Adaptation technology choice and implications for heat-related health risk[*,†]

Filippo Pavanello[‡] Ian Sue Wing[§]

Abstract

This paper investigates the consequences of inequality in heat adaptation, examining the effectiveness of alternative cooling technologies in mitigating mortality associated with extreme heat in India for the period 2014-2019. Our empirical results highlight a critical trade-off in heat adaptation. Air conditioning is highly effective in moderating heat-related mortality, but it is expensive, with generally low ownership that tends to be restricted to high-income cities. Conversely, many Indian households, including low-income ones, purchase evaporative coolers, which are much cheaper but do not robustly mitigate the adverse health consequences of humid heat. We show that coolers' limited effectiveness is due to their inability to operate in the humid ambient conditions that prevail over the Indian subcontinent for much of the year, and the small amount of indoor temperatures reduction they provide.

Keywords: Heat, Humidity, Adaptation, Mortality, Inequality, India

JEL Classification: D12, O13, O15, F24, Q4

[*]First version: November 2023. This Version: November 2025. An earlier version of this paper was circulated under the title "Adapting to Heat Extremes with Unequal Access to Cooling: Evidence from India".

[†]Filippo Pavanello is indebted to Annalisa Loviglio and Anastasios Xepapadeas for their comments and guidance. We are also grateful to Pietro Biroli, Alberto Bisin, Elisabetta De Cao, Enrica De Cian, Francois Cohen, Francesco Pietro Colelli, Hélia Costa, Namrata Kala, Bruno Conte Leite, Karen Pittel, Vincenzo Scrutinio and Guglielmo Zappalà for valuable feedbacks. We also thank attendees at the 2nd ERC-ENERGYA Workshop, the 1st Padova Workshop on Environmental Economics, 12th IAERE Conference, 29th EAERE Conference, and 2024 Summer AERE Conference. The paper has also benefitted from comments and suggestions by seminar participants at University of Bologna, CMCC, Boston University, ESSEC, University of Barcelona, and ifo Institute. This research was supported by the ENERGYA project, funded by the European Research Council (ERC), under the European Union's Horizon 2020 research and innovation program, through grant agreement No. 756194. The views expressed here are those of the authors. The authors are solely responsible for any errors in the manuscript.

[‡]ifo Institute; LMU Munich; CESifo; Ca' Foscari; EIEE. Email: pavanello@ifo.de

[§]Boston University. Email: isw@bu.edu

1 Introduction

Adverse effects of heat on health and well-being are a growing concern as extreme high temperature exposures intensify with climate warming. High temperatures, especially combined with high humidity, are associated with a range of adverse health outcomes.[1] Households attempt shield themselves from exposure to these ambient weather conditions by using cooling technologies, particularly air conditioning (AC, Davis and Gertler, 2015; De Cian et al., 2025; Davis et al., 2021).

Cooling appliances moderate indoor temperatures, providing thermal comfort and protecting against the morbidity and mortality effects of heat exposures (Barreca et al., 2016; Park et al., 2020; Somanathan et al., 2021). Yet, across much of the developing world, low incomes and credit constraints limit the adoption of expensive cooling appliances such as AC units, resulting in highly unequal access to cooling and its associated benefits. This "cooling gap" can potentially be bridged by more affordable cooling technologies, but the extent to which the latter can substitute for their more expensive counterparts has not been systematically explored.

In this paper we examine the effectiveness of alternative cooling appliances in mitigating mortality impacts from extreme heat in India. We shed light on the trade-off between affordability and health protection for different heat adaptation technologies, specifically evaporative coolers and air conditioners. The former are an affordable, passive, open-loop cooling technology that reduces indoor temperatures by forcing hot ambient air over water-saturated material, leveraging evaporation (which uses energy to convert water from the liquid to the vapor phase) to remove thermal energy from the air stream, lowering its temperature. These devices can reduce indoor temperatures up to 4.5°C relative to ambient levels, but their effectiveness sharply diminishes with high ambient humidity, and the passive character of the evaporation process means that they lack the ability to precisely control indoor temperatures. By contrast, air conditioning (AC) is an active cooling technology in which thermal energy in the air is absorbed by expansion of a refrigerant that is mechanically compressed in a closed loop. The result is much larger indoor temperature reductions—up to 20°C—but at substantially higher capital[2] and energy costs. Consequently, evaporative coolers are less effective but considerably more

[1] The non-market costs of extreme heat include impacts on mortality (Barreca et al., 2016; Burgess et al., 2017; Yu et al., 2019; Carleton et al., 2022; Liao et al., 2023; Weinberger et al., 2020; Asseng et al., 2021), morbidity (Basu and Samet, 2002; Sun et al., 2021), mental health (Burke et al., 2018; Hua et al., 2022; Mullins and White, 2019; Nori-Sarma et al., 2022), mood (Baylis, 2020; Noelke et al., 2016), aggressive behaviour and crime (Ranson, 2014; Baysan et al., 2019; Blakeslee et al., 2021), learning (Park et al., 2020) and labour productivity (Somanathan et al., 2021; Dasgupta et al., 2021).

[2] AC prices in India vary widely based on type and features. Window ACs start at around 20,000 rupees, split ACs range from 25,000 to 60,000 rupees, while central systems can exceed 80,000 rupees. This is about 11%-44% of median annual household income in 2019 in India ($\approx$ 181,000 rupees).

accessible,[3] particularly for low-income households, due to their simpler design, lower up-front investment, and reduced electricity usage.[4]

To address our research question, we combine a new rich longitudinal household-level survey data set with district-level mortality data and high-resolution meteorological information in India for the period 2014-2019. Our empirical analysis proceeds in three phases.

We first study the choice of cooling technology among Indian households using longitudinal data from eighteen waves of the the Consumer Pyramids Household Survey (CPHS), which records quarterly ownership of air conditioners and evaporative coolers. Descriptive evidence reveals that most households still lack access to cooling technology of any kind. When cooling technologies are present, both AC and coolers are more prevalent in richer and warmer parts of India. However the spatial pattern of cooler prevalence depends critically on how heat exposure is measured: metrics that ignore humidity suggest highest ownership in the hottest areas, but measures that adjust for humidity reveal concentration in drier, cooler regions and much lower prevalence in regions that are both hot and humid.

Over the sample period, ownership of AC units and coolers both grow rapidly, a phenomenon that is associated predominantly with income growth and urbanization relative to temperature exposure. However, linear probability models employing household and survey wave fixed effects reveal sharply differences in adoption: high-income and urban households tend to acquire air conditioners, while low- and middle-income households rely on more affordable coolers. We show that the dominant driver of this pattern is household income, a 10 percent increase in which raises the probability of owning an air conditioner by 0.13 percentage points (0.32-0.35 among richer and urban households) and an evaporative cooler by 0.35 percentage points. Climatic conditions matter less on average but interact strongly with income, with only wealthier households responding to hotter, more humid conditions by adopting AC units.

Second, we quantify the health protection benefits of air conditioners and coolers, quantifying their mediating effects on district-level temperature-related mortality. We exploit plausibly exogenous variation in the distribution of wet-bulb temperatures to determine the association between hot and humid days and mortality. We find that, relative to a day with average wet-bulb temperatures of 14-24°C, an additional day at or above 29°C is associated with a 1 percentage point increase in annual mortality rates. The magnitude of the response to dry-bulb temperatures is significantly smaller, even when considering very hot days with dry-bulb temperatures exceeding 35°C.

We augment our baseline specification by interacting wet-bulb temperature with the annual

[3] The average price of an evaporative cooler ranges between 3,000 and 15,000 rupees, corresponding to about 2%-8% of annual household income in 2019.
[4] U.S. Department of Energy, Home Cooling Systems

penetration rates of both technologies computed from the CPHS, while flexibly controlling for annual changes and state-specific differences in the direct effects of temperature on mortality. When adaptation is included, the two technologies have statistically different mediating effects on the temperature-mortality relationship. On average, a 1% increase in air conditioning prevalence reduces the mortality impact of an additional day with wet-bulb temperatures at or above 29 °C by 2.7%, whereas the same increase in cooler prevalence yields only a 0.05% reduction, which suggests that AC is substantially more effective in mitigating temperature-related mortality.

Importantly, although variation air conditioner and cooler ownership rates are not quasi-random, our main specification allows the effects of temperature to vary flexibly across states and years, allowing us to control for annual changes and state-specific differences in the direct effects of temperature on mortality that are also potentially correlated with cooling technology adoption. Our main results are corroborated by a battery of robustness checks. We do not find significant effects of interactions between cooling appliances and cold temperatures, suggesting that adoption of these technologies is uncorrelated with factors that determine the overall mortality rate. Our findings are also robust to the inclusion of interactions between temperature and income.

The third phase of our analysis sheds light on the mechanisms behind evaporative coolers' small mediating effect. We begin by examining novel hourly building data from Tasgaonkar et al. (2022) for three Indian cities to assess whether evaporative coolers can improve thermal comfort by lowering indoor temperatures. We find that they can cool indoor temperatures by up to 4.2 °C, but become ineffective when outdoor dry-bulb temperatures exceed 43 °C or when humidity exceeds 66%. Next, we examine how different cooling appliances' mitigating effects on temperature-related mortality vary by humidity. Dividing our district-year sample into terciles of humidity, we find that *both* coolers and AC units significantly reduce mortality in drier districts, with no statistically significant difference between them. But in more humid conditions, only air conditioners provide significant protection. Given this finding, we address the question of why households would choose to incur the costs of investing in technology that is seemingly inefficient by explore whether evaporative coolers offer morbidity, as opposed to mortality, reduction benefits. Using an individual self-reported well-being measure from the CHPS survey, we find—consistently across fixed effects specifications—that the presence of coolers is associated with higher well-being on days with 24-29°C wet-bulb temperatures, but worsen well-being when wet-bulb temperatures exceed 29°C. Air conditioners, by contrast, yield consistent morbidity benefits even during the hottest and most humid days.

Taken together, our findings suggest that evaporative coolers are effective at providing cooling only within a relatively narrow meteorological window, while air conditioners remain effective across a far broader range of conditions. This limitation translates into substantially weaker aggregate mortality protection from coolers compared to AC.

Our results contribute to several strands of literature. We provide new evidence about the effectiveness of alternative heat adaptation technologies that are both available and actively being utilized (Auffhammer and Mansur, 2014). We also contribute to the literature on inequality in heat adaptation (Davis and Gertler, 2015; Mastrucci et al., 2019; Davis et al., 2021; Pavanello et al., 2021; Romitti et al., 2022). Income inequality is a well-characterized determinant of disparities in access to air conditioning. Our contribution is to elucidate the novel and heretofore unexplored dimension of technology choice. The key implication is that when households attempt to adapt to heat exposures, income and credit constraints can limit the scope of feasible alternatives to cooling appliances that are at best only modestly effective, resulting in an unequal distribution of residual health risk. Distinct from previous literature, features of our data facilitate exploration of not only the distribution of technologies across households, but also the determinants of adoption of the different alternatives. This provides new insights into the drivers of demand for cooling in developing country settings.

We also estimate mortality-heat exposure response functions, which in developing countries have been limited by lack of data and issues of reliability and measurement error. We contribute to the burgeoning literature on temperature as a driver of mortality (Barreca et al., 2016; Carleton et al., 2022; Burgess et al., 2017; Liao et al., 2023). While mortality-heat exposure responses for India have previously been characterized using annual district-level mortality data for 1957-2001 (Burgess et al., 2017), we provide updated responses for the contemporary pre-COVID period.[5] Our constribution is to pinpoint humidity as a key driver of mortality. High levels of ambient humidity can exacerbate heat stress by impairing the body's ability to cool itself through evaporating perspiration off of the skin (Barreca, 2012). We show that annual mortality rates increase strongly with the number of days in the year that are both extremely hot and humid.

Our work is also closely related to the few studies that combine empirical analysis of both the mortality impacts of temperature extremes and the mitigating effects of heat adaptation. Deschênes and Greenstone (2011) and Yu et al. (2019) document the relationship between daily temperatures and annual mortality rates and daily temperatures and annual residential energy consumption in the United States and in China respectively, but the two dose-responses are studied separately. Conversely, Barreca et al. (2016) combine information on adaptation mediated

[5] Burgess et al. (2017) digitises mortality data from various issues of the publication Vital Statistics of India, which, as of today, are available only from 2009 onward.

by AC, daily temperatures, and state-level monthly mortality rates in the United States. They find that the diffusion of residential AC reduced hot day–related mortality by 80% in the United States. The present study provides a more comprehensive analysis of heat adaptation responses, exploring heterogeneities across margins, income levels and technologies, by comparing alternatives' protective effects to elucidate cost-performance tradeoffs in households' choices among alternatives, and highlighting how income shapes the distribution of health protection benefits arising from cooling technologies.

Finally, we demonstrate a novel application of recently available building-level datasets that record indoor and outdoor temperatures at high frequency, offering a context-specific elaboration of cooling technologies' effects on indoor environments that aggregated sources cannot provide. In our setting, such granularity allows for more accurate policy evaluation and for deeper insight into the mechanisms underlying heat adaptation decisions. We exploit these data to test whether evaporative coolers reduce indoor temperatures under varying outdoor conditions throughout the day. To our knowledge, this is the first study to provide econometric evidence on the extent to which cooling technologies lower indoor temperatures.

