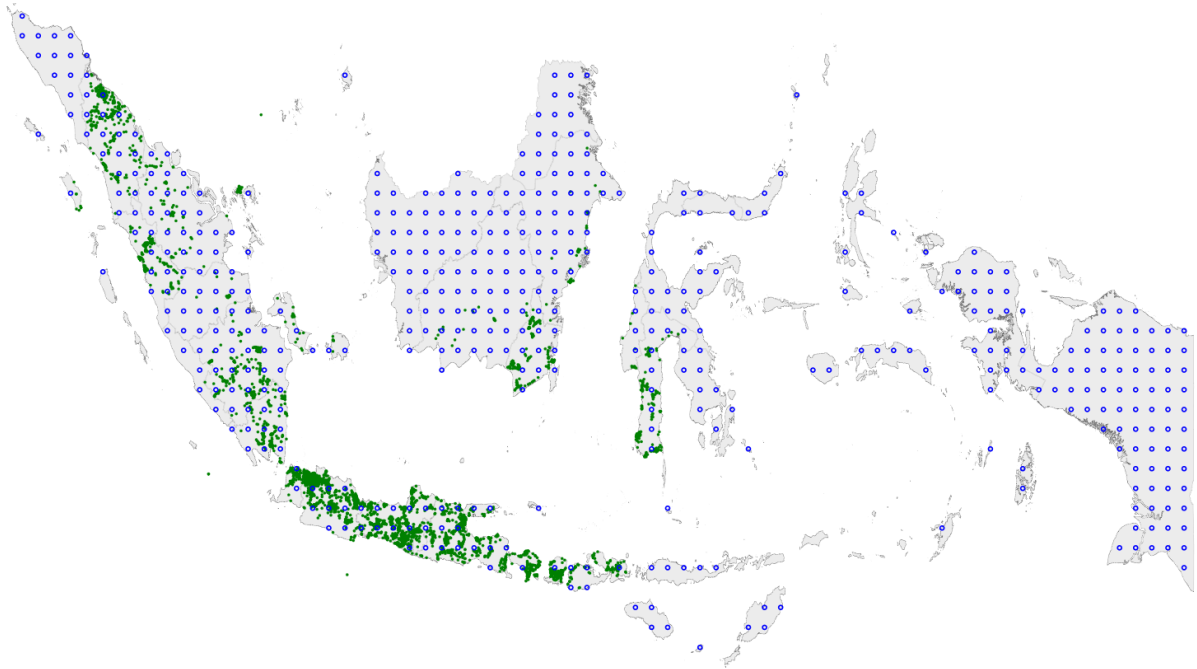
Notes: The above figure shows a map of the Indonesian territory plotting NASA's MERRA-2 grids represented by the blue circles as well as the villages covered in IFLS5 represented by the green dots. Map created by authors.

Figure 2. Map of IFLS villages in North Sumatra by constructed climate zones

●	R Alt <50 Co <30
●	R Alt <50 Co 30-60
●	R Alt <50 Co 60+
●	R Alt 50-100 Co <30
●	R Alt 50-100 Co 30-60
●	R Alt 50-100 Co 60+
●	R Alt 100-500 Co <30
●	R Alt 100-500 Co 30-60
●	R Alt 100-500 Co 60+
●	R Alt 500+ Co <30
●	R Alt 500+ Co 30-60
●	R Alt 500+ Co 60+
●	U Alt <50 Co <30
○	U Alt <50 Co 30-60
○	U Alt <50 Co 60+
○	U Alt 50-100 Co <30
○	U Alt 50-100 Co 30-60
○	U Alt 50-100 Co 60+
○	U Alt 100-500 Co <30
●	U Alt 100-500 Co 30-60
●	U Alt 100-500 Co 60+
●	U Alt 500+ Co <30
●	U Alt 500+ Co 30-60
●	U Alt 500+ Co 60+
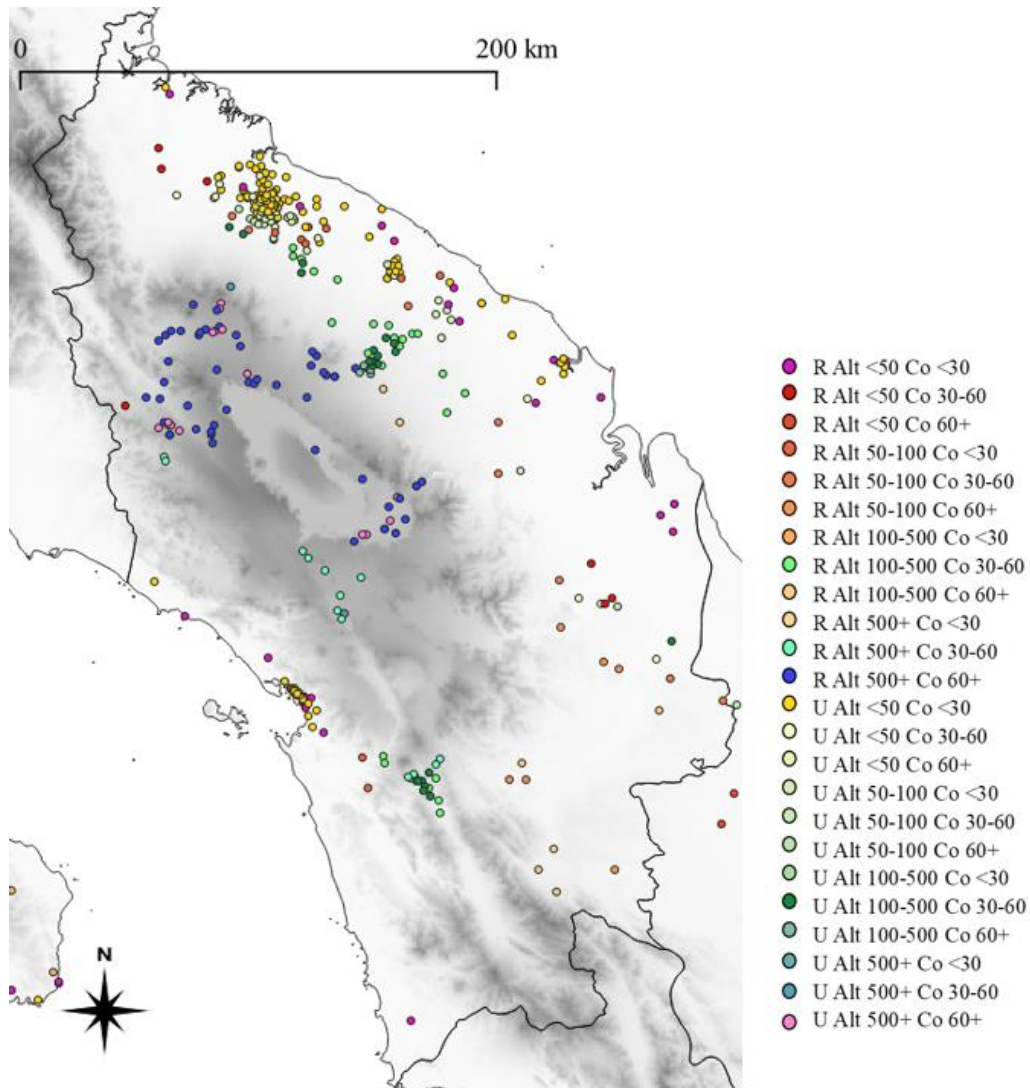
Notes: The above figure shows the map of the Indonesian province of North Sumatra with elevation in the background and IFLS villages in bins grouped by urban or rural, 4 altitude groups (meters) and 3 distance to the coast groups (kilometers) resulting in 19 sub-groups for this province.

