Temperature, Health and Liveability:
Evidence from Informal Settlements

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Abstract

How does temperature affect the health, vitality and thermal comfort of informal settlement residents? We examine this question using unique survey data from 24 informal settlements in Indonesia and Fiji. Our findings show that hotter weeks significantly decrease people's vitality, increase heat related discomfort inside homes and worsen self-reported poor health among Indonesian adults. Fijian adults experience a similar increase in low vitality and discomfort indoors, but not in poor health. These effects are larger when measured using more precise settlement-level temperature data but the differences are not statistically significant. Next, we use unique, high-frequency *indoor* temperature data to study how these respondents' households use assets and building materials to modify how outdoor temperature heats their homes. Our findings show that few assets make a dent in the burden of heat experienced indoors. The only cooling assets are air-conditioners in Indonesia and plants for shade in Fiji. Having building materials associated with higher SES such as solid walls, traps heat inside homes especially during the night hours. These findings suggest that informal settlement residents experience large deteriorations in their health and wellbeing as a result of high temperatures, and that their houses afford little to no protection against rising temperatures.

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1. Introduction

A hotter future is now inevitable. That is one of the main conclusions of the latest report of the Intergovernmental Panel on Climate Change (IPCC, 2021). The world is on average 1.2°C hotter than during the pre-industrial era and all projections predict further warming by the middle of the century. As a result, countries with higher temperature baselines are now more frequently recording life threatening heat extremes. Therefore, where these extremes occur and how they will affect people's health and liveability will not be spread evenly. For example, Raymond et al. (2020) show that the doubling in extreme humid heat since 1979 has been especially concentrated in coastal and subtropical areas. Moreover, rising temperatures due to climate change are exacerbated in cities by urban heat island effects (UHI). These occur when cities develop their own hotter microclimates as buildings and roadways replace green spaces, thus absorbing more sunlight and radiating more heat (Corburn, 2009).

Within cities, we encounter unique spaces that are home to more than one billion people: slums and informal settlements. Here too, are high temperatures more prevalent than in surrounding areas. For example, Scott et al. (2017) find that when Nairobi gets hot during summertime, its slums get even hotter by about 1.83°C - 3.1°C. A similar phenomenon has been recorded in Johannesburg (Naicker et al., 2017), Delhi, Dhaka and Faisalabad (Tasgaonkar et al., 2022). Some of the temperatures recorded in these spaces are dangerously close to known limits of human survival. Increased warming could mean that such "physiological limits could be reached regularly and more often in coming decades" (Ebi et al., 2021, p. 705).

Despite this evidence, causal studies on the deleterious effects of heat on health and liveability in slums and informal settlements are scarce. This is likely related to the lack of high-quality health and wellbeing data in low- and middle-income countries (LMICs), which is even more difficult to obtain from residents of informal settlements. Elsewhere, an alarming pattern of high temperatures leading to increased morbidity and mortality, and a generalised decrease in wellbeing is emerging (Barreca et al., 2016; Burgess et al., 2017; Deschênes & Greenstone, 2011; Gasparrini et al., 2015; White, 2017; Andalón et al., 2016; Burke et al., 2018; Carleton, 2017; Mullins & White, 2019). Most of these studies come from developed countries, with few exceptions. None study informal settlement populations.

This increasing knowledge of the many ways in which heat affects our lives has given birth to a new branch of the environmental health literature focusing on adaptation pathways. So far, the strongest evidence that adaptation is in fact possible, comes from studies focusing on the use of air-conditioning. For example, Barreca et al. (2016) and Deschênes (2022) show that the expansion of residential air conditioning is largely responsible for the decline in heat-related mortality in the United States since the 1960s. Others show that air-conditiong and high electricity consumption can moderate the negative effects of heat on students' learning outcomes (Park et al., 2020) and people's decision-making abilities (Escobar et al., 2022).

Using air-conditioning to cope with heat stress is however not a viable option for residents of informal settlements, where 24% of the global urban population lives (United Nations, 2019). Their defining characteristic, tenure insecurity (Zhang, 2021), implies the constant threat of eviction. This is a significant disincentive for households to invest in heat protective building materials and cooling assets (WHO, 2018). Further, although electrification is almost universal in most of the developing world, energy poverty in the form of unreliable power supply is still prevalent. All of this suggests that both indoor and outdoor temperatures in informal settlements are likely higher than in most other settings and most importantly, that the effects of heat on their residents' health and wellbeing is likely to be significant.

This paper seeks to explore this issue in two ways. First, we study the effects of outdoor temperature on people's self-reported poor health, heat-related discomfort inside homes and a global indicator of vitality which captures sleep quality, ability to concentrate and effort needed to perform normal daily activities. In the second part of this paper, we study the burden of heat *inside* dwellings and the role of wealth in modifying the transfer of heat from outdoor spaces to the indoor areas of homes. To do so, we employ longitudinal individual and household survey data collected from 24 informal settlements in the cities of Makassar, Indonesia, and Suva, Fiji. We complement these data with temperature measurements from two main sources: a) *in situ* temperature from iButton data loggers, small, low-cost sensors deployed inside and outside a subset of the households surveyed and b) gridded reanalysis temperature data from NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA-2) with a spatial resolution of approximately 50 x 60 kilometers.

Our findings show that during hotter weeks, vitality drops, heat related discomfort inside homes increases and the likelihood of experiencing poor health rises across the Indonesian settlements. The estimates show that a 1°C increase in average weekly temperature leads to a decrease in vitality by 2.6% of a standard deviation, a 20.8% increase in heat related discomfort inside homes, and a 9.6% increase in self-reported poor health. In Fiji, where average temperatures are cooler by about 1-2°C during our observation period, the effects of heat on vitality and discomfort in the past week are larger. A 1°C increase in average weekly temperature leads to a decrease in vitality of 11.3% of a standard deviation, and to a 25.6% increase in heat-related discomfort inside homes. However, we do not find a significant effect of heat on poor health. Finally, we find that when present, these deleterious effects of temperature are greater at higher levels of humidity. This is especially true in Makassar, Indonesia, where the entire temperature distribution is higher than in Fiji.

Next, we make a methodological contribution to the literature on temperature measurement instruments. The results described above were generated using NASA temperature data, which our estimates suggest can underestimate the true extent of heat experienced in urban informal settlements, especially in Indonesia. Using local outdoor temperature data from a network of ibuttons, we reestimate our models and find that both the average effects of temperature and the confidence intervals are larger, but not significantly so. This gap is only observed in Indonesia, where the UHI effect is particularly strong. This suggests that researchers should be careful in their choice of temperature sensing instrument. Although the marginal effects of temperature across instruments might not be significantly different, postestimation and back of the envelop calculations done using the downward biased instrument could run the risk of underestimating the true extent of the effects of temperature on health and possibly other economically relevant outcomes.

In the second part of this paper we study the burden of heat *inside* dwellings. Our unique indoor temperature data shows that indoor temperatures in the settlements are consistently *higher* than outdoor temperatures across most observed days. Given this finding, we investigate what is the relationship between household assets, building materials, and indoor temperature to study the reasons behind this gap. The estimates show that there is very little that households can do to reduce their indoor temperatures. For example, although our estimates show that owning air-conditioning substantially reduces indoor temperatures in Indonesia, only 5% of households actually own one. Even fewer households own one in Fiji, at 2%. We also find that some households assets and building materials make indoor temperatures worse. For example, having solid walls made of bricks and cement, without proper or any form insulation, is actually facilitating the storage of heat driving minimum temperatures upwards. However, our estimates suggest that low-cost investments such as plants for shade can make a significant difference in indoor temperatures, as long as outdoor temperatures are not extremely high.

This study contributes to three distinct bodies of literature. First, we contribute to the emerging literature on life and wellbeing in informal settlements (Alves, 2021; Binzel & Fehr, 2013; Bird et al., 2017; Egondi et al., 2012; Nakamura, 2017; Zhang, 2021). Secondly, we advance the current knowledge on the relationship between temperature and different aspects of wellbeing (Escobar et al., 2022; Mullins & White, 2019; Park et al., 2020a; 2020b; Su et al., 2021; Tawatsupa et al., 2012). Finally, we contribute to the literature that studies how temperature affects the built environment (Naicker et al., 2017; Ramsay et al., 2021; Scott et al., 2017; Tasgaonkar et al., 2022; Wilby et al., 2021).

The rest of the paper is organized as follows: Section 2 describes the survey and environmental data used in the analyses. Section 3 outlines the econometric strategies employed. In Section 4, we discuss the estimated effects of temperature on health and liveability. Section 5 presents the results of our analyses of the relationship between wealth, assets and indoor temperature. Finally, section 6 provides a summary discussion and concludes.

2. Data and summary statistics

2.1 Survey data

Data on health and wellbeing were obtained from the individual and household modules of the Revitalising Informal Settlements and their Environment (RISE) survey (Leder, et al., 2021). RISE is a randomized-controlled trial testing a water-sensitive cities approach to the upgrading of 12 informal settlements in Makassar, Indonesia and 12 settlements in Suva, Fiji, as depicted in Figure 1. The RISE surveys consist of 5 individual waves in Indonesia and 4 waves in Fiji, all collected prior to the start of the building phase of the RCT. The survey modules were rolled out at different times in each country but generally have a 6-month gap between waves. Survey data collection in Indonesia began in November 2018 (wave 1) and ended in March 2021 (wave 5). The Fijian surveys span the periods between June 2019 (wave 1) and April 2021 (wave 4). For the full timeline of data collection across all nine waves, please refer to Figure 2.

A. Low vitality

In 6 of these survey waves, several indicators of vitality were collected from an adult respondent in each house. Each respondent went through a face-to-face survey in which they were asked a questionnaire that included questions on the frequency of restless sleep, feeling that everything is an effort, and trouble concentrating. The reference period of each question is the 7 days prior to survey. These frequencies were then dichotomized such that ‘a moderate amount of time’ and ‘all the time’ would result in a value of 1, and 0 otherwise.

Our review of the literature on the relationship between temperature and wellbeing suggests that temperature is likely to affect a person’s sleep quality, their cognitive resources and their levels of energy and productivity (Connolly, 2013; Noelke et al., 2016; Obradovich et al., 2017; Park et al., 2020). All of these outcomes are critical to people’s mental health, productivity and overall wellbeing. In order to capture all these different aspects of a person’s vitality while preserving statistical power, we construct a latent variable using factor analysis that is standardized in nature, with a mean of zero and standard deviation of one, and is increasing in low vitality. This is further explained in Table 1.

As per the individual components of this variable, 16% of Fijian respondents reported to have had trouble concentrating, 14% suffered from restless sleep and 26% felt that everything was an effort in the 7 days prior to survey. In contrast, only 7% of Indonesian adults had trouble sleeping, 12% had difficulty concentrating and 9% felt that everything they did required a lot of effort in the past week.

B. Heat-related discomfort inside homes

Studies from the United States, Canada and Europe suggest that people spend approximately 90% of their time indoors (Brasche & Bischof, 2005; EPA, 2021; Licea, 2018). Differences in demographics, education and financial prosperity across countries mean that this figure could be higher or lower for people in LMICs. However, OECD data comparing time use across high- and middle income countries suggest that how people spend their time is very similar across countries (Ortiz-Ospina, 2020). After all, we all sleep, work, eat and enjoy leisure. Most of these activities are done indoors.

A large proportion of the respondents surveyed in the RISE settlements are women, who’s primary activity takes places inside their homes. It is therefore critical that we understand whether they perceive that their homes are uncomfortably hot. As a result, we included a heat stress module in our household survey where we asked respondents about the frequency of heat-related discomfort *inside* the house. Homes should be a place in which to find shelter from heat, yet 50% of Indonesian respondents often or almost always felt uncomfortably hot inside their home in the past 4 weeks. In line with the slightly cooler conditions prevalent in Fiji, only 36% of respondents in Suva reported frequent discomfort inside their homes.