The remainder of the paper is structured as follows. Section 2 describes the data used in our analysis. Section 3 presents an adaptation theoretical framework that guides the empirical analysis. Section 4 describes the data. Empirical results are discussed in sections 5 to 7. Section 8 concludes with a discussion of caveats and next steps.

2 Data

This section describes the data employed in our analysis.[6] To address our research questions, we require data with several features. First, we need a household survey that provides information on adoption of multiple heat adaptation appliances, as well as socio-economic and demographic characteristics of households to also exploring the inequality dimension. Second, we require data that allows us to determine the impact of temperature on mortality in India, while also studying the mitigating effects of cooling adaptation technologies.

Household data. Our primary data to study cooling adaptation is the Consumer Pyramids Household Survey conducted by Center for Monitoring Indian Economy (CMIE) for the period 2014-2019. CPHS provides a large and representative panel survey of Indian households, covering nearly the whole of India. It employs stratified sampling to ensure representativeness at various level, particularly national and regional level, and region × urban status.

[6] Table S1 summarizes the datasets used for each of the analyses in the paper.

CPHS surveys each household every four months, with sampling staggered so that a representative 25% of all households are sampled in any given month. The survey provides information on size, origin, and distribution of Indian households' income and expenditures levels. In particular, we use recorded expenditures and income, which are reported at the monthly level. Each CPHS wave also collects information on households' characteristics, housing, and owned assets, as well as individual-specific information. These records make it possible to determine whether households have air conditioners and evaporative coolers installed in their dwelling every four months.

Mortality data. To assess the impact of temperature on mortality, we collect district-level information on deaths from the Indian Civil Registration System. In particular, following Burgess et al. (2017), we digitize public reports in the "Vital Statistics of India" series for the years 2014-2019. Each report provides tables with the number of all-age all-causes deaths that occurred in each Indian district and state. Reports also distinguish between deaths occurring in rural and urban areas.[7]

During the sample period, some districts split to create new administrative units. We track these changes, constructing a cross-walk of districts, which we then fix to 2014 geographic boundaries. We then aggregate subsequently partitioned districts back to their original parent administrative units.

Our outcome of interest is district-level mortality rates—as opposed to counts of deaths. To construct this variable, we obtain population information from the Gridded Population of the World (GPW) v4 (CIESIN, 2018), which provides estimated population counts for the years 2010, 2015, and 2020, consistent with national censuses and population registers, on an $\sim$1 km grid. We sum grid cell populations to our 2014 district boundaries, and exponentially interpolate the resulting district population estimates between each five year-period. Finally, we divide district-level death counts by these annual populations to generate mortality rates.

Weather data. Household and mortality data are merged with population-weighted[8] weather data at the most disaggregated geographical information available, the district.

Weather variables are taken from the ERA5 reanalysis product developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), which provides hourly data on 2m air temperature, 2m dewpoint temperature, and precipitation at 0.25 °spatial resolution (Hersbach et al., 2020). Relying on information from weather stations, satellites, and sondes, this reanalysis

[7] Each report also provides the distinction between male and female deaths. However, this information is missing for several districts and years. For this reason, we focus on all-gender number of deaths.

[8] To weight our climate data we again use GPW 1 km population counts, aggregated to ERA5 grid cells.

data is less prone to station weather bias but might be biased via the meteorological models that are used to generate a gridded product (Auffhammer et al., 2013). Furthermore, this type of data set is increasingly being used in climate econometrics, especially in developing countries, where the quality and quantity of station-level data can be limited.

To capture physiological stress induced by exposure to heat and humidity, we compute wet-bulb globe temperature (WBGT) using the 2-meter air and dewpoint temperatures, following Bernard's methodology (Lemke and Kjellstrom, 2012). WBGT provides a more comprehensive measure of thermal stress than air temperature alone, as it accounts for relative humidity—an important modifier of heat-related health risks (Barreca, 2012; Geruso and Spears, 2018) and labour productivity (Adhvaryu et al., 2020; LoPalo, 2023). This is particularly relevant in the humid tropics, where elevated humidity impairs the body's ability to cool through sweating, amplifying heat stress. For this reason, our primary exposure variable throughout the analysis is wet-bulb temperature.[9] Throughout the paper we show that employing wet-bulb temperature is appropriate for our analysis.

Leveraging the above hourly weather series, we construct several exposure measures at the monthly, 4-monthly, and annual level. These include binned measures of wet bulb and dry bulb temperature, specific humidity,[10] and Cooling Degree Days (CDD), where CDDs are calculated for both wet- and dry- bulb temperatures using a 24°C threshold.[11]

Additional data. We complement our main analysis with granular, high-frequency microdata on indoor and outdoor thermal measurements collected at the household level (Tasgaonkar et al., 2022). This dataset spans 206 dwellings in five low-income districts of South Asian cities—Yavatmal and Jalna (Maharashtra, India), as well as Delhi (India), Dhaka (Bangladesh), and Faisalabad (Pakistan)—over the period March 2016 to February 2019. Hourly indoor temperatures were recorded using data loggers installed within each dwelling, while outdoor conditions were measured using site-specific automated weather stations. For the purposes of our study, we restrict the sample to locations in India and retain only those dwellings with available contextual information, yielding a final sample of 95 households.

The dataset further includes information on ownership of heat adaptation appliances. While the presence of AC units was not recorded, households report ownership of electric fans and evaporative coolers. We leverage this high-resolution data in our analysis of mechanisms to assess the effectiveness of evaporative cooling technologies in generating thermal comfort, re-

[9] Wet-bulb and dry-bulb temperatures coincide only at 100% relative humidity; otherwise, the wet-bulb measure is strictly numerically lower.

[10] Specific humidity is calculated following the method described in Bolton (1980).

[11] Cooling Degree Days are computed as $CDD = \sum_{i=1}^{n}(T_i - \overline{T})$, where T_i denotes the daily average temperature and $\overline{T}$ is a fixed threshold.

ducing indoor heat exposure.

3 The choice of cooling technology

In this section we examine the interplay between temperature and income in the choice of the heat adaptation technology across Indian households.

3.1 Stylized facts

The role of economic development. Table A1 displays descriptive statistics for the CHPS sample. On average, about one-third of Indian households own at least one evaporative cooler, while air conditioners are relatively rare, with an ownership rate of 6% However, these figures mask large heterogeneities across income levels. To see this, Figure 1 displays the ownership rates of the two technologies at the state level, with states ordered by average household income. The trends clearly highlight disparities in technological choices along the income distribution. High-income urban settings such as Chandigarh and Delhi demonstrate almost full saturation of evaporative cooler ownership by the beginning of the sample period, as well as rapid increases in AC prevalence. Put in perspective, in the United States the rate of AC ownership increased by about 25 percentage points over the decade of the 1960s (Barreca et al., 2016), while in Delhi in increased by 30 percentage points in half that time. Conversely, most states in India are still in the process of catching up to the saturation of demand for evaporative coolers. This highlights the variations in cooling technology preferences and access to higher-income households and urban areas compared to other regions and income groups.

Distribution across climatic conditions. Figure 2 explores these patterns in more detail, dividing households into nine categories based on long-run temperature conditions—measured using a 30-year average of either dry-bulb or wet-bulb CDD—and average 4-month household income. Two key findings emerge. First, technology choice differs markedly across income levels: evaporative coolers diffuse more rapidly among low- and middle-income households, whereas demand for air conditioners rises primarily among high-income households.

Second, penetration of the two technologies is sensitive to climate, but in different way. Air conditioners are concentrated in the warmer regions of the country, regardless of the heat exposure metric used. By contrast, evaporative cooler ownership depends critically on the chosen measure of heat exposure. Using dry-bulb CDDs, the prevalence of coolers appears to be highest in the hottest areas. Using wet-bulb CDD—which incorporates humidity—rates of ownership of evaporative coolers are substantially lower, and exhibit flatter trends, in areas that are both hot and humid.

Relying solely on dry-bulb temperatures therefore omits the key dimension of humidity as a driver of adaptation inequality and technological choice in India.

Determinants of ownership. We quantify these relationships by estimating separate linear probability models for each appliance type. Each model includes long-term climatic CDDs (wet-bulb or dry-bulb), its interaction with household income, and a set of controls, along with state and wave fixed effects.

The results corroborate the descriptive patterns above (Table 1). Looking first at dry-bulb CDDs, a one-hundred degree-day increase is associated with a 1.04 percentage-point increase in cooler ownership (18.6% relative to the mean), with stronger effects at higher incomes. Considering wet-bulb CDDs, the same increase is associated with a negligible and statistically insignificant change (0.03 percentage points). AC ownership responds positively to CDDs in all specifications, with larger effects among richer households—consistent with substitution toward air conditioning in hotter, more humid conditions.

Income itself is a strong predictor for both technologies, with similar elasticities. A 10 percent increase in 4-month income raises the probability of owning an air conditioner by 0.48–0.55 percentage points and of owning an evaporative cooler by 0.36–0.62 percentage points.

Other household characteristics matter as well. Residing in an urban area increases the probability of owning an air conditioner by 3.8 percentage points, but has little effect on cooler ownership. Additional hours of daily electricity supply raise cooler ownership by 1.3 percentage points, and generator ownership increases adoption of both technologies, which suggests that constraints on their utilization associated with unreliable electricity service are mitigated by backup power supplies. Technology ownership also increases with the age of the household head; for air conditioners, education is an additional positive determinant, while larger households are less likely to own either technology.

Finally, we draw attention to the fact that living in a wetter climate does not have a significant effect on AC ownership, but is negatively associated with owning an evaporative cooler. Given the latter technology's mechanism of operation, this result is consistent with a story of lower prevalence in more humid areas being the result of diminished effectiveness. This is theme to which we will return below.

3.2 Adoption of cooling appliances

Empirical framework. Our descriptive results suggest that the distribution of the technologies across Indian households is highly sensitive to the combined influences of temperature and humidity. However, one might be concerned that this finding is contaminated by unobserved confounders that affect the sorting of populations across locations different climates. Distinct from previous studies (e.g., De Cian et al., 2025), the longitudinal character of our dataset facilitates investigation of the influence of climatic conditions on not only the prevalence of cooling appliances—the variation across households, but also their actual adoption—the *within*-household variation.

To study households' decision to invest in cooling, we then separately estimate the following linear probability model (LPM) for each appliance:

$$C_{a,iw} = \beta_1 \widetilde{CDD}^{WB}_{d(i)w} + \beta_2 I_{iw} + g[P_{d(i)w}] + \mu_i + \delta_w + \theta_{1,s(i)} y + \theta_{2,s(i)} y^2 + \zeta_{iw} \tag{1}$$

where the outcome variable is a binary indicator of whether household i owns at least an unit of the appliance a (either cooler or air conditioner) in wave w,[12] $g(P_{d(i)w})$ is a second-degree polynomial of cumulative precipitation experienced by the household, and ζ_{iw} is the error term, which we cluster at the district level. We weight regressions using survey weights that make results representative at the country level.

Importantly, our specification includes household fixed effects, μ_i, which control for idiosyncratic variation in household characteristics, e.g., sensitivity to climatic conditions. We also include wave fixed-effects, δ_w, and state-level quadratic annual trends, $\theta_{1,s(i)} y$ and $\theta_{2,s(i)} y^2$. These control for high-frequency shocks to the dependent variable that are common across Indian regions, and unobserved interannual trending influences in each state, respectively.

Our temperature is measure wet-bulb CDD. However, cooling appliances' long lifetimes suggests that households will base their investment decisions on expectations about climatic conditions, i.e., the average of weather over long periods (Auffhammer and Mansur, 2014; Cohen et al., 2017).[13] Thus, instead of contemporaneous values, we specify $\widetilde{CDD}^{WB}_{d(i)w}$ as the 10-year moving average of quarterly wet-bulb CDDs in district d in the decade before the wave w,[14] which is an indicator of households' medium-run expectations of the climate where they live.

Equation 1 also includes the natural algorithm of household income across each wave period, I_{iw}. Given the rapid spread of the two cooling technologies over the sample period, we expect economic development, proxied by income, to play a key role in their adoption. In complementary regressions we also include the interaction between income and climatic wet-bulb CDDs to investigate how income moderates the response of households to changes in expected climatic

[12] In our sample there are 18 waves.

[13] Cohen et al. (2017) finds that in US households mostly rely on expectations about the past 7-8 years.

[14] For example, for the wave January-April 2014, cooling degree days are averaged for the same months over the years 2003-2013.

conditions.

Results. Our baseline estimates for the average Indian household are given in Table 2. Confirming our hypothesis, economic development is the primary driver of cooling technology adoption: a 10 percent increase in household income raises the probability of owning an air conditioner by 0.13 percentage points and an evaporative cooler by 0.35 percentage points.

The magnitude of the responses to long-run climatic expectations are modest by comparison. A one-hundred degree-day increase in wet-bulb CDD increases air conditioner adoption by only 0.05 percentage points, but is associated with a 0.18 percentage point *reduction* in the probability of evaporative cooler adoption. Only for AC does the climate effect increase with income.

Descriptive evidence also suggested heterogeneity along the income distribution. Table A2 confirms this: only richer households adopt air conditioners in response to hotter, more humid conditions. For this group, a one-hundred degree-day increase in wet-bulb CDD increases adoption by 0.23 percentage points—about 1% relative to the mean. Income effects are likewise concentrated among the rich, for whom a ten percent increase in income raises the probability of owning an air conditioner by 0.35 percentage points. The magnitude of this effect is eleven and six times larger than that for low- and middle-income households, respectively. In the case of evaporative coolers, middle-income households are twice as likely as other groups to invest additional income in the technology, whereas both poor and rich households are less likely to adopt it in response to hot, humid conditions. The mechanisms likely differ: richer households substitute toward the superior technology, air conditioning, while poorer households face additional financial constraints when temperatures and humidity rise.