Figure 3. Within climate zone temperature variation
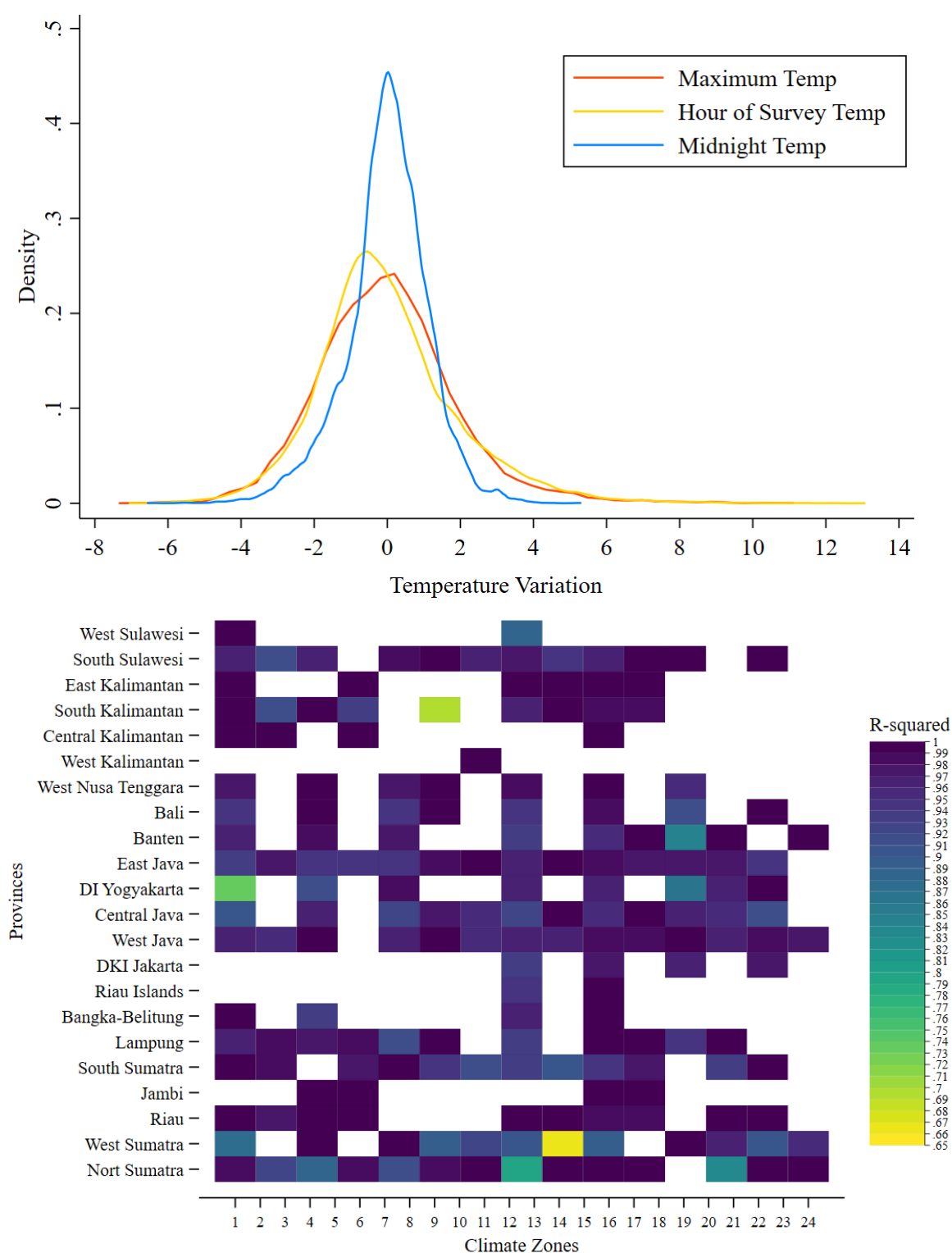
Notes: Figure 3a (top) shows the density functions of maximum temperature on the day of the survey, at the hour when the surveys began and on the midnight before the survey, using a bandwidth of 0.1688. The with-in bin variation is the result of subtracting from each individual's temperature, the average temperature in their corresponding bin. Figure 3b (bottom) shows the proportion of the variation in maximum temperature (R^2) explained by date-of-survey fixed effects in individual regressions for every climate zone. Blank squares are either climate zones that do not exist in the province, zones where no people were surveyed, or zones with too few observations to execute the regression.

Figure 4. Nonlinear effects of *midnight temperature* on time and risk preferences
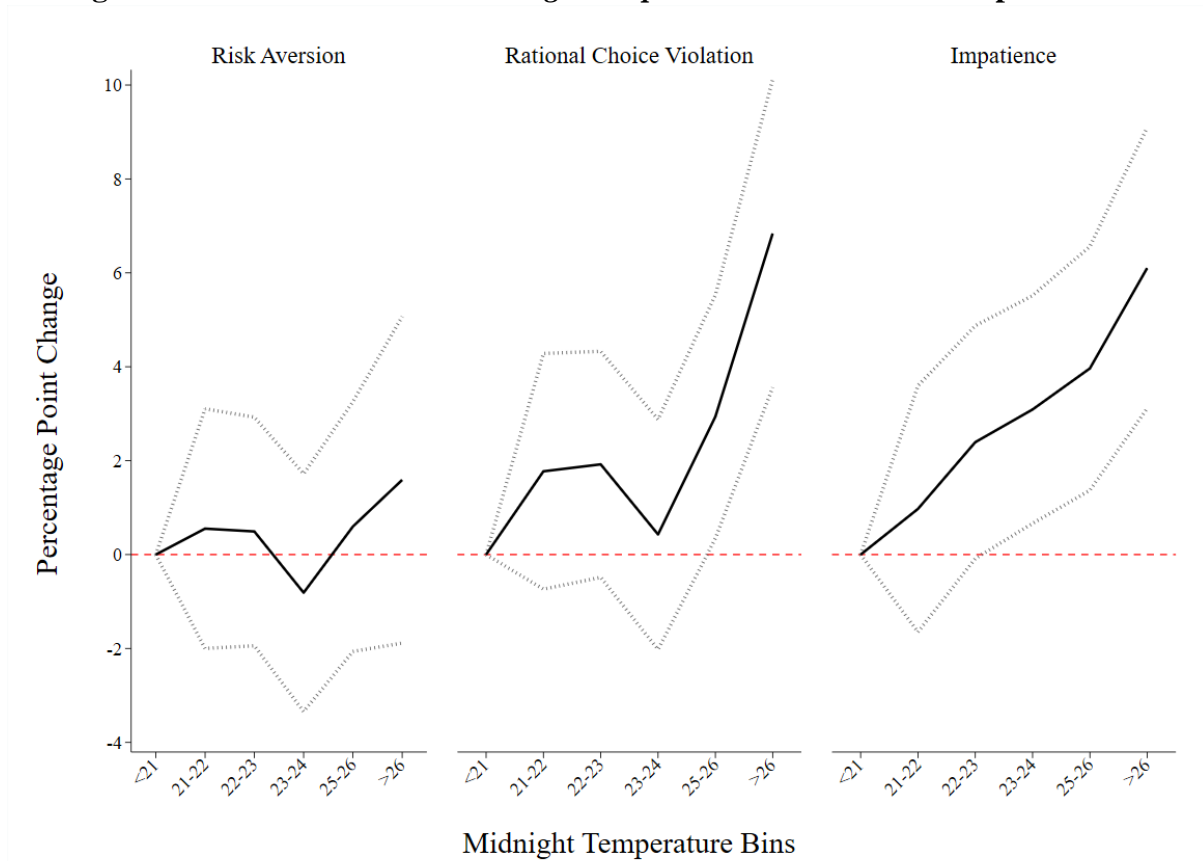
Notes: The above figure shows nonlinear effects of midnight temperature bins on the probability of making a rational choice violation, being in the most risk averse category, and in the most impatient category.

Figure 5. Heterogeneous effects of *midnight temperatures* by sub-samples
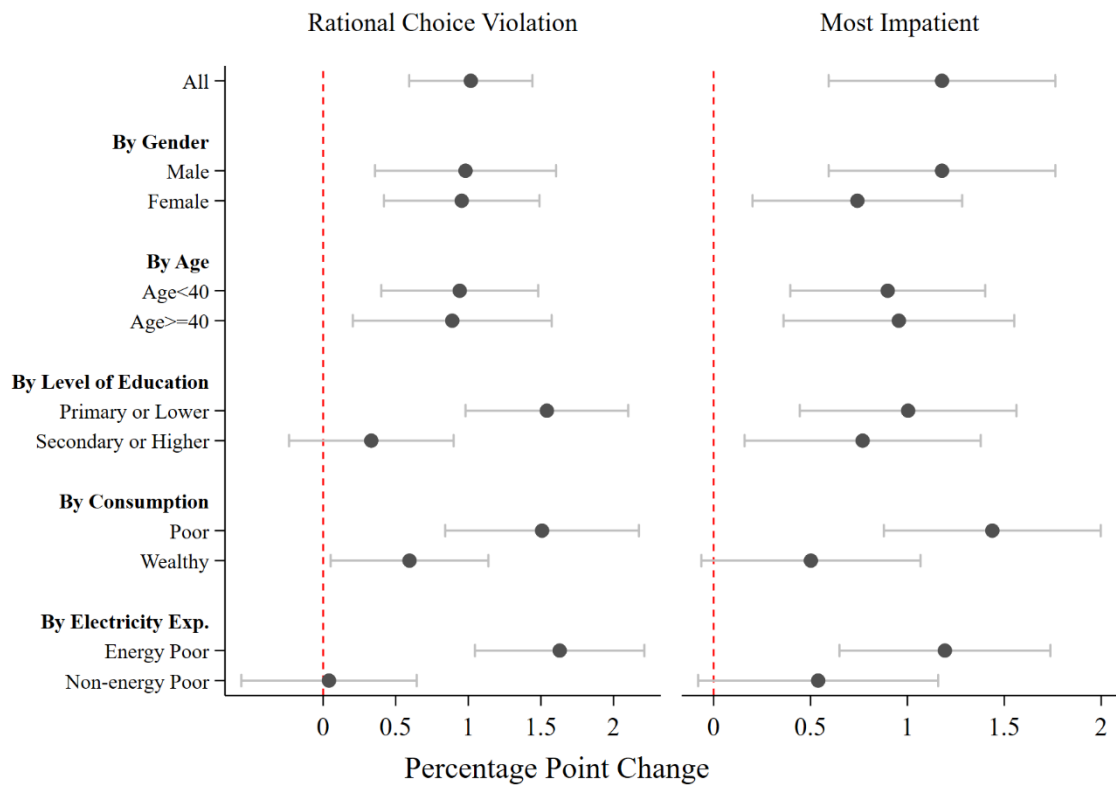
Notes: The above figure shows heterogeneous effects of temperature at midnight the day before the survey on rational choice violations and impatience in percentage points, by gender, age groups, level of education, and equivalized consumption expenditure.

