The Effects of Temperature on Economic Preferences

Michelle Escobar Carias¹, David Johnston, Rachel Knott, Rohan Sweeney
Centre for Health Economics, Monash University
Version: October 5th, 2021

Abstract

The empirical evidence suggests that key accumulation decisions and risky choices associated with economic development depend, at least in part, on economic preferences such as one’s willingness to take risk and patience. This paper studies whether temperature could be one of the potential channels that influences such economic preferences. Using data from the Indonesia Family Life Survey and NASA’s Modern-Era Retrospective Analysis for Research and Applications data we exploit quasi-exogenous variations in outdoor temperatures caused by the random allocation of survey dates. This approach allows us to estimate the effects of temperature on elicited measures of risk aversion, rational choice violations, and impatience. We then explore three possible mechanisms behind this relationship: cognition, sleep, and mood. Our findings show that higher temperatures lead to significantly increased rational choice violations and impatience, but do not significantly increase risk-aversion. These effects are mainly driven by night-time temperatures on the day prior to the survey and less so by temperatures on the day of the survey. This impact is quasi-linear and increasing when midnight outdoor temperatures are above 22°C. The evidence shows that night-time temperatures significantly deplete cognitive functioning, mathematical skills in particular. Based on these findings we posit that heat-induced night-time disturbances cause stress on critical parts of the brain, which then manifest in significantly lower cognitive functions that are critical for individuals to perform economically rational decision-making.

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

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

¹ Corresponding author: michelle.escobar.carias@monash.edu. Address: 900 Dandenong Road, CHE Monash University, Caulfield East, 3145, Australia.
1. Introduction

The empirical evidence suggests that key decisions associated with economic well-being are influenced by time and risk preferences. Studies show that economic choices such as accumulating savings or investing in critical human capital inputs such as child immunizations and schooling, partly depend on the individual’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, or even optimal use of fertilizer, depend on an individual’s willingness to take risk (Kihlstrom & Laffont, 1979; Liu & Huang, 2013). In the neoclassical theory, preferences towards time and risk are assumed to be static (Stigler & Becker, 1977).

A growing body of literature shows that economic preferences are malleable. That is to say, that short-term shocks can affect time and risk preferences in non-trivial ways. For instance, Cameron & Shah (2015) find that a sample of Indonesian individuals who have recently experienced a flood or an earthquake exhibit more risk-averse tendencies in lottery games. In contrast, Hanaoka et al. (2018) find that men who experienced greater intensity during the 2011 Great East Japan Earthquake became more risk-tolerant a year post-shock and gambled more. These effects persisted even five years after the shock. Callen (2015) finds that exposure to the Indian Ocean Earthquake tsunami increased patience in a sample of Sri Lankan salaried workers up to two and a half years post-shock. Levin & Vidart (2020) find that in periods of increased macroeconomic volatility in Mexico and Indonesia, elicited measures of risk aversion are significantly higher. This collection of studies suggest that economic preferences are not stable and can change in the short and medium-term in response to negative shocks.

In this study, we investigate the effects of temperature on economic preferences as a potential short-term shock on a large sample of Indonesian adults. To do so, we use data from the Indonesia Family Life Survey (IFLS) and NASA’s Modern-Era Retrospective Analysis for Research and Applications (MERRA-2). These data allow us to exploit two sources of variation in temperature. First, temporal variations in temperature caused by the random allocation of survey dates throughout two waves and four years of data collection. Second, spatial variations in temperature caused by microclimates within provinces resulting from the interaction of a village’s level of urbanity, altitude, distance to the coast and latitude. Combined, these allow us to estimate the effects of quasi-exogenous temperature shocks on elicited measures of risk-aversion, rationality and impatience. We then explore cognition, sleep, and mood as potential mechanisms behind a causal relationship between temperature and economic preferences.
Our findings show that higher temperatures lead to increased violations of expected utility-based theories and higher impatience, but do not significantly affect risk aversion. We show that these effects are mainly driven by night-time temperatures on the day prior to the survey and less so by temperatures on the day of the survey. Our exploration of potential mechanisms indicates that higher night-time temperatures significantly reduce cognitive functioning the following day, mathematical skills in particular, but bear no effects that we could detect on sleep or mood. Based on these findings, we posit that heat-induced night-time disturbances cause stress on critical parts of the brain such as the prefrontal cortex, which then manifest in significantly lower cognitive functions. These functions are critical for individuals to perform economically rational decision-making. This, in turn, is reflected in a substantial increase in sup-optimal economic preferences such as rational choice violations and impatience, when theory suggests that the opposite would be utility maximizing.

We perform further explorations of temperature non-linearities and heterogeneous treatment effects by individual characteristics. The former shows that there is a quasi-linear increase in rational choice violations and impatience when midnight outdoor temperatures are above 22°C. Considering that 24% of our sample experienced midnights above that threshold the night prior to survey, these findings are relevant for a large portion of the Indonesian population. In regards to heterogeneous temperature effects by different sub-samples, we find that individuals with lower schooling are significantly more likely to make rational choice violations due to elevated night-time temperatures than individuals with higher schooling. Likewise, individuals residing in households in the bottom half of the consumption expenditure distribution are significantly more impatient and more likely to make rational choice violations as night-time temperatures rise, than wealthier individuals. We found no significant differences by age or gender.

These findings contribute a small collection of studies that so far have only been conducted in controlled laboratory environments. Overall, these studies show little consensus on whether or not the relationship is significant, and when significant, on the direction of such effects. A recent study by Almås, et al. (2020) among university students in Berkley, California, and Nairobi, Kenya, finds no evidence that heat stress affects risk-taking, time preferences, cognition, or social behavior except for destructive tendencies. 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 operating in warmer temperatures are less likely to gamble and purchase innovative products. The main strength of
these studies is their ability to randomly assign temperatures to individuals, thus overcoming the potential selection biases present in real world data.

Our study improves upon this existing literature, and builds on the findings by Almås, et al. (2020) in several ways. Although the temperature variations we exploit in this study are not purposely randomized as they would be in a laboratory-controlled experiment, we leverage a natural quasi-experimental design which causes temperatures to be as good as random. Further, we overcome other disadvantages of laboratory experiments such as their (usually) small sample sizes and limited experimental subject pool. Our sample is significantly larger than the best powered study on the subject (Almås, et al., 2020), and our samples are composed of everyday individuals age 15 to 90 years old from all socio-economic statuses and income-generating activities. This makes our study especially relevant for wider populations in developing countries. Finally, in contrast to the cited experimental studies, we do not assume an immediate nature of the temperature effects, and instead allow for heterogeneity in the timing and duration of exposure. For instance, having available data on sleep, cognition, and mood for each of these individuals, allows us to explore links between night-time temperature and these potential mechanisms, helping us explain how more prolonged exposure to treatment could explain the gap in our respective findings.

Our study also contributes to a wider range of economics literature showing that temperature can affect high-stakes decisions made by judges (Heyes & Saberian, 2019), consumer behavior and purchase decisions (Busse et al., 2015), human capital in the short- and long-run (Zivin, Hsiang, & Neidell, 2018), and even violent interactions among incarcerated populations (Mukherjee & Sanders, 2021). We also contribute to the literature linking temperature, climate change, and economic development (Ortiz-Bobea et al., 2021; Burke et al., 2015; Dell, Jones, & Olken, 2012; 2009). Finally, our study also builds on the work by Mani, et al. (2013) and Schilbach et al. (2016) who show that mentally taxed individuals are less likely to engage in System 2 processes, and propose that factors such as sleep deprivation and even heat can affect one's mental bandwidth. Our findings corroborate these assertions.

The rest of the paper proceeds as follows. Section 2 describes the relevant empirical literature and potential channels linking temperature and economic preferences. Section 3 outlines the sources of data, outcome and treatment measures. Section 4 outlines the empirical strategy. Section 5 provides a discussion of the main findings, robustness checks and placebo tests, and section 6 concludes.
2. Related Literature

The short-term temperature-prefences relationship is likely to operate via three potential channels: cognition, sleep, and mood. In the following sections we discuss the literature that has found links between these potential channels and different types of time and risk preferences. Next, we discuss the most recent findings showing that temperature can significantly affect cognitive function, decrease sleep quality and quantity, and trigger aggressive responses. Finally, we discuss the relevant studies on temperature and economic preferences.

2.1 Cognition, Sleep, Mood and Economic Preferences

The evidence shows that there is a significant link between cognition and economic preferences. Multiple studies have shown that higher cognitive skills are associated with higher impatience and lower risk aversion. For instance, Benjamin et al. (2013) find that Chilean high-school students with higher standardized math test scores show lower risk aversion in small-stakes gambles and less short-run discounting. Similarly, in their paper on the Global Preference Survey, Falk et al. (2018) use self-reported math skills of individuals from 76 countries as a proxy for cognitive skills and find that this type of skill is “uniformly positively linked to patience, risk taking, and social preferences” (p. 1647).