We also examine heterogeneity by urban and rural location (Table A3). For air conditioners, the income elasticity in urban households is nearly six times that in rural households. For evaporative coolers, income elasticities are statistically similar across the two settings. Urban households, however, are about twice as responsive to changes in wet-bulb CDD as rural households.

Combining the income and urban/rural dimensions (Table A4) reveals further patterns. For air conditioners, income elasticity rises with income and is larger in urban areas. For evaporative coolers, income effects are more homogeneous across the income distribution, with middle-income and urban poor households emerging as the most likely adopters. Only richer households—urban or rural—respond significantly to hotter, more humid conditions by adopting air conditioning.

Importantly, splitting our sample based on long-term level of specific humidity provide further results consistent with our descriptive findings (Table A5). While for air conditioners the magnitude of the income elasticity is similar across different levels of humidity, evaporative coolers are much more responsive to an increase income in low- and moderate-humidity climates.

Table A6 and Table A7 present robustness checks for the air conditioner and cooler specifications, respectively. Columns 1–2 test alternative thresholds for wet-bulb CDD, while Columns 3–5 use dry-bulb CDD at various thresholds. For the average Indian household, neither air conditioner nor cooler adoption is highly responsive to a one-hundred degree-day increase in 10-year CDD. Columns 6–7 replace the 10-year moving average of CDD with the change in CDD between survey waves, thereby capturing short-run weather shocks rather than slow-moving climatic trends. The results remain consistent.

Columns 8–9 examine potential nonlinearities in the relationship, allowing for up to a cubic polynomial. Air conditioner adoption appears linear, whereas cooler adoption follows a nonlinear pattern, consistent with technology diffusion approaching saturation for coolers, while air conditioners remain at an early stage of adoption.

Finally, Column 10 uses state-level clustered standard errors. The main results are robust to this specification.

4 The implications for temperature-related mortality

This section examines the impact of temperature on mortality in India, and how cooling technologies may mediate it. First, we analyse the relationship between annual mortality rates and wet-bulb temperature distribution in India districts. Second, we introduce cooling adaptation into our analysis, testing whether the uptake of air conditioning and cooler can offset the negative impact of temperature, and how the appliances differ in effectiveness.

4.1 Empirical framework

Mortality and temperature. To estimate the relationship between mortality and temperature, our main specification is as follows:

$$M_{dt} = f(T_{dt}^{WB}) + g(P_{dt}) + \mu_d + \mu_t + \varepsilon_{dt} \tag{2}$$

where M_{dt} is the natural logarithm of all-age all-cause mortality rate in district d in year t. $f(T_{dt}^{WB})$ is some function of daily average wet-bulb temperatures in a given district-year. In the main specification, $f(T_{dt}^{WB})$ is a vector of wet-bulb temperature bins counting the number of days in year t with daily average wet-bulb temperature within a given interval. Our main specification includes five temperature bins—from < 9 to ≥ 29 °C, using 14-24 °C as reference category.[15] We also estimate specification employing dry-bulb temperature bins, using 15-20 °C as the omitted bin category.

To account for potential confounding from precipitation, as in Barreca et al. (2016) and Burgess et al. (2017), we include indicators for whether total annual precipitation in a given district-year falls below the 25th or above the 75th percentile, $g(P_{dt})$. For specifications using dry-bulb temperature, we also control for specific humidity. Specifically, we include two extreme humidity bins: "very arid" days (0–3 g/kg) and "very humid" days (≥18 g/kg). In a further extension, we interact dry-bulb temperature bins with average annual specific humidity to examine whether the effects of heat differ under arid versus humid conditions.

Our specification also includes district fixed-effects μ_d, which absorb all unobserved region-specific time invariant determinants of the outcomes, and year fixed-effects μ_t, which instead absorb for time-varying differences in the dependent variable that are common across regions. In additional specifications, we also control for climatic region-level quadratic time trends, $\lambda_{r(d)}t$ and $\lambda_{r(d)}t^2$, that take account shocks or time-varying factors that affect health may not be common across states.[16]

Equation 2 is estimated using Weighted Least Squares (WLS), where weights correspond to the square root of the district population. This approach accounts for heteroskedasticity in mortality rates due to population size and ensures that the estimates are representative of the average individual rather than the average district. Standard errors are clustered at the district level.

Modelling heat adaptation. To assess whether access to cooling technologies mitigates the mortality effects of extreme heat, we next augment the model with information on adaptation. We restrict the sample to districts covered by the CHPS survey for the period 2014–2019, and merge mortality data with district-level shares of households owning evaporative coolers or air conditioners, derived from household survey responses using sampling weights. We estimate the following interaction model:

$$\begin{aligned} M_{dt} = \sum_{j \in AC,C} \gamma_j \left[f(T^{WB}_{dt}) \times C_{j,dt} \right] + g(P_{dt}) + \\ + \mu_s f(T^{WB}_{dt}) + \mu_t f(T^{WB}_{dt}) + \mu_d + \mu_t + \varepsilon_{dt} \end{aligned} \tag{3}$$

[15]We opt for estimating the response function using temperature bins, since (1) as too-high and too-low temperatures can both harm human health, it is likely that the temperature-mortality relationship is nonlinear; (2) the nice property of temperature bins is that they are more able to capture response to temperature extremes.

[16]Following Burgess et al. (2017) we use the information from India's Meteorological Department, which divides the country into five regions based on their climates.

We define $\mathcal{C}_{dt}^{j}$ as the district-year share of households owning each adaptation technology $j \in \{AC, C\}$, where AC refers to air conditioning and C to evaporative coolers. To isolate the impact of each technology, we compute cooler shares using only households that own an evaporative cooler but not an air conditioner. We instead assume that owners of air conditioners will prefer air conditioning over evaporative cooling, thus avoiding overlap in usage attribution.

To simplify the interaction structure, we define $f(T_{dt}^{WB})$ using only the upper two wet-bulb temperature bins, where heat mortality risks are expected to be highest. If adaptation technologies mitigate heat-related mortality, we expect the coefficients γ_j to be negative.

As in Barreca et al. (2016), heat adaptation is not identified through a quasi-experimental setting. A potential concern is that adaptation may be endogenous to unobserved characteristics correlated with mortality. To rule out as much as possible this concern, we allow for fixed differences in the effect of temperature across space and time, interacting temperature bins for state and year dummies. In our specification, $\mu_s f(T_{dt}^{WB})$, captures any time-invariant differences across states in the mortality-temperature relationship that are also correlated with the adoption of the two technologies, such as climatic conditions, income, and education level; while, $\mu_t f(T_{dt}^{WB})$, absorbs any time-varying differences across years, such as national policies, that have changed the mortality-temperature relationship and adoption of cooling appliances over time.

In further robustness checks, we extend the interaction to include all temperature bins, verifying that adaptation has no significant association with mortality at lower temperatures—when cooling devices are unlikely to be in use. Moreover, in additional specifications we control for income per capita (log-transformed) and its interaction with temperature bins to ensure that observed adaptation effects are not merely capturing the benefits of residing in wealthier districts with broader access to both public and private coping mechanisms.

4.2 Results: mortality-temperature

Figure 3 presents the estimated coefficients associated with an additional day in each wet-bulb temperature bin, using the 14–24 °C interval as the omitted category. Our findings indicate that both extreme cold and warm wet-bulb temperatures have statistically significant effects on mortality. These effects remain robust to the inclusion of precipitation controls and climatic region-specific time trends (Table A8).

Because our data do not allow us to identify cause-specific mortality, the estimated effects reflect both direct physiological impacts—e.g., heatstroke or hypothermia—and indirect effects mediated through other conditions—e.g., cardiovascular, respiratory, or renal illnesses.

In our preferred specification, we find that an additional day below < 9 °C is associated with a 0.603% increase in the annual mortality rate. However, while this effect is noteworthy and statistically significant, the largest mortality impacts are concentrated in the upper tail of the temperature distribution. Specifically, compared to a day between 14-24 °C, an additional day at or above 29 °C increases annual mortality rate by 0.987%. This estimate implies that, on average, approximately 6 deaths per 100,000 population can be attributed to a single additional day in the hottest temperature bin.[17]

The magnitude of the heat effect is consistent with Burgess et al. (2017), who find that a day above 35 °C (95 °F) increases the mortality rate by 0.74%. However, in contrast to their findings, our estimates for cold temperatures are both statistically significant and precise when using humidity-adjusted wet-bulb temperature.

When we replicate the analysis using dry-bulb temperatures (Table A9), the results differ in important ways.[18] The estimated effect of an additional day at or above 35 °C is smaller in magnitude (0.261%) and only marginally significant, while estimates for cold temperature bins remain similar to those in the wet-bulb specification. We further examine the role of humidity and find that, when entered independently, specific humidity has no significant association with mortality, even when isolating extremely arid or humid conditions (Table A9, column 2). This is in contrast to the U-shaped relationship documented in Barreca (2012) for the United States.

However, once we introduce interaction terms between temperature bins and annual average specific humidity (Table A9, column 3), a clear pattern emerges. The effect of days at or above 35 °C remain not precisely estimated, while the interaction terms are large and highly significant. These results imply that the health impacts of high temperatures are substantially amplified under humid conditions. Taken together, these findings underscore the importance of accounting for humidity in measuring the full health burden of heat exposure and provide further justification for our use of wet-bulb temperature in the main specification.

4.3 Results: the mitigating effects of heat adaptation technologies

Table 3 presents the interaction coefficients from estimating Equation 3 to examine the protective effect of heat adaptation technologies. For all regressions where both technologies are included we report the t-test comparing the interactions with the warmest wet-bulb temperature bin.

Columns 1 and 2 show the coefficients when modelling the interaction with only one of the two technologies. We find strong evidence that only air conditioning ownership is associated with a significant decrease in mortality due to days with daily average wet-bulb temperature at or above 29 °C. In contrast, the protective effect of evaporative cooler is negative, yet not

[17] Calculated as $0.00987 \times \overline{M} \times 100{,}000$.

[18] We use Burgess et al. (2017) reference point (20-25 °C) for the dry-bulb temperature bins specification.

significant and small in magnitude.

In column 3, we include both appliances in the same specification. The results again suggest that only air conditioning mitigates heat stress, and that the two technologies have a significant differential effect (p-val = 0.001). Estimates remain consistent even when we control for state- and year-level trends in temperature-mortality relationship. However, the effect of air conditioning slightly diminishes with respect to previous specifications (columns 4-5).

To understand the magnitudes, we take our preferred and most conservative specification (column 5). Our coefficients suggest that a one-percentage point increase in residential air conditioning and cooler ownership is associated with a decrease in the mortality effect of a day with daily average wet-bulb temperature at or above 29 °C by 0.0276 and 0.005 percentage points, respectively. This corresponds to approximately 2.3% and 0.4% of the mortality effect of such hot days when no adaptation is taking place. The effect for air conditioners is in line with the one found by Barreca et al. (2016). They find that a 10 percentage points increase in the penetration rate of air conditioning reduces by 10% the effect of a day above 32 °C (90 °F).

The large difference in the mitigating effect between the two technologies can be observed as follows: the higher the penetration of these cooling technologies, the greater the reduction in the impact of extreme hot days. For example, in Delhi, where air conditioning penetration increased by 25 percentage points between 2014 and 2019, the mortality effect of days at or above 29 °C was reduced by a further 57%.[19]

We test the consistency of our findings through several robustness checks. First, in Table A10 we interact the two shares with all the wet-bulb temperature bins. The results are slightly less precisely estimated but consistent in sign and magnitude. Importantly, we do not find that interactions with colder temperatures are statistically significant. Second, we introduce income as control, as well as we interact it with temperature bins as further controls (Table A11 and Table A12). The coefficients remain in the same order of magnitude, and in the latter test they are even better identified. These robustness checks suggest that it is unlikely that our estimates of the protective effect of heat adaptation are correlated with unobserved determinants of mortality. Finally, our results are also robust to adding climatic region-specific trends (Table A13); specifying the rates in levels rather than in logarithmic terms (Table A14); clustering standard errors at the state level (Table A15); and unweighted estimates (Table A16).

[19] This is computed as follows: $(0.25 \times -0.0276)/0.0121$

5 Understanding the mechanisms

Our findings indicate that high temperatures, particularly during extremely hot and humid days, significantly increase mortality in India. Although evaporative coolers are more widely adopted than air conditioners due to their lower cost, our previous evidence suggests that they provide substantially less protection against heat-related mortality. In this section, we investigate potential mechanisms that may account for their limited effectiveness. Additionally, we assess whether evaporative coolers yield non-fatal health benefits, which may also help explain their widespread adoption despite their limited efficacy in reducing mortality.

5.1 Evaporative coolers' effectiveness in moderating indoor temperatures

Thus far we have quantified the moderating effect of the prevalence of space conditioning equipment on the association between population exposures to ambient humid heat and aggregate mortality rates. The finding that evaporative coolers do not have a significant mortality reduction benefit raises the question of their effectiveness in cooling indoor environments. As stated in the introduction, the physical mechanism of coolers' operation limits the ambient - indoor temperature differential they can sustain to 4°C. In this section we elucidate the implications for low-income residents in India, leveraging indoor temperature and humidity measurements from Tasgaonkar et al. (2022).