Tables

Table 1. Key variables used in IFLS regression analyses

Variables	Description	Mean	SD
(A) Treatment			
Max temperature on day of survey (ºC)	Maximum temperature on the day of the survey	28.67	2.24
Temperature at start of survey (ºC)	Average temperature at hour when the survey started	24.55	2.35
Midnight temperature yesterday (ºC)	Temperature at midnight the day before the survey	23.64	1.85
Midnight yesterday above 25ºC	Binary indicator if midnight prior to survey was 25ºC+	0.24	0.43
# Nights above 25ºC	Number of midnights above 25ºC in the past 7 days	1.65	2.66
(B) Standard Economic Preferences			
Risk Aversion	Binary indicator for highest level of risk aversion excluding rational choice violations	0.37	0.48
Rational Choice Violation	Individual chooses a) IDR 800K over b) a coin toss between IDR 1.6 M or IDR 800 K	0.31	0.46
Impatience	Binary indicator for highest level of present bias from a ladder-type lottery game	0.62	0.49
(C) Mechanisms			
Sleep Disturbance	Binary indicator for a person who has a moderate to severe sleep disturbance (t-score >= 60)	0.16	0.37
Feeling poorly next day Z-Score	Factors of joint PCA analysis of ten indicators of sleep disturbance (e.g. trouble sleeping, poor sleep quality, problems during the day because of poor sleep, hard time getting things done.	0	1
Poor sleep quality Z-Score		0	1
Cognition Z-Score	PCA score of Fluid Intelligence, TICS, Raven's Matrix and Math	0	1
Angry	Binary indicator for a person who felt a little, somewhat, quite a bit or very angry yesterday	0.31	0.46
Enthusiastic	Binary indicator for a person who felt quite a bit or very enthusiastic yesterday	0.58	0.49
Happy	Binary indicator who a person who felt quite a bit or very happy yesterday	0.64	0.48

Notes: All treatment variables are created using data from NASA's Modern-Era Retrospective Analysis for Research and Applications, Version 2. Outcome variables for risk aversion, rational choice violations, and impatience use the combined IFLS4 + IFLS5 sample. Sleep, and mood outcomes use exclusively IFLS5 data. Cognition outcomes use both IFLS4 and IFLS5 data.

Table 2. Accumulation decisions, risky choices and economic preferences

	Accumulation decisions		Risky Choices			
	Savings	Higher Education	Self Employed	Plan to Start Business	Use Tobacco	Number Cigarettes
	(1)	(2)	(3)	(4)	(5)	(6)
Impatience	-0.033***	-0.088***				
	(0.004)	(0.004)				
Risk Aversion			-0.013***	-0.010***	-0.000	-0.298**
			(0.005)	(0.003)	(0.004)	(0.148)
Rational Choice Violation			-0.006	-0.012***	0.003	-0.301**
			(0.004)	(0.003)	(0.004)	(0.140)
Outcome Mean	0.21	0.48	0.27	0.07	0.34	11.65
Observations	38,463	52,432	51,778	49,190	49,574	16,227

Notes: All models are estimated using province-urban, month and year fixed effects. They also include controls for respondents' age, gender, marital status, religion, employment status, education (except for column 2) and household characteristics such as number of people and children in the house and equivalized monthly household expenditure. Robust standard errors are in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

<h3 style="text-align:center">**Table 3. Linear effects of temperature on time and risk preferences**</h3>

	Risk Aversion	Rational Choice Violation	Impatience
	(1)	(2)	(3)
Panel A			
Max Temperature on Day of Survey (ºC)	-0.000	0.003	0.004**
	(0.002)	(0.002)	(0.002)
Panel B			
Temperature during hour of survey (ºC)	0.001	0.007***	0.004**
	(0.002)	(0.002)	(0.002)
Panel C			
Midnight Temperature Yesterday (ºC)	0.000	0.010***	0.009***
	(0.003)	(0.003)	(0.003)
Panel D			
Max Temperature on Day of Survey (ºC)	-0.000	0.001	0.002
	(0.002)	(0.002)	(0.002)
Midnight Temperature Yesterday (ºC)	0.001	0.009***	0.009***
	(0.003)	(0.003)	(0.003)
p-value	0.7904	0.0480	0.0763
Outcome Mean	0.37	0.31	0.62
Observations	32,119	48,953	47,566

Notes: The p-values in panel D, test whether the coefficients for maximum temperature on the day of the survey and midnight temperature are significantly different from each other. All models include climate zone fixed effects which are the result of interacting province of residence, urbanity of the village, altitude groups, and distance to coast groups, as well as month and year fixed effects, and village latitude. The results exclude individuals living more than 50 kms from the closest grid. All models control for individual and household characteristics. Individual controls include: gender, age, marital status, income generating activity, marital status, religion, highest level of education, day of the week when the individual's survey took place and hour when the survey started. Household controls include: gender of the household head, their age, marital status, education level, number of children and adults in the household, and a squared function of equivalized consumption. We also include linear controls for pollution (PM 2.5), precipitation and wind speed. Columns 1-3 are estimated on the combined IFLS4 + IFLS5 sample. Robust standard errors clustered on village level are in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 4. Alternative specifications - Effects of temperature on time and risk preferences

	Rational Choice Violation			Impatience		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Midnight Temperature Yesterday (ºC)	0.010***	0.008***	0.007***	0.009***	0.009***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Panel B						
Max Temperature on Day of Survey (ºC)	0.001	0.001	0.000	0.002	0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Midnight Temperature Yesterday (ºC)	0.009***	0.008***	0.007***	0.009***	0.008***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
p-value	0.0180	0.0898	0.0417	0.3335	0.1165	0.0459
Outcome Mean	0.31	0.31	0.31	0.62	0.62	0.62
Observations	48,953	48,953	48,953	47,566	47,566	47,566
Humidity	Y			Y		
Longitude		Y			Y	
Interviewer FE			Y			Y

Notes: The p-values in panel D, test whether the coefficients for maximum temperature on the day of the survey and midnight temperature are significantly different from each other. All models include climate zone fixed effects which are the result of interacting province of residence, urbanity of the village, altitude groups, and distance to coast groups. The results exclude individuals living more than 50 kms from the closest grid. All models control for individual and household characteristics and also include linear controls for pollution, precipitation and wind speed. Individual controls include: gender, age, marital status, income generating activity, marital status, religion, highest level of education, day of the week when the individual's survey took place and hour when the survey started. Household controls include: gender of the household head, their age, marital status, education level, number of children and adults in the household, and a squared function of equivalized consumption. Columns 1-6 are estimated on the combined IFLS4 + IFLS5 sample. Robust standard errors clustered on village level are in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table 5. Cumulative effects of midnight temperature

	Rational Choice Violation	Impatience
	(1)	(2)
Panel A - Contemporaneous Effects		
Midnight Temp Yesterday above 25ºC	0.023**	0.013*
	(0.009)	(0.008)
Panel B - Cumulative Effects		
Midnight Temp Yesterday above 25ºC	0.022*	0.016
	(0.012)	(0.012)
# Midnights above 25ºC Last Week	0.007**	0.005*
	(0.003)	(0.003)
Interaction of above temperature variables	-0.007	-0.006
	(0.005)	(0.004)
F-test	2.87	1.80
p-value	0.0567	0.1655
Outcome Mean	0.31	0.62
Observations	48,953	47,566

Notes: Columns 1 and 2 include data from both IFLS4 and IFLS5. All models include climate zone fixed effects, the result of interacting province of residence, urbanity of the village, altitude groups and distance to coast groups, plus month and year fixed effects and linear controls for pollution, precipitation and wind speed. All regressions exclude individuals living more than 50 kms from the closest grid. We include the p-value of the test of joint significance for the cumulative temperature variables: # of midnights with temperature above 25ºC and the interaction term in Panel B. Robust standard errors clustered on village level are in parentheses.

 * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 6. Nighttime temperature in the past week and sleep

	# Nights > 25 in past 7 days	5-7 nights in past week > 25
	(1)	(2)
Panel A - Sleep Disturbance 0/1		
Sleep disturbance dummy	0.004**	0.024***
	(0.001)	(0.009)
Mean	0.16	0.16
Panel B - Sleep Disturbance Factors		
Feeling poorly the next day z-score	0.009***	0.055***
	(0.003)	(0.019)
Self-reported poor sleep z-score	0.001	0.007
	(0.003)	(0.017)

Notes: Models include data from IFLS5 only, as well as climate zone fixed effects which are the interaction of province of residence, urbanity of the village, altitude groups, and distance to coast groups, plus month and year fixed effects. The regressions exclude individuals living more than 50 kms from the closest grid. Robust standard errors are clustered on village level in parentheses * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 7. Temperature, cognition and mood

	Wave 4		Wave 5	
Panel A – Cognition				
Cognition factor z-score	-0.036**	(0.017)	-0.016**	(0.006)
Math z-score	-0.039***	(0.014)	-0.013**	(0.006)
Panel B – Mood				
Angry (0/1)	-		-0.002	(0.003)
Enthusiastic (0/1)	-		-0.003	(0.003)
Happy (0/1)	-		-0.003	(0.003)

Notes: Outcomes in panel A are regressed on temperature on the night before the survey. Panel B outcomes use 'yesterday' as reference so they are regressed on midnight temperature the day before yesterday. Models include data from IFLS5 only, as well as climate zone fixed effects which are the interaction of province of residence, urbanity of the village, altitude groups, and distance to coast groups, plus month and year fixed effects. The regressions exclude individuals living more than 50 kms from the closest grid. Robust standard errors are clustered on village level in parentheses * p<0.1; ** p<0.05; *** p<0.01.

Appendix A – Figures

Appendix Figure A1. Risk preferences flowchart
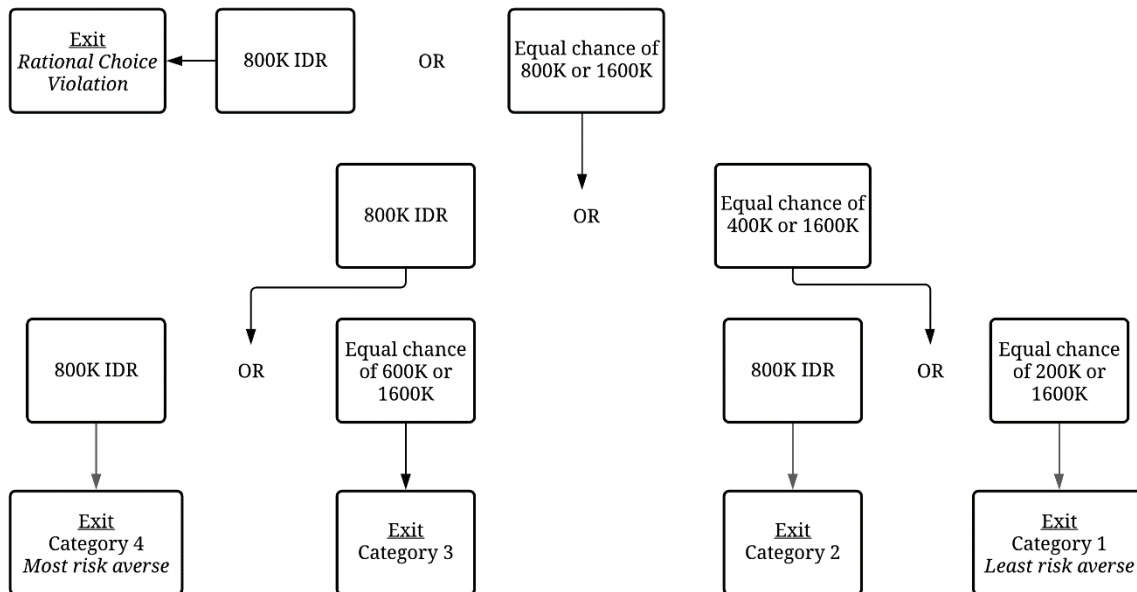
Notes: The above figure shows a flowchart adapted from IFLS4 and IFLS5 illustrating the elicitation of risk preference module based on figure by Ng (2013).

Appendix Figure A2. Time preferences flowchart
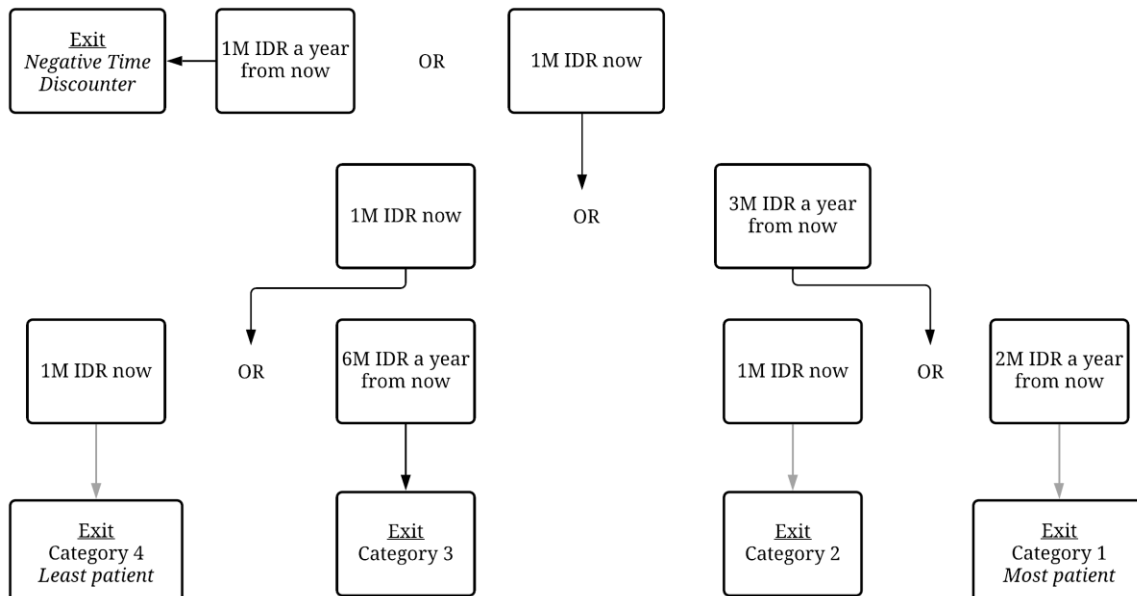
Notes: The above figure shows a flowchart adapted from IFLS4 and IFLS5 illustrating the elicitation of time preference module based on figure by Ng (2013).

Appendix Figure A3. Number of days to roll out survey by climate zone
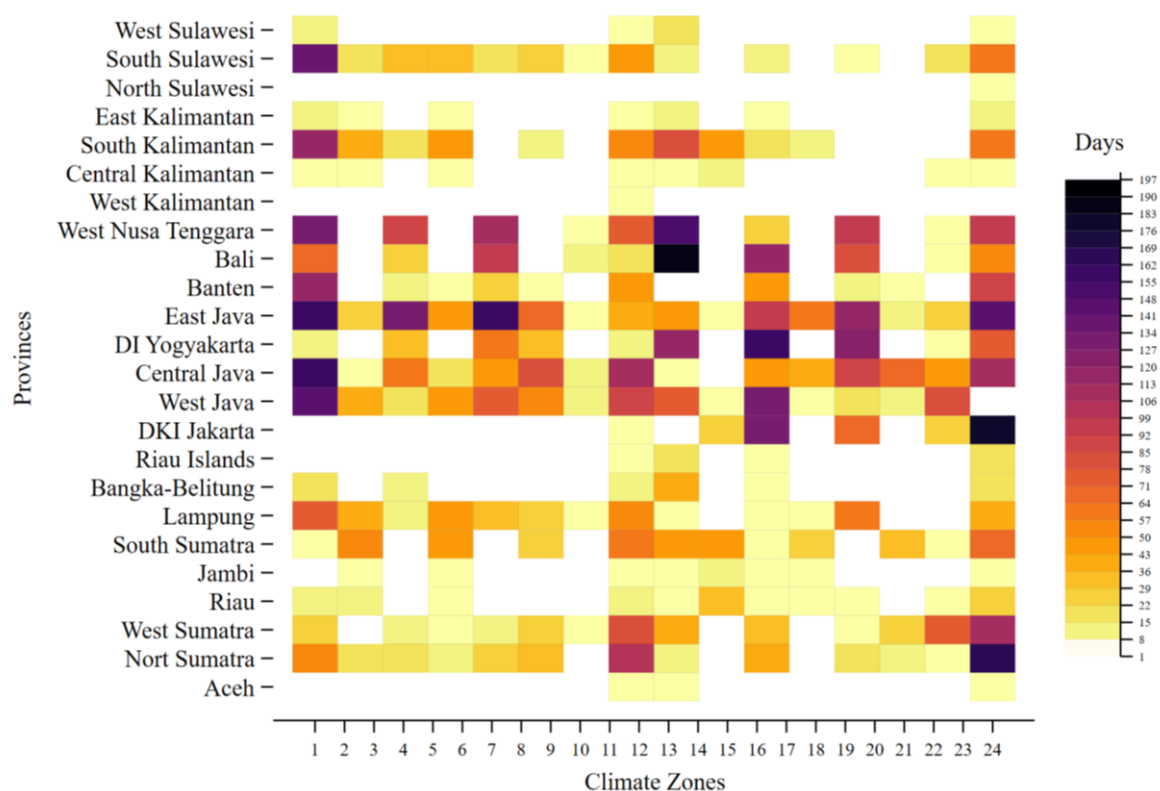
Notes: The figure above shows the total number of days it took to rollout the IFLS survey in each climate zone. Blank squares are either climate zones that do not exist in the province or zones where no people were surveyed.