C. Self-reported health

Given the existing evidence showing that high temperatures can lead to significant increases in morbidity and mortality, we investigate whether there are traces of this relationship in our setting using a frequently collected outcome: self-reported general health. As Figure 1 shows, all 9 waves of data asked respondents about general health. We dichotomize this such that having moderate, bad or very bad health results in a value of 1 and 0 otherwise. As Table 1 shows, Indonesian respondents report a higher frequency of poor general health at 24%. Meanwhile, approximately 13% of Fijian adults were in poor general health.

2.2 Environmental data

The environmental data employed in this study comes from three main sources. First, we measure temperature locally: i) inside a random sample of households (10 houses per settlement) participating in the RISE survey and, ii) outside the selected dwellings using iButton data loggers. Next, we supplement these measures with precipitation and temperature data from NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA-2). Lastly, humidity data was collected from weather stations in Makassar, Indonesia and Suva, Fiji.

2.2.1 Microclimate data from RISE iButtons

As a part of environmental monitoring and assessment of the RISE intervention, microclimate temperature and humidity monitoring was undertaken concurrently with surveys. A network of ~65 iButton data loggers were deployed in each settlement (Ramsay et al., 2021). Five iButtons were deployed outdoors in each settlement, measuring hourly temperature and humidity. Additionally, six loggers measuring temperature only were deployed in each of the ten randomly sampled houses in each settlement. Household loggers were deployed in three pairs (one measuring hourly and one two-hourly), in three different locations in and around the house according to practical requirements and the preference of the householder. The loggers remained in place over the RISE baseline monitoring period and data were downloaded quarterly, except for periods during the Covid-19 pandemic.

Data retrieval was limited by logger loss and failure, and fieldwork limitations over the Covid-19 pandemic. Therefore, data was not retrieved for all loggers or for all time periods. To obtain representative microclimate measurements of settlements and households, we only included time periods where data was retrieved for at least two outdoor *iButtons in a settlement*, and for households where data was retrieved for *iButtons* in two different locations within a house.

This data collection process resulted *in situ* hourly outdoor temperature measures for each informal settlement, over a period of 522 days in Suva (August 2019 – January 2021) and 744 days in Makassar (October 2018 – January 2022). Corresponding hourly indoor temperature data was collected over a period of 696 days in Suva (August 2019 – July 2021) and 764 days in Makassar (October 2018 – January 2022).

Using these hourly data, we compute weekly averages of mean *outdoor* temperature recorded over the 7 days prior to each respondent's survey date for the first part of our analysis on the effects of temperature on health and liveability. We also compute daily maximum, mean, and minimum *indoor* temperature for the second part of this study on the relationship between assets, wealth and indoor thermal comfort. The latter results in 41,816 and 46,411 house-date records in Indonesia and Fiji, respectively.

2.2.2 NASA MERRA-2 Dataset

Next, we obtained hourly and daily records of temperature and precipitation from NASA's MERRA-2 dataset for the period of time in which the individual health surveys were rolled out (November 2018 - December 2021). MERRA-2 provides environmental estimates for 0.5º x 0.625º cells (approximately 50 kms x 60 kms) at hourly and daily time scales from 1981 to 2022 (Rienecker, et al., 2011).

MERRA-2 climate records are matched to RISE respondents through the GPS coordinates of the cities of Suva, Fiji and Makassar, Indonesia. All RISE residents in each city are matched to the closest MERRA-2 grid. Being relatively small cities, only two MERRA-2 grids, one per country, were employed in the matching process. With these data, we construct three exogenous outdoor temperature measures employed in the first part of our analysis measuring the effects of heat on health and liveability: a) the average of maximum, midnight and mean temperatures on the seven days prior to the RISE individual health survey, b) a more flexible measure where these averages are split into temperature bins, and c) the sequence of days in the week prior to the survey above a certain average weekly temperature threshold: 25°C in Makassar and 24°C in Suva.

The coarseness of the data (i.e., its approximately 50 kms x 60 kms resolution) represents a clear disadvantage when compared to the more 'precise' and outdoor temperature collected with the iButtons. However, in contrast to the iButton data, NASA's temperature records have no temporal gaps, which allowed us to assign each respondent in our household survey to a measure of weekly temperature. Therefore, our benchmark results use NASA data as the main source of outdoor temperature exposure.

2.2.3 Weather Station Data

Temperature and humidity data were also obtained from 3 weather stations in Makassar, Indonesia and from a weather station in Suva, Fiji. Although weather data from the 3 stations in Makassar, is, to the best of our knowledge, of high quality and generated with enough frequency to generate reliable averages of the daily minimum, maximum and mean, the same cannot be said of the Fijian data. For example, the Laucala Bay Met Office, the only weather station in Suva, has significant gaps on weekends and in the evening hours. Therefore, daily averages from the Fijian weather station might not be the best reflection of weather conditions in the area of interest. In light of this, we defer to the NASA dataset as our main source of temperature data and only utilise humidity data from the aforementioned weather stations.

2.2.4 The burden of heat in Indonesia and Fiji: Differences by setting and instrument

Indonesia is a vast country that consists of 17,504 islands scattered over both sides of the equator. As a result, its climate remains relatively even all-year round with no summer or winter extremes. For most of the country, the climate is tropical. During the period of study, the city of Makassar, reported weekly average temperatures of 25.7°C, maximum temperatures of 31.6°C and minimum temperatures of 22°C. Humidity is also high year-round, ranging from 60-100% with an average of 80% as shown in Figure A1.

Fiji, is a much smaller country in comparison with 332 relatively small islands. The country lies south of the equator and as a result, it experiences a tropical marine climate with high temperature and rainfall throughout the year (Ongoma, et al., 2021). During the period of study, the city of Suva reported weekly average temperatures of 24.8°C, maximum temperatures of 28.8°C and minimum temperatures of 21.5°C as shown in Table 1. As is the case in Indonesia, humidity is consistently high, ranging from 50-100% with an average of 77% (Figure A1).

Despite their similarities, temperatures vary substantially between both cities. According to NASA's records (Fig 3a), the entire distribution of temperatures in Makassar, Indonesia is approximately 2°C higher than in Suva, Fiji. Moreover, Makassar's distribution is narrower indicating that most people experience consistently high temperatures throughout the year whereas in Suva, people experience a larger range of temperatures. Figure 3 also reveals that temperatures recorded by NASA and the iButtons differ. Figures 3a and 3b, show that the *in-*

situ data loggers record a larger tail at the right of the Fijian distribution, indicating that NASA smooths down some observations, underreporting instances when temperatures were up to 4°C higher in the settlements. Even more remarkable, is the outside shift of the entire Indonesian distribution showing that iButton temperatures are much higher by approximately 2°C than the NASA temperatures suggest. The settlements are much hotter than they would appear based on NASA data.

Figure 4 presents this phenomenon from a different perspective. If the iButtons and NASA produced the exact same measures at all temperature ranges on any given day, the plot would follow a 45° angle. However, in Indonesia, we observe that not only is there a gap along the entire distribution, as seen in Figure 3, but this gap is even larger at cooler ranges for all measures of temperatures. Indeed, the settlements are always hotter than what NASA suggests but this difference becomes smaller at higher temperature ranges. In Fiji, on the other hand, this difference is overall smaller but relatively constant across all ranges for the maximum, whereas the minimum and average temperatures converge at higher ranges.

We argue that this phenomenon can be explained by the level of urbanity of each city. The city of Makassar, is significantly more urban, has fewer green spaces than Suva, and has more dense concentrations of pavement and buildings. This is likely to cause a stronger UHI effect (Ramsay, et al., 2023). Because reanalysis data are a blend of observations that combine satellite and weather data from areas much larger than the cities in question, it is likely to produce attenuated measures of temperature, especially in the presence of strong UHIs. A potential implication of this is that reanalysis weather records might not the best representation of the heat burden experienced by some urban populations. We explicitly test this in section 4.

3. Empirical Strategy

Given that our sample is mainly formed by women who spend a large majority of their time indoors, the ideal empirical strategy would estimate the effects of indoor temperature on health, discomfort and vitality. But indoor temperature is very likely endogenous. That is, factors that determine how hot it is inside people's homes could also determine their health and wellbeing. Moreover, problems with reverse causality can also arise if people with poor health and low vitality behave in ways that could modify their indoor temperature. Given these concerns, in the first part of this study we use outdoor temperature as an exogenous proxy for indoor heat, to estimate the effects of temperature on health, discomfort inside homes and vitality.

Next, we investigate what is the actual gap between indoor and outdoor temperatures, and what is the role of wealth in modifying indoor temperatures. Wealth in this instance is measured using a detailed list of assets and building materials. Given the different temperature profiles of each country described in the previous section, we analyse Indonesia and Fiji separately for both research questions.

3.1 Outdoor temperature specifications

To identify the causal impacts of temperature on our indicators of health and liveability, we adopt a panel fixed effects methodology fairly similar to that employed in the climate economic literature. The classical approach uses an area-by-month fixed effects methodology. The assumption being that year-to-year variations in weather within a given area and year are random. Although a disadvantage of our data is that our panel does not cover a large number of years, a big advantage over these studies is that our panel tracks individuals. This allows us to control for time invariable unobservable characteristics that could affect both the outcome and the treatment variable. As a result, we employ individual fixed effects models such that our estimates are identified from random variations in weekly temperature for that same individual over a three-year period.

As shown in equation (1) our main outcomes, for individual *i* in wave *t* (Y_{it}), are regressed on NASA outdoor temperatures ($OutNasaTemp_t$), precipitation ($Rain_t$), individual fixed-effects (σ_i), and wave fixed effects (δ_t):

$$Y_{it} = \alpha + \beta_1 OutNasaTemp_t + \beta_2 Rain_t + \sigma_i + \delta_t + \varepsilon_{it} \quad (1),$$

Y_{it} corresponds to 3 main outcomes (low vitality, discomfort inside home and poor health). Our treatment variable *OutNasaTemp* represents the average of daily mean temperatures in the seven days prior to each survey wave as measured by NASA's MERRA-2. We also expand these estimates, adding a continuous interaction of de-meaned NASA temperatures with de-meaned relative humidity (%). The objective of this is to estimate the additional effect of temperature when humidity is high. Finally, we also consider the possibility that any potential effects could be non-linear in nature. In more flexible non-parametric specifications, we employ temperature bins which vary in range for each country (see Appendix Figures A4 and A5), and we also study the sequence of days above a certain temperature threshold in the past week (see Appendix Tables 4 and 5).

3.2 Indoor temperature specification

Next, we estimate the relationship between wealth and indoor temperature. To do so, we compare neighbors within settlements in every one of the almost 700 days when indoor temperatures are available. Specifically, we use neighbor-by-date fixed effects, which allows us to hold constant all daily outdoor weather conditions common to each neighbor grouping on every observed day. The remaining variation in indoor temperatures is then explained by the assets and building materials owned by households within the different neighbor pairings.[2]

As shown in Equation 2, we regress the *indoor* maximum, minimum and mean daily temperature of house *h*, in neighbor-group *n* and day *t*, on a set of assets, material of the walls, roof, and floor, neighbor-by-date fixed-effects γ_{nt}, and a vector of additional controls (X'_{ht}):

$$IndoorTemp_{hnt} = \alpha + \delta_1 Assets'_h + \delta_2 BuildingMat'_h + \delta_3 X'_{ht} + \delta_4 iButton'_h + \gamma_{nt} + \varepsilon_{hnt} \quad (2),$$

Parameter $Assets$ is a list of household items including: air-conditioning, fan (Indonesia only), gas or electric stove, and plants for shade. $BuildingMat$ includes dummies for houses with solid walls (bricks, blocks or wood), improved roofs (mainly tin) and improved floors (non-earthen). Parameter X'_{ht} includes household characteristics that could modify the way in which people use their homes and the time when they are present, thus also modifying indoor conditions: density (number of people per room), age of the respondent, schooling level of the respondent, whether or not there is a homemaker in the house, and number of children under 5 in the home. Finally, parameter $iButton'_h$ controls for the number of iButtons that generated each house-date temperature reading and the average height of all the iButtons installed inside the dwelling. Standard errors are clustered on the house level in parentheses to account for the fact that each house is observed multiple times.