Likewise, better sleep quality is associated with lower discounting rates, less present bias, and less loss aversion\(^2\) (Nofsinger & Shank, 2019). Lack of sleep has also been shown to increase financial risk taking in studies using different tasks such as lottery choices (McKenna, et al., 2007), the Balloon Analog Risk Task (Killgore, 2007), and the Iowa Gambling Task (Killgore, et al., 2012). The latter examines the functioning of the prefrontal cortex (Lawrence, et al., 2009). This is especially relevant because functional magnetic resonance (fMRI) imaging shows that while performing arithmetic tasks, brain regions such as the prefrontal cortex, which typically activate among rested individuals during such tasks, are less activated when subjects are sleep deprived (Drummond, et al., 1999).

The third and final channel, aggressive mood, is associated with higher financial risk-taking (Cueva, et al., 2015). Induced changes in hormones associated with aggression such as cortisol and testosterone, have been shown to shift financial investments toward riskier assets. Anger

\(^2\) Loss aversion is an economic concept that captures when individuals value more avoiding losses than acquiring equivalent gains.
is also associated and a higher propensity towards risky behaviour such as speeding, reckless driving, and traffic violations (Deffenbacher, et al., 2003; Arnett, et al., 1997).

2.2 Temperature and its Effects on Cognition, Sleep, and Mood

A growing body of evidence shows that high temperatures have the potential to impair different forms of cognition. This is related to the fact that different cognitive functions are housed in different parts of the brain, the most heat sensitive organ in our bodies (Dewhirst, et al., 2003). Under high environmental temperatures and intense physical activity, brain temperatures can rise up to 2.5°C (Kiyatkin, 2007). Links have been established between heat and productivity in office settings (Seppänen et al., 2006), execution of complex tasks among military personnel (Fine & Kobrick, 1978; Froom et al., 1993), and a recent series of studies on learning and human capital accumulation among school-age children (Zivin et al., 2018; Park et al., 2020a; 2020b). For example, Zivin et al. (2018) find that temperature changes lead to statistically significant decreases in math scores but not reading scores, with a monotonic decline when outdoor temperatures are above 21°C. Park et al. (2020) conduct a similar study and show that cumulative heat significantly lowers test scores.

Our second channel of interest, sleep, has also been shown to be affected by higher temperatures. A recent study by Minor et al. (2020) using over 7 million night-time sleep records across 68 countries shows that rising night-time temperatures shorten sleep duration by delaying its onset, and increase the probability of insufficient sleep. These effects were substantially larger among residents of lower income countries. Additional studies show that the thermal environment is a key determinant of sleep because our bodies' thermoregulation and sleep are interrelated processes. According to Gilbert et al. (2004), “changes in temperature may trigger, either directly or indirectly, somnogenic brain areas to initiate sleep” (p. 81).

Finally, the temperature-aggression hypothesis posits that on hotter days, individuals develop more aggressive tendencies and potentially show a higher tolerance for risk. The link between higher temperatures and aggressive tendencies has been documented in multiple settings and agents from American football and baseball players (Craig et al., 2016; Krenzer & Splan, 2018), to prison inmates (Mukherjee & Sanders, 2021), university students (Almås et al., 2020), and even among court judges in the form of more punitive rulings (Heyes & Saberian, 2019).

Altogether, this body of evidence suggests that temperatures could change time and risk preferences in different directions. Both the sleep and cognition channels predict that higher
temperatures would increase risk aversion and rational choice violations. Conversely, if aggression was the operating channel, this would predict the opposite, such that higher temperatures could cause decreased risk aversion and an increase in risk-taking. All three channels are relatively unequivocal in their predicted effect on time discounting. They all predict a significant increase in impatience. That is, people would value present consumption much more than future consumption.

2.3 Temperature and Economic Preferences

In an ideal setting, temperature would have to be randomly assigned in order to measure its causal effects on economic preferences. In reality, individuals exposed to higher temperature, and those who have lower cognition, poorer sleep, and worse mood, are likely different from their counterparts. This partly explains why the empirical literature on the topic is mainly composed of studies in controlled laboratory environments. For instance, in a series of 5 lab experiments on students, Cheema & Patrick (2012) manipulate indoor temperatures to be either warm (77°F ~ 25°C) or cold (67°F ~ 20°C) and consequently vary the difficulty of the task, the depletion of resources, and the perceived level of innovation associated with a product. They provide evidence that individuals in warmer ambient temperatures are a) less likely to gamble, especially if the gamble is difficult; b) less likely to purchase innovative products; c) more likely to rely on quick, heuristic-based processing that is relatively effortless instead of relying on systematic rule-based processing; and d) more likely to perform poorly on cognitive tasks that require greater processing capabilities.

A more recent study by Almås et al. (2020) experiments on approximately 2,000 participants in Nairobi, Kenya, and California, United States in which university students were randomly assigned to either a heat treatment (30°C) or a control group (22°C). Their main outcomes of interest were economic preferences such as risk and time, as well as social behavior and cognition. After substantial first stage effects where the heat treatment significantly affected actual measured temperature, decreased alertness, and happiness among participants, the experiment results show that the main outcomes of interest were mainly unaffected. Overall there was no evidence that heat stress significantly increased risk-taking, rational choice violations, patience, or time inconsistency. The only highly significant and consistent effect

---

3 Precision, fluid intelligence and cognitive reflection.
4 The authors define each economic preference as follows, a) risk taking: participant chosen variance in outcome from a coin toss, where choosing a higher variance outcome is risk-loving; b) rational choice violation: when coin toss A is preferred to coin toss B, and B is preferred over C, but coin toss A is not preferred to coin toss C; c) patience: how one weights two future periods or time discounting; and d) time inconsistency: how one weighs the present versus the future or present bias.
of temperature across all specifications was found on destructive behavior, and these effects were context-dependent.

The experimental design of the study by Almås, et al. (2020) offers several opportunities for further work. While its biggest strength with respect to the previous literature relies on the significantly larger sample size paired with the random assignment to treatment, two key elements of their design can be improved upon. First, their sample is not representative of populations that might be of greater economic interest in developing countries. Their subjects are primarily young adults between the ages of 20 ± 2.7 years in California and 22 ± 2.4 years in Nairobi, and most have parents with a relatively high socioeconomic. A second key factor is the time and duration of exposure to treatment. Due to ethical concerns, their study was limited in terms of the level of duration of exposure to the high temperature treatment. As the authors state in their conclusion, “it is possible that different results may be achieved if subjects are exposed over a longer duration to temperatures higher than 30ºC” (p. 30). Further, if heat affects economic preferences via sleep quantity and quality, these laboratory studies, which were not setup to randomise overnight sleep temperatures, would not be able to detect such effects. Finally, the existence of only one treatment arm, and therefore the comparison of groups who were either exposed to 22ºC or 30ºC leaves a gap for the study of non-linear effects of heat on economic preferences.

3. Data

To address the question and fill these gaps, we combine two data sources on economic preferences and temperature, the IFLS and MERRA-2. First, we draw on individual-level data on time and risk preferences, as well as cognition, sleep, and mood measured in waves 4 and/or 5 of the longitudinal dataset Indonesia Family Life Survey (IFLS), collected in 2007-2008 and 2014-2015, respectively. IFLS respondents reside in more than 3800 villages across 38 provinces. This leaves us with a combined sample of approximately 50,000 observations.

Next, we obtain hourly and daily records of temperature, relative humidity, precipitation, wind speed, and particulate matter 2.5 as a measure of pollution, from NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA-2). This reanalysis dataset integrates both station and satellite data. It helps is avoid potential sources of bias, due to the extensive landmass of the Indonesian territory and the potentially endogenous location of land-based stations in more developed areas and urban centres over time. MERRA-2 provides global
environmental estimates for 0.5° x 0.625° cells (approximately 50 kms x 60 kms) at hourly and daily time scales from 1981 to 2021 (Rienecker, et al., 2011).

Using the IFLS time modules recording the hour and date in which individuals completed the relevant questionnaires, we assign climate records corresponding to their village of residence for the day and night prior to the survey, following the approach by Thiede & Gray (2020) and Sellers & Gray (2019). As shown in Appendix Figure 1, each Indonesian village is matched to the nearest MERRA-2 grid such that all individuals live within a 50-kilometre radius or less of their assigned grid. In order to decrease measurement error, we exclude observations beyond the 50-kilometre mark.

3.1 Outcomes

A. Risk Preferences. Combined, IFLS4 and IFLS5 contain data on economic preferences for 55,927 individuals, 73% of which were surveyed in both waves. Our measure of risk aversion is derived from a staircase-type instrument which consists of a series of hypothetical low- and high-stakes choices between a safe amount and a risky lottery which offers an equal probability of an $x$ times higher the safe amount or a $c$ times smaller amount. Based on their initial response, each individual is sorted into subsequent questions used to yield as detailed a measure of risk aversion as desired. As a result, individuals are sorted into five bins which provide an ordinal measure from least risk-averse to most risk-averse. Appendix Figure 2 contains a flowchart with the complete sequence of the corresponding survey items and resulting bins.