Appendix Figure A4. Effects of *midnight temperatures* on cognition
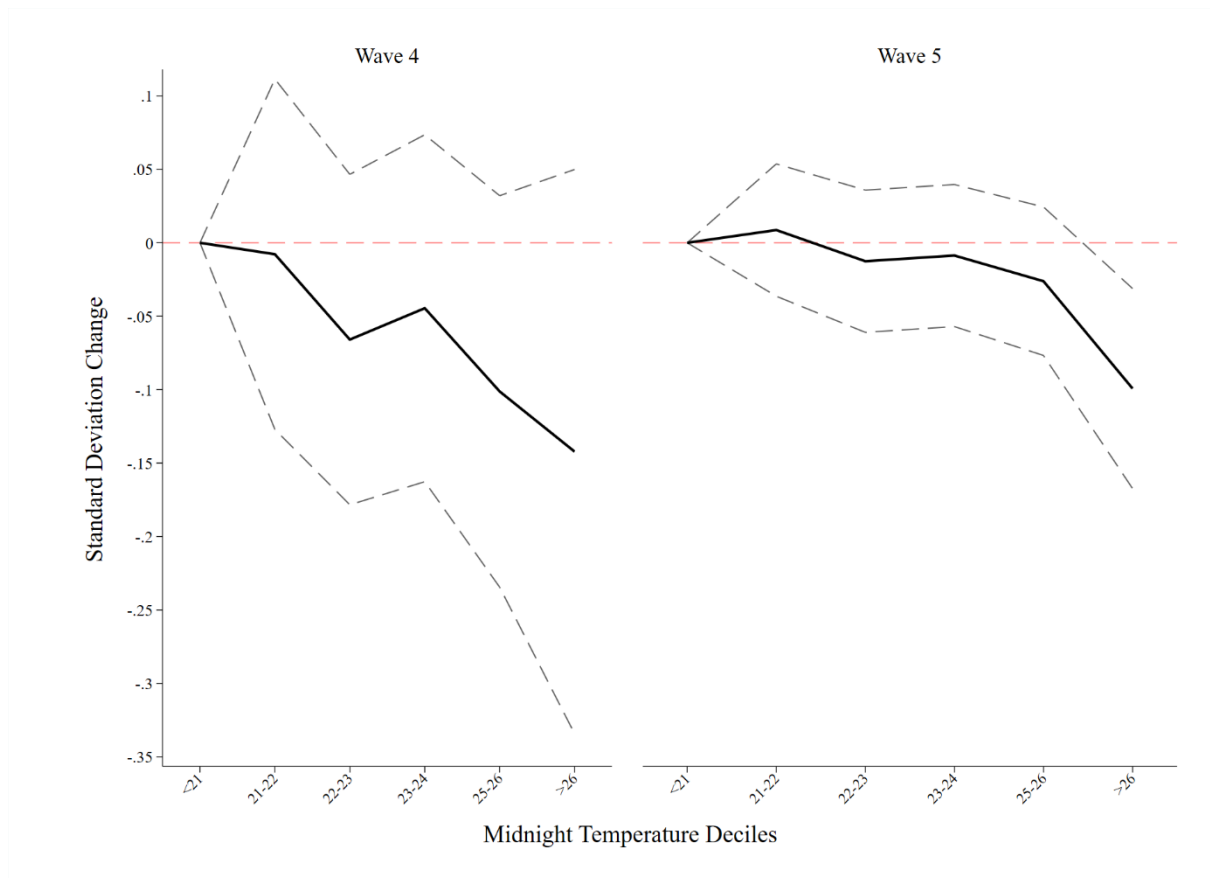
Notes: The above figure shows nonlinear effects of midnight temperature on cognition by temperature bins and IFLS waves.

Appendix B – Heat Matrix

The results presented in panel D of Table 3, Section 4, suggest that midnight temperatures are driving our main effects on rational choice violations and impatience. However, concerns regarding this approach can arise given the high correlation between all three measures of temperature. We therefore produce a heat matrix as an alternative approach that produces seven different combinations of midnight temperature and maximum temperature (Figure B1a) and of midnight temperature and temperature at the hour of the survey (Figure B1b).

Appendix Figure B1, shows how the different combinations where created and the proportion of observations in our sample within each category. Appendix Tables B1-B2 show the new estimated coefficients when the treatment is a categorical variable composed of all seven combinations. In both specifications, the reference category is when both temperatures are low.

The three main categories for midnight temperature where created based on the shape of the relationship between midnight temperature and our main outcomes as shown in Figure 4, where temperatures $< 21°C$ are the reference category. Here it serves as the lowest level. The splits between low, medium and high at the hour of survey and for maximum temperature are based on percentiles of such variables. Temperatures at or below the 10th percentile are the lowest category and temperatures at or above the 90th percentile make up the highest category.

Appendix Figure B1. Combinations in the Heat Matrix

a) Midnight and maximum temperature on the day of the survey

	Low Max < 26 C	Medium Max 26 - 31C	High Max > 31 C
Low Midnight < 21 C	A) 3%	B) 5%	
Medium Midnight 21 - 26 C	C) 4%	D) 59%	E) 8%
High Midnight > 26 C		F) 5%	G) 17%

b) Midnight and temperature at the Hour of Survey (HoS)

	Low HoS < 22 C	Medium HoS 22 - 27 C	High HoS > 27 C
Low Midnight < 21 C	A) 5%	B) 3%	
Medium Midnight 21 - 26 C	C) 6%	D) 57%	E) 8%
High Midnight > 26 C		F) 4%	G) 18%

Notes: The above figure shows how each combination in both heat matrices was built. Figure A shows the combinations of midnight temperature on the night prior to the survey and maximum temperature on the day of the survey. Figure B shows the combination of midnight temperature on the night prior to the survey and temperature at the hour when the survey started. In both figures, combinations B and F are a merge of two different categories which individually had very few observations.

Appendix Table B1. Heat Matrix - Temperature at Midnight and Maximum on Day of Survey

	(1) Rational Choice Violation	(2) Impatience
B - Low midnight - med/high max	-0.009	0.012
	(0.019)	(0.018)
C - Medium midnight - low max	0.005	0.008
	(0.023)	(0.022)
D - Medium midnight - med maximum	0.010	0.033*
	(0.023)	(0.018)
E - Medium midnight - high max	0.007	0.033
	(0.026)	(0.021)
F - High midnight - low/med max	0.043	0.044**
	(0.027)	(0.021)
G - High midnight - high max	0.070**	0.084***
	(0.031)	(0.026)
Observations	49,162	47,772

Notes: The reference category is A) low midnight on the night prior to the survey and low maximum on the day of the survey.

Appendix Table B2. Heat Matrix - Temperature at Midnight and at the Hour of Survey (HoS)

	(1) Rational Choice Violation	(2) Impatience
B - Low midnight - med/high HoS	0.017	0.019
	(0.017)	(0.017)
C - Medium midnight - low HoS	0.014	0.027
	(0.019)	(0.018)
D - Medium midnight - med HoS	0.023	0.030*
	(0.017)	(0.016)
E - Medium midnight - high HoS	0.043**	0.023
	(0.020)	(0.018)
F - High midnight - low/med HoS	0.059***	0.049**
	(0.022)	(0.021)
G - High midnight - high HoS	0.081***	0.053**
	(0.024)	(0.021)
Observations	49,162	47,772

Notes: The reference category is A) low midnight and low temperature at the time of the survey.