A major challenge that besets rigorous quantification of the health benefits of cooling is the severe lack of data on the temperatures of the indoor environments inhabited by households exposed to heat. During hot weather, indoor spaces are potentially cooler due to the passive effects of shading and the thermal insulating properties of roofing and wall materials, in addition to active space conditioning through the use of appliances such as air conditioning units, evaporative coolers and fans. The implication is that the deaths observed in the previous sections actually result from indoor temperatures that could substantially *understate* ambient levels recorded in reanalysis datasets. The only way to observe the corresponding indoor-outdoor temperature differentials is measurement campaigns, which are costly, time-consuming and necessarily limited in spatial and/or temporal extent due to the unavoidable need to install and maintain sensors inside individual dwellings.

Tasgaonkar et al. (2022) conducted one such campaign over the period 2016-18, recording hourly indoor and outdoor temperatures and ambient relative humidity in low-income dwellings in five sites—two rural (Yavatmal and Jalna, in Maharastra state) and three urban (Delhi, India, Faisalabad, Pakistan, and Dhaka, Bangladesh). Consistent with the present geographic focus, we use their records for 41 dwellings in Delhi, 20 dwellings in Yavatmal and 16 dwellings in

Jalna, for a total of 456,687 complete hourly observations.[20] Of these dwellings, 36 had fans, 36 had evaporative coolers, and none had both a fan and a cooler. These data enable us to empirically characterize the additional temperature reduction benefit of these cooling technologies on top of the indoor-outdoor temperatures differential attributable to the structure itself.

Our approach is the following reduced-form specification:

$$\Delta T_{bhdmy} = \sum_k \beta_k \{\mathbb{1} \times T_{bhdmy} \in k\} + \sum_{j \in F,C} \sum_k \gamma_{j,k} \mathcal{C}_{j(b)} \{\mathbb{1} \times T_{bhdmy} \in k\}$$
$$+ \boldsymbol{X}_{bhdmy} \boldsymbol{\lambda} + \mu_b + \mu_h + \mu_d + \tau_{ym} \tag{4}$$

where T and ΔT denote ambient temperature and the indoor-ambient temperature differential for building b at hour h, day of week d, month m and year y, and $\mathcal{C}$ is a dummy variable indicating whether a building is equipped with cooling technology j (a fan or evaporative cooler). The covariates of interest are k hourly ambient temperature bins. Associated estimated parameters identify the mean hourly indoor-outdoor temperature differential corresponding to ambient temperature at that hour ($\boldsymbol{\beta}$) and the additional impacts across the temperature distribution of having a fan or cooler (γ_j). We include a vector of controls ($\boldsymbol{X}$)—daylight hours interacted with the presence of a tin roof (capturing re-radiation of heat into the building envelope from energy absorbed by sunlight), precipitation and wind speed, as well as building fixed effects and time effects that absorb unobserved idiosyncratic hour-of-day, day-of-week and year-month shocks.

The results, shown in Figure 4, suggest that the insulating effects of the structure alone lower temperatures monotonically by an average of 0.45 °C per degree of ambient temperature in excess of 24 °C, reducing indoor temperatures at extremely hot hours (>45 °C) by as much as 12 °C relative to outdoor air. Beyond this, fans do not have a significant cooling effect, and during the hottest hours could actually further warm indoor spaces by up to 2.5 °C. Conversely, evaporative coolers are associated with significant additional cooling, between 1.6 °C and 4.2 °C when ambient temperatures are in the 33-43 °C range, with peak effectiveness toward the upper end of this interval. Notably, for the locations sampled, median relative humidity declines monotonically with ambient temperature. Thus, the temperatures at which coolers appear to be effective coincide with hourly relative humidity values in the 7-70% range, overwhelmingly below the sample median.

We generalize this finding by identifying building-hour observations in our sample that match the high temperature and moderate relative humidity intervals over which evaporative

[20] The dwellings surveyed exhibited considerable variation, with wall materials ranging from mud and tin to brick and concrete, roofing material ranging from thatch and tin to stone, tile or cement, with other units above in a multistory structure.

coolers have been shown to significantly amplify the indoor-outdoor temperature differential. Figure 5 plots the result as a fraction of total surveyed building hours by location, indicating that coolers have considerable potential in the pre-monsoon season (18-55% of building hours over March-June), and modest potential in the post-monsoon season (5-14% of building hours over September-October) to moderate indoor temperatures.

5.2 Implications of evaporative cooler prevalence for potential heat exposure mitigation

What are the implications of the building-level results? While we cannot directly map our estimates into health outcomes, we can assess the extent to which evaporative coolers mitigate exposure to humid heat. To do so, we use ERA5 hourly temperature and humidity to compute, first, hourly WBGT, and, then, cumulating over hours with WBGT≥24°C, monthly wet bulb globe cooling degree hours (WBGCDH24) at the district level. The latter captures cumulative ambient humid heat exposure. We then repeat this last calculation step, restricting the summand to hours in each district and month when temperature and humidity coincide with conditions where evaporative coolers are associated with a significant ambient-indoor temperature differential (Figure 4). The result is a measure of humid heat exposure that could potentially be mitigated with 100% cooler prevalence. Finally, we scale the foregoing potential values by the annual average rates of household prevalence of evaporative coolers observed in CPHS, to obtain an estimate of the humid heat exposure that is actually mitigated by evaporative coolers.[21]

The results generally corroborate our findings drawn from observations of a limited number of buildings. Figure 6 shows the district-level intersection between ambient exposure and exposure that is actually mitigated. On average, slightly more than half of annual WBGCDH24 exposures have the potential to be mitigated by coolers. This fraction is much larger early in the year (70% in March) and declines as humidity increases with the onset of the monsoon (37% in June). However, due the geography of evaporative cooler prevalence, the fraction of WBGCDH24 exposures that are actually mitigated is only 19% overall, 23-25% over March-May, declining to 14% in June. Coolers have their largest impact in the high ambient exposure April-June pre-monsoon months over a swath of relatively high-prevalence districts stretching from Rajasthan in the northwest to Telangana in the southeast. But to the northeast and southwest of this corridor, lower cooler prevalence and higher humidity coincide with substantial moist heat

[21] These should be thought of as "extensive margin" exposure measures, as we lack sufficient information to estimate the extent to which coolers might reduce indoor temperatures below ambient levels. The latter depends on a host of building attributes and households members' activity patterns, none of which are observed.

exposures that go unmitigated. These temporal and spatial gradients become much less steep in the second half of the year, when there is much lower ambient WBGCDH24.

Figure 7 collapses these results over districts, multiplying by the number of residents to summarize the implications for nationwide population heat exposures. March, April and May account for 60% of the nearly 6,900 billion annual person cooling degree hours of exposure (PCDH24). Overall, PCDH24 actually mitigated by coolers accounts for only 36% of the exposure that could potentially be mitigated. A key implication of our building results is that massive increase of the prevalence of evaporative cooling has the potential to significantly expand indoor temperature moderation benefits. Even so, it is clear that even such increases might at best end up mitigating only about half of the humid heat exposure faced by India's population. In the next sections we investigate this issue, developing further insights into what the benefits of evaporative cooling-driven indoor temperature moderation might be.

5.3 Humidity's role in evaporative coolers' mortality reduction benefits

Our previous estimates highlight a potential explanation for the low protective effect of evaporative coolers, relating to their mechanism of operation: the effectiveness of evaporation depends critically on ambient humidity. In humid environments, the rate of evaporation is reduced, which limits coolers' ability to decrease air temperature. Since our main results point to the heightened mortality risks of extreme heat under humid conditions, this feature of how the technology operates may explain its limited efficacy.

We provide two empirical tests for this channel. First, we re-estimate our main specification separately by terciles of average humidity (Table 4). In the driest tercile (Panel A), the interaction between cooler prevalence and high WBGT yields negative and statistically significant coefficients, with magnitudes comparable to that of air conditioning. However, in more humid environments (Panels B and C), only air conditioning appears to offer meaningful protection against heat-related mortality, while coolers lose statistical significance and protective power.

Second, we estimate Equation 3 using dry-bulb temperature bins rather than wet-bulb temperature as the heat exposure measure. Results are reported in Table 5. The interaction between cooler ownership and exposure to extreme heat ($T \geq 35°$C) is initially negative and statistically significant. However, once we control for state-level temperature trends—which absorb unobserved heterogeneity such as baseline climate and humidity—the interaction becomes insignificant. This attenuation again suggests that the apparent effectiveness of coolers is largely confined to low-humidity environments.

Taken together, these findings underscore the limitations of evaporative cooling as a widespread adaptation strategy, particularly in regions where high temperatures are accompanied by elevated humidity levels.

5.4 Beyond mortality: assessing the implications for morbidity reductions

Finally, we examine whether evaporative coolers offer health benefits along non-fatal margins, focusing in particular on self-reported health status. Identifying such effects may help explain the widespread diffusion of these technologies, despite their limited protective capacity against heat-related mortality. Using individual-level data from the CHPS, we estimate the following specification:

$$H_{iw} = \sum_{j \in AC,C} \gamma_j \left[f(T^{WB}_{dw}) \times C^j_{hw} \right] + g(P_{dw}) + \mu_{dq} + \mu_w + \varepsilon_{iw} \tag{5}$$

where H_{iw} is a binary indicator equal to 1 if individual ii, surveyed in wave w, reports being in poor health; while, C^j_{hw} is a dummy variable equal to 1 if household h owns appliances $j \in \{AC, C\}$. The specification includes district-quarter (μ_{dq}) and wave (μ_w) fixed effects.[22] Standard errors are clustered at the district level, and regressions are weighted by individual survey weights. We estimate Equation 5 for the full sample, and separately by age group: children under five, adults aged 5–64, and the elderly (65+).

Table 6 displays our results. Consistent with our mortality findings, owning air conditioning significantly reduces the likelihood of poor self-reported health, particularly among older adults. Evaporative coolers also appear protective, but only under moderate thermal conditions—specifically, when wet-bulb temperatures fall between 24°C and 29°C. Even in this more favourable range, however, the magnitude of the effect is modest, ranging between 0.13 and 0.23 percentage points relative to the unconditional mean. At higher temperatures, the interaction term between cooler use and heat becomes significantly positive, suggesting that additional humidity generated by evaporative cooling may exacerbate thermal discomfort and reduce perceived health status. More complex fixed effects specification confirms the results (Table A17).

We emphasize that these estimates should be interpreted with caution. In particular, they do not account for selection into ownership of cooling technologies. If individuals with lower income are both more likely to own only evaporative coolers and more likely to report poor health, this could bias our estimates upward (De Cian et al., 2025). As such, these results should be viewed as suggestive.

However, together, these results suggest that while low-cost technologies such as coolers may offer partial protection under moderate conditions, their effectiveness diminishes as thermal stress intensifies. This may help explain both the widespread adoption of evaporative coolers

[22] District-quarter fixed effects compare, for instance, individuals interviewed in the first quarter of 2014 with those interviewed in the first quarter of 2015, thereby controlling for seasonality and location-specific shocks.

across India and the persistence of mortality risks during extreme heat events.

6 Conclusion

Our study contributes to understanding the critical nexus of climate adaptation, household technology choices, and mortality outcomes in the context of rising temperatures and energy demand in India.

We underline the pivotal role of economic development in shaping cooling technology adoption. Rising incomes drive the adoption of heat mitigation appliances. Yet, households' adaptive capacity to extreme heat is still not uniform. Lower and middle-income households predominantly opt for evaporative coolers, whereas wealthier households invest in air conditioning.

Critically, this divergence in technological choice has important consequences for health. Our estimates point to a marked difference in the mitigating effect of the two technologies against extreme hot and humid days. Air conditioners prove to highly effective at reducing heat-related deaths under all climatic conditions. In contrast, evaporative coolers, while more accessible to credit constrained households, on average, exhibit a comparatively quite modest effect. They are effective only under specific circumstances, especially dry settings. As a result, even when lower income households adapt, they remain exposed to the health effect of extreme heat. This disparity in outcomes underscores the pressing need for equitable technology dissemination, ensuring that economic benefits from cooling are not prerogative of few.

Our work opens avenues for future research. Firstly, we provide an example of how two competing adaptation technologies may contribute to inequality in exposure to climate change. In this sense, new applications to other adaptation strategies, such as in the agriculture sector, would be key to provide the right framework for policymakers to operate. Secondly, framing our findings within a projection context could yield valuable insights. In India income is expected to keep quickly growing in the next decades. This would relax credit constraints, allowing even lower income families to have access to the benefits of air conditioning. However, rising income will not be able to solve cooling inequality alone (Pavanello et al., 2021; Davis et al., 2021). We can so expect to still have part of the population exposed to extreme heat. Thirdly, our investigation underscores the significance of the cost of cooling appliances. Exploring structural simulations of policies aimed at alleviating inequality could be highly informative. Such policies might encompass subsidies on capital costs and investments in technological advancements for these appliances. Fourthly, extending our analysis to determine the external validity of our results is an intriguing prospect. This entails investigating whether the observed technological inequality in heat adaptation is a distinctive feature of India or if it characterises other countries as well.