4. Temperature, health and liveability

4.1 Benchmark results

The main results for health, discomfort indoors and liveability are summarized in Table 2. We show the estimated coefficients of the effects of temperature for Indonesia (Panel A) and Fiji

[2] Using aerial photographs, we divide each settlement in quadrants when no natural grouping of dwellings could be identified. This was mostly the case in Fiji where the randomly selected indoor ibutton houses were spread throughout the large settlements. We also aimed at grouping neighbours that shared distinctive features such as roads and forests which could change the way in which outdoor temperatures influenced indoor temperatures.

(Panel B), respectively. Next, in Table 3, we present the estimates for the interaction of temperature and humidity.

As Table 2 shows, in Indonesia, we find that low vitality, poor health and heat-related discomfort increase significantly in response to hotter weeks. The estimates imply that a 1°C increase in average weekly temperature leads to a 2.6% of a standard deviation increase in low vitality, a 20.8% increase in heat related discomfort inside the home, and a 9.6% increase in self-reported poor health. In Fiji, we also find a positive relationship between vitality, discomfort and heat, but the effects are much larger. For every additional degree of mean temperature in the past week, vitality decreases by 11.3% of a standard deviation, heat-related discomfort inside the home increases by 25.6%. Notice that in contrast to Indonesia, we do not find any statistically significant effects of temperature on physical health in Fiji. This might suggest that a higher threshold might be necessary to trigger deleterious physical health effects whereas vitality and discomfort indoors start to worsen at lower levels of heat.

The medical literature suggests that the interaction of hot and humid days might lead to even larger effects because evaporative mechanisms used by our bodies to get rid of excess heat become less efficient when humidity is high. The graph in figure A2 shows that this might not be a trivial matter in the cities we study. For example, although Suva, Fiji doesn't reach as high temperatures as Indonesia does, the days with high average temperatures are characterized by high levels of humidity of up to 87%. Meanwhile, Makassar, a densely populated city with less vegetation than Suva, is characterized by hotter but relatively less humid days (although 60% humidity at 30°C is still considered a health hazard).

In panels A and B of Table 3, we probe this issue. In this instance, we center both temperature and humidity around the mean of each variable such that the estimates can be interpreted as a) the effect of a 1°C increase in mean weekly temperatures for weeks with average humidity and b) the additional effect of a 1°C increase when humidity rises by 1 percentage point. As the medical literature suggests, we find that the estimated deleterious effects of temperature are greater at higher levels of humidity (Mora, et al., 2017).

4.2 NASA versus iButton temperature effects

We have previously shown in *section 2.2.4* that outdoor temperatures throughout the settlements are much hotter than what NASA data would suggest. This could imply that the estimates discussed before where underestimating the true effects of heat on health and liveability. To test this, we re-estimate our main specification using both instruments, NASA and iButtons, but now restrict our sample to respondents where corresponding iButton temperature measures were available. The results of this exercise are plotted in Figures 5 and 6.

As Figure 5 shows, in Indonesia, when outdoor temperatures are measured using coarse reanalysis data as opposed to *in situ* data, the average effects of temperature on vitality are smaller. For all outcomes, these confidence intervals overlap and the differences between models are not statistically significant. This gap is only observed in Indonesia, possibly due to the strong UHI effect in the city of Makassar. In contrast, in Fiji, both instruments are remarkably consistent, as shown in Figure 6. Although the main point of this paper is not a methodological one, these findings are interesting by themselves. They show that measurement error across temperature sensing products can be a non-issue in some settings, like Suva, but it can also lead to underestimating the true effects of heat in other settings, especially if these estimates and temperature measures are to be used for back-of-the-envelope calculations.

4.3 Heterogeneous effects

Next, we explore whether the observed effects of temperature on health and liveability vary systematically by individual characteristics such as gender, age, and the location of one's primary activity (Appendix Table 2). We do not perform a heterogeneity test between males and females because males only represent 12% of our sample in Indonesia and 33% in Fiji. Therefore, male-only estimates would not have a meaningful interpretation. Nevertheless, we include a females-only set of coefficients in Panel A of Appendix Table 2 to show that our benchmark results in Table 2 are largely driven by women and not by outliers among the small male sample.

In Panel B, we split our sample by the median age of our respondents to observe whether older adults are more affected by heat, as previous studies have found. We find some suggestive evidence that adults age 40+ are significantly more likely to experience poor health after hotter weeks in Indonesia, than younger adults. None of the differences between both groups are statistically significant in Fiji. Next, in Panel C, we explore whether more than spent indoors makes a difference in the relationship between temperature, health and liveability. The evidence is mixed. In both countries we find that temperature has a stronger effect on low vitality if the respondent's primary activity is performed outside their homes. However, we find some suggestive evidence that in Fiji, temperature has a stronger effect on discomfort at home and on poor health for respondent's whose primary activity is done at home.

4.4 Non-linear effects

Studying the presence of non-linear effects of temperature is important because these estimates can help us explore whether there is evidence of adaptive or protective behaviors at temperature extremes. In Figures A4 and A5 in the Appendix we report these estimates for maximum and midnight temperatures, for Indonesia and Fiji, respectively. Several interesting observations arise from this exercise. First, we find that in Indonesia the deleterious effects of heat on vitality and discomfort indoors plateau at about 34°C of maximum temperature. We also observe an inverse-U shaped relationship between temperature and poor health, suggesting that Indonesian adults might indeed be engaging in avoidance behaviors during temperature extremes. In Fiji, we find a U-shaped relationship between temperature and low-vitality, such the latter increases at both temperature extremes. In contrast, we find a strong linear and positive relationship between heat and discomfort indoors.

4.5 Robustness checks

We estimate several additional models to determine whether our main results are robust to alternative specifications. First, in Appendix Table 3 we re-estimate our benchmark results using temperature data recorded from weather stations. The potential concern being that the coarseness of the reanalysis data might be off because it is capturing heat from irrelevant sources to the populations of Makassar and Suva, that is, sources other than the local weather stations. We do not find that to be the case. In fact, across most outcomes, the estimated effects of temperature for both adults and children are very similar regardless of whether we use NASA or weather station data.

Next, we study different ways of expressing weekly temperatures. So far, our main 'treatment variable' has been expressed as the average of mean daily temperatures over a 7-day period. In Appendix Tables 4 and 5 we re-examine the relationship between health, liveability and temperature by separately estimating the effect of each day in the past week if each day registered mean temperatures above 25°C in Indonesia and 24°C in Fiji. Appendix Tables 4 and 5 then present the linear sum of these coefficients from the day of the survey t-1 to day t-6. This exercise shows that the estimated effects of temperature for each additional day of above-average heat in the past week, stabilize at about day t-4 at which point the coefficients in Tables 2 become almost identical if we divide the latter by the number of days in a week.

5. The indoor-outdoor temperature gap

For homes to be places where people can seek shelter to prevent the deleterious effects of heat we found earlier, temperature inside homes ought to be lower than temperature outdoors. But this is not the case in our sample of informal settlements. We see this in Figure 7, where we plot daily outdoor ibutton temperatures (x-axis) against indoor ibutton temperatures (y-axis). In an ideal scenario, the plots of max, min and average temperatures should be to the right and under the 45° line, signaling that the inside of homes is cooler than the immediately adjacent outdoors. Instead, we find that in Fiji, indoor temperatures are consistently *higher* than outdoor temperatures across most observed days. This gap is constant across all temperature ranges. Heat is actually worse inside than outside their homes. In Indonesia we find more heterogeneity, with differences across measures of temperature. For example, while average temperatures are consistently higher indoors, houses do provide some degree of protection during the peak hours of extreme heat. The opposite happens with minimum temperatures. It appears that dwelling characteristics that are helping to keep houses cooler during the peak of day, also facilitate the storage of heat at night.

5.1 The association between wealth and the indoor-outdoor temperature gap

So far, the graphical evidence suggests that households in these settlements are largely unable to cool down their homes, especially in Fiji. In this section we investigate what role are assets and building materials playing in the transfer of heat from the outdoors to the inside of homes. The estimates presented in Tables 4 and 5 are based on Equation 2. In a nutshell, the coefficients show how ownership of different assets and building materials explain the differences in indoor temperatures within groups of neighbors in each day and settlement. We do this for average, maximum, and minimum indoor temperature.

The regression analyses corroborate what the graphical evidence suggests. We find that there is very little that households can currently do to reduce their indoor temperatures and, in some cases, their assets and building materials make indoor temperatures worse. As one would expect, owning air-conditioning substantially reduces indoor temperatures in Indonesia. For example, it decreases maximum temperatures by almost a full degree Celsius. However, only 5% of households actually own one. We also find that for Indonesian households, having solid walls made of bricks and wood, without proper or any insulation, is actually facilitating the storage of heat driving minimum temperatures upwards. This goes in line with the plots in Figure 7. But the graphs also show that maximum temperatures indoors are lower than outdoors so in Appendix Table 6, we investigate whether certain assets and building materials become more protective when heat outdoors is high. These new estimates show that outdoor temperatures get hotter, having plants for shade and solid walls become more protective in Indonesia.

Table 5 shows the corresponding estimates for Fiji. As was the case in Indonesia, air-conditioning ownership in these settlements is extremely low, with only 2% of households reporting to have one. It is therefore not surprising that we find a negative but imprecise association between ownership of air-conditioners and temperature. In Fiji we also find that having 'improved' building materials such as solid walls and tin roofs is associated with higher minimum indoor temperatures. The only consistently protective asset, appears to be having plants for shade, which significantly decreases maximum indoor temperatures. However, as one might expect, when outdoor temperatures are extremely high (Appendix Table 6), having plants is no longer as protective.

The results presented above are not surprising is we remember the context. Cooling assets, which are proven to reduce both indoor temperatures and the effects of heat on health, are scarce in these settings, and this very likely explained by the informal nature of the settlements. The constant threat of eviction precludes these households from doing the necessary investment to cool their homes, and instead we see higher ownership rates of more expensive but also more fluid assets such as vehicles. However, the results do suggest that investments as low-cost as having plants for shade can make a big difference as long as outdoor temperatures are not extremely high.

6. Discussion and conclusion

Throughout this paper we have presented causal evidence of the negative effects of heat on the health, comfort and vitality of people living in informal settlements. We find that, despite the fact that the respondents in our study are constantly exposed to high temperatures year-round, their health and vitality are highly sensitive to short-term changes in temperature. This suggests that for populations with little to no means to invest in heat moderating assets, there is no natural adaptation to high temperatures.

Methodologically, our study shows that the choice of temperature sensing instrument used to estimate these effects only matters if the area of study has large concentrations of built-surfaces and little vegetation. This is the case in Indonesia, where the raw temperature data presented graphically earlier, shows that the urban-heat-island effect leads reanalysis instruments to underestimate the true dimensions of heat. Awareness of the caveats of different temperature sensing instruments is important and caution in our choice of instruments should be exercised, especially when the subjects of study are populations living in urban areas.