Appendix C – Robustness Checks and Placebo Tests

Appendix Table C1. Correlates of economic preferences and rationality

	Risk Aversion	Rational Choice Violation	Impatience
	(1)	(2)	(3)
Female	0.072***	0.030***	-0.013**
	(0.007)	(0.006)	(0.006)
Age	-0.005***	-0.001	0.008***
	(0.002)	(0.001)	(0.001)
Age^2	0.000***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)
Religion: Islam	0.004	-0.011	0.021
	(0.019)	(0.013)	(0.016)
Married or cohabitating	0.024**	0.007	0.018**
	(0.011)	(0.008)	(0.009)
Working in past week	-0.011	-0.019**	0.004
	(0.012)	(0.009)	(0.010)
Secondary education or +	0.012	-0.056***	-0.040***
	(0.009)	(0.007)	(0.007)
Cognition global z-score	0.007	-0.053***	-0.055***
	(0.005)	(0.004)	(0.004)
Female head of household	-0.008	-0.004	-0.008
	(0.012)	(0.009)	(0.010)
Age of household head	0.001*	0.000	0.001*
	(0.000)	(0.000)	(0.000)
Number of members per household	-0.002	0.000	-0.001
	(0.002)	(0.002)	(0.002)
Household equivalized expenditure	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Household equivalized expenditure^2	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Outcome Mean	0.38	0.29	0.64
Observations	19,426	27,183	26,257

Notes: Models include data from IFLS5. All regressions also include climate zone fixed effects (the result of interacting province of residence, urbanity of the village, altitude groups, and distance to coast groups), plus month and year fixed effects. The regressions exclude individuals living more than 50 kms from the closest grid. Robust standard errors clustered on village level are in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Appendix Table C2. Endogenous selection of movers based on preferences

	Δ in Max T (Year of Survey)	Δ in Mean T (Year of Survey)	Δ in Midnight T (Year of Survey)
	(1)	(2)	(3)
Irrational (IFLS4)	-0.016	-0.051	-0.034
	(0.070)	(0.072)	(0.083)
Risk Averse (IFLS4)	0.009	0.001	0.036
	(0.072)	(0.072)	(0.083)
Impatient (IFLS4)	-0.087	-0.112	-0.122
	(0.067)	(0.068)	(0.078)
Age	0.007	0.007*	0.006
	(0.005)	(0.004)	(0.004)
Female	0.041	-0.009	-0.034
	(0.031)	(0.031)	(0.036)
Married	-0.032	0.027	0.038
	(0.070)	(0.071)	(0.080)
Religion: Islam	0.174	0.277	0.315
	(0.203)	(0.221)	(0.270)
Working in past week	-0.132*	-0.164**	-0.115
	(0.077)	(0.076)	(0.084)
Secondary education or +	-0.023	-0.004	-0.019
	(0.072)	(0.071)	(0.080)
Log Expenditure	-0.056	-0.114**	-0.118*
	(0.053)	(0.053)	(0.062)
R-squared	0.365	0.362	0.341
Observations	1,167	1,167	1,160

Notes: The change in maximum, average and midnight temperatures (on the year of survey) between the IFLS5 villages - IFLS4 villages for movers only, is regressed on IFLS4 preferences, individual and household characteristics, as well as climate zone, month and year fixed effects. Robust standard errors clustered on village level are in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Appendix Table C3. Alternative specifications - Effects of temperature on time and risk preferences

	Rational Choice Violation			Impatience		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Max Temperature on Day of Survey (ºC)	0.003**	0.003*	0.002	0.004**	0.003**	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Panel B						
Temperature during hour of survey (ºC)	0.007***	0.006***	0.004***	0.004**	0.003**	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Panel C						
Midnight Temperature Yesterday (ºC)	0.010***	0.008***	0.007***	0.009***	0.009***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Panel D						
Max Temperature on Day of Survey (ºC)	0.001	0.001	0.000	0.002	0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Midnight Temperature Yesterday (ºC)	0.009***	0.008***	0.007***	0.009***	0.008***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
p-value	0.0180	0.0898	0.0417	0.3335	0.1165	0.0459
Outcome Mean	0.31	0.31	0.31	0.62	0.62	0.62
Observations	48,953	48,953	48,953	47,566	47,566	47,566
Humidity	Y			Y		
Longitude		Y			Y	
Interviewer FE			Y			Y

Notes: All models include climate zone fixed effects which are the result of interacting province of residence, urbanity of the village, altitude groups, and distance to coast groups. The results exclude individuals living more than 50 kms from the closest grid. All models control for individual and household characteristics and also include linear controls for pollution, precipitation and wind speed. Individual controls include: gender, age, marital status, income generating activity, marital status, religion, highest level of education, day of the week when the individual's survey took place and hour when the survey started. Household controls include: gender of the household head, their age, marital status, education level, number of children and adults in the household, and a squared function of equivalized consumption. Columns 1-6 are estimated on the combined IFLS4 + IFLS5 sample. Robust standard errors clustered on village level are in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	Rational Choice Violation			Impatience		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Max Temperature on Day of Survey (ºC)	0.003	0.003	0.003	0.004**	0.005**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Panel B						
Temperature during hour of survey (ºC)	0.007***	0.007***	0.007***	0.004**	0.004*	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Panel C						
Midnight Temperature Yesterday (ºC)	0.010***	0.010***	0.009***	0.009***	0.012***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Panel D						
Max Temperature on Day of Survey (ºC)	-0.001	0.001	0.001	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature during hour of survey (ºC)	0.005**	-	-	-0.001	-	-
	(0.002)			(0.002)		
Midnight Temperature Yesterday (ºC)	0.006*	0.009***	0.009***	0.009***	0.010***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
p-value	-	0.0484	0.0990	-	0.0730	0.0586
Outcome Mean	0.31	0.31	0.33	0.62	0.62	0.62
Observations	48,953	48,953	39,067	47,566	47,566	38,038
Ramadan		Y			Y	
Exclude >1 Visit			Y			Y

Notes: Columns 1 and 4 include all three measures of temperature in Panel D, maximum temperature on the day of the survey, temperature at the hour when the survey started, and midnight temperature on the night prior to the survey to assess which is dominant. Columns 2 and 5 include controls for individuals surveyed during Ramadan (1.59% of the sample). Columns 3 and 6 exclude 19% of the sample who received more than 1 visit to complete the time and risk survey modules. The p-values in panel D test whether the coefficients of maximum and midnight temperature are significantly different from each other. All models include climate zone fixed effects (the interaction of province-urban-altitude-distance to coast), plus month and year fixed effects and exclude individuals living more than 50 kms from the closest grid. Models also include village altitude, environmental, individual and household level controls. All models are estimated on the combined IFLS4 + IFLS5 sample. Robust standard errors clustered on village level are in parentheses.
 * p<0.1; ** p<0.05; *** p<0.01.

Appendix Table C5. Only climate zones where date of survey explains >90% of the variation in temperatures

	Most Risk Averse	Rational Choice Violation	Most Impatient
	(1)	(2)	(3)
Panel A			
Max Temperature on Day of Survey (ºC)	0.000	0.002	0.005**
	(0.002)	(0.002)	(0.002)
Panel B			
Temperature during hour of survey (ºC)	0.001	0.005**	0.004**
	(0.002)	(0.002)	(0.002)
Panel C			
Midnight Temperature Yesterday (ºC)	0.002	0.008***	0.010***
	(0.003)	(0.003)	(0.003)
Panel D			
Max Temperature on Day of Survey (ºC)	-0.000	-0.001	0.002
	(0.002)	(0.002)	(0.002)
Midnight Temperature Yesterday (ºC)	0.002	0.009***	0.009***
	(0.003)	(0.003)	(0.003)
p-value	0.6819	0.0458	0.1009
Outcome Mean	0.37	0.32	0.62
Observations	28,348	43,452	42,227

Notes: All models include climate zone fixed effects which are the result of interacting province of residence, urbanity of the village, altitude groups, and distance to coast groups. The results exclude individuals living more than 50 kms from the closest grid and those who live in climate zones where date of survey fixed effects explain less than 90% of the variation in temperatures. All models control for individual and household characteristics. Individual controls include: gender, age, marital status, income generating activity, marital status, religion, highest level of education, day of the week when the individual's survey took place and hour when the survey started. Household controls include: gender of the household head, their age, marital status, education level, number of children and adults in the household, and a squared function of equivalized consumption. Columns 1-3 are estimated on the combined IFLS4 + IFLS5 sample. Robust standard errors are clustered on village level in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Appendix Table C6. Placebo test - Maximum temperature in 2 weeks