Yet, we also acknowledge limitations of our study. First, we do not observe appliance-specific electricity use. This is relevant for the mortality analysis, since ownership may not fully capture utilization. Additionally, our mortality data lack the granularity to differentiate across age categories and diseases, which would have helped to explore even more in depths some mechanisms. Moreover, the relatively short time span and annual frequency of our data limit the variation we can exploit to identify the effect of temperature and adaptation. Finally, the employed building data lacks information on household health, preventing a direct mapping of indoor temperature reductions into health outcomes. Likewise, they also lack air conditioning ownership information, which would allow for a more direct comparison with coolers within the econometric framework.

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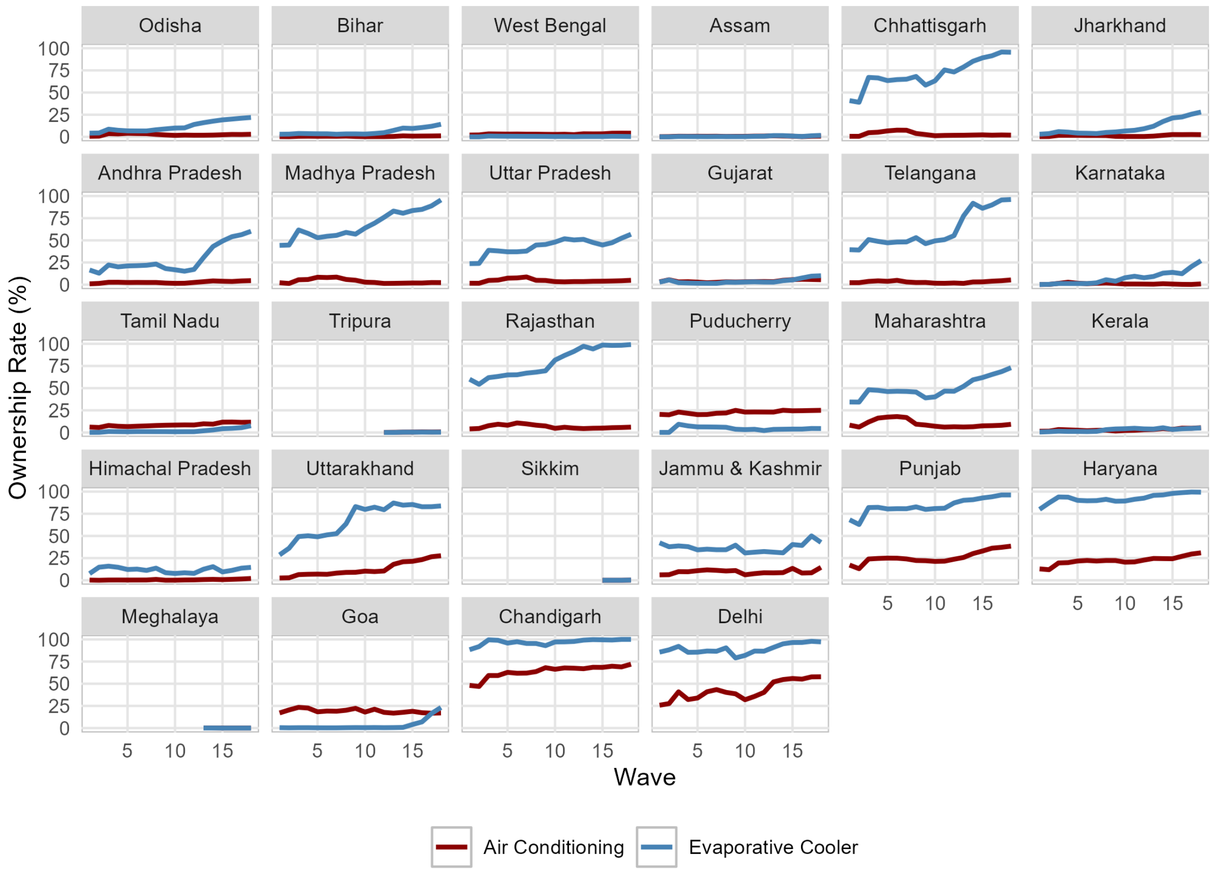
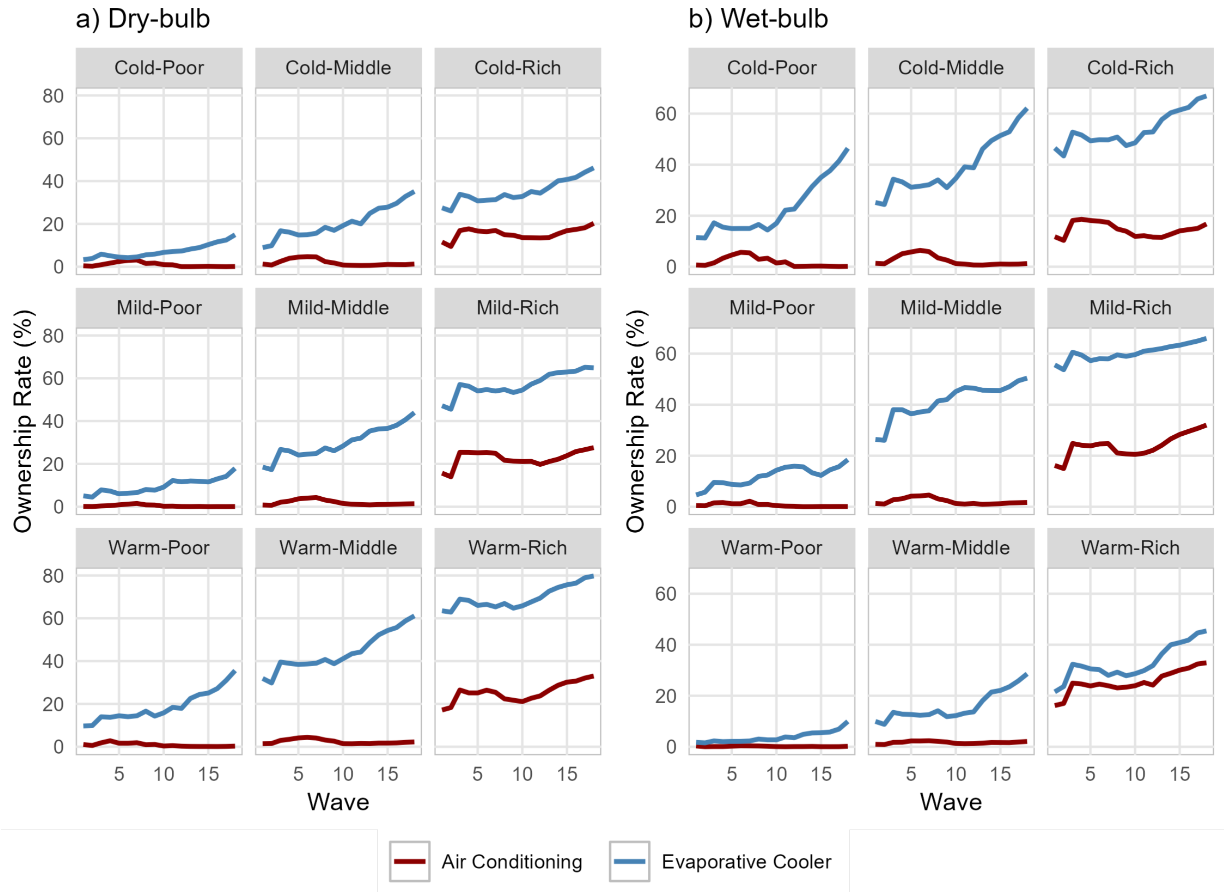
Tables and Figures

Figure 1: State-level trends in ownership of air conditioning and evaporative coolers



Notes: The figure plots the trends in the ownership of air conditioning and evaporative coolers across CHPS waves, obtained applying sample weights. Indian states are ordered based on quarterly household income.

Figure 2: The role of dry-bulb and wet-bulb temperatures



Notes: The figure plots the trends in the ownership of air conditioning and evaporative coolers across CHPS waves, obtained applying sample weights. 'Cold', 'Mild', and 'Warm' are terciles of a 30-year long average of annual (wet-)dry-bulb cooling degree days. 'Poor', 'Middle', and 'Rich' groups household using household income percentiles: < 20th, 20th-80th, > 80th, respectively.

Table 1: Drivers of the ownership of cooling appliances

	Air conditioning		Evaporative cooler	
	(1)	(2)	(3)	(4)
Log(Income)	0.0500***	0.0482***	0.0358***	0.0621***
	(0.005)	(0.005)	(0.010)	(0.008)
$\overline{\text{CDD}^{24}_{DB}}$ (100s)	-0.0257***		-0.0360***	
	(0.007)		(0.010)	
$\overline{\text{CDD}^{24}_{DB}} \times$ Log(Income)	0.00237***		0.00432***	
	(0.001)		(0.001)	
$\overline{\text{CDD}^{24}_{WB}}$ (100s)		-0.0831***		0.0763***
		(0.018)		(0.028)
$\overline{\text{CDD}^{24}_{WB}} \times$ Log(Income)		0.00804***		-0.00706**
		(0.002)		(0.003)
$\overline{\text{Precipitation}}$ (mm)	0.00000478	-0.00000738	-0.0000909***	-0.0000553**
	(0.000)	(0.000)	(0.000)	(0.000)
$\overline{\text{Precipitation}}^2$	-2.20e-09	2.29e-09	2.39e-08*	7.15e-09
	(0.000)	(0.000)	(0.000)	(0.000)
Urban (Yes = 1)	0.0382***	0.0382***	-0.00563	-0.00800
	(0.006)	(0.006)	(0.017)	(0.017)
Head Age	0.000679***	0.000673***	0.000742***	0.000751***
	(0.000)	(0.000)	(0.000)	(0.000)
Head Gender (Male = 1)	0.0103***	0.0103***	0.00336	0.00299
	(0.002)	(0.002)	(0.003)	(0.003)
Head Employed (Yes = 1)	-0.0247***	-0.0247***	-0.00277	-0.00214
	(0.004)	(0.003)	(0.005)	(0.005)
Primary	0.0123***	0.0122***	0.0369***	0.0373***
	(0.002)	(0.002)	(0.004)	(0.004)
Secondary	0.0337***	0.0334***	0.0701***	0.0707***
	(0.005)	(0.005)	(0.006)	(0.006)
Post-secondary	0.153***	0.153***	0.0991***	0.100***
	(0.013)	(0.013)	(0.008)	(0.008)
2-5 Members	-0.0376***	-0.0374***	0.0247**	0.0255**
	(0.005)	(0.005)	(0.012)	(0.012)
5-10 Members	-0.0618***	-0.0617***	0.0153	0.0162
	(0.007)	(0.007)	(0.015)	(0.015)
$\geq$ 11 Members	-0.0861***	-0.0861***	0.0224	0.0238
	(0.012)	(0.012)	(0.023)	(0.023)
Power availability	-0.00108	-0.00106	0.0109***	0.0112***
	(0.001)	(0.001)	(0.003)	(0.003)
Generator	0.143***	0.141***	0.583***	0.594***
	(0.022)	(0.021)	(0.052)	(0.053)
House ownership (Yes = 1)	0.0434***	0.0431***	0.0504***	0.0523***
	(0.007)	(0.007)	(0.014)	(0.014)
State FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Mean Outcome	0.056	0.056	0.325	0.325
Observations	2471755	2471755	2471755	2471755

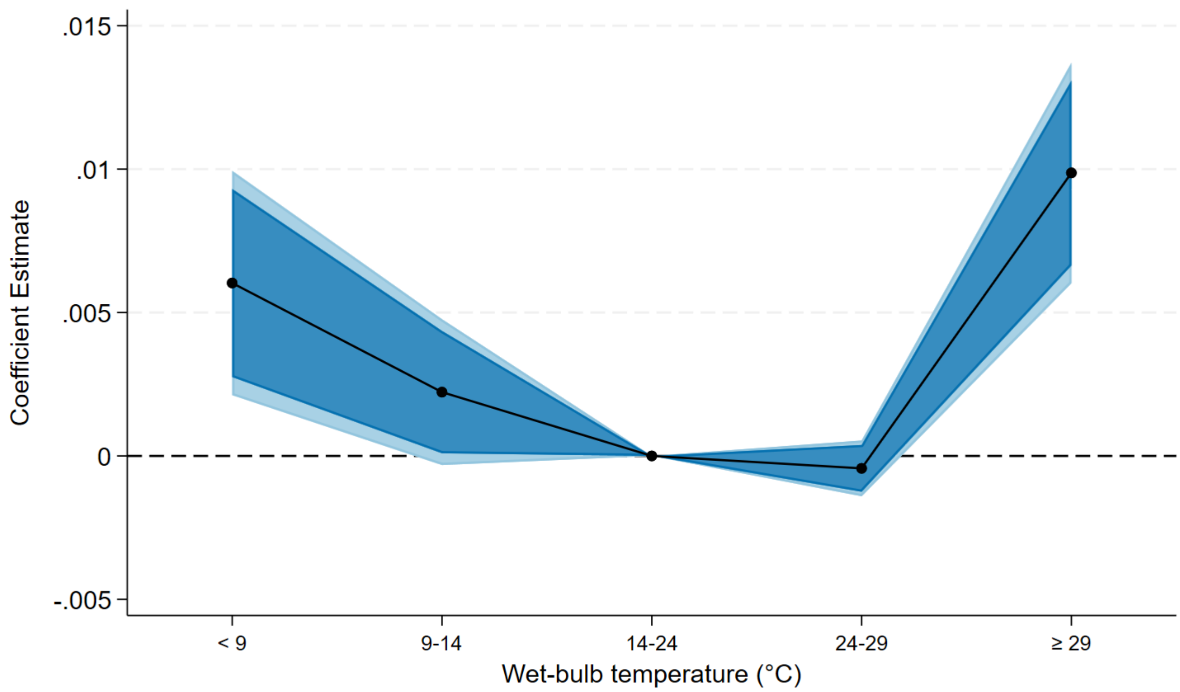
Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. For the categorical variables the omitted categories are: 'No Education', '1 Member', and 'Tile'. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by survey weights.