In the first question of the module, individuals are given a choice between a sure amount and a coin flip. In this gamble, they could earn the amount of the safe option or twice that value. It should be clear to participants that the profit-maximizing option is the coin flip. Nevertheless, approximately 30% and 40% of the sample in each wave, choose the safe option and refuse the gamble, even after being made aware through a follow-up prompt that the probability-based option assures them at least as much as the safe choice. A priori, it is unclear whether this choice reflects an extreme form of risk aversion, or a violation of expected utility theory (henceforth rational choice violation). Since the objective of this paper is to study whether temperature induces irrational behavior, we do not discard individuals who engage in this behavior, which has been the standard approach thus far in other studies using this dataset (Anandari & Nuryakin, 2019; Bharati, Chin, & Jung, 2015; Ng, 2013). Instead, we construct two binary measures for risk aversion, one for rational choice violations and a second one
where we exclude this 30-40\% of the sample whose choice might be considered irrational and with the resulting individuals we construct an indicator for those who show strictly risk-averse tendencies. By this definition, approximately 37\% of the restricted sample is considered risk-averse.

B. Time Preference. Our measure of impatience is derived from a similar staircase-type instrument with a series of hypothetical choices which start from 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 3 for the complete sequence of decisions). As a result, five bins are created, where the first bin measures negative time preferences and the subsequent bins range from least to most impatient. As with risk aversion, the first question 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. From the resulting bins, we construct a binary measure for myopic preferences where respondents are assigned a value of 1 if they score as most impatient and 0 otherwise. About 62\% of individuals are in the most impatient category.

C. Cognition. We restrict the main analysis of temperature and cognition to the IFLS5 sample, where all individuals ages 15-90 years old who also played the lottery games, participated in a series of tests of cognition and mathematical numeracy. Some of these items were missing in IFLS4, where only adults age 15-31 were invited to participate in the relevant cognition tests. The first item we examine 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 was designed after the test used in the Health and Retirement Study (Fisher et al., 2014) and found to be closely correlated with financial wealth (Smith, McArdle, & Willis, 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 item of interest is a date awareness and word recall module. In IFLS5, this module 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. Together a set of nine questions designed after the Telephone Interview of
Cognitive Status (Fong, et al., 2009), measure mental intactness. 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 use two additional indicators for cognition, which had previously been applied in IFLS4 but only to adults under the age of 31, namely the Raven’s Progressive Matrices, which measure non-verbal abilities, and a test for mathematical skills. In IFLS5 these two tests were then extended to the totality of the adult sample. 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 detailed in Table 1. 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 score is then standardized.

D. Sleep. The fifth wave of the IFLS survey contains a module that prompts individuals to report the time when they went to bed the night prior to the survey and the time when they woke up. Using these two variables, we construct a measure for how many hours that individual slept the night before. On average, our sample of adults went to bed at around 22:30 hours, woke up at around 5:14 am, and spent on average 6.8 hours in bed.

E. Mood. To test whether we can find a similar effect of temperature on aggressive mood as reported by Almås, et al. (2020), we extract four questions from 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, these responses which range from ‘not at all’ to ‘very’ are then coded as dummies. On average 31% of adults reported having felt angry, 45% felt tired, 58% felt enthusiastic, and 64% felt happy.

3.2 Treatment Variables

The IFLS dataset also contains detailed recordings of the hour and day when every individual’s book containing the time and risk preference modules took place. This data is used to match individuals to the outdoor temperatures recorded in MERRA-2 on the day of the survey, and the night prior. The average maximum temperature across survey dates was 28.67°C, with some individuals experiencing close to 40°C on a given survey date. We also build a variable capturing the outdoor temperature at the hour when the interview began. These temperatures span from 14°C to 38°C with a mean of 24.55°C. On average, midnights were substantially cooler
than both the maximum records the following day and, the temperature at the hour when the surveys started, with a mean of 23.64°C. These three indicators, temperature at the hour of the survey, maximum temperatures on the date of the survey, and midnight temperatures the night prior to survey, are used in the following section to provide a linear estimation of the relationship between heat and our dependent variables of interest.

4. Empirical Strategy

We take two approaches to identifying the effects of temperature on time and risk preferences. First, we exploit temporal variations in temperature caused by the random allocation of survey dates within a given province. Next, we exploit spatial variations in temperature by constructing microclimates within provinces. Combined, these approaches allow us to compare individuals within the same province and type of microclimate, whose temperatures vary only as a result of the time it took to roll-out the survey instrument. In this section, we describe in detail the technical details behind the construction of these microclimates and the main assumptions behind this approach.

One of our main identifying assumptions is that outdoor temperatures on the day of the survey and the night prior are exogenous. We argue that the differences in maximum and midnight outdoor temperatures among individuals in the same area, month and year come only from the day when they were visited by the surveyors, and by extension that the date of the survey is as good as random. Since respondents cannot manipulate outdoor temperatures or the day of their interview based on their potential outcomes, we argue this assumption holds.

Appendix Table 2 tests whether outdoor temperatures were random by regressing maximum and midnight temperatures on a set of environmental, individual, and household characteristics. As one would expect, wind speed, rainfall, pollution, and latitude are significantly correlated with temperature. Other than these main environmental controls, only age of the respondent and education of the household head appear to be weakly correlated with maximum and midnight temperatures, respectively. A test of the joint significance of the individual and household characteristics shows that jointly, they can only partially explain the outdoor

---

5 In Appendix Table 3, we show that only 19% of the respondents had the opportunity to complete the survey in more than one visit. Our main results hold even after excluding that 19% of the sample who could have potentially self-selected into different temperatures.
maximum temperatures \((p = 0.0355)\) but not midnight temperatures \((p = 0.8021)\) experienced by the individuals in our sample.

We then exploit variations in temperature within provinces to estimate the main temperature effects. We choose to use province-level rather than regency or district-level fixed effects for one fundamental reason. As Figure 1a illustrates, the rollout of the survey occurred simultaneously across all the surveyed provinces. Figure 1b shows that each province took between 150 and 350 days to complete all surveys. This provides us with some natural temporal variation in temperature within provinces, as a function of the way in which the instrument was rolled out. As we zoom into smaller administrative units within provinces, this variation in temperature shrinks substantially. The time needed to complete rolling out the instrument within a single village would be no more than a week or a couple of days.

However, a number of potential endogeneity concerns may arise if we simply compare any and all individuals within a province. Four key factors that affect temperature are altitude, latitude, distance to the sea and the level of urbanity. Each of these factors are also likely to influence economic preferences as well as individual and household-level responses to heat. Altitude, the height measured from the sea level, is negatively correlated with temperature. As altitude increases, temperature gradually falls by 1°C for every 100 meters. At the same time, altitude has been found to be correlated with low socio-economic status and poor physical health (Giussani et al., 2001). Both are likely limit one’s preference towards risk and shorten an individual’s time horizon. Latitude, or distance to the equator, causes temperatures to drop the further away from the equator. While latitude influences climate, it has also been found to affect economic output (Hall & Jones, 1999), settlement patterns, and even disease environment (Mellinger, Sachs, & Gallup, 2000), all of which could be linked to economic preferences.

Distance to the sea has a positive relationship with temperature. As the former increases, the latter also rises. This factor raises several endogeneity concerns. Individuals living closer to the coast often have very different wealth profiles than those further inland. The former could be wealthier, which would affect their adaptation strategies to heat, such as ownership of air-conditioners. At the same time, financial constraints and wealth could influence an individual’s response to the time and risk lotteries, with budget constrained individuals potentially choosing less risky gambles and showing higher discount rates. Finally, the level of urbanity of the spatial unit of residence can cause what is now known as the ‘urban heat island effect’. This
occurs when “cities replace natural land cover with dense concentrations of pavement, buildings, and other surfaces that absorb and retain heat” (EPA, 2021). Simultaneously, residents of urban areas are likely to have very different risk profiles than rural residents and therefore, a different tolerance towards risk.

We address these concerns by creating smaller sub-groups within provinces. These microclimates are the result of interacting a binary indicator of the village’s urban or rural status, four altitude groups (<50 meters, 50-100 meters, 100-500 meters, 500+ meters), and three distance-to-the-coast groups (<30 km, 30-60 kms, 60+ kms). The map in Figure 2 provides an example of the resulting groups in the province of North Sumatra, which contains 19 smaller bins. Elevation is drawn in the background. Figure 3 then plots the resulting within-bin variation in maximum temperatures on the day of the survey, the hour when the survey began, and the midnight prior to the survey. It shows that after performing this reduction by microclimates within provinces, there is still enough variation left for the estimation of our preferred specification.

The resulting 285 bins are used as area fixed effects in the following basic regression form:

\[ Y_{ipbt} = \alpha + \beta \text{temperature}_{ipvt} + \lambda_{ipvt} + X_{ipbt} + \rho_m + \tau_y + \phi_b + \epsilon_{ipbt} \]  (1)

where \( Y_{ipbt} \) is the outcome variable of interest (economic preferences, cognition, sleep, and mood) of individual \( i \), residing in province \( p \), and urban-altitude-distance bin \( b \) in time \( t \). Parameters \( \lambda_{ipvt} \) and \( X_{ipbt} \) are vectors of covariates that include village latitude and environmental controls for precipitation, wind speed, and particulate matter 2.5 in province \( p \) and village \( v \), as well as individual and household-level characteristics such as age, gender, marital status, religion, religiosity, 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 members in the house, day of the week, and hour when the interview began.

Temperature treatment is a set of parametric indicators of maximum, midnight and average temperature at the hour when the survey began measured on village \( v \) and time \( t \). Finally, \( \rho_m \), \( \tau_y \), and \( \phi_b \), are a set of month, year and province-urban-altitude-distance to coast fixed effects, respectively. Using month fixed effects allow us to control for potential seasonal patterns and festivities that could affect exposure to heat, cognition, sleep and economic preferences. Year
fixed effects allow us to control for broader climatic changes between 2007 and 2015, the years where the survey waves were rolled out. We cluster standard errors by village, the level of variation in our treatment variable (Abadie et al., 2017).