	Rational Choice Violation	Impatience
	(1)	(2)
Panel A		
Max Temperature on Day of Survey (ºC)	0.003	0.003*
	(0.002)	(0.002)
Max Temperature on Day T+14 (ºC)	0.002	0.002
	(0.002)	(0.002)
Panel B		
Temperature during hour of survey (ºC)	0.007***	0.003*
	(0.002)	(0.002)
Max Temperature on Day T+14 (ºC)	0.001	0.002
	(0.002)	(0.002)
Panel C		
Midnight Temperature Yesterday (ºC)	0.009***	0.009***
	(0.003)	(0.003)
Max Temperature on Day T+14 (ºC)	0.001	0.001
	(0.002)	(0.002)
Panel D		
Max Temperature on Day of Survey (ºC)	0.000	0.001
	(0.002)	(0.002)
Midnight Temperature Yesterday (ºC)	0.009***	0.008***
	(0.003)	(0.003)
Max Temperature on Day T+14 (ºC)	0.001	0.001
	(0.002)	(0.002)
Outcome Mean	0.31	0.62
Observations	48,953	47,566

Notes: All models include climate zone fixed effects, the interaction of province-urban-altitude groups-distance to coast groups, plus month and year fixed effects. All regressions exclude individuals living more than 50 kms from the closest grid. Models also include village altitude, environmental, individual and household level controls. Robust standard errors clustered on village level are in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Appendix Table C7. Placebo Test - Temperature and Demographics

	Female	Age	Married	Equivalised Expenditure
	(1)	(2)	(3)	(4)
Panel A				
Midnight Temperature Yesterday (ºC)	0.000	0.004	0.001	-1.0e+04
	(0.002)	(0.091)	(0.003)	(1.0e+04)
Panel B				
Max Temperature on Day of Survey (ºC)	0.000	0.020	0.001	8561.983
	(0.001)	(0.059)	(0.002)	(6110.675)
Panel C				
Mean Temperature on Day of Survey (ºC)	-0.001	-0.030	0.001	862.665
	(0.002)	(0.091)	(0.003)	(9472.537)
Observations	54,102	53,598	53,604	53,570

Notes: All models include climate zone fixed effects which are the result of interacting province of residence, urbanity of the village, altitude groups, and distance to coast groups. Columns 1-4 are estimated on the combined IFLS4 + IFLS5 sample. Robust standard errors are clustered on village level in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Appendix Table C8. Heterogeneity in the temperature-sleep nexus

	Sleep Disturbance 0/1	Feeling poorly next day z-score
	(1)	(2)
Panel A – Consumption		
Bottom half	0.005***	0.008**
	(0.002)	(0.004)
Top half	0.002	0.008
	(0.002)	(0.006)
Panel B – Electricity Expenditure		
Energy poor	0.005**	0.012***
	(0.002)	(0.004)
Non-energy poor	0.004*	0.003
	(0.002)	(0.005)
Panel C – Air-conditioning rates		
Ownership < 5%	0.004**	0.007*
	(0.002)	(0.004)
Ownership 5-15%	-0.002	-0.006
	(0.004)	(0.008)

Notes: All outcomes are regressed on the number of nights in the past week with midnight temperatures above 25°C. Panel C splits the sample into districts where <5% of households own air-conditioning and districts where 5-15% own the assets. The national average between 2014 and 2015, when IFLS5 was collected was ~5%. Models include data from IFLS5 only, as well as climate zone fixed effects which are the interaction of province of residence, urbanity of the village, altitude groups, and distance to coast groups, plus month and year fixed effects. The regressions exclude individuals living more than 50 kms from the closest grid. Robust standard errors are clustered on village level in parentheses * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Appendix Table C9. Potential mechanisms behind temperature effects - Cognition

Outcomes	Midnight Temperature Yesterday (ºC)		
	IFLS4 age 15-31	IFLS5 age 15-31	IFLS5 full sample
	(1)	(2)	(3)
Cognition global z-score	-0.036**	-0.005	-0.016**
	(0.017)	(0.008)	(0.006)
TICS z-score	-0.033**	0.005	-0.004
	(0.015)	(0.009)	(0.006)
Raven's Matrix z-score	-0.006	-0.015**	-0.020***
	(0.013)	(0.007)	(0.005)
Math z-score	-0.039***	-0.001	-0.013**
	(0.014)	(0.009)	(0.006)
Observations	7,131	11,026	26,900
Bin FE	Y	Y	Y
Month FE	Y	Y	Y
Year FE	Y	Y	Y
Latitude	Y	Y	Y
Pollution, Rain & Wind	Y	Y	Y

Notes: Models include controls for village altitude and environmental variables such as pollution, precipitation and wind, and exclude individuals living more than 50 kms from the closest grid. Robust standard errors clustered on village level are in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Appendix D – Cognition Outcomes

We measure the effects of temperature on four different tests of cognition and mathematical numeracy. We separate this analysis by IFLS wave as there were between-wave differences in the composition of these tests. Specifically, IFLS5 asked these four tests of all individuals age 15-90 years old (who also played the lottery games). However, in IFLS4, some of these tests were only asked of adults age 15-31 and one item, fluid intelligence, was not included at all.

The first test we examine, *Fluid Intelligence,* is an adaptive-number series test, which "measures a specific form of fluid intelligence related to quantitative reasoning" (Strauss et al., 2017, p. 6). It is based on the test used in the Health and Retirement Study (Fisher et al., 2014) and found to be closely correlated with financial wealth (Smith et al., 2010). It consists of a series of numbers where one of the values is missing and the respondent must fill in the missing number. The difficulty of the subsequent series is increasing with the number of correct answers. These are then scored using a standardized score called a W-Score, which appears as *Fluid Intelligence z-score* in Table 1.

The second test we examine is designed after the Telephone Interview of Cognitive Status (Fong, et al., 2009), and measures mental intactness. This test includes a date awareness and word recall module. In IFLS5, it also includes a set of subtraction questions that ask the respondent to subtract 7 from 100, five successive times, and a final exercise where the respondent draws a figure of two overlapping pentagons. The number of correct answers is added to generate a score from 0 – 30, this score is then standardized to create what we call in Table 1 the *TICS z-score*.

We also use the Raven's Progressive Matrices, which measures non-verbal abilities (Raven, 2000), and a test of mathematical skills which includes a series of addition, subtraction, division and multiplication questions. These two tests were asked of all adults inIFLS5, but only adults 15-31 years old in IFLS4. For both tests, we calculate the percentage of correct answers and then standardize the resulting scores to create the *Raven's Progressive Matrices z-score* and *Math z-score*. Finally, we create a composite measure of cognition by performing principal component analysis with the z-scores of all the items described above: fluid intelligence z-score, TICS z-score, Raven's Matrices, and math z-scores. The resulting global score is then standardized.

Appendix E – Multiple Hypothesis Testing

We adjust for the fact that we are testing multiple hypotheses in several sections of this study by computing Westfall-Young stepdown adjusted p-values which also control the familywise error rate and allow for dependence amongst p-values. This report details which coefficients in the main results section of this study have Westfall-Young p-values which change the results from being statistically significant at, at least the 10% to being not statistically significant according to this standard. The adjusted p-values are computed for all treatments and outcomes in each panel of Tables (E) 2 – 6.

Table (E)2: Accumulation decisions, risky choices and economic preferences.

The coefficient for the relationship between risk-aversion and the number of cigarettes consumed in a household (column 6) was statistically significant at 10% in the non-adjusted model and is now not significant at this threshold (wyoung p-value = 0.13). All other coefficients presented in table (E) 2 which were significant at the 1%, 5% and 10% level remain significant at the 10% level or less and the interpretation of the results remains unchanged.

Table (E)3: Linear effects of temperature on time and risk preferences.

The coefficient for maximum temperature and impatience reported in column 3 of Panel A was significant at 5% in the unadjusted model (model p-value = 0.04) but under Westfall-Young adjusted p-values, it is now no longer statistically significant (wyoung p-value = 0.18). All other coefficients presented in table (E) 3 which were significant at the 1%, 5% and 10% level remain significant at the 10% level or less and the interpretation of the results remains unchanged.

Table (E)4: Alternative specifications – linear effects of temperature on time and risk preferences

All coefficients presented in table (E) 4 which were significant at the 1%, 5% and 10% level remain significant at the 5% level or less and the interpretation of the results remains unchanged.

Table (E)5: Cumulative effects of midnight temperature

The coefficients in column 2 of Panel A, column 1 of Panel B, column 2 of Panel C which were testing for cumulative effects of midnight temperatures above 25ºC in the week prior to the survey have Westfall-Young adjusted p-values above 0.10 and are no longer statistically significant.

Table (E)6: Potential mechanisms behind temperature effects

All coefficients presented in table (E) 6 which were significant at the 1%, 5% and 10% level remain significant at the 10% level or less and the interpretation of the results remains unchanged.