Table 2: The impact of temperature and income on the adoption of cooling appliances

	Air conditioning		Evaporative cooler	
	(1)	(2)	(3)	(4)
Log(Income)	0.0129***	0.0106***	0.0342***	0.0355***
	(0.001)	(0.001)	(0.003)	(0.003)
$\widetilde{CDD_{24}^{WB}}$ (100s)	0.000562*	-0.0187***	-0.00181**	0.00949
	(0.000)	(0.003)	(0.001)	(0.007)
$\widetilde{CDD_{24}^{WB}} \times$ Log(Income)		0.00179***		-0.00105
		(0.000)		(0.001)
Precipitations Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Quadratic State $\times$ Year Trend	Yes	Yes	Yes	Yes
Mean Outcome	0.056	0.056	0.326	0.326
Observations	2461601	2461601	2461601	2461601

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Figure 3: Mortality and wet-bulb temperature



Notes: The figure plots the relationship between all-age mortality (in logs) and wet-bulb daily average temperature (in bins). Light blue areas are 95% confidence intervals; dark blue areas are 90% confidence intervals.

Table 3: Protective effects of heat adaptation appliances

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{WB} (24-29)	-0.000104	-0.0000459	-0.0000211		
	(0.001)	(0.001)	(0.001)		
T^{WB} ($\geq$ 29)	0.0119***	0.0101***	0.0121***		
	(0.002)	(0.003)	(0.003)		
AC $\times$ T^{WB} (24-29)	-0.000699		-0.000732	-0.00155	-0.000500
	(0.002)		(0.002)	(0.002)	(0.002)
AC $\times$ T^{WB} ($\geq$ 29)	-0.0340***		-0.0340***	-0.0248**	-0.0276**
	(0.009)		(0.009)	(0.012)	(0.013)
Cooler $\times$ T^{WB} (24-29)		0.0000146	-0.000165	0.000998	0.00147
		(0.001)	(0.001)	(0.001)	(0.001)
Cooler $\times$ T^{WB} ($\geq$ 29)		-0.000877	-0.000291	0.00422	-0.00481
		(0.005)	(0.005)	(0.009)	(0.010)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins $\times$ State	No	No	No	Yes	Yes
Temperature Bins $\times$ Year	No	No	No	No	Yes
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)			0.001	0.005	0.021
Mean Outcome	0.007	0.007	0.007	0.007	0.007
Observations	2754	2754	2754	2754	2754

Notes: The dependent variable is the natural logarithm of mortality rate. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table 4: Protective effect of heat adaptation appliances (Humidity terciles)

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
Panel A: 1st Tercile					
T^{WB} (24-29)	0.0000182	-0.00137	-0.00112		
	(0.001)	(0.001)	(0.001)		
T^{WB} ($\geq$ 29)	-0.000245	0.00643*	0.0176**		
	(0.002)	(0.004)	(0.008)		
AC $\times$ T^{WB} (24-29)	-0.00411*		-0.00275	-0.00557	-0.00485
	(0.002)		(0.003)	(0.003)	(0.004)
AC $\times$ T^{WB} ($\geq$ 29)	-0.00704		-0.0222**	-0.0187**	-0.0158*
	(0.005)		(0.009)	(0.008)	(0.008)
Cooler $\times$ T^{WB} (24-29)		0.00227	0.00200	0.00203	0.00251
		(0.002)	(0.002)	(0.002)	(0.002)
Cooler $\times$ T^{WB} ($\geq$ 29)		-0.00932**	-0.0201**	-0.0143**	-0.0111
		(0.004)	(0.008)	(0.006)	(0.007)
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)			0.663	0.427	0.393
Mean Outcome	0.006	0.006	0.006	0.006	0.006
Observations	921	921	921	921	921
Panel B: 2nd Tercile					
T^{WB} (24-29)	0.0000561	0.000288	0.0000332		
	(0.001)	(0.001)	(0.002)		
T^{WB} ($\geq$ 29)	0.0173***	0.00976	0.0132*		
	(0.004)	(0.007)	(0.008)		
AC $\times$ T^{WB} (24-29)	0.00562		0.00586	0.00450	0.00231
	(0.004)		(0.004)	(0.005)	(0.005)
AC $\times$ T^{WB} ($\geq$ 29)	-0.0351**		-0.0335**	-0.0315	-0.0230
	(0.014)		(0.015)	(0.024)	(0.023)
Cooler $\times$ T^{WB} (24-29)		-0.000822	-0.000781	-0.000630	-0.000554
		(0.002)	(0.002)	(0.002)	(0.003)
Cooler $\times$ T^{WB} ($\geq$ 29)		0.00828	0.00747	0.0156	0.00256
		(0.011)	(0.011)	(0.016)	(0.017)
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)			0.010	0.024	0.214
Mean Outcome	0.005	0.005	0.005	0.005	0.005
Observations	919	919	919	919	919
Panel C: 3rd Tercile					
T^{WB} (24-29)	0.000906	0.000850	0.00131		
	(0.001)	(0.001)	(0.001)		
T^{WB} ($\geq$ 29)	0.0121***	0.0105***	0.0129***		
	(0.003)	(0.003)	(0.004)		
AC $\times$ T^{WB} (24-29)	-0.0101*		-0.00924*	-0.00117	-0.00176
	(0.005)		(0.005)	(0.005)	(0.005)
AC $\times$ T^{WB} ($\geq$ 29)	-0.0732***		-0.0715***	-0.0338**	-0.0465***
	(0.021)		(0.020)	(0.015)	(0.016)
Cooler $\times$ T^{WB} (24-29)		-0.00482	-0.00418	0.00543*	0.00651**
		(0.004)	(0.004)	(0.003)	(0.003)
Cooler $\times$ T^{WB} ($\geq$ 29)		-0.00602	-0.00499	0.00860	0.00483
		(0.006)	(0.005)	(0.007)	(0.007)
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)			0.000	0.010	0.003
Mean Outcome	0.009	0.009	0.009	0.009	0.009
Observations	914	914	914	914	914
Precipitation controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins $\times$ State	No	No	No	Yes	Yes
Temperature Bins $\times$ Year	No	No	No	No	Yes

Notes: The dependent variable is the natural logarithm of mortality rate. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table 5: Protective effects using dry-bulb temperature

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{DB} (30-35)	0.0000928	-0.000555	-0.000524		
	(0.001)	(0.001)	(0.001)		
T^{DB} ($\geq$ 35)	0.00539***	0.00847***	0.0106***		
	(0.002)	(0.003)	(0.003)		
AC $\times$ T^{DB} (30-35)	0.00207		0.00162	0.00277	0.00143
	(0.003)		(0.003)	(0.004)	(0.004)
AC $\times$ T^{DB} ($\geq$ 35)	-0.0258***		-0.0285***	-0.0222**	-0.0229**
	(0.008)		(0.008)	(0.011)	(0.012)
Cooler $\times$ T^{DB} (30-35)		0.00250**	0.00222*	0.00364*	0.00236
		(0.001)	(0.001)	(0.002)	(0.002)
Cooler $\times$ T^{DB} ($\geq$ 35)		-0.00588*	-0.00718**	0.00146	-0.000377
		(0.003)	(0.003)	(0.004)	(0.006)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins $\times$ State	No	No	No	Yes	Yes
Temperature Bins $\times$ Year	No	No	No	No	Yes
AC $\times$ T^{DB} = Cooler $\times$ T^{DB} (pval)			0.005	0.024	0.028
Mean Outcome	0.007	0.007	0.007	0.007	0.007
Observations	2754	2754	2754	2754	2754

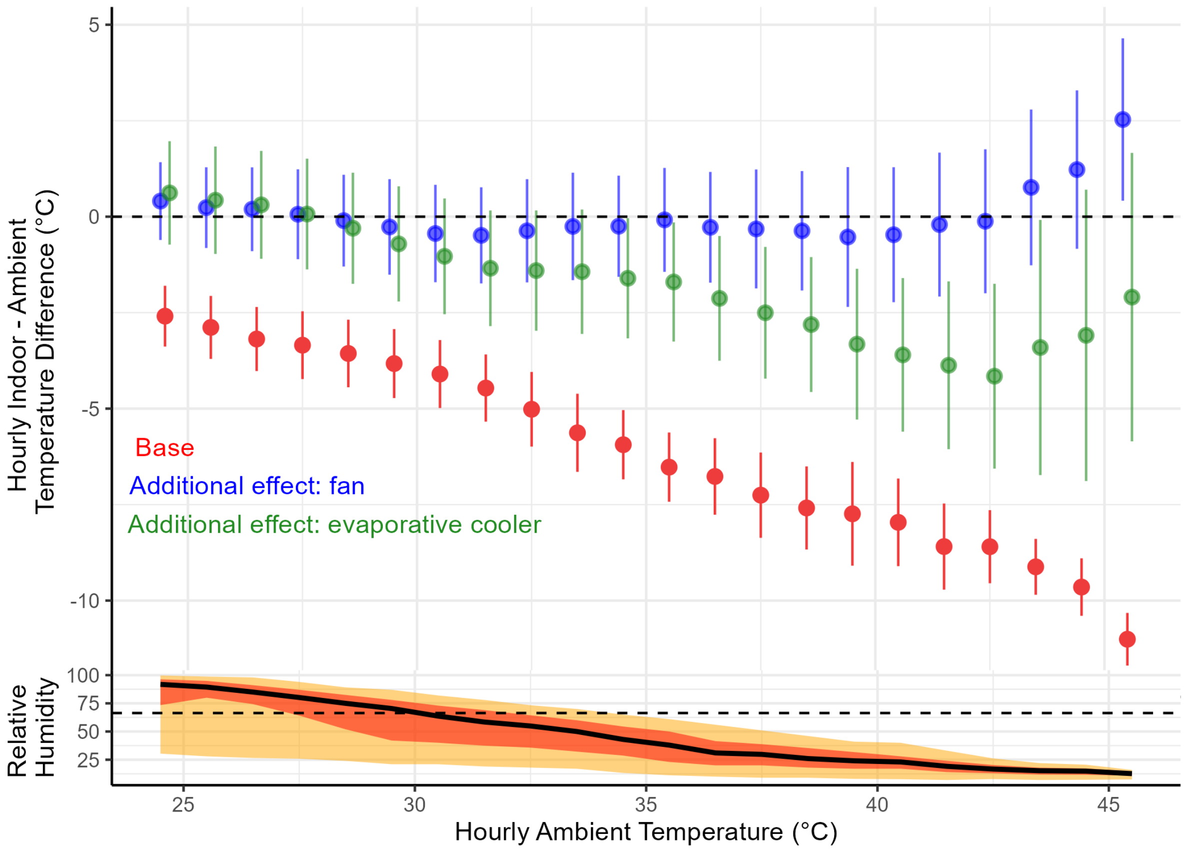
Notes: The dependent variable is the natural logarithm of mortality rate. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table 6: Wet-bulb temperature, health status, and heat adaptation

	Full	< 5 yro.	5-64 yro.	$\geq$ 65 yro.
	(1)	(2)	(3)	(4)
T^{WB} (24-29)	-0.0000121	-0.0000752*	-0.000000591	-0.0000961
	(0.000)	(0.000)	(0.000)	(0.000)
T^{WB} ($\geq$ 29)	0.0000634	0.0000837	0.0000712	0.000725
	(0.000)	(0.000)	(0.000)	(0.002)
AC $\times$ T^{WB} (24-29)	0.0000390*	-0.0000163	0.0000173	0.000190*
	(0.000)	(0.000)	(0.000)	(0.000)
AC $\times$ T^{WB} ($\geq$ 29)	0.0000558	-0.000224	-0.0000548	-0.00191**
	(0.000)	(0.000)	(0.000)	(0.001)
Cooler $\times$ T^{WB} (24-29)	-0.0000530***	-0.00000161	-0.0000358***	-0.000412***
	(0.000)	(0.000)	(0.000)	(0.000)
Cooler $\times$ T^{WB} ($\geq$ 29)	0.000515**	0.0000653	0.000278*	0.00429***
	(0.000)	(0.000)	(0.000)	(0.001)
District-Quarter FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Mean Outcome	0.027	0.015	0.018	0.175
Observations	10106841	361399	9210234	535203