We also consider the possibility that any potential effects could be of a non-linear shape. 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 >).

5. Results

5.1 Preferences and Economic Outcomes

In the following section, we validate our measures of rational choice violations, risk aversion, and impatience by studying the correlation between them and individual behaviors which the economic literature associates with long-run development. Following the approach of Falk et al. (2018) used to validate the measures obtained in the Global Preference Survey (GPS), we create two groups of outcomes, namely accumulation decisions and risky choices. Next, we regress these outcomes on either impatience, risk aversion, or the probability of making rational choice violations in a variation of equation (1):

\[ Y_{ipbt} = \alpha + \delta_{\text{preference}_{ipvt}} + \lambda_{ipvt} + \chi_{ipbt} + \rho_{m} + \tau_{y} + \phi_{b} + \epsilon_{ipbt} \]  

(2)

where \( Y_{ipbt} \) are accumulation decisions or risky choices of individual \( i \) of province \( p \) and bin \( b \) at time \( t \). As Falk et al. (2018) indicate, economic theory relates patience with the ability of individuals to save and invest in education 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, thus considered myopic or very impatient, she might not want to save. In columns 1 and 2 of Table 2 we show that indeed, for our sample of IFLS respondents, impatience is correlated with a 3-percentage point reduction in the probability of saving and an 8.8 percentage point decrease in the probability of achieving secondary education or higher.

Next, we investigate whether rational choice violations and risk aversion are significantly different for risky choices such as being self-employed, planning to open a business, and using tobacco. All of these are behaviors associated with a higher preference for risk (Cameron & Shah, 2015). 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. Although
statistically insignificant, both are less likely to use tobacco, and conditional on smoking, both consume a significantly lower number of cigarettes. By including both measures in the models, we show that rational choice violations capture an intangible property that is highly correlated with risk aversion. This justifies our choice to keep those who make rational choice violations in our main investigation of heat effects.

Another possibility is that rational choice violations are partly capturing a form of impatience. However, a correlation matrix shows that the correlation coefficient between rational choice violations and impatience is low, only 0.2787. Appendix Table 1 further investigates the characteristics associated with individuals who make rational choice violations, are risk averse, and impatient. The estimates show that some key characteristics of impatient individuals and those who make rational choice violations are different. For instance, women are significantly more likely to make rational choice violations but are less impatient. Impatience has an inverted u-shape relationship with age whereas age and rational choice violations are not correlated. Individuals who make rational choice violations were significantly more likely to be unemployed, while employment status was not significantly correlated with impatience.

However, impatient individuals and those who make rational choice violations share two key characteristics: they are both significantly less likely to have secondary schooling, and they have significantly lower cognitive scores. Altogether this suggests that qualitatively, individuals who make rational choice violations and impatient ones are different but both sets of preferences are shaped by an individual’s cognitive skill set. In contrast, being risk-averse is not significantly correlated with cognition in our sample. If cognition is indeed the dominant mediating channel between temperature and economic preferences, this would predict significant temperature effects on rational choice violations and impatience, but not on risk-aversion.

5.2 Temperature Effects on Time and Risk Aversion

In this section, we present the main results from estimating equation (1). Table 3 shows estimates of the linear effects of maximum temperatures on the day of the survey (Panel A), the temperature at the hour when the survey began (Panel B), and midnight temperature on the night before the survey (Panel C). The model in Panel D then tries to determine which of the

---

6 Although maximum and midnight temperatures are positively correlated, the models in panel D can be successfully estimated and the relative contribution of each can be disentangled because the level of correlation
two treatment variables with the highest effect is dominant. For all outcomes, we then model non-linear temperature effects in Figure 4.

In regards to risk preferences, our estimated results suggest that higher a temperature, regardless of how it is measured, does not have a statistically significant effect on the likelihood of being risk-averse (column 1). These results are consistent with the findings of Almås, et al. (2020) obtained in a laboratory-controlled environment. However, when we include in our sample the 30% to 40% of individuals who exhibit rational choice violations (column 2), we find that each additional degree of temperature on the day of the survey increases the likelihood of making a rational choice violation by 0.3 to 0.7 percentage points, both statistically significant at 5% and 1% level. We find even higher effects when instead, we use temperature on the midnight before the survey, with every 1°C increasing rational choice violations by 1 percentage point. This effect is equivalent to one-third of the gender gap in Appendix Table 1.

Since these three measures of temperature are positively correlated, in Panel D we re-estimate the previous model using both maximum temperature on the day of the survey and midnight temperature. These two temperature measures have the lowest correlation coefficients, which allows us to avoid issues with multicollinearity. The results show that the maximum temperature coefficients shrink and lose statistical significance, while midnight temperatures become completely dominant. Re-estimating these effects by temperature bins, Figure 4 shows an increasing and quasi-linear response to temperature, with a monotonic increase in rational choice violations when outdoor midnight temperatures are above 23°C.

Turning to time preferences (column 3), we observe similar temperature effects as those found on rational choice violations. When we estimate this model with maximum temperatures during the day of the survey and temperatures at the hour when the survey began, our results show that each additional degree Celsius increases an individual’s likelihood of being impatient by 0.4 percentage points on average (both significant at 5%). Each additional degree of midnight temperature increases impatience by more than twice that effect, 0.9 percentage points. This effect is larger than that of an additional year of age on impatience (0.8 pp). We then regress impatience on both maximum temperature and temperature at midnight, and our findings show that again, the latter completely dominates maximum temperature just as we observed in models of rational choice violations. Exploring the shape of this relationship in the last panel between these two variables is smaller (approximately 0.35) in the larger provinces with more residents, where most of our observations are concentrated.
of Figure 4 shows a linear and increasing effect of midnight temperatures on impatience, statistically significant from the 22°C mark. This is consistent with Zivin et al. (2018) who find significant declines in math performance above 21°C.

In Table 4, we test the robustness of these findings to alternative specifications. In columns 1 and 4, we test the sensitivity of our results to the inclusion of humidity as a linear control. The concern being that we might be confounding the effects of temperature for those of humidity by not including both in the specification. In columns 2 and 5 we include controls for longitude, a geographic coordinate that specifies the east-west position in reference to the prime meridian and which has also been found to be correlated with temperature. Finally, in columns 3 and 6 we include interviewer fixed effects to our original specification, to account for the possibility that interviewers might have an influence in a) the timing of the survey, b) the prompting of interviewees to switch choices in the lottery games, and c) that interviewers themselves could be affected by heat. Our results remain stable in all three alternative specifications.

5.3 Temperature Effects on Cognition

In light of the previous findings, the next logical question is why are night-time temperatures having such a stark effect on rational choice violations and impatience. In this section we will explore three potential mechanisms: cognition, sleep, and mood.

In their paper on the Global Preference Survey, Falk et al. (2018) use self-reported math skills as a proxy for cognitive skills and find that cognition is positively correlated with patience, and risk-taking. Indeed, when individuals are faced with a set of tasks and options for which they need to perform mathematical calculations, doing so is cognitively demanding and implies that the individual has a certain stock of cognitive skills to trigger this process. We propose that if cognitive functioning and numerical skills, in particular, are depleted by prolonged exposure to high temperature as demonstrated by Zivin et al. (2018) and Park et al. (2020), individuals will default to the apparently safest option and not the optimal one, which theory suggests is engaging in the gamble and choosing the higher albeit later payment.

Our cognition estimates in IFLS5, measure different levels of cognitive functioning, namely fluid intelligence, mental intactness, non-verbal ability, and mathematical skills for individuals between the ages of 15 and 90 years old. This allows us to test whether such functions which have been previously associated with economic preferences, like math skills, are more or less affected by night-time heat. Panel A of Table 5 shows the results of this exercise. Each
additional degree of midnight temperature prior to the survey, significantly reduces global cognitive scores by 1.6% of a standard deviation. The bulk of this effect comes from a decrease of 1.6% of a standard deviation on the fluid intelligence score, a 2% of a standard deviation drop in non-verbal ability measured by the Progressive Raven’s Matrices, and a drop of 1.3% of a standard deviation in math scores for each additional degree of midnight temperatures.

Consistent with our previous findings for rational choice violations and impatience, Appendix Figure 4a shows that these effects start to manifest above 22-23°C of midnight temperatures. Next, in Appendix Figure 4b we show that these effects are widely homogeneous, with no statistically significant differences by age, gender, schooling or consumption. However, we can observe that the estimated effects of temperature on all forms of cognition are substantially larger for individuals in the bottom half of the consumption distribution. This is remarkably consistent with the heterogeneous treatment effects discussed in Section 5.6.

In Appendix Table 4, we then utilise the cognition data collected in IFLS4 which was only obtained from a restricted portion of the total sample, adults age 15-31 in 2007/2008 (column 1). In column 2, we provide comparable estimates for the sample age 15-31 in IFLS5, and column 3 presents the estimates for the full sample surveyed in IFLS5 for comparison. Altogether, these estimates show that the temperature effects are substantially higher for the sample surveyed in IFLS4; with every additional degree of night-time temperature decreasing math scores by 3.9% of a standard deviation. This is significantly larger than the 1.3% of a standard deviation drop for the full IFLS5 sample which combines young and older individuals.