Table E2. Accumulation decisions, risky choices and economic preferences

	Accumulation decisions		Risky Choices			
	Savings	Higher Education	Self Employed	Plan to Start Business	Use Tobacco	Number Cigarettes
	(1)	(2)	(3)	(4)	(5)	(6)
Most Impatient	-0.033***	-0.088***				
	(0.004)	(0.004)				
wyoung p-values	{0.00}	{0.00}				
Most Risk Averse			-0.013***	-0.010***	-0.000	-0.298**
			(0.005)	(0.003)	(0.004)	(0.148)
wyoung p-values			{0.01}	{0.00}	{1.00}	{0.13}
Rational Choice Violation			-0.006	-0.012***	0.003	-0.301**
			(0.004)	(0.003)	(0.004)	(0.140)
wyoung p-values			{0.41}	{0.00}	{0.44}	{0.09}
Outcome Mean	0.21	0.48	0.27	0.07	0.34	11.65
Observations	38463	52432	51778	49190	49574	16227

Notes: All models are estimated using bin fixed effects which are the result of interacting province of residence, urbanity of the village, altitude groups and distance to coast groups, plus month and year fixed effects. Robust standard errors in parentheses * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Westfall-Young adjusted p-values reported in {}.

Table E3. Linear Effects of Temperature on Time and Risk Preferences

	Most Risk Averse	Rational Choice Violation	Most Impatient
	(1)	(2)	(3)
Panel A			
Max Temperature on Day of Survey (°C)	-0.000	0.003	0.004**
	(0.002)	(0.002)	(0.002)
model p-values	[0.9314]	[0.1174]	[0.0409]
wyoung p-values	{0.96}	{0.23}	{0.18}
Panel B			
Temperature during hour of survey (°C)	0.001	0.007***	0.004**
	(0.002)	(0.002)	(0.002)
model p-values	[0.7313]	[0.0002]	[0.0386]
wyoung p-values	{0.79}	{0.00}	{0.10}
Panel C			
Midnight Temperature Yesterday (°C)	0.000	0.010***	0.009***
	(0.003)	(0.002)	(0.003)
model p-values	[0.8683]	[0.0004]	[0.0003]
wyoung p-values	{0.9}	{0.00}	{0.00}
Panel D			
Max Temperature on Day of Survey (°C)	-0.000	0.001	0.002
	(0.002)	(0.002)	(0.002)
model p-values	[0.8382]	[0.6911]	[0.3788]
wyoung p-values	{0.98}	{0.98}	{0.84}
Midnight Temperature Yesterday (°C)	0.001	0.009***	0.009***
	(0.003)	(0.003)	(0.003)
model p-values	[0.8167]	[0.001]	[0.001]
wyoung p-values	{0.98}	{0.02}	{0.02}
p-value	0.7904	0.0480	0.0763
Outcome Mean	0.37	0.31	0.62
Observations	32119	48953	47566

Notes: All models include bin fixed effects which are the result of interacting province of residence, urbanity of the village, altitude groups, and distance to coast groups. The results exclude individuals living more than 50 kms from the closest grid. All models control for individual and household characteristics. Individual controls include: gender, age, marital status, income generating activity, marital status, religion, highest level of education, day of the week when the individual's survey took place and hour when the survey started. Household controls include: gender of the household head, their age, marital status, education level, number of children and adults in the household, and a squared function of equivalised consumption. Columns 1-3 are estimated on the combined IFLS4 + IFLS5 sample. Robust standard errors are clustered on village level in parentheses * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Westfall-Young adjusted p-values reported in {}.

Table E4. Alternative Specifications - Linear Effects of Temperature on Time and Risk Preferences

	Rational Choice Violation			Most Impatient		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Midnight Temperature Yesterday (ºC)	0.010***	0.008***	0.007***	0.009***	0.009***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
model p-values	[0.0004]	[0.0039]	[0.0042]	[0.0003]	[0.0011]	[0.0114]
wyoung p-values	{0.01}	{0.01}	{0.01}	{0.01}	{0.01}	{0.01}
Panel B						
Max Temperature on Day of Survey (ºC)	0.001	0.001	0.000	0.002	0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
model p-values	[0.6997]	[0.7515]	[0.9614]	[0.3744]	[0.3998]	[0.7208]
wyoung p-values	{0.95}	{0.96}	{0.97}	{0.7}	{0.75}	{0.96}
Midnight Temperature Yesterday (ºC)	0.009***	0.008***	0.007***	0.009***	0.008***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
model p-values	[0.0016]	[0.0089]	[0.0056]	[0.0019]	[0.0055]	[0.0113]
wyoung p-values	{0.01}	{0.05}	{0.01}	{0.01}	{0.01}	{0.05}
p-value	0.0180	0.0898	0.0417	0.3335	0.1165	0.0459
Outcome Mean	0.31	0.31	0.31	0.62	0.62	0.62
Observations	48953	48953	48953	47566	47566	47566
Humidity	Y			Y		
Longitude		Y			Y	
Interviewer FE			Y			Y

Note: All models include bin fixed effects which are the result of interacting province of residence, urbanity of the village, altitude groups, and distance to coast groups. The results exclude individuals living more than 50 kms from the closest grid. All models control for individual and household characteristics. Individual controls include: gender, age, marital status, income generating activity, marital status, religion, highest level of education, day of the week when the individual's survey took place and hour when the survey started. Household controls include: gender of the household head, their age, marital status, education level, number of children and adults in the household, and a squared function of equivalised consumption. Columns 1-6 are estimated on the combined IFLS4 + IFLS5 sample. Robust standard errors are clustered on village level in parentheses * p<0.1; ** p<0.05; *** p<0.01. Westfall-Young adjusted p-values reported in {}.

Table E5. Cumulative Effects of Midnight Temperature

	Rational Choice Violation	Most Impatient
	(1)	(2)
Panel A - Contemporaneous Effects		
Midnight Temp Yesterday above 25ºC	0.023**	0.013*
	(0.009)	(0.008)
model p-values	[0.0109]	[0.0964]
wyoung p-values	{0.05}	{0.13}
Panel B - Cumulative Effects		
Midnight Temp Yesterday above 25ºC	0.022*	0.016
	(0.012)	(0.012)
model p-values	[0.0751]	[0.1889]
wyoung p-values	{0.32}	{0.32}
# Midnights above 25ºC Last Week	0.007**	0.005*
	(0.003)	(0.003)
model p-values	[0.0173]	[0.0803]
wyoung p-values	{0.09}	{0.32}
Midnight Temp Yesterday above 25ºC *	-0.007	-0.006
# Midnights above 25ºC Last Week	(0.005)	(0.004)
model p-values	[0.1036]	[0.1008]
wyoung p-values	{0.32}	{0.32}
F-test	2.87	1.80
p-value	0.0567	0.1655
Outcome Mean	0.31	0.62
Observations	48953	47566

Notes: Columns 1 and 2 include data from both IFLS4 and IFLS5. Columns 3-6 include data from IFLS5 only. All models include bin fixed effects, the result of interacting province of residence, urbanity of the village, altitude groups and distance to coast groups, plus month and year fixed effects. All regressions exclude individuals living more than 50 kms from the closest grid. We include the p-value of the test of joint significance for the cumulative temperature variables: # of midnights with temperature above 25C and the interaction term in Panel B. Robust standard errors are clustered on village level in parentheses * p<0.1; ** p<0.05; *** p<0.01. Westfall-Young adjusted p-values reported in {}.

Table E6. Potential mechanisms behind temperature effects

	Wave 4			Wave 5		
Panel A - Sleep						
Sleep Disturbance (0/1)	-			0.004**	(0.001)	{0.03}
Sleep factor - feeling poorly next day z-score	-			0.009***	(0.003)	{0.05}
Sleep factor - poor sleep quality z-score	-			0.001	(0.003)	{0.77}
Panel B - Cognition						
Cognition factor z-score	-0.036**	(0.017)	{0.08}	-0.016**	(0.006)	{0.02}
Math z-score	-0.039***	(0.014)	{0.02}	-0.013**	(0.006)	{0.04}
Panel C - Mood						
Angry (0/1)	-			-0.002	(0.003)	{0.65}
Enthusiastic (0/1)	-			-0.003	(0.003)	{0.65}
Happy (0/1)	-			-0.003	(0.003)	{0.65}

Note: Outcomes in panel A are regressed on a numerical variable that measures the number of nights in the past week with midnight temperatures above 25 degrees Celsius. Outcomes in panel B are regressed on temperature on the night before the survey. Panel C outcomes use 'yesterday' as reference so they are regressed on midnight temperature the day before yesterday. Models include data from IFLS5 only, as well as bin fixed effects which are the interaction of province of residence, urbanity of the village, altitude groups, and distance to coast groups, plus month and year fixed effects. The regressions exclude individuals living more than 50 kms from the closest grid. Robust standard errors are clustered on village level in parentheses * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Westfall-Young adjusted p-values reported in {}.