Finally, our study provides a unique view into the ability of low-income households in informal settlements to protect their homes from heat. Our findings are not entirely encouraging. The results show that Fijian informal settlement residents are worse-off in terms of heat exposure inside their homes than outside in the open. We find that this is likely associated with the use of building materials and assets that trap heat instead of insulating them from it. The one encouraging factor is that an investment as low-cost as having plants for shade can make a positive difference. Meanwhile, in Indonesia, where the entire outdoor temperature distribution is higher than in Fiji, only air-conditioning ownership and having solid walls reduces indoor temperatures during the peaks of heat.

The findings in this study provide supporting evidence to the calls of institutions like the Asian Development Bank (2022) for pro-poor policies to build urban resilience to extreme heat. Future research should explore whether policies such as improving security of tenure, setting up early warning systems, integrating more blue and green spaces, and installing low-cost heat sensors can be helpful in reducing heat stress in informal settlement, and in preventing the its deleterious effects of people’s lives.

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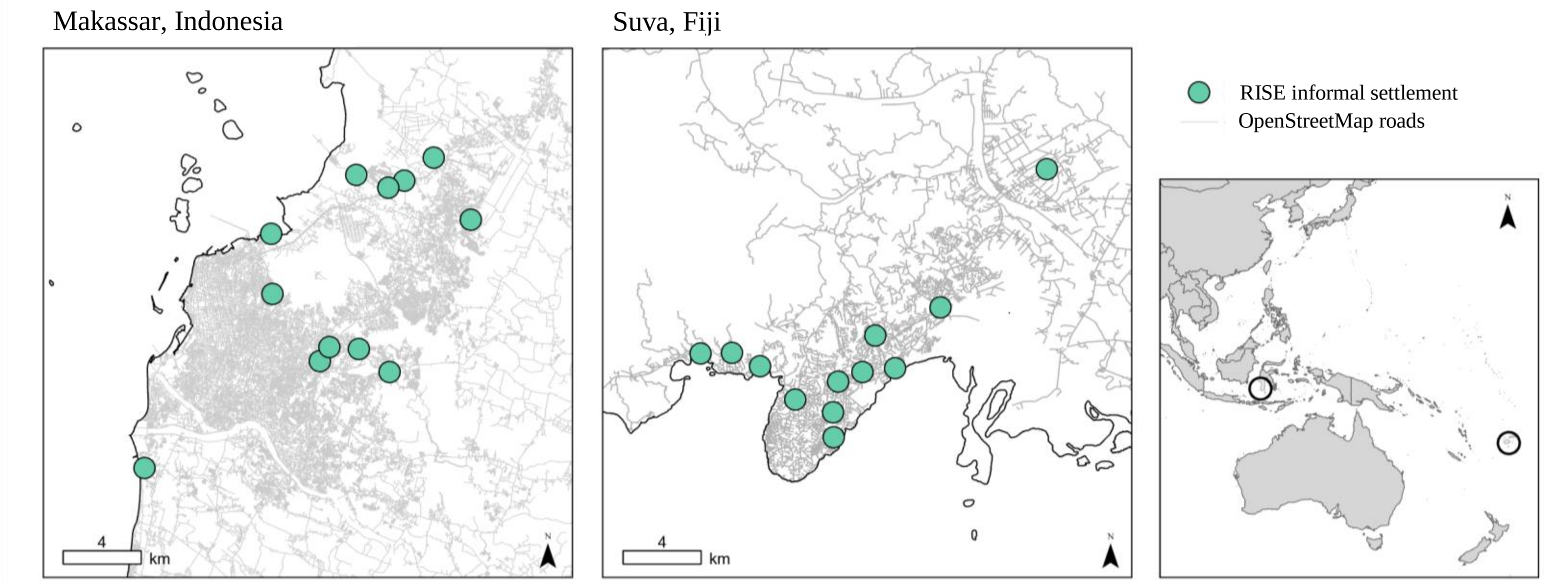
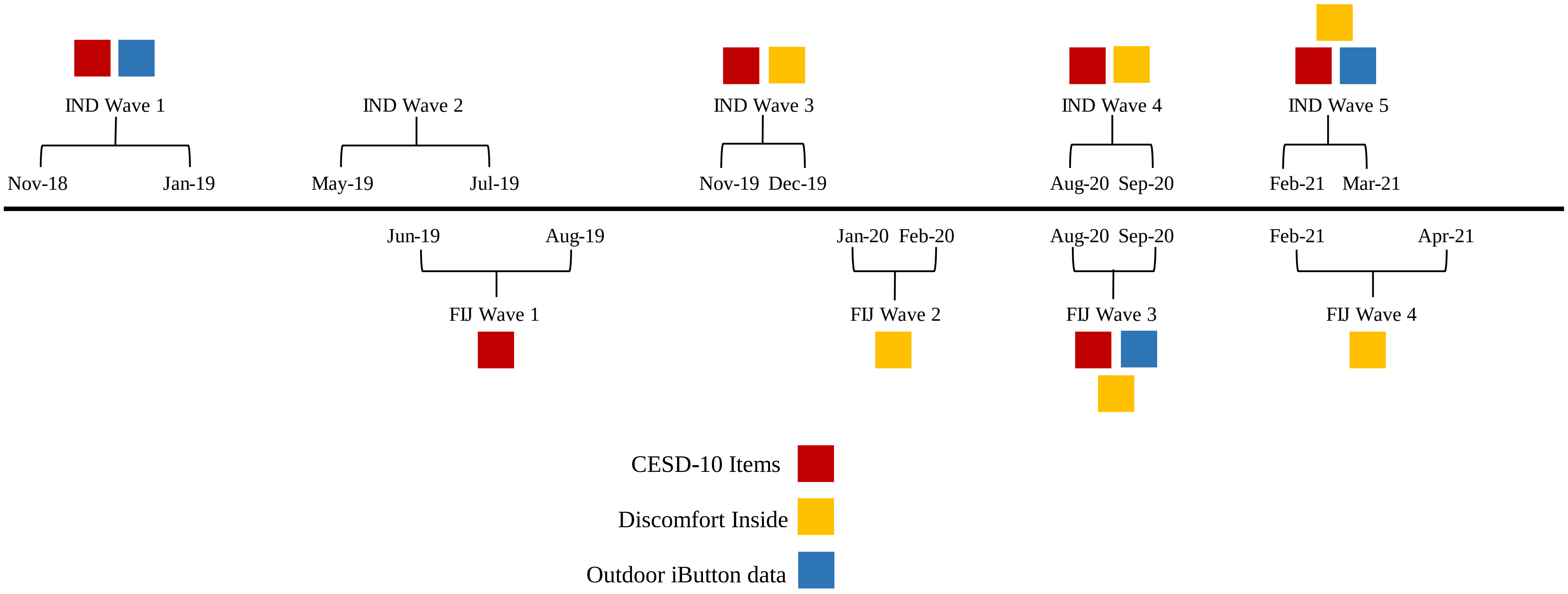
Figures

Figure 1. Maps of Makassar, Indonesia and Suva, Fiji, showing locations of informal settlements where loggers were deployed



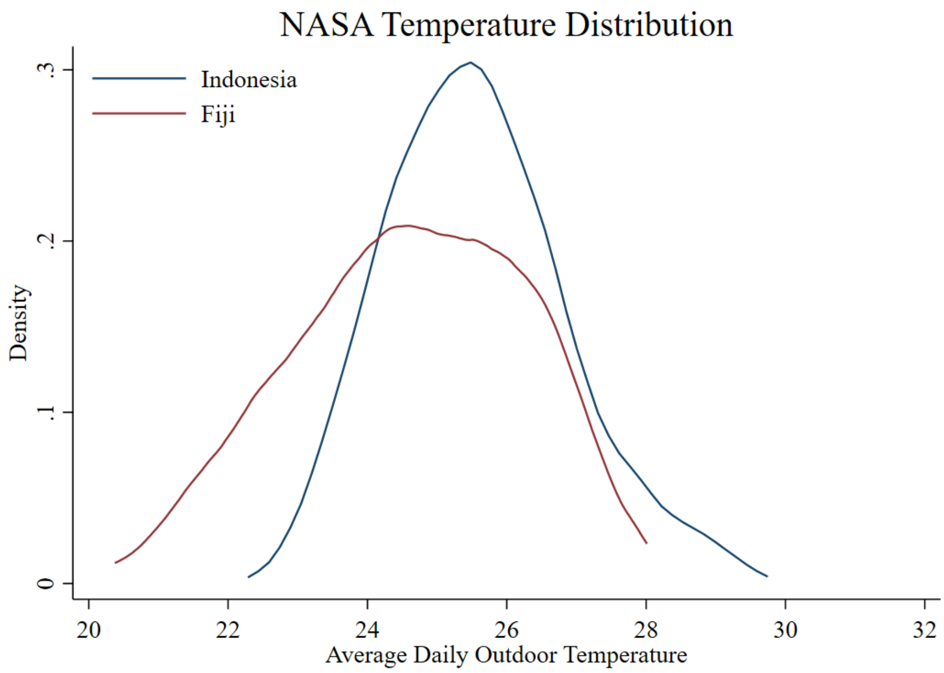
Note: The maps above depict the 24 informal settlements participating in the RISE RCT in Makassar, Indonesia and Suva, Fiji.

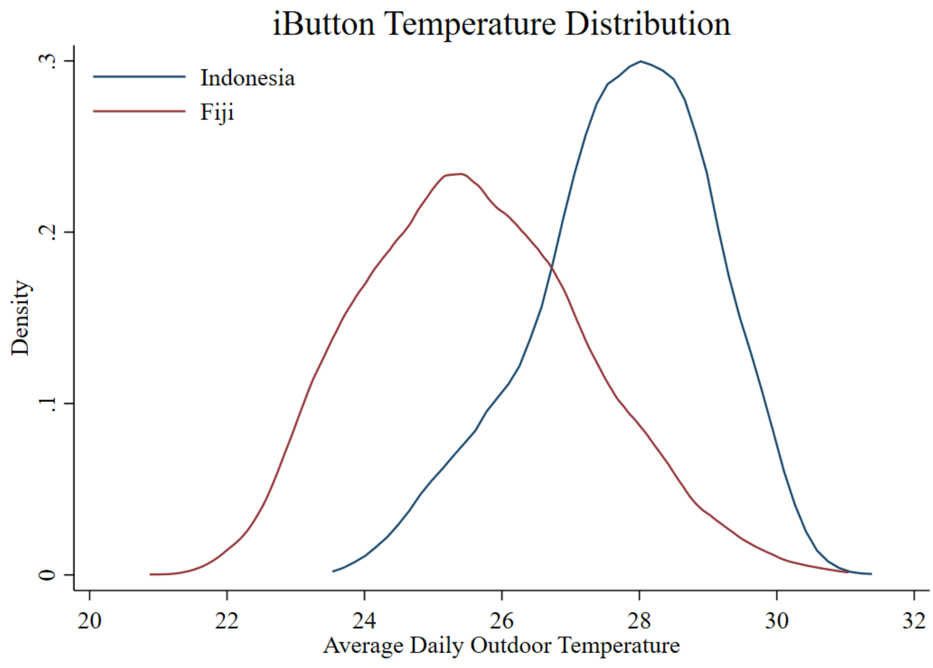
Figure 2. Timeline of data collection



Note: Adult and child poor general health and PedsQL items are available in all 5 Indonesian waves and all 4 Fijian waves.