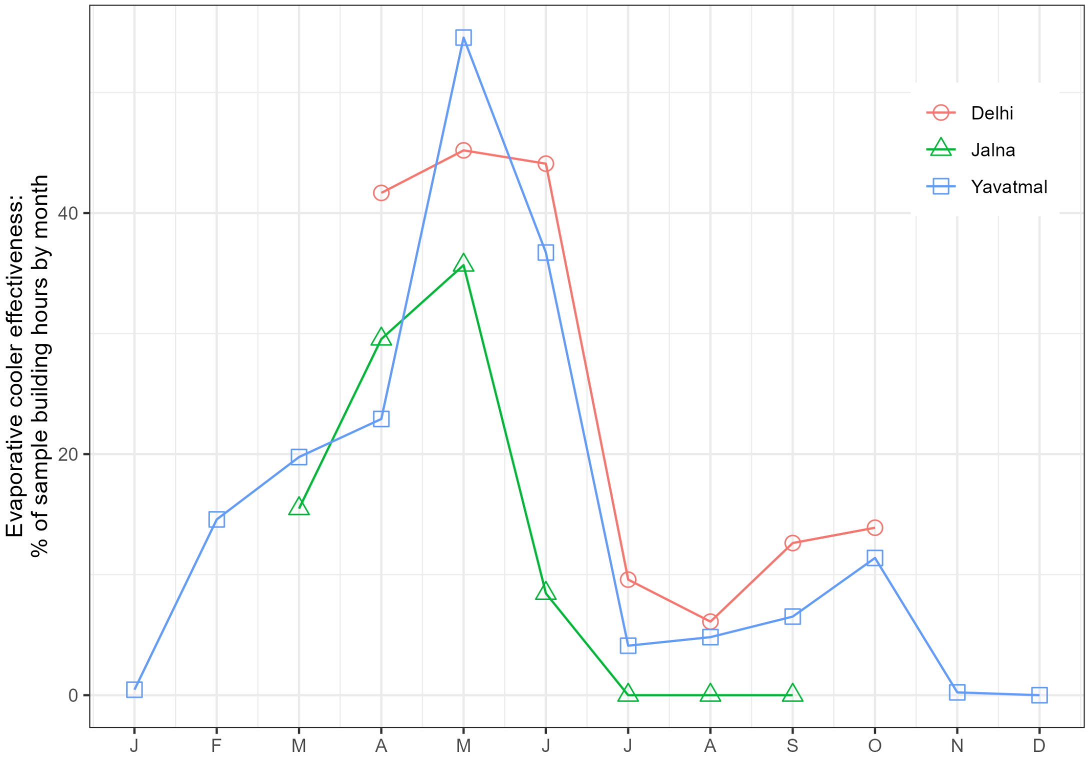
Notes: The dependent variable is a dummy variable for self-reported health status (= 1 if negative). Reference category for temperature is bin 14-24 °C. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by individual survey weights.

Figure 4: Indoor-outdoor temperature differential: low-income dwellings in three locations



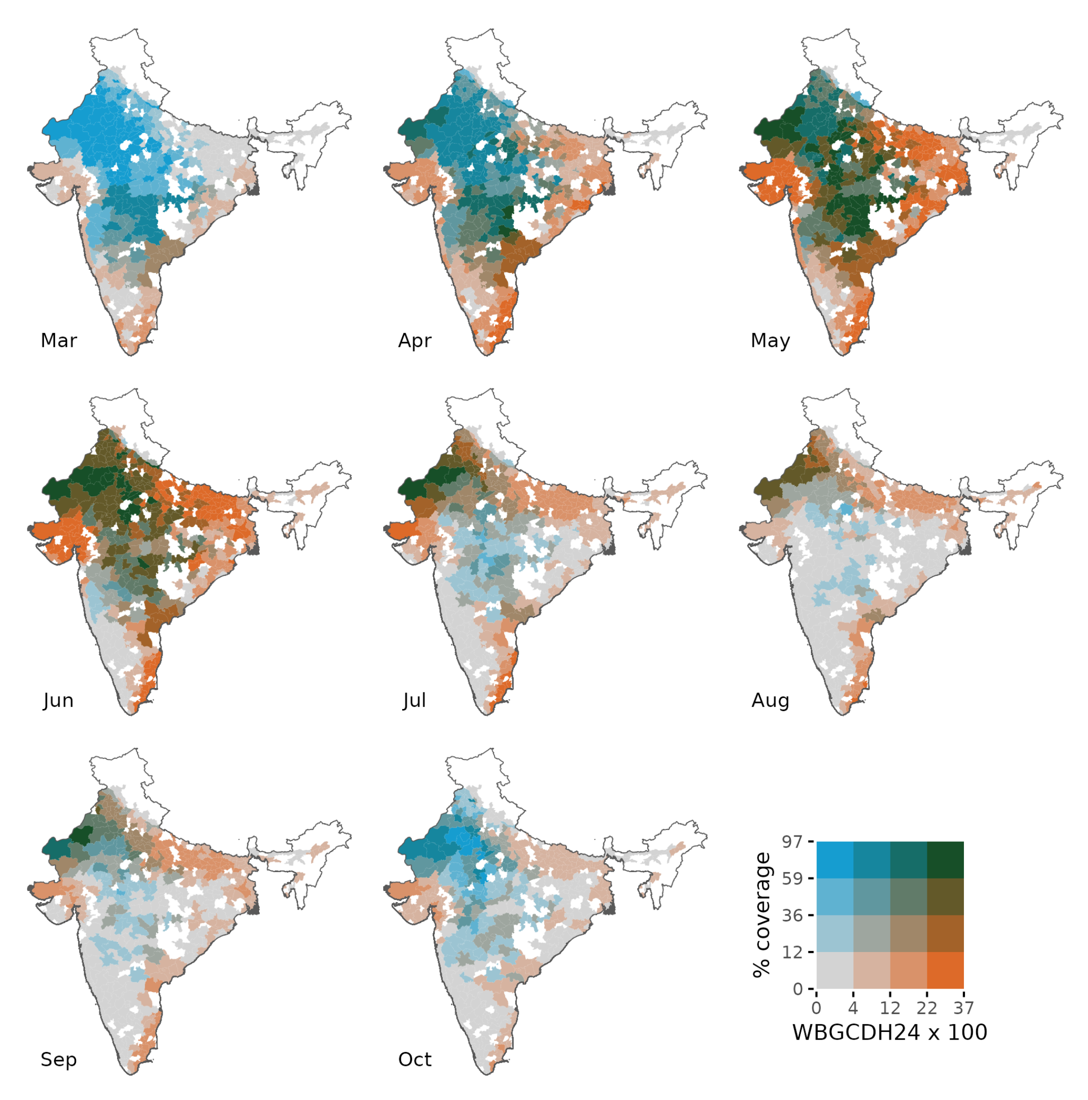
Notes: The figure plots the estimated coefficients of Equation 4 along with their 95% confidence intervals (for standard errors clustered at the building level), showing across the ambient temperature distribution the average indoor-outdoor temperature differential (base: $\widehat{\beta}$) as well as the additional effects of cooling equipment (fans and evaporative coolers: $\widehat{\gamma}$). Also shown is the distribution of ambient relative humidity at each temperature, yellow: 95th percentile, orange: interquartile range, black: median. The dashed horizontal line indicates relative humidity at the sample median, 66.4%.

Figure 5: The meteorological window of opportunity for effective evaporative cooling



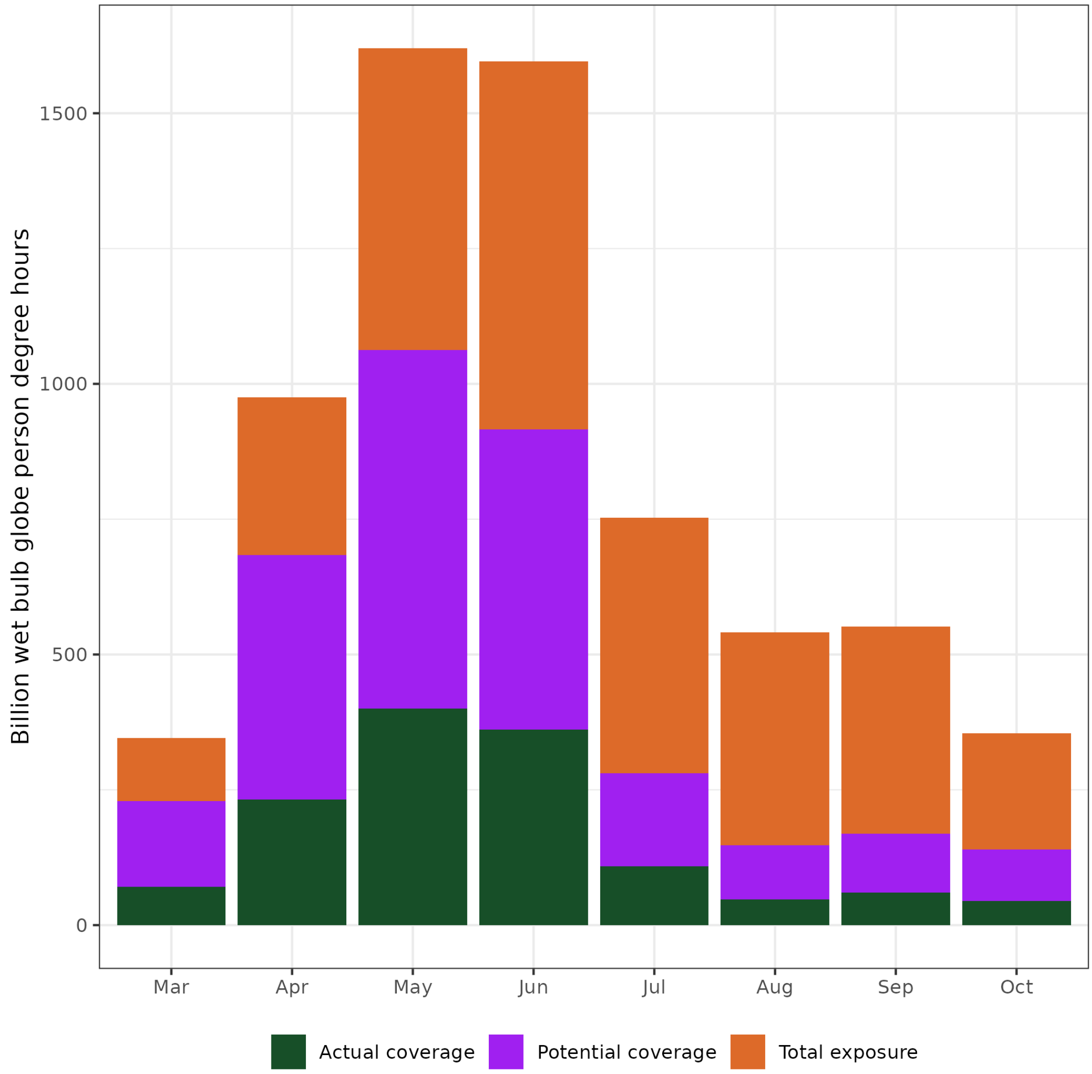
Notes: The figure plots the fraction of building hours surveyed by Tasgaonkar et al. (2022) that in each month correspond to the ranges of ambient temperature and humidity for which the estimated coefficients of Equation 4 show evaporative coolers significantly reduce indoor temperatures relative to ambient levels.

Figure 6: Potential for the prevalence of evaporative cooling to mitigate humid heat exposure



Notes: The figure plots bivariate choropleth maps of the 2014-2019 average monthly accumulated humid heat exposures (wet bulb globe cooling degree hours, 24°C base), and exposures that correspond to the ranges of ambient temperature and humidity for which evaporative coolers significantly reduce indoor temperatures relative to ambient levels. Each map shows the district-level intersection of ambient cooling degree hours (orange) with the fraction of cooling degree hours that can be significantly mitigated, accounting for evaporative coolers prevalence (blue). Darker colors indicate more intense ambient humid heat exposures that are mitigated.

Figure 7: Evaporative coolers and the adaptation cooling deficit



Notes: The figure aggregates Figure 6 over space, plotting 2014-2019 average monthly population humid heat exposures (person-degree hours = wet bulb globe cooling degree hours, 24°C base × exposed population), total (red), exposures potentially mitigated by evaporative coolers—corresponding to the ranges of ambient temperature and humidity for which those appliances significantly reduce indoor temperatures (purple), and exposures actually mitigated—potential exposures scaled by evaporative cooler prevalence (green).