5.4 Temperature Effects on Sleep

The previous findings suggest that there is a pattern, where night-time temperatures are negatively affecting both economic preferences and cognitive functioning of a large sample of Indonesian adults. A potential explanation behind this link could be that poor sleep is depleting cognition, which in turn is affecting economic preferences. To further investigate whether this might be the case, we extend equation (1) and change our dependent variable to sleep onset (the time when individuals went to bed), sleep offset (the time when individuals woke up), and the subtraction of these two which produces a measure of how many hours an individual spent in bed. Our findings in Panel B of Table 5 do not allow us to confirm this hypothesis as the

---

7 We know based on the results in Appendix Table 1, that for every 1-standard deviation drop in cognition, rational choice violations increase by 5.3 pp and impatience increases by 5.5 pp.
reported coefficients in Panel B are economically small and statistically insignificant. We must note however, that the main caveat of these self-reported measures of sleep is that they fail to capture sleep efficiency, the percentage of time asleep in relation to time spent in bed. More accurate measures of sleep quality should be used to further investigate this hypothesis.

5.5 Temperature Effects on Mood

Our third and final potential mechanism is mood. Previous studies have shown that exposure to high temperatures can cause extreme responses such as violent acts of aggression. As mentioned earlier, these findings are relevant to our study because aggression is positively correlated with risk-taking behavior (Deffenbacher et al., 2003; Arnett, Offer, & Fine, 1997). According to this hypothesis, on hotter days individuals would develop more aggressive tendencies and potentially show a higher tolerance for risk and become more impatient. Observe that, in contrast to the sleep and cognition channels, this would suggest that higher temperatures should decrease rational choice violations and risk aversion. This is the opposite of what we find in Table 3. In panel C of Table 5, we find that midnight temperatures prior to the survey do not have a significant effect on the likelihood of feeling anger, tiredness, happiness, or enthusiasm. Thus far these findings suggest that it is cognition and not anger or sleep, the most likely and dominating channel through which temperatures, night-time temperatures in particular, are affecting rational choices and impatience.

5.6 Effect Heterogeneity

Next, we explore whether the effects of temperature on economic preferences and cognition vary systematically by individual characteristics such as gender, age, and socioeconomic status as defined by one’s level of education and consumption. As Figure 5 shows, temperature effects on risk, rational choice violations and impatience are not statistically different by gender or age group. We then decompose the effects of temperature on economic preferences using two proxies for socio-economic status, an individual’s level of education, and their wealth as defined by their OECD-equivalised consumption expenditure. Since it is plausible that individuals with a lower SES could be less able to protect themselves from the scourge of high temperatures, both during the day and at night, we expect a significant and positive response in this decomposition. Figure 5 shows that indeed, individuals with primary schooling or lower, experience higher midnight temperature effects on rational choice violations than individuals with at least one year of secondary education. This difference is statistically significant \( p = \)
We also find that individuals in the bottom half of the consumption expenditure distribution are significantly more likely to make rational choice violations \((p = 0.099)\) and be impatient \((p = 0.074)\) than the wealthier half, as a result of high night-time temperatures. These results suggest that the economic preferences of the poor are on average made less optimal by temperature than the preferences of the wealthy.

### 5.7 Cumulative Effects

In this section, we consider the possibility that the estimated effects reported in Table 3 of are the result of build-up over several nights of intense heat. In Table 6, we explore whether repeated nights of high temperatures could be having a cumulative effect leading to a larger depletion of cognitive skills, sleep, mood, and economic preferences, than what a single night of high temperatures could cause. This must necessarily be the cause. The human body could adapt to high night-time temperatures as these become more frequent, as long as these do not exceed the upper threshold of human adaptability (Raymond, et al., 2020).

In Table 6, we test if such effects exist by regressing our main outcomes of interest on the number of nights above 25°C of night-time temperature in the past 7 days. The choice of this threshold is based on the results of Figure 4 which shows a strictly increasing effect above this point. This is also supported by the findings of Minor et al. (2020) showing that night-time minimum temperatures above 25°C significantly increase the probability of getting less than 7 hours of sleep by delaying sleep onset and advancing sleep offset. We then interact a dummy for temperatures above 25°C on the night prior to survey and the number of nights in the past seven days. This allows last night’s temperature to have an effect that could be higher or lower depending on the number of nights in the past week that were also hot.

The estimates in column 1 suggest that both midnight temperature the night prior to the survey, and the cumulative number of hot nights during the past week increase rational choice violations, however their interaction does not. We observe a similar effect for impatience (column 2), where our binary estimate for midnight temperatures above 25°C becomes statistically insignificant, and every night of intense heat in the past week significantly increases impatience by 0.5 percentage points. Thereafter, we only find significant effects of temperature the night prior on math z-scores. In line with the results in Table 5, we find no cumulative effects of temperature on sleep.
5.8 Robustness Checks

In the final section of this paper, we perform several additional robustness checks and placebo tests to examine whether our main results hold under different sample exclusions and the inclusion of further controls. In Appendix Table 3, we repeat the estimates in Table 3 but now include all three relevant measures of temperature in Panel D. We do this to determine the dominance of each measure. The effects of the midnight temperature are comparable to temperature on the hour of the survey in determining the likelihood of making rational choice violations. However, midnight temperatures completely dominate in models of impatience. Further, it is worth noting that our preferred estimates in Table 3, ideally contain the temperature measures with the lowest correlation coefficients, to avoid concerns regarding multicollinearity.

Next, in columns 2 and 5 we test the stability of our results to the inclusion of controls for individuals who were surveyed during Ramadan. During this period, those who observe the mandate would normally change their eating and sleeping patterns. Typically, this time is also characterized by high temperatures. The concern would therefore be, that we are confounding the effect of Ramadan on economic preferences and attributing it solely to high temperatures. Only 1.6% of our sample was surveyed during Ramadan so this is unlikely to be a significant determinant of our results. Nevertheless, we test this and the results show that adding controls for whether or not the surveys occurred during Ramadan has no effect on the magnitude or significance of our original estimates.

Then, we revisit the main assumption behind our empirical strategy, i.e. that temperatures are exogenous because survey dates are as good as random. In columns 3 and 6, we check the stability of our coefficients when we exclude those adults who were visited more than once to complete the module where the time and risk aversion questions are asked. More than one visit could give individuals or even the interviewer, an opportunity to choose a cooler day or a cooler hour, and this choice could be correlated with their cognitive skills and economic preferences thus biasing our results. As the coefficients show, this does not appear to be the case, such that even after excluding the 19% of the sample with more than one visit, the results remain stable.

Finally, we perform a placebo test using future temperatures. In Appendix Table 5 we add to our original equation (1) the maximum temperature of the same day but two weeks later. Being in the future, this variable should have no statistically or economically significant effect on any
of our dependent variables as long as current and future temperatures are not perfectly or very highly correlated. The results Appendix Table 5 corroborate this, such that our estimates for midnight temperatures remain stable and the effects of future temperature on rational choice violations, and impatience are close to zero and statistically insignificant.

6. Discussion

Using longitudinal data eliciting economic preferences, in combination with climate records from NASA’s MERRA-2 dataset, we study the links between temperature and time and risk preferences. Employing a rich set of province-urban-altitude-distance to coast and time fixed effects, paired with exogenous variations in temperatures caused by the random allocation of survey dates, we design an approach which allows us to provide some of the first causal non-laboratory evidence linking high temperatures, impatience and rational choice violations elicited by lottery games.

The evidence in this study shows that higher temperatures on the day and the night prior to the survey, significantly increase the likelihood of making rational choice violations and being impatient. Further, we show that when included simultaneously in the same regression, night-time temperatures entirely dominate maximum temperatures. Next, we demonstrate that these deleterious night-time temperature effects are quasi-linear in nature and increasing above 22°C. We also show that night-time temperatures significantly reduce cognitive scores, mathematical skills in particular. Finally, we provide evidence in support of a model of cumulative heat effects, such that multiple nights of intense heat lead to substantially higher rational choice violations and impatience.

Altogether, these findings indicate that heat-induced night-time disturbances appear to cause stress on critical parts of the brain, leading to significantly lower cognitive functions following day. These lower cognitive skills in turn, prevent individuals from engaging their system 2 processes and performing economically rational decision-making. As Cheema & Patrick (2012) suggest, it appears as though the physical and psychological stress that prolonged exposure to heat imposes upon individuals, leads them to rely more often on intuition and lower-level processing, also known as system 1, as critical functions housed in more heat-affected parts of the brain suffer. This, in turn, is reflected in a substantial increase in sup-optimal economic preferences such as rational choice violations and impatience, where theory would suggest that the opposite is wealth and utility maximizing.
Our decomposition of temperature effects by gender, age, and socio-economic status suggests that adults with lower schooling are significantly more disadvantaged by heat than individuals with higher schooling, becoming more likely to make rational choice violations with every additional degree of night-time temperature. This is further reinforced in our decomposition by wealth, where individuals in the bottom half of the consumption expenditure distribution become more likely to make rational choice violations and impatient as night-time temperatures rise. A similar pattern is observed for cognitive scores which are on average lower for adults in the bottom half of the consumption distribution as a result of rising night-time heat. We argue that these findings build on the work by Schilbach et al. (2016) and Mani et al. (2013), in showing that thermal stress, especially at night, decreases an individual’s bandwidth the following day. This in turn affects important decision-making tied to their future well-being.