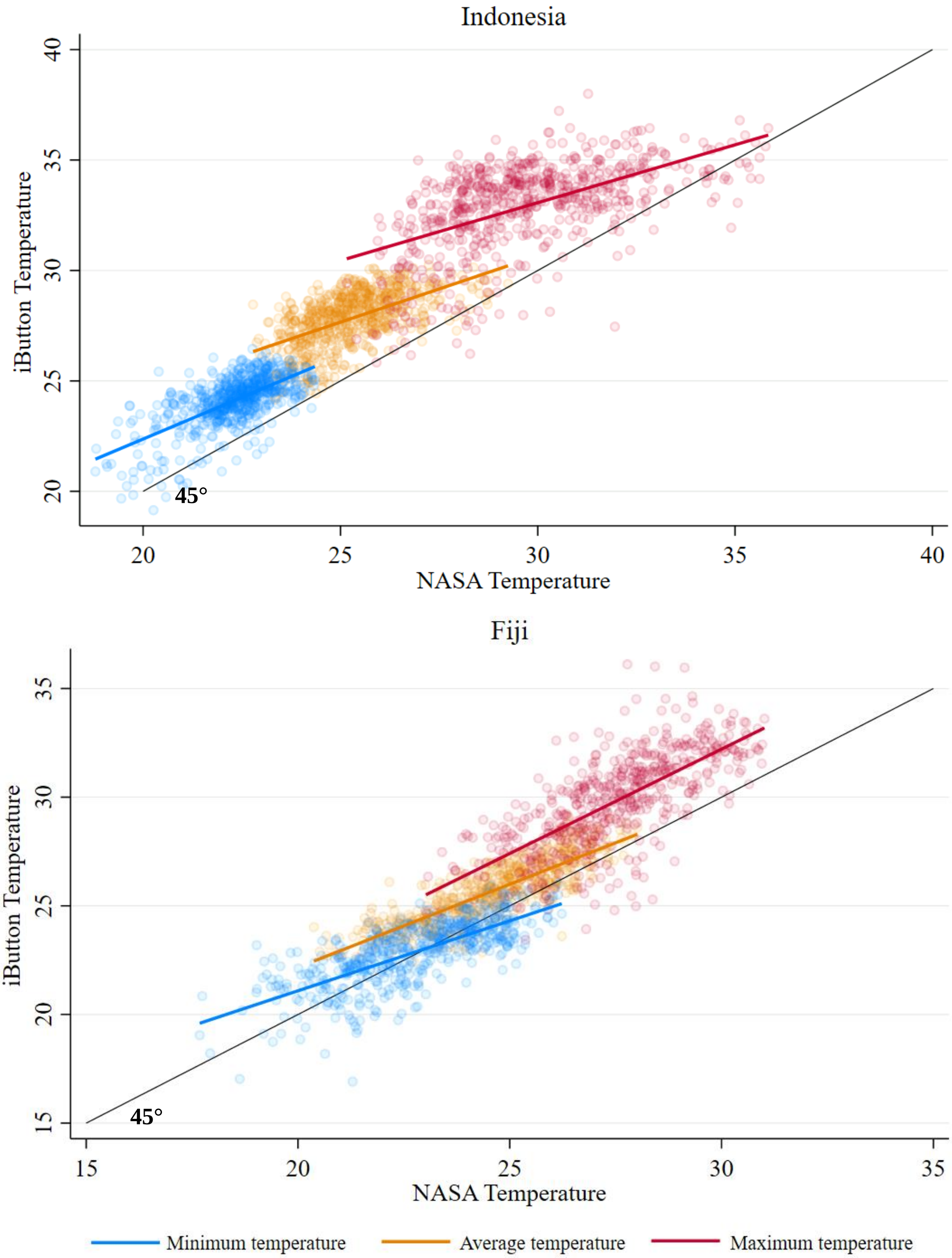
Figure 3. Distribution of average daily temperatures in the RISE settlements





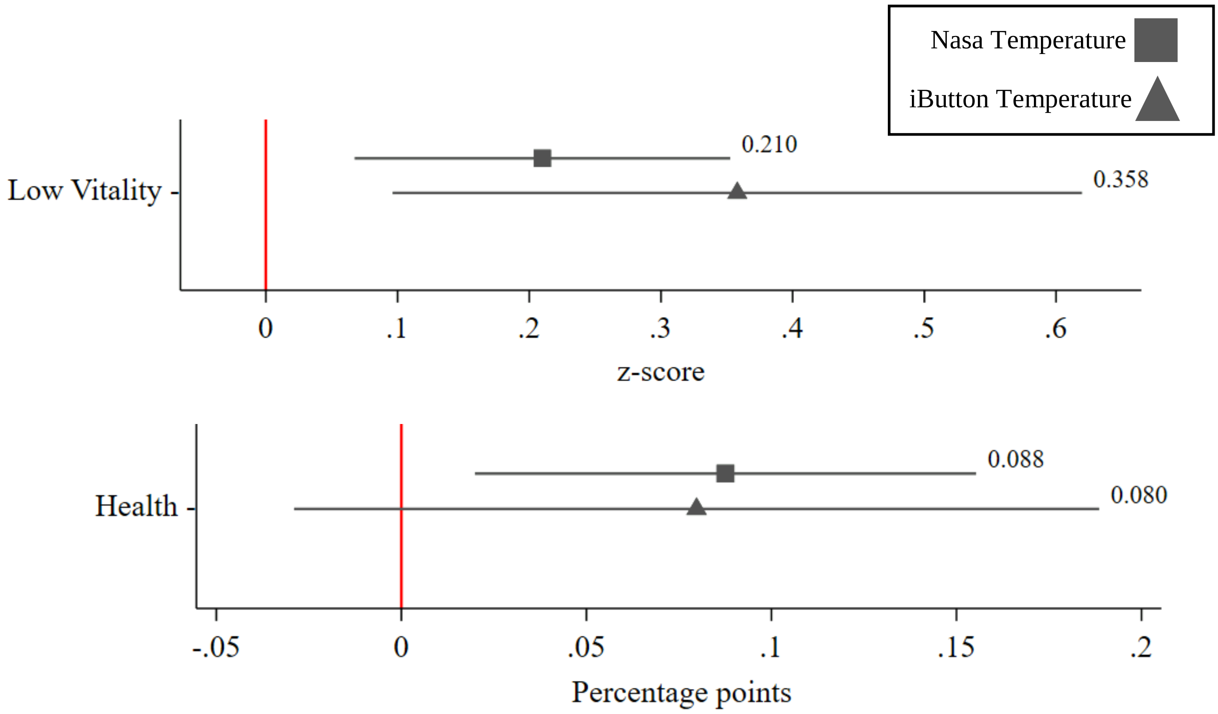
Note: Figure 3a) shows the distribution of temperatures as recorded by NASA's MERRA-2 dataset across Indonesia and Fiji between October 2018 – January 2022 and August 2019 – January 2021, respectively. Figure 3b) shows the distribution of temperatures recorded with the outdoor iButtons in the same period of time. The discrepancies, especially visible for Indonesia, are a depiction of the strong 'urban heat island effect' present in Makassar, Indonesia.

Figure 4. Overlap of daily outdoor local temperatures and NASA temperatures



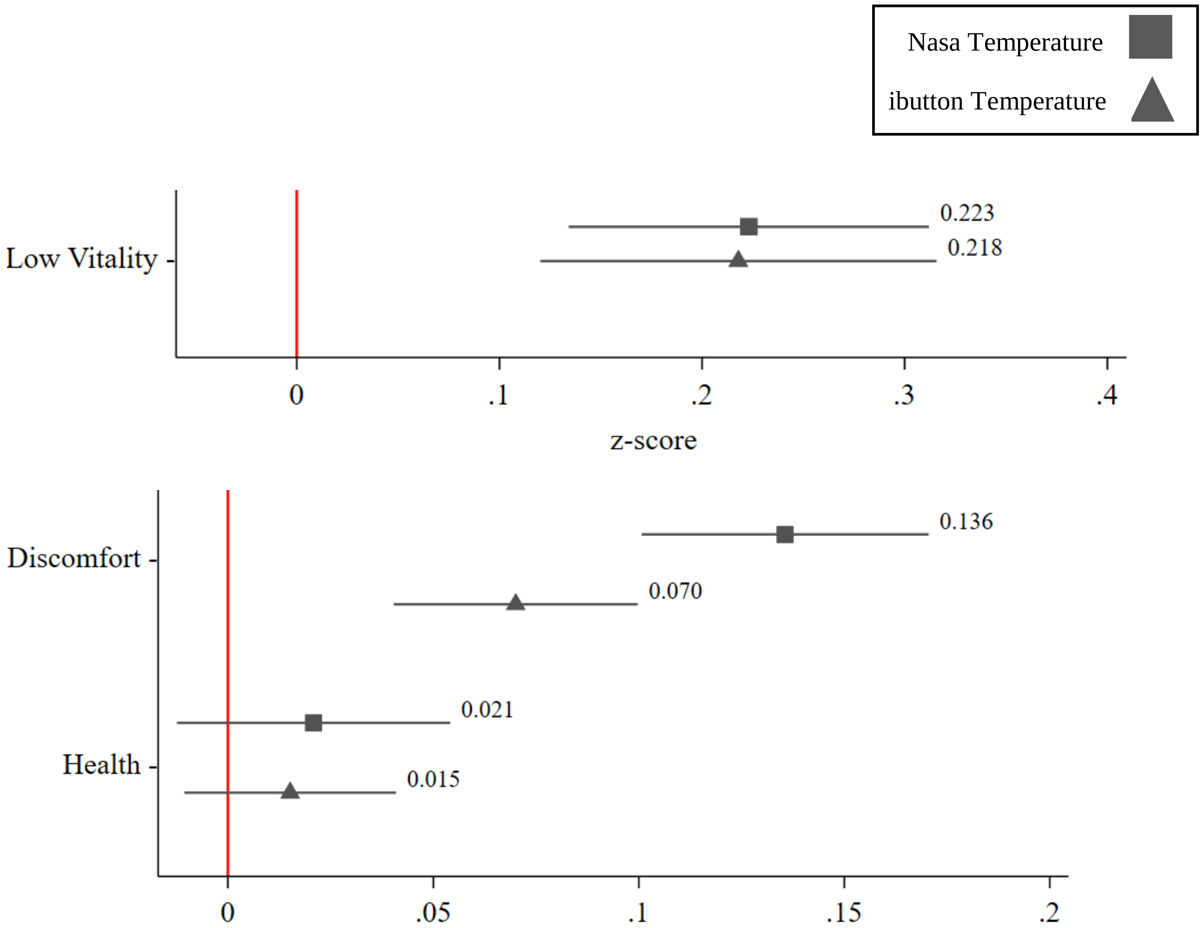
Note: Figures 4a and 4b plot NASA daily temperatures against iButton outdoor daily temperatures for Indonesia and Fiji, respectively. It also plots the 45° line as a reference. If both instruments recorded the exact same daily temperatures, the plots of minimum, average and maximum temperature would converge with the 45° line.

Figure 5. Stability of coefficients across measures of temperature – Indonesian iButton sample



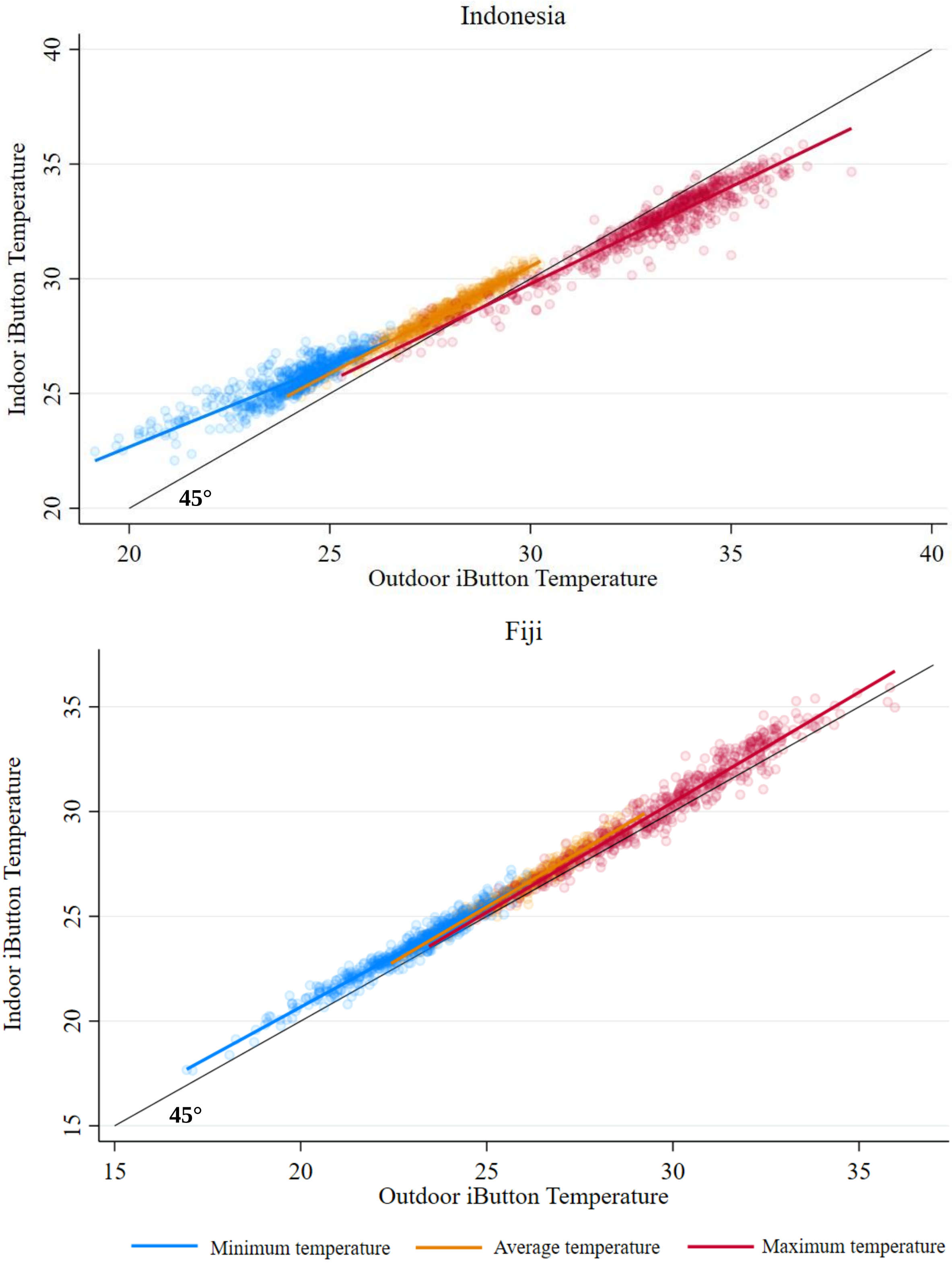
Note: Figure 5 shows the estimated effects of average NASA and ibutton temperatures in Indonesia on low vitality (z-score) and poor general health (in percentage points) using individual FE models and is restricted to the sample of observations with ibutton temperature values. Plots used 90% CIs.

Figure 6. Stability of coefficients across measures of temperature – Fijian ibutton sample



Note: Figure 6a shows the estimated effects of average NASA and ibutton temperatures in Fiji on low vitality, discomfort inside the home due to heat and poor general health using individual FE models and is restricted to the sample of observations with ibutton temperature values. Plots used 90% CIs.

Figure 7. Overlap of daily indoor temperature and outdoor local ibutton temperatures



Note: Figures 7a and 7b plot outdoor ibutton temperatures against indoor ibutton daily temperatures for Indonesia and Fiji, respectively. It also plots the 45° line as a reference. If indoor and outdoor temperatures are exactly the same on any given day, the plots of minimum, average and maximum temperature would converge with the 45° line.

Tables

Table 1. Description and mean of key variables used in the regression analyses

Variables	Description	Indonesia	Fiji
(A) Temperature			
Mean outdoor NASA temperature (ºC)	Average of NASA mean temperatures in 7 days prior to wellbeing survey	25.70	24.77
Mean outdoor ibutton temperature (ºC)	Average of outdoor ibutton mean temperatures in 7 days prior to survey	27.55	25.71
Mean daily indoor ibutton temperature (ºC)	Daily indoor ibutton maximum temperatures	28.46	26.34
Maximum daily indoor ibutton temperature (ºC)	Daily indoor ibutton maximum temperatures	32.23	30.46
Minimum daily indoor ibutton temperature (ºC)	Daily indoor ibutton minimum temperatures	25.67	23.56
Mean relative humidity (%)	Average humidity in 7 days prior to survey	80.35	78.93
(B) Adult Survey Outcomes			
Low Vitality (z-score)	Z-score of low vitality obtained via factor analysis of 3 variables: having trouble concentrating, restless sleep and feeling that everything is an effort (a moderate amount of the time or all the time in the seven days prior to the survey)	0	0
Discomfort Inside Home (0/1)	Binary variable indicating that in the 4 weeks prior to the survey, the respondent often or almost always felt uncomfortably hot inside their home	0.50	0.36
Poor Health (0/1)	Binary indicator of having moderate, bad or very bad general health	0.24	0.13

Note: The reported statistics provide the means across all available waves for each country.

Table 2. Temperature and Wellbeing - NASA outdoor temperature (Individual FE)

	Low Vitality Z-score	Discomfort Inside Home	Poor Health
	(1)	(2)	(3)
Indonesia			
Panel A			
Mean NASA Temp in Past Week	0.026**	0.104***	0.023***
	(0.013)	(0.007)	(0.006)
Outcome Mean	0	0.50	0.24
Observations	2,064	1,484	2,566
# Waves	4	3	5
# Weeks	32	22	39
Fiji			
Panel B			
Mean NASA Temp in Past Week	0.113**	0.092***	0.007
	(0.046)	(0.007)	(0.004)
Outcome Mean	0	0.36	0.13
Observations	1,473	2,248	2,839
# Waves	2	3	4
# Weeks	13	20	27

Note: All models control for individual fixed effects and total precipitation in the week prior to the survey. Standard errors clustered on the individual level in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Table 3. The additional effect of humidity on wellbeing - NASA outdoor temperature (Individual FE)

	Low Vitality Z-score	Discomfort Inside Home	Poor Health
	(1)	(2)	(3)
Indonesia			
Panel A			
Mean Temp in Past Week	0.048***	0.132***	0.049***
	(0.018)	(0.009)	(0.007)
Mean Humidity in Past Week	0.006	-0.016***	0.010***
	(0.005)	(0.003)	(0.002)
Temp * Humidity in Past Week	0.006**	0.009***	0.007***
	(0.002)	(0.002)	(0.001)
Outcome Mean	0	0.50	0.24
Observations	2,064	1,484	2,566
# Waves	4	3	5
# Weeks	32	22	39
Fiji			
Panel B			
Mean Temp in Past Week	0.103*	0.099***	0.007
	(0.061)	(0.007)	(0.004)
Mean Humidity in Past Week	0.018	-0.022***	-0.000
	(0.024)	(0.004)	(0.002)
Temp * Humidity in Past Week	0.023	-0.011***	-0.002
	(0.022)	(0.003)	(0.002)
Outcome Mean	0	0.36	0.13
Observations	1,473	2,248	2,839
# Waves	2	3	4
# Weeks	13	20	27

Note: All models control for individual fixed effects and total precipitation in the week prior to the survey. The variable average relative humidity in the past week is measured in % and ranges from 0 to 100. Indonesia has an average humidity of 80% and Fiji has an average humidity of 78%. Standard errors clustered on the individual level in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Table 4. Assets, building materials, and indoor temperature in Indonesia

	Mean (1)	Indoor Mean Temperature C° (2)	Indoor Max Temperature C° (3)	Indoor Min Temperature C° (4)
Air-conditioning	0.05	-0.240**	-0.615	-0.126
		(0.098)	(0.431)	(0.220)
Fan	0.87	0.103	0.174	0.050
		(0.109)	(0.438)	(0.216)
Gas/Electric Stove	0.96	0.220	-0.048	0.412
		(0.217)	(0.852)	(0.300)
Plants for shade	0.28	-0.127	-0.006	-0.157
		(0.123)	(0.336)	(0.186)
HHD Density	0.96	-0.001	0.006	-0.011
		(0.02)	(0.010)	(0.008)
Solid Walls	0.86	0.425***	0.190	0.554***
		(0.118)	(0.389)	(0.149)
Improved Roof	1			
Improved Floor	0.95	-0.032	-0.046	0.037
		(0.185)	(0.434)	(0.212)
Age of respondent	44.4	-0.002	0.002	-0.003
		(0.005)	(0.018)	(0.006)
Resp. has secondary schooling	0.52	-0.061	-0.236	0.122
		(0.089)	(0.313)	(0.135)
Homemaker in the house	0.76	-0.010	-0.167	0.066
		(0.118)	(0.346)	(0.149)
# children under 5 in the house	0.72	0.045	0.009	0.058
		(0.075)	(0.148)	(0.106)
Adjusted R-squared		0.8732	0.7043	0.7704
Within R-squared		0.1246	0.1078	0.2480
Observations		29,896	29,896	29,896
# Neighbour Groups		42	42	42
# Houses		108	108	108
# Days		674	674	674

Note: All models include neighbour-date fixed-effects and controls for mean height of the indoor ibuttons and number of indoor ibuttons that generated the indoor temperature readings for each dwelling. Standard errors clustered on house level in parentheses. * p<0.1; ** p<0.05; *** p<0.01

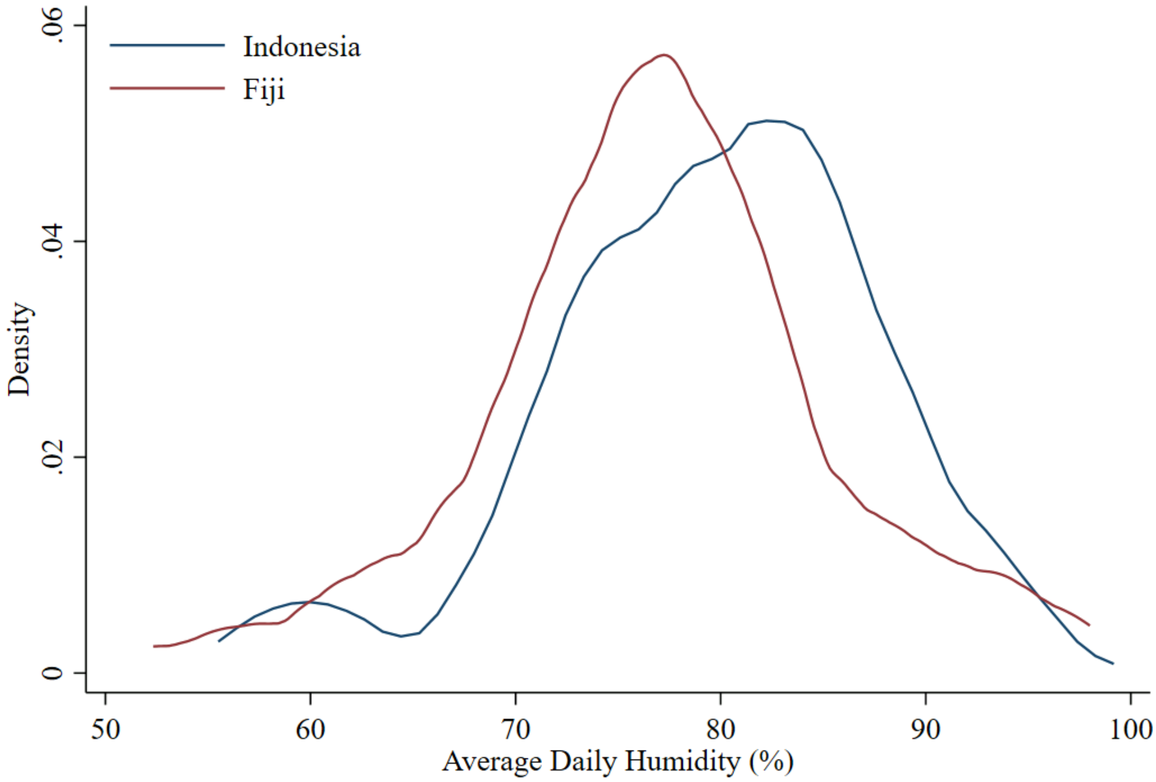
Table 5. Assets, building materials, and indoor temperature in Fiji