Further, there are reasons to believe that on a wider scale, the effects of rising temperatures on suboptimal decision-making will not be spread evenly. These effects are especially likely to differ between low- and high-income households and between developed and developing countries. One of the most relevant defining factors will likely be their different abilities to adapt to higher temperatures. If in fact, people in low- and middle-income countries and in low-income households are more vulnerable to higher temperatures due to their restricted ability to cool their dwellings, our findings predict that we should expect larger impacts of heat on suboptimal economic behaviors in those settings. Greater macroeconomic and household wealth mean that air-conditioning coverage across the developed world is becoming widespread in homes, office spaces, and even in public transport so individuals in wealthier nations can, to a large extent, 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 however, the financial and infrastructural capacity to deal with high temperatures is significantly lower. Dwellings need to be connected to a power grid to begin with, yet 13% of the world does not have access to electricity (World Bank, 2021). In addition, the energy infrastructure must be able to cope with the demands that high energy use imposes on the system. Finally, households need to have the purchasing power to acquire air-conditioning units. They also need to be able to pay the electricity bills from using fans and air-conditioners. Yet, just 8% of the 2.8 billion people living in the hottest parts of the world
own air conditioning units (IEA, 2018). Further, families in low-cost dwellings will likely be especially vulnerable, as their houses tend to be built with materials that store heat rather than insulate their inhabitants from it (Naicker, et al., 2017). As this occurs, we need to pay further attention to how the poor make critical investment decisions and risky choices associated with economic development, and whether or not these are systematically less optimal in regions of the world that are heating up faster.

Finally, the findings presented in this study also have implications for households which already are in possession of cooling mechanisms, which could attenuate the effects of temperature on decision-making. Our findings suggest that households should allocate their cooling budget, time- and money-wise, during the night hours. In theory, if our findings had indicated that there are higher impacts on preferences during the day, the cost of cooling could be absorbed by the employer, conditional on individuals spending most of the daytime hours at work. However, our findings clearly show that the strongest effects are caused by high night-time temperatures. This indicates that the cost of coping with the rising night-time temperatures would have to be borne entirely by the household, where wealthier ones who can afford higher electricity bills, would fare significantly better off. This could further increase the existing inequalities between the wealthy and the poor.
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

Allen, M. R., Dube, O. P., Solecki, W., Aragón-Durand, F., Cramer, W., Humphreys, S., . . . Zickfeld, K. (2018). Global Warming of 1.5°C: An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change. In V. Masson-Delmotte, P. Zhai, H. -O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, . . . T. Waterfield (Eds.), *Framing and Context*. IPCC.

Almás, 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

Anandari, A., & Nuryakin, C. (2019). The effect of risk preferences on choice between public and private sector employment in Indonesia. *International Journal of Business and Society*, 20(S1), 177-196.

Anderson, C. A. (1989). Temperature and Aggression: Ubiquitous Effects of Heat on Occurrence of Human Violence. *Psychological Bulletin, 106*(1), 74-96. doi:https://doi.org/10.1037/0033-2909.106.1.74

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

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

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:10.1136/bmj.c2220

Barreca, A., Clay, K., Deschênes, 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/10.1086/668458

Basu, R., Gavin, L., Pearson, D., Ebisu, K., & Malig, B. (2018). Examining the Association Between Apparent Temperature and Mental Health-Related Emergency Room Visits in California. *American Journal of Epidemiology, 187*(4), 726-735. doi:10.1093/aje/kwx295

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., Schildbach, 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

Bharati, T., Chin, S., & Jung, D. (2015). Does education affect time preference? *USC-INET Research Paper No. 17-09*. doi:http://dx.doi.org/10.2139/ssrn.2880879
Binswanger, H. P. (1980). Attitudes toward Risk: Experimental Measurement in Rural India. *American Journal of Agricultural Economics, 62*(3), 395-407. doi:10.2307/1240194

Binswanger, H. P. (1981, December). Attitudes toward Risk: Theoretical Implications of an Experiment in Rural India. *The Economic Journal, 91*(364), 867-890. doi:10.2307/2232497

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature, 527*, 235–239. doi:10.1038/nature15725

Busse, M. R., Pope, D. G., Pope, J. C., & Silva-Risso, J. (2015). The Psychological Effect of Weather on Car Purchases. *The 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

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

Cao, M., & Wei, J. (2005). Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance, 29*, 1559-1573. doi:10.1016/j.jbankfin.2004.06.028

Cardenas, J. C., & Carpenter, J. (2013, July). Risk attitudes and economic well-being in Latin America. *Journal of Development Economics, 103*, 52-61. doi:https://doi.org/10.1016/j.jdeveco.2013.01.008

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

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.js hs.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

Deak, M. C., & Stickgold, R. (2010). Sleep and cognition. *Wiley Interdiscip Rev Cogn Sci., 1*(4), 491-500. doi:10.1002/wcs.52

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

Dell, M., Jones, B. F., & Olken, B. A. (2009). Temperature and Income: Reconciling New Cross-Sectional and Panel Estimates. *American Economic Review: Papers & Proceedings, 99*(2), 198–204. doi:http://www.aeaweb.org/articles.php?doi=10.1257/aer.99.2.198

Dell, M., Jones, F. B., & Olken, B. A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics, 4*(3). doi:http://dx.doi.org/10.1257/mac.4.3.66

Dewhurst, M. W., Viglianti, V. L., Lora-Michiels, M., Hanson, M., & Hoopes, P. J. (2003). Basic principles of thermal dosimetry and thermal thresholds for tissue damage from hyperthermia. *Int J Hyperthermia, 19*(3), 267-294. doi:10.1080/0265673031000119006
Drummond, S. P., Brown, G. G., Stricker, J. L., Buxton, R. B., Wong, E. C., & Gillin, J. C. (1999). Sleep deprivation-induced reduction in cortical functional response to serial subtraction. *NeuroReport, 10*(18), 3745-3748. doi:https://doi.org/10.1097/00001756-199912160-00004

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. *The Quarterly Journal of Economics, 133*(4), 1645-1692. doi:10.1093/qje/qjy013

Fine, B. J., & Kobrick, J. L. (1978). Effects of Altitude and Heat on Complex Cognitive Tasks. *Human Factors: Journal of Human Factors and Ergonomics Society, 20*(1), 115-122. doi:https://doi.org/10.1177/001872087802001115

Fisher, G. G., McArdle, J. J., McCammon, R. J., Sonnega, A., & Weir, D. R. (2014). New measures of fluid intelligence in the HRS: Quantitative reasoning, verbal reasoning, verbal fluency. *HRS Documentation Report DR-027*. Ann Arbor, MI: Survey Research Center, University of Michigan.

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

Froom, P., Caine, Y., Shochat, I., & Ribak, J. (1993). Heat stress and helicopter pilot errors. *Journal of Occupational and Environmental Medicine, 35*(7), 720-732. doi:https://doi.org/10.1097/00043764-199307000-00016

Gilbert, S. S., van den Heuvel, C. J., Ferguson, S. A., & Dawson, D. (2004). Thermoregulation as a sleep signalling system. *Sleep Medicine Reviews, 8*(2), 81–93. doi:https://doi.org/10.1016/S1087-0792(03)00023-6

Giussani, D. A., Phillips, P. S., Anstee, S., & Barker, D. J. (2001). Effects of Altitude versus Economic Status on Birth Weight and Body Shape at Birth. *Pediatric Research, 4*, 490-494. doi:https://doi.org/10.1203/00006450-200104000-00009

Hall, R. E., & Jones, C. I. (1999). Why do Some Countries Produce So Much More Output Per Worker than Others? *The 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

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

IEA. (2018). *The Future of Cooling*. Paris: International Energy Agency. Retrieved from https://www.iea.org/reports/the-future-of-cooling

IPCC. (2014). *IPCC Climate Change 2014: Synthesis Report*. IPCC. eds Core Writing Team; Pachauri, Rajendra K.; Meyer, Leo.
Kihlstrom, R. E., & Laffont, J.-J. (1979). A General Equilibrium Entrepreneurial Theory of Firm Formation Based on Risk Aversion. *Journal of Political Economy, 87*(4), 719-748. doi:https://www.jstor.org/stable/1831005

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

Kiyatkin, E. A. (2007). Brain temperature fluctuations during physiological and pathological conditions. *Eur J Appl Physiol, 101*, 3-17. doi:10.1007/s00421-007-0450-7

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

Lawrence, N. S., Jollant, F., O'Daly, O., Zelaya, F., & Philips, M. L. (2009). Distinct roles of prefrontal cortical subregions in the Iowa Gambling Task. *Cerebral Cortex, 19*(5), 1134–1143. doi:https://doi.org/10.1093/cercor/bhn154

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

Liu, E. M. (2013, October). Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China. *The Review of Economics and Statistics, 95*(4), 1386-1403. doi:https://doi.org/10.1162/REST_a_00295

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.