	Mean	Indoor Mean Temperature C°	Indoor Max Temperature C°	Indoor Min Temperature C°
	(1)	(2)	(3)	(4)
Air-conditioning	0.02	0.131	-0.814	0.583
		(0.566)	(0.856)	(0.505)
Fan				
Gas/Electric Stove	0.65	0.161	0.163	0.190**
		(0.101)	(0.185)	(0.089)
Plants for shade	0.02	-0.163	-0.574**	-0.064
		(0.165)	(0.269)	(0.169)
HHD Density	1.83	0.016	0.022	0.008
		(0.015)	(0.030)	(0.011)
Solid Walls	0.26	0.049	-0.113	0.174*
		(0.125)	(0.250)	(0.104)
Improved Roof	0.95	0.400	0.581	0.386*
		(0.297)	(0.574)	(0.231)
Improved Floor	1			
Age of respondent	44.84	-0.000	-0.001	0.001
		(0.004)	(0.008)	(0.003)
Resp. has secondary schooling	0.82	0.039	-0.382*	0.311***
		(0.118)	(0.230)	(0.096)
Homemaker in the house	0.5	-0.115	-0.033	-0.185**
		(0.091)	(0.171)	(0.080)
# children under 5 in the house	0.82	-0.034	-0.057	-0.028
		(0.040)	(0.067)	(0.044)
Adjusted R-squared		0.8608	0.7947	0.8509
Within R-squared		0.0599	0.062	0.0895
Observations		38,938	38,938	38,938
# Neighbour Groups		24	24	24
# Houses		110	110	110
# Days		696	696	696

Note: All models include neighbour-date fixed-effects and controls for mean height of the indoor ibuttons and number of indoor ibuttons that generated the indoor temperature readings for each dwelling. Standard errors clustered on house level in parentheses. * p<0.1; ** p<0.05; *** p<0.01

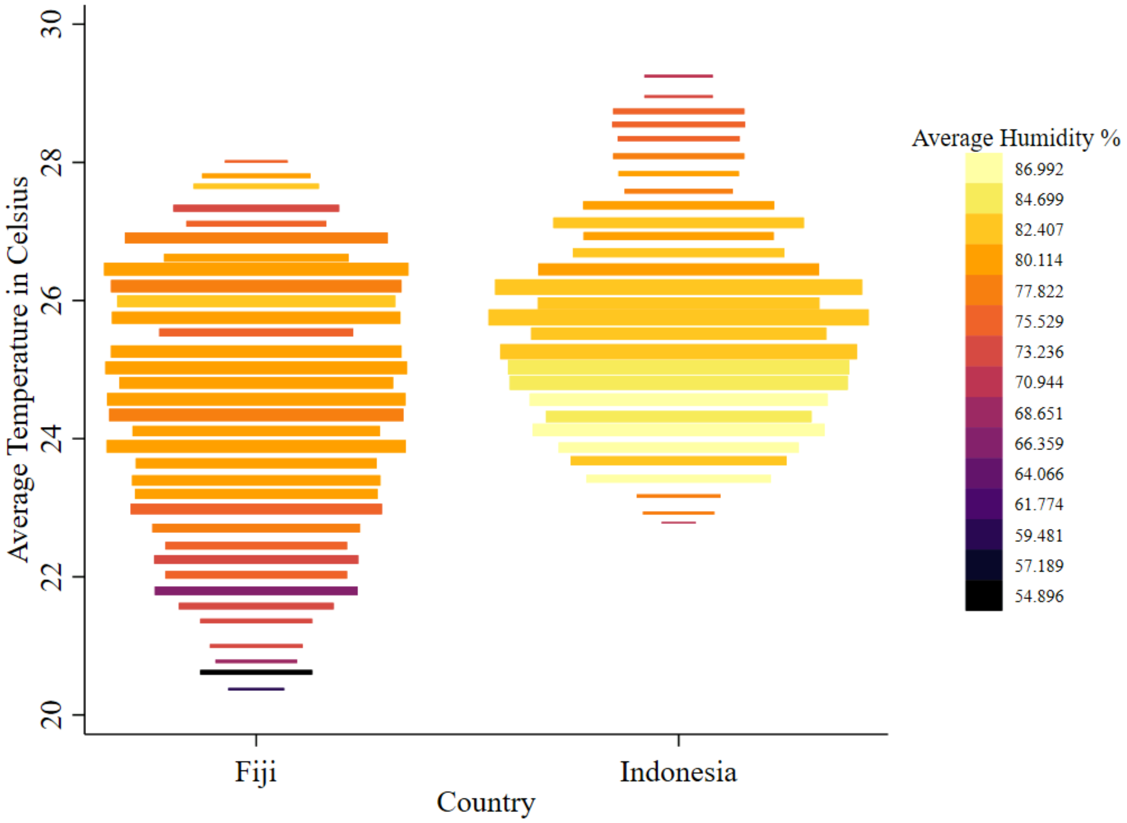
Appendix A - Figures

Figure A1. Distribution of average daily relative humidity by country



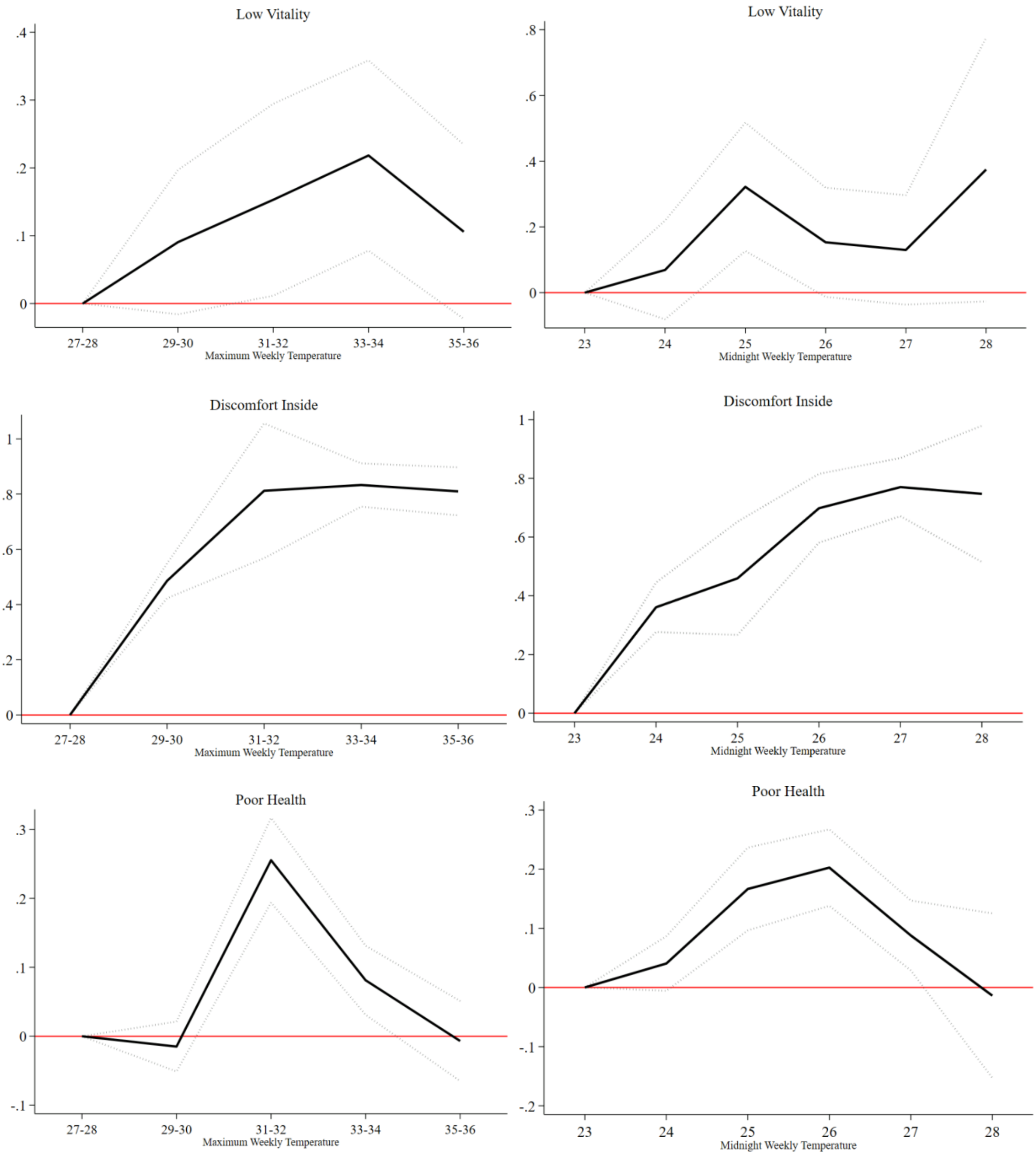
Note: Figure A1 plots the distribution of average daily relative humidity in Indonesia and Fiji, as measured by the local weather stations. Average humidity in Makassar, Indonesia is 80% and in Suva, Fiji is 77%.

Figure A2. Overlap of hot and humid days in the settlements



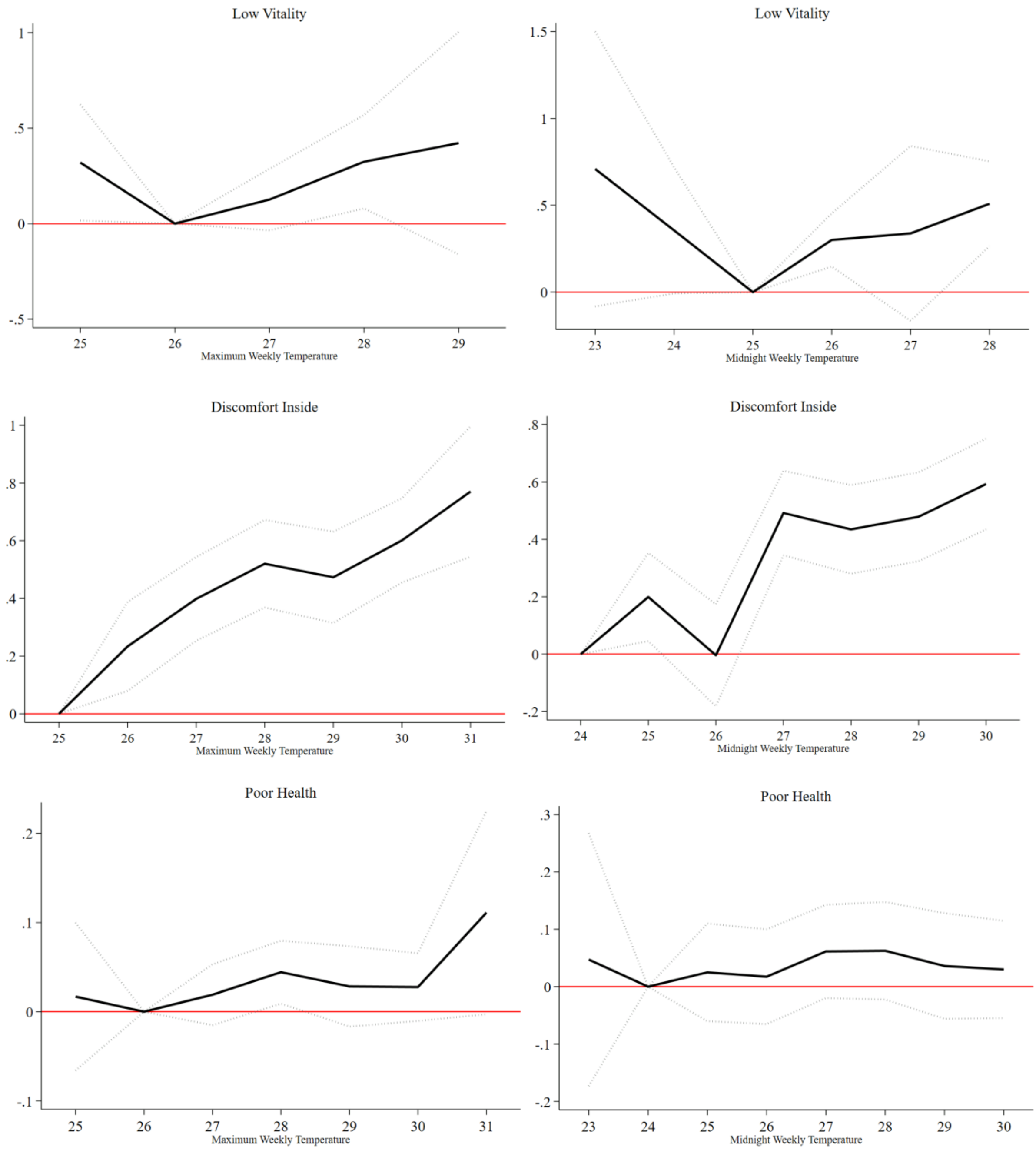
Note: Figure A2 plots the distribution of maximum temperature in the settlements, their relation to relative humidity (%), and where this places households to the limit of human survival of 35°C of wet-bulb temperature.

Figure A3. Non-linear (NASA) temperature effects among Indonesian adults



Note: Figures A3 plots the estimated distribution of effects of different measures of weekly temperature in 1-2°C bins, among Indonesian adults on the low vitality, discomfort inside one's home, and having poor general health in the past week. Plots use 90% CIs.

Figure A4. Non-linear (NASA) temperature effects among Fijian adults



Note: Figures A4 plots the estimated distribution of effects of different measures of weekly temperature in 1-2°C bins, among Fijian adults on low vitality, discomfort inside one's home, and having poor general health in the past week. Plots use 90% CIs.

Appendix B – Additional results and robustness checks

Appendix Table 1. Sample characteristics

Characteristic	Respondents	
	Indonesia	Fiji
Individual Characteristics		
Age	40.88	43.18
Gender = Male	12%	33%
Household Characteristics		
# People in house	4.83	6.05
# Children in house	1.56	1.87
Solid Walls	79%	30%
Solid Roof	100%	97%
Improved Floor	97%	99%
Assets		
Electricity	98%	-
Air-Conditioner	5%	2%
Fans	90%	-

Note. Mean statistics reported for the overall sample by country and age group

Appendix Table 2. Heterogeneity in Heat Effects (NASA data)

	Indonesia			Fiji		
	Low Vitality z-score	Discomfort Inside Home	Poor Health	Low Vitality z-score	Discomfort Inside Home	Poor Health
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Gender						
Female	0.025*	0.106***	0.022***	0.093*	0.092***	0.003
	(0.013)	(0.008)	(0.006)	(0.054)	(0.008)	(0.005)
Panel B - Age						
Young <40	0.026	0.101***	0.009	0.154**	0.084***	0.003
	(0.019)	(0.010)	(0.007)	(0.071)	(0.010)	(0.005)
Old 40+	0.031*	0.110***	0.039***	0.071	0.099***	0.005
	(0.018)	(0.011)	(0.009)	(0.062)	(0.010)	(0.006)
Panel C - Primary Activity						
Outside	0.045	0.102***	0.020	0.207*	0.082***	0.004
	(0.033)	(0.022)	(0.012)	(0.116)	(0.014)	(0.006)
Home	0.023	0.108***	0.023***	0.097	0.092***	0.008
	(0.015)	(0.009)	(0.007)	(0.063)	(0.010)	(0.006)

Note: Home includes housewives, retired, sick/disabled/ and unemployed people. Standard errors clustered on individual level in parentheses.
* p<0.1; ** p<0.05; *** p<0.01

Appendix Table 3. Effects of Heat (Individual FE - Weather Station Data)

	Low Vitality z-score	Discomfort Inside Home	Poor Health
	(1)	(2)	(3)
Panel A - Indonesia			
Outdoor Mean Temp in Past Week	0.029	0.314***	0.013
	(0.028)	(0.015)	(0.012)
Outcome Mean	0.00	0.50	0.24
Observations	2,064	1,484	2,566
Panel B - Fiji			
Outdoor Mean Temp in Past Week	0.083*	0.098***	0.006
	(0.045)	(0.007)	(0.004)
Outcome Mean	0.00	0.36	0.13
Observations	1,473	2,248	2,839

Note: Temperature data in these regressions comes from weather stations in Makassar, Indonesia and Nadi, Fiji. Standard errors clustered on individual level in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Appendix Table 4 - Cumulative Effects – Heat and Wellbeing in Indonesia (NASA data)

	Low Vitality z-score	Discomfort Inside Home	Poor Health
	(1)	(2)	(3)
Today's mean temperature above 25C	0.141	0.344***	0.085***
	(0.127)	(0.030)	(0.019)
Sum of coefficients up to day t-1	-0.031	0.376***	0.093***
	(0.766)	(0.031)	(0.020)
Sum of coefficients up to day t-2	0.095	0.413***	0.097***
	(0.338)	(0.031)	(0.021)
Sum of coefficients up to day t-3	0.065	0.432***	0.103***
	(0.530)	(0.032)	(0.022)
Sum of coefficients up to day t-4	0.062	0.432***	0.120***
	(0.505)	(0.033)	(0.022)
Sum of coefficients up to day t-5	0.025	0.328***	0.125***
	(0.094)	(0.061)	(0.031)
Sum of coefficients up to day t-6	0.125**	0.457***	0.129***
	(0.058)	(0.033)	(0.023)

Note: Standard errors clustered on individual level in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Appendix Table 5 - Cumulative Effects – Heat and Wellbeing in Fiji (NASA data)

	Low Vitality z-score	Discomfort Inside Home	Poor Health
	(1)	(2)	(3)
Today's mean temperature above 24C	-0.067	0.311***	0.005
	(0.114)	(0.031)	(0.016)
Sum of coefficients up to day t-1	0.068	0.329***	0.011
	(0.122)	(0.032)	(0.017)
Sum of coefficients up to day t-2	0.078	0.337***	0.021
	(0.114)	(0.033)	(0.017)
Sum of coefficients up to day t-3	-0.007	0.357***	0.033*
	(0.146)	(0.033)	(0.018)
Sum of coefficients up to day t-4	-0.074	0.362***	0.033*
	(0.147)	(0.033)	(0.018)
Sum of coefficients up to day t-5	-0.065	0.140*	0.027
	(0.153)	(0.079)	(0.025)
Sum of coefficients up to day t-6	0.343**	0.395***	0.023
	(0.155)	(0.033)	(0.016)

Note: Standard errors clustered on individual level in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Appendix Table 6. Wealth, building materials, and their interaction with outdoor temperature

	Indonesia			Fiji		
	Mean Indoor Temp C°	Max Indoor Temp C°	Min Indoor Temp C°	Mean Indoor Temp C°	Max Indoor Temp C°	Min Indoor Temp C°
	(1)	(2)	(3)	(4)	(5)	(6)
Air-conditioning * Outdoor Temp	-0.006	0.086	-0.058	0.061	0.014	0.063
	(0.045)	(0.091)	(0.062)	(0.102)	(0.114)	(0.128)
Fan * Outdoor Temp	-0.040	-0.01	0.028	-	-	-
	(0.044)	(0.055)	(0.100)			
Gas/Electric Stove * Outdoor Temp	0.014	0.114*	-0.287**	0.043	0.027	0.049*
	(0.032)	(0.058)	(0.116)	(0.027)	(0.042)	(0.027)
Plants for shade * Outdoor Temp	-0.053*	-0.044	-0.072	0.087***	0.173***	0.054**
	(0.028)	(0.037)	(0.052)	(0.029)	(0.054)	(0.024)
HHD Density * Outdoor Temp	0.001	-0.002	-0.005**	-0.001*	-0.002**	-0.001
	(0.008)	(0.010)	(0.003)	(0.001)	(0.001)	(0.001)
Solid Walls * Outdoor Temp	-0.024	-0.067	-0.032	-0.003	-0.041	-0.003
	(0.028)	(0.043)	(0.049)	(0.038)	(0.058)	(0.039)
Improved Roof * Outdoor Temp	-	-	-	-0.051	-0.075	0.004
				(0.098)	(0.107)	(0.105)
Improved Floor * Outdoor Temp	0.009	-0.066	0.135***	-	-	-
	(0.046)	(0.072)	(0.050)			
Adjusted R-squared	0.8615	0.7210	0.7565	0.8647	0.7982	0.8532
Within R-squared	0.0949	0.1512	0.234	0.0569	0.0595	0.0499
Observations	32,155	32,155	32,155	44,229	44,229	44,229
# Neighbour Groups	44	44	44	37	37	37
# Houses	118	118	118	114	114	114
# Days	771	771	771	697	697	697

Note: All models include neighbour-date fixed-effects. All dwellings have tin roofs in Makassar and improved floors in Suva so their coefficients are omitted. Standard errors clustered on house level in parentheses.
* p<0.1; ** p<0.05; *** p<0.01

Appendix C – iButton Data

In situ temperature measurements were collected from a network of iButton data loggers deployed in the RISE informal settlements in Suva, Fiji and Makassar, Indonesia. Loggers were deployed in five outdoor locations and in ten randomly sampled houses in each settlement.

Outdoor loggers were deployed in solar radiation shields (see Ramsay et al. 2021; modified from Scott et al. 2017) at approximately 2-meter height, attached to trees or other suitable structures. Three pairs of loggers were deployed in each house, with one sampling one-hourly and one sampling two-hourly. Pairs were deployed in and around the house according to practical requirements and the preference of the householder, aiming to place one pair high, one low, and one in between. Where necessary, household iButtons were also deployed in solar radiation shields.

Data were downloaded from loggers quarterly. Logger loss, failure and fieldwork limitations meant that data was not recovered for all loggers or for all time periods. In particular, no data were recovered between May and November 2020 in Makassar and between August 2021 and January 2022 in Suva owing to working from home requirements. In total, 1080 loggers were deployed across Suva and Makassar. Data were recovered for at least one quarter for 452 loggers in Suva and 528 loggers in Makassar.

To mitigate any remaining effects of solar radiation, despite the use of solar radiation shields, we calculated the 95th percentile of all temperature measurements at each hourly time point (pooled across years), separately for each city and for houses and outdoor loggers. Any data points exceeding the 95% percentile were adjusted down to this threshold. All analyses and data processing use these adjusted temperature values.

Temperature can vary significantly over small spaces, especially in urban areas. Therefore, to provide representative values of settlement and household temperatures we only included data where it was retrieved for at least two outdoor loggers in a settlement or loggers in at least two locations in a household. We then calculated hourly mean temperature for all loggers in each house or outdoors in each settlement. Finally, daily mean, minimum and maximum temperature were computed for each house and each settlement.