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

Mosley, P., & Verschoor, A. (2005). Risk Attitudes and the ‘Vicious Circle of Poverty’. *The European Journal of Development Research, 17*(1), 59-88. doi:10.1080/09578810500066548

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

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

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

Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., & Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change, 11*, 306–312. doi:https://doi.org/10.1038/s41558-021-01000-1

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

Porcelli, A. J., & Delgado, M. R. (2009). Acute stress modulates risk taking in financial decision making. *Psychological Science, 20*(3), 278-283.

Raymond, C., Matthews, T., & Horton, R. M. (2020, May). The emergence of heat and humidity too severe for human tolerance. *Science Advances, 6*(19), 1-8. doi:10.1126/sciadv.aaw1838

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 Economic Review: Papers & Proceedings, 106*(5), 435-440. doi:http://dx.doi.org/10.1257/aer.p20161101

Sellers, S., & Gray, C. (2019). Climate shocks constrain human fertility in Indonesia. *World Development, 117*, 357-369. doi:https://doi.org/10.1016/j.worlddev.2019.02.003

Seppänen, O., Fisk, W. J., & Lei-Gomez, Q. (2006). Effect of temperature on task performance in office environment. *5th International Conference on Cold Climate Heating, Ventilating and Air Conditioning* (pp. 3-11). Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley, CA (US).

Smith, J. P., McArdle, J. J., & Willis, R. (2010). Financial Decision Making and Cognition in a Family Context. *The Economic Journal, 120*(548), F363-F380. doi:https://doi.org/10.1111/j.1468-0297.2010.02394.x

Stigler, G. J., & Becker, G. S. (1977). De Gustibus Non Est Disputandum. *The 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.
Syndicus, M., Wiese, B. S., & van Treeck, C. (2018). In the heat and noise of the moment: Effects on risky decision making. *Environment and Behavior, 50*(1), 3-27. doi:https://doi.org/10.1177/0013916516680700

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review, 100*(1), 557-571. doi:10.1257/aer.100.1.557

Thiede, B. C., & Gray, C. (2020). Climate exposures and child undernutrition: Evidence from Indonesia. *Social Science & Medicine, 265*(113298). doi:https://doi.org/10.1016/j.socscimed.2020.113298

Van Dongen, H. P., Maislin, G., Mullington, J. M., & Dinges, D. F. (2003). The cumulative cost of additional wakefulness: Dose-response effects of neurobehavioral functions and sleep physiology from chronic sleep restriction and total sleep deprivation. *Sleep, 26*(2), 117 - 126.

Vartanian, O., Bouak, F., Caldwell, J. L., Cheung, B., Cupchik, G., Jobidon, M.-E., . . . Smith, I. (2014). The effects of a single night of sleep deprivation on fluency and prefrontal cortex function during divergent thinking. *Frontiers in Human Neuroscience, 8*(214). doi:http://dx.doi.org/10.3389/fnhum.2014.00214

Wang, X. (2017, May). 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

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.** Survey rollout in IFLS5 by province

Notes: The above figure shows cumulative frequencies of individuals surveyed in IFLS5 between the last quarter of 2014 and the last quarter of 2015 by province (Left), and the cumulative distribution of the number of days required to complete all surveys in IFLS5 by province (Right). The smallest provinces with few surveys such as Aceh and Bali were omitted from the graph.
**Figure 2.** Map of IFLS villages in North Sumatra by bins used for fixed effects

**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 2 levels of rurality, 4 altitude groups (meters) and 3 distance to the coast groups (kilometres) resulting in 19 sub-groups for this province.
Figure 3. Within Bin Temperature Variation

Notes: The above figure shows the Kernel Epanechnikov density functions of maximum temperature on the day of the survey, at the hour when the surveys began and on the midnight prior to the survey, using a bandwidth of 0.1688. The with-in bin variation is the result of subtracting from each individual’s measure of temperature, the average temperature in their corresponding bin.
Figure 4. Nonlinear effects of midnight temperatures 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 equivalised 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**                      |                                                                              |       |      |
| Cognition Z-Score                       | PCA score of Fluid Intelligence, TICS, Raven's Matrix and Math               | 0     | 1    |
| Fluid Intelligence Z-Score              | Standardized constructed w-abil scores for fluid intelligence available in IFLS5 only | 0     | 1    |
| TICS Z-Score                            | Standardized scores of mental intactness using questions from the TICs available in IFLS4 and IFLS5 | 0     | 1    |
| Raven's Matrix Z-Score                  | Standardized score of % of correct answers to Raven's Matrix exercises available in IFLS4 and IFLS5 | 0     | 1    |
| Math Z-Score                            | Standardized score of % of correct answers to math exercises available in IFLS4 and IFLS5 | 0     | 1    |
| Sleep Onset                             | Time when individuals went to bed the night before the survey                | 22.32 | 1.75 |
| Sleep Offset                            | Time when individuals woke up the next day                                   | 5.12  | 1.56 |
| Time in Bed                             | Total hours an individual spent in bed (sleep offset - sleep onset)          | 6.8   | 1.88 |
| Angry                                   | Binary indicator for a person who felt a little, somewhat, quite a bit or very angry yesterday | 0.31  | 0.46 |
| Tired                                   | Binary indicator for a person who felt somewhat, quite a bit or very tired yesterday | 0.45  | 0.50 |
| 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 most risk averse, rational choice violation, and most impatient use the combined IFLS4 + IFLS5 sample. All sleep, cognition and mood outcomes use exclusively IFLS5 data.
|                          | Accumulation decisions | Risky Choices |
|--------------------------|------------------------|---------------|
|                          | Savings (1)            | Self Employed (3) |
| Impatience               | -0.030***              | -0.013***     |
|                          | (0.004)                | (0.005)       |
| Risk Aversion            | -0.088***              | -0.010***     |
|                          | (0.004)                | (0.003)       |
| Rational Choice Violation| 0.005                  | -0.011***     |
|                          | (0.004)                | (0.003)       |
| Outcome Mean             | 0.21                   | 0.27          |
|                          | 0.48                   | 0.07          |
| Observations             | 38,463                 | 51,778        |
|                          | 52,432                 | 49,190        |
|                          | 16,227                 |               |

Notes: Robust standard errors clustered on village level are in parentheses * p<0.1; ** p<0.05; *** p<0.01. 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.
Table 3. Linear Effects of Temperature on Time and Risk Preferences

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

Bin FE: Y
Month FE: Y
Year FE: Y
Latitude: Y
Pollution, Rain & Wind: Y

Notes: Robust standard errors clustered on village level are in parentheses * p<0.1; ** p<0.05; *** p<0.01. 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.
| Panel A | Rational Choice Violation | Impatience |
|---------|---------------------------|------------|
|         | (1) | (2) | (3) | (4) | (5) | (6) |
| Max Temperature on Day of Survey (°C) | 0.003** | 0.003* | 0.002 | 0.004** | 0.003** | 0.001 |
|         | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) | (0.002) |
| Temperature during hour of survey (°C) | 0.007*** | 0.006*** | 0.004*** | 0.004** | 0.003** | 0.001 |
|         | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) | (0.002) |
| Midnight Temperature Yesterday (°C) | 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 (°C) | 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 (°C) | 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 |
| Bin FE | Y | Y | Y | Y | Y | Y |
| Month FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Latitude | Y | Y | Y | Y | Y | Y |
| Pollution, Rain & Wind | Y | Y | Y | Y | Y | Y |
| Humidity | Y | | | | | |
| Longitude | Y | | | | | |
| Interviewer FE | | | | | Y | Y |

**Notes:** Robust standard errors clustered on village level are in parentheses * p<0.1; ** p<0.05; *** p<0.01. 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.
### Table 5. Potential mechanisms behind temperature effects

| Outcomes                  | Midnight Temperature Yesterday/Before Yesterday (ºC) | IFLS5 (1) | Outcome Mean (2) |
|---------------------------|--------------------------------------------------------|-----------|------------------|
| **Panel A - Cognition**   |                                                        |           |                  |
| Cognition global z-score  | -0.016** (0.006)                                       | 0         |                  |
| Fluid Intelligence z-score| -0.016*** (0.006)                                      | 0         |                  |
| TICS z-score              | -0.004 (0.006)                                         | 0         |                  |
| Raven's Matrix z-score    | -0.020*** (0.005)                                      | 0         |                  |
| Math z-score              | -0.013** (0.006)                                       | 0         |                  |
| **Panel B - Sleep**       |                                                        |           |                  |
| Sleep Onset               | -0.003 (0.011)                                         | 22.32     |                  |
| Sleep Offset              | 0.004 (0.011)                                          | 5.12      |                  |
| Sleep Duration            | 0.007 (0.011)                                          | 6.8       |                  |
| **Panel C - Mood**        |                                                        |           |                  |
| Angry                     | -0.002 (0.003)                                         | 0.31      |                  |
| Tired                     | -0.004 (0.003)                                         | 0.45      |                  |
| Enthusiastic              | -0.003 (0.003)                                         | 0.58      |                  |
| Happy                     | -0.003 (0.003)                                         | 0.64      |                  |

**Notes:** Robust standard errors clustered on village level are in parentheses * p<0.1; ** p<0.05; *** p<0.01. Outcomes in panels A and B are regressed on temperature 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. All regressions include 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, controls for latitude, pollution (PM2.5), rain and wind speed. The regressions exclude individuals living more than 50 kms from the closest grid.
Table 6. Cumulative Effects of Midnight Temperature

|                         | Rational Choice | Impatience | Cognition Global z-score | Math z-score | Sleep Onset | Sleep Offset |
|-------------------------|-----------------|------------|---------------------------|-------------|-------------|--------------|
| (1)                     | (2)             | (3)        | (4)                       | (5)         | (6)         |
| **Midnight Temp Yesterday above 25°C** | 0.023**        | 0.013*     | -0.054***                 | -0.087***   | -0.039      | 0.011        |
|                         | (0.009)         | (0.008)    | (0.020)                   | (0.019)     | (0.036)     | (0.032)      |
| **Panel A - Linear Effects** |                |            |                           |             |             |              |
| **Midnight Temp Yesterday above 25°C** | 0.022*         | 0.016      | -0.023                    | -0.041*     | 0.078       | 0.011        |
|                         | (0.012)         | (0.012)    | (0.027)                   | (0.025)     | (0.055)     | (0.048)      |
| **# Midnights above 25°C Last Week** | 0.007**        | 0.005*     | -0.003                    | -0.003      | -0.007      | -0.009       |
|                         | (0.003)         | (0.003)    | (0.005)                   | (0.006)     | (0.011)     | (0.010)      |
| **Midnight Temp Yesterday above 25°C* # Midnights above 25°C Last Week** | -0.007         | -0.006     | -0.006                    | -0.011      | -0.027      | 0.009        |
|                         | (0.005)         | (0.004)    | (0.009)                   | (0.009)     | (0.017)     | (0.014)      |
| **F-test**              | 2.87            | 1.80       | 0.85                      | 2.47        | 3.28        | 0.37         |
| **p-value**             | 0.0567          | 0.1655     | 0.4254                    | 0.0849      | 0.0378      | 0.6916       |
| **Outcome Mean**        | 0.31            | 0.62       | 0                         | 0           | 22.32       | 5.12         |
| **Observations**        | 48,953          | 47,566     | 26,900                    | 36,311      | 28,164      | 28,891       |
| **Bin FE**              | Y               | Y          | Y                         | Y           | Y           | Y            |
| **Month FE**            | Y               | Y          | Y                         | Y           | Y           | Y            |
| **Year FE**             | Y               | Y          | Y                         | Y           | Y           | Y            |
| **Latitude**            | Y               | Y          | Y                         | Y           | Y           | Y            |
| **Pollution, Rain & Wind** | Y             | Y          | Y                         | Y           | Y           | Y            |

**Notes:** Robust standard errors clustered on village level are in parentheses *p<0.1; **p<0.05; ***p<0.01. 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 25°C and the interaction term in Panel B.
Appendix

Appendix 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 prepared by authors.
Appendix Figure 2. 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 3. 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 4. *Midnight temperatures* effects on cognition

Notes: The above figure shows (A) nonlinear effects of midnight temperature on cognition by temperature bins, and (B) heterogeneous effects of temperature at midnight the day before the survey on global cognition, fluid intelligence and math z-scores in standard deviations.

44
### Appendix Table 1. Correlates of Time and Risk Preferences

|                              | Risk Aversion (1) | Rational Choice Violation (2) | Impatience (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)        |
| Age²                         | 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 equivalised expenditure | -0.000***             | -0.000***                     | -0.000***      |
|                              | (0.000)           | (0.000)                       | (0.000)        |
| Household equivalised expenditure² | 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:** Standard errors clustered on village level are in parentheses * p<0.1; ** p<0.05; *** p<0.01. Models include data from IFLS5. All regressions also 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. The regressions exclude individuals living more than 50 kms from the closest grid.
### Appendix Table 2. Was outdoor temperature random?

|                                             | Maximum Daily Temperature (ºC) | Temperature Midnight Yesterday (ºC) |
|---------------------------------------------|--------------------------------|-----------------------------------|
|                                             | (1)                            | (2)                               |
| Max daily precipitation - mm/day            | -0.003***                      | 0.000**                          |
|                                             | (0.000)                        | (0.000)                          |
| Max daily PM2.5 - mcg/m3                   | 0.305***                       | 0.018                            |
|                                             | (0.033)                        | (0.020)                          |
| Max daily wind speed - m/s                 | -0.141***                      | 0.012                            |
|                                             | (0.020)                        | (0.014)                          |
| Village Latitude                            | 1.051***                       | 0.813***                         |
|                                             | (0.117)                        | (0.104)                          |
| Female                                      | 0.003                          | 0.001                            |
|                                             | (0.009)                        | (0.006)                          |
| Age                                         | -0.005**                       | -0.003                           |
|                                             | (0.002)                        | (0.002)                          |
| Age^2                                       | 0.000**                        | 0.000                            |
|                                             | (0.000)                        | (0.000)                          |
| Married or cohabitating                     | 0.012                          | 0.010                            |
|                                             | (0.021)                        | (0.015)                          |
| Religion: Islam                             | -0.151*                        | -0.112                           |
|                                             | (0.084)                        | (0.060)                          |
| Working in past week                        | -0.016                         | 0.003                            |
|                                             | (0.021)                        | (0.014)                          |
| Secondary education or +                    | -0.002                         | -0.021                           |
|                                             | (0.020)                        | (0.016)                          |
| Female head of household                    | -0.039                         | -0.017                           |
|                                             | (0.031)                        | (0.023)                          |
| Age of household head                       | -0.001                         | -0.000                           |
|                                             | (0.001)                        | (0.000)                          |
| HHD head worked in past week                | -0.031                         | 0.017                            |
|                                             | (0.029)                        | (0.021)                          |
| HHD head has secondary educ +               | -0.000                         | -0.039*                          |
|                                             | (0.026)                        | (0.020)                          |
| Number of members per household             | -0.006                         | -0.000                           |
|                                             | (0.006)                        | (0.005)                          |
| Household equivalised expenditure           | 0.000                          | -0.000                           |
|                                             | (0.000)                        | (0.000)                          |
| Household equivalised expenditure^2         | -0.000                         | 0.000                            |
|                                             | (0.000)                        | (0.000)                          |
| Outcome Mean                                | 28.67                          | 23.64                            |
| Observations                                | 53,551                         | 53,320                           |
| R-squared                                   | 0.609                          | 0.729                            |
| F-test                                      | 1.81                           | 0.66                             |
| p-value                                     | 0.0355                         | 0.8021                           |

**Notes:** Robust standard errors clustered on village level are in parentheses * p<0.1; ** p<0.05; *** p<0.01. Models include bin fixed effects, plus month and year fixed effects. All regressions exclude individuals living more than 50 kms from the closest grid. F-tests conducted on all controls except environmental controls, altitude, bin, month and year dummies.
### Appendix Table 3. Robustness check - Sample exclusions and Ramadan

|                          | Rational Choice Violation | Impatience |
|--------------------------|----------------------------|------------|
|                          | (1) (2) (3)                | (4) (5) (6) |
| Max Temperature on Day of Survey (°C) | 0.003 0.003 0.003 | 0.004** 0.005** 0.004** |
| Temperature during hour of survey (°C) | 0.007*** 0.007*** 0.007*** | 0.004** 0.004* 0.004** |
| Midnight Temperature Yesterday (°C) | 0.010*** 0.010*** 0.009*** | 0.009*** 0.012*** 0.010*** |
| Max Temperature on Day of Survey (°C) | -0.001 0.001 0.001 | 0.002 0.002 0.002 |
| Temperature during hour of survey (°C) | 0.005** - - | -0.001 - - |
| Midnight Temperature Yesterday (°C) | 0.006* 0.009*** 0.009*** | 0.009*** 0.010*** 0.009*** |

| 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 |

| Bin FE | Y | Y | Y | Y | Y | Y |
| Month FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Latitude | Y | Y | Y | Y | Y | Y |
| Pollution, Rain & Wind | Y | Y | Y | Y | Y | Y |
| Ramadan | Y | | | | | |
| Exclude >1 Visit | Y | | | | | Y |

**Notes:** Robust standard errors clustered on village level are in parentheses * p<0.1; ** p<0.05; *** p<0.01. 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. All models include bin fixed effects which are 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.
Appendix Table 4. Potential mechanisms behind temperature effects

| Outcomes                          | Midnight Temperature | IFLS4 age 15-31 | IFLS5 age 15-31 | IFLS5 full sample |
|-----------------------------------|----------------------|-----------------|-----------------|------------------|
| 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: Robust standard errors clustered on village level are in parentheses * p<0.1; ** p<0.05; *** p<0.01. Outcomes in panels A and B are regressed on maximum daily temperature on the day of the survey and temperature the night before. Panel C outcomes use ‘yesterday’ as reference so they regressed on maximum temperature yesterday and midnight temperature the day before yesterday. Models include data from IFLS5 only, as well as province-urban-altitude-distance to coast plus month and year fixed effects, controls for village altitude as well as environmental variables, and exclude individuals living more than 50 kms from the closest grid.
Appendix Table 5. Placebo Test - Maximum Temperature in 2 weeks

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

Notes: Robust standard errors clustered on village level are in parentheses * p<0.1; ** p<0.05; *** p<0.01. All models include bin 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.