Appendix

Table A1: Descriptive statistics (CHPS)

	Mean	SD
Air conditioning (Yes = 1)	0.056	0.230
Evaporative cooler (Yes = 1)	0.325	0.468
$\widetilde{\mathrm{CDD}}^{24}_{WB}$	143.186	140.750
$\widetilde{\mathrm{CDD}}^{24}_{DB}$	399.197	282.096
Income (quarterly, rupees)	62978.601	63044.118
Urban (Yes = 1)	0.328	0.469
Age	49.606	12.188
Female (Yes = 1)	1.891	0.311
No educ. (Yes = 1)	0.574	0.495
Primary educ. (Yes = 1)	0.256	0.436
Secondary educ. (Yes = 1)	0.075	0.264
Post-sec. educ. (Yes = 1)	0.095	0.293
Employed (Yes = 1)	0.809	0.393
Members (1)	0.022	0.146
Members (2-5)	0.803	0.397
Members (6-10)	0.172	0.377
Members (> 11)	0.003	0.056
House ownership (Yes = 1)	0.991	0.095
Electricity access (Yes = 1)	0.978	0.146
Power availability (hours/day)	21.729	3.780
Generator (Yes = 1)	0.120	0.325
Observations	2475928	

Table A2: The impact of temperature and income on the adoption of cooling appliances (Income level)

	Air conditioning			Evaporative cooler		
	Poor	Middle	Rich	Poor	Middle	Rich
Log(Income)	0.00275***	0.00739***	0.0345***	0.0274***	0.0426***	0.0226***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
$\widetilde{CDD}_{24}^{WB}$ (100s)	-0.000336	0.000186	0.00231***	-0.00332***	-0.00106	-0.00190**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.008	0.021	0.211	0.107	0.328	0.536
Observations	306800	1431755	723046	306800	1431755	723046

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table A3: The impact of temperature and income on the adoption of cooling appliances (Urban-rural divide)

	Air conditioning		Evaporative cooler	
	Rural	Urban	Rural	Urban
Log(Income)	0.00573***	0.0327***	0.0358***	0.0312***
	(0.001)	(0.002)	(0.003)	(0.004)
$\widetilde{CDD}_{24}^{WB}$ (100s)	0.000671**	0.00108*	-0.00140	-0.00261**
	(0.000)	(0.001)	(0.001)	(0.001)
Precipitations Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Quadratic State $\times$ Year Trend	Yes	Yes	Yes	Yes
Mean Outcome	0.018	0.134	0.282	0.417
Observations	795563	1666038	795563	1666038

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights

Table A4: The impact of temperature and income on the adoption of cooling appliances (Urban-rural divide and income level)

Dep. Var.: Air conditioning	Rural			Urban		
	Poor	Middle	Rich	Poor	Middle	Rich
Log(Income)	0.00241***	0.00424***	0.0156***	0.00524***	0.0172***	0.0586***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.004)
$\widetilde{CDD}_{24}^{WB}$ (100s)	-0.000235	0.000386	0.00345***	-0.000429	0.0000338	0.00181*
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.007	0.013	0.065	0.011	0.037	0.311
Observations	164510	497228	133825	142290	934527	589221
Dep. Var.: Evaporative cooler	**Rural**			**Urban**		
	Poor	Middle	Rich	Poor	Middle	Rich
Log(Income)	0.0256***	0.0418***	0.0285***	0.0392***	0.0455***	0.0161***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.005)	(0.003)
$\widetilde{CDD}_{24}^{WB}$ (100s)	-0.00267**	-0.000903	-0.000530	-0.00669***	-0.00183	-0.00320***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.092	0.307	0.552	0.198	0.378	0.526
Observations	164510	497228	133825	142290	934527	589221

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights

Table A5: The impact of temperature and income on the adoption of cooling appliances (Humidity terciles)

	Air conditioning			Evaporative cooler		
	Dry	Mild	Humid	Dry	Mild	Humid
Log(Income)	0.0155***	0.0100***	0.0115***	0.0418***	0.0454***	0.0150***
	(0.002)	(0.001)	(0.001)	(0.004)	(0.005)	(0.004)
$\widetilde{CDD}_{24}^{WB}$ (100s)	0.00189**	0.00109**	-0.000642*	-0.00465***	0.00240	-0.00140
	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.094	0.035	0.045	0.628	0.358	0.078
Observations	826290	814250	821061	826290	814250	821061

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights

Table A6: The impact of temperature and income on the adoption of air conditioning (Robustness)

	CDD^{WB}_{18} (1)	CDD^{WB}_{21} (2)	CDD^{DB}_{18} (3)	CDD^{DB}_{21} (4)	CDD^{DB}_{24} (5)	Short (WB) (6)	Short (DB) (7)	Quadratic (8)	Cubic (9)	State SEs (10)
Log(Income)	0.0129***	0.0129***	0.0129***	0.0129***	0.0129***	0.0129***	0.0129***	0.0129***	0.0130***	0.0129***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$\widetilde{CDD}^{WB}_{18}$ (100s)	0.000246									
	(0.000)									
$\widetilde{CDD}^{WB}_{21}$ (100s)		0.000364								
		(0.000)								
$\widetilde{CDD}^{DB}_{18}$ (100s)			0.000154							
			(0.000)							
$\widetilde{CDD}^{DB}_{21}$ (100s)				0.000171						
				(0.000)						
$\widetilde{CDD}^{DB}_{24}$ (100s)					0.000231					
					(0.000)					
CDD^{WB}_{24} (100s)						0.000297				
						(0.000)				
CDD^{DB}_{24} (100s)							0.000230			
							(0.000)			
$\widetilde{CDD}^{WB}_{24}$ (100s)								0.000577	-0.00247	0.000562
								(0.001)	(0.002)	(0.000)
$(\widetilde{CDD}^{WB}_{24})^2$								-0.00000313	0.00181	
								(0.000)	(0.001)	
$(\widetilde{CDD}^{WB}_{24})^3$									-0.000277	
									(0.000)	
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056
Observations	2461601	2461601	2461601	2461601	2461601	2461601	2461601	2461601	2461601	2461601

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. Standard errors clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table A7: The impact of temperature and income on the adoption of evaporative cooler (Robustness)

	CDD^{WB}_{18} (1)	CDD^{WB}_{21} (2)	CDD^{DB}_{18} (3)	CDD^{DB}_{21} (4)	CDD^{DB}_{24} (5)	Short (WB) (6)	Short (DB) (7)	Quadratic (8)	Cubic (9)	State SEs (10)
Log(Income)	0.0342***	0.0342***	0.0343***	0.0342***	0.0342***	0.0342***	0.0342***	0.0342***	0.0341***	0.0342***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
$\widetilde{CDD}^{WB}_{18}$ (100s)	-0.000350									
	(0.000)									
$\widetilde{CDD}^{WB}_{21}$ (100s)		-0.000565								
		(0.001)								
$\widetilde{CDD}^{DB}_{18}$ (100s)			-0.000614**							
			(0.000)							
$\widetilde{CDD}^{DB}_{21}$ (100s)				-0.000695**						
				(0.000)						
$\widetilde{CDD}^{DB}_{24}$ (100s)					-0.000801*					
					(0.000)					
CDD^{WB}_{24} (100s)						-0.00151*				
						(0.001)				
CDD^{DB}_{24} (100s)							-0.000334			
							(0.000)			
$\widetilde{CDD}^{WB}_{24}$ (100s)								-0.00234	0.0138**	-0.00181
								(0.003)	(0.006)	(0.002)
$(\widetilde{CDD}^{WB}_{24})^2$								0.000115	-0.00951***	
								(0.001)	(0.004)	
$(\widetilde{CDD}^{WB}_{24})^3$									0.00147***	
									(0.001)	
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.326	0.326	0.326	0.326	0.326	0.326	0.326	0.326	0.326	0.326
Observations	2461601	2461601	2461601	2461601	2461601	2461601	2461601	2461601	2461601	2461601

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. Standard errors clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table A8: The effect of wet-bulb temperature on all-age mortality

	Log(Mortality rates per 100,000s people)		
	(1)	(2)	(3)
T^{WB} (<9)	0.00602***	0.00603***	0.00514**
	(0.002)	(0.002)	(0.002)
T^{WB} (9-14)	0.00205	0.00223*	0.00194
	(0.001)	(0.001)	(0.001)
T^{WB} (24-29)	-0.000484	-0.000432	0.000176
	(0.000)	(0.000)	(0.001)
T^{WB} (≥ 29)	0.00982***	0.00987***	0.00963***
	(0.002)	(0.002)	(0.002)
P (1^{st})		-0.0167	-0.0162
		(0.024)	(0.025)
P (3^{rd})		0.0735***	0.0628**
		(0.026)	(0.026)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Climatic region × Year trend	No	No	Yes
Mean Outcome	0.006	0.006	0.006
Observations	3896	3896	3896

Notes: The dependent variable is the natural logarithm of mortality rate. Reference category for temperature is bin 14-24 °C. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table A9: The effect of dry-bulb temperature on all-age mortality

	Log(Mortality rates per 100,000s people)		
	(1)	(2)	(3)
T^{DB} (< 10)	0.00584**	0.00602***	0.00126
	(0.002)	(0.002)	(0.007)
T^{DB} (10-15)	-0.000611	-0.000861	0.0129**
	(0.002)	(0.002)	(0.005)
T^{DB} (15-20)	-0.00279**	-0.00286**	0.0188***
	(0.001)	(0.001)	(0.004)
T^{DB} (25-30)	-0.00145***	-0.00137***	0.00134
	(0.000)	(0.000)	(0.003)
T^{DB} (30-35)	-0.00133**	-0.00151**	-0.0000947
	(0.001)	(0.001)	(0.003)
T^{DB} (≥ 35)	0.00282*	0.00261*	-0.0176*
	(0.001)	(0.001)	(0.009)
P (1^{st})	0.00336	0.000595	-0.00174
	(0.025)	(0.025)	(0.026)
P (3^{rd})	0.0697***	0.0722***	0.0726***
	(0.026)	(0.027)	(0.026)
H (0-3)		-0.00176	0.00340
		(0.004)	(0.004)
H (≥ 18)		-0.000926*	-0.000612
		(0.001)	(0.001)
Avg. Humidity			0.0688
			(0.059)
T^{DB} (< 10) $\times$ Avg. Hum.			0.000570
			(0.001)
T^{DB} (10-15) $\times$ Avg. Hum.			-0.00120**
			(0.000)
T^{DB} (15-20) $\times$ Avg. Hum.			-0.00168***
			(0.000)
T^{DB} (25-30) $\times$ Avg. Hum.			-0.000214
			(0.000)
T^{DB} (30-35) $\times$ Avg. Hum.			-0.000137
			(0.000)
T^{DB} (≥ 35) $\times$ Avg. Hum.			0.00144**
			(0.001)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Climatic region $\times$ Year trend	Yes	Yes	Yes
Mean Outcome	0.006	0.006	0.006
Observations	3896	3896	3896

Notes: The dependent variable is the natural logarithm of mortality rate. Reference category for temperature is bin 20-25 °C. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table A10: Protective effects of heat adaptation appliances (Full bins specification)

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{WB} (<9)	0.00395	0.00503*	0.00497		
	(0.002)	(0.003)	(0.003)		
T^{WB} (9-14)	0.00196	0.00175	0.00167		
	(0.001)	(0.002)	(0.002)		
T^{WB} (24-29)	0.0000667	0.000168	0.000181		
	(0.001)	(0.001)	(0.001)		
T^{WB} (≥ 29)	0.0122***	0.0105***	0.0125***		
	(0.002)	(0.003)	(0.003)		
AC $\times$ T^{WB} (<9)	0.00326		0.00257	0.00554	0.00439
	(0.008)		(0.009)	(0.010)	(0.009)
AC $\times$ T^{WB} (9-14)	0.00201		0.00188	0.00421	0.00306
	(0.004)		(0.004)	(0.004)	(0.005)
AC $\times$ T^{WB} (24-29)	0.000144		0.000117	0.000142	-0.000842
	(0.002)		(0.002)	(0.002)	(0.002)
AC $\times$ T^{WB} (≥ 29)	-0.0345***		-0.0343***	-0.0226*	-0.0268**
	(0.010)		(0.010)	(0.013)	(0.013)
Cooler $\times$ T^{WB} (<9)		-0.00259	-0.00243	-0.00194	-0.00255
		(0.004)	(0.004)	(0.003)	(0.003)
Cooler $\times$ T^{WB} (9-14)		0.00154	0.000774	0.000268	0.00141
		(0.002)	(0.002)	(0.003)	(0.003)
Cooler $\times$ T^{WB} (24-29)		-0.0000857	-0.000360	0.00103	0.00156
		(0.001)	(0.001)	(0.001)	(0.001)
Cooler $\times$ T^{WB} (≥ 29)		-0.00169	-0.000851	0.00253	-0.00340
		(0.005)	(0.004)	(0.009)	(0.010)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins $\times$ State	No	No	Yes	Yes	Yes
Temperature Bins $\times$ Year	No	No	Yes	Yes	Yes
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)			0.001	0.026	0.032
Mean Outcome	0.007	0.007	0.007	0.007	0.007
Observations	2754	2754	2754	2754	2754

Notes: The dependent variable is the natural logarithm of mortality rate. Reference category for temperature is bin 14-24 °C. Standard errors are clustered at the district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table A11: Protective effects of heat adaptation appliances (Controlling for income)

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{WB} (24-29)	-0.0000935	-0.0000144	-0.00000214		
	(0.001)	(0.001)	(0.001)		
T^{WB} ($\geq$ 29)	0.0119***	0.0101***	0.0121***		
	(0.002)	(0.003)	(0.003)		
AC $\times$ T^{WB} (24-29)	-0.000537		-0.000568	-0.00146	-0.000405
	(0.002)		(0.002)	(0.002)	(0.002)
AC $\times$ T^{WB} ($\geq$ 29)	-0.0339***		-0.0340***	-0.0247**	-0.0275**
	(0.009)		(0.009)	(0.012)	(0.013)
Cooler $\times$ T^{WB} (24-29)		-0.00000600	-0.000182	0.000989	0.00147
		(0.001)	(0.001)	(0.001)	(0.001)
Cooler $\times$ T^{WB} ($\geq$ 29)		-0.000912	-0.000317	0.00418	-0.00486
		(0.005)	(0.005)	(0.009)	(0.010)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
Income per capita	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins $\times$ State	No	No	Yes	Yes	Yes
Temperature Bins $\times$ Year	No	No	Yes	Yes	Yes
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)			0.001	0.005	0.022
Mean Outcome	0.007	0.007	0.007	0.007	0.007
Observations	2754	2754	2754	2754	2754

Notes: The dependent variable is the natural logarithm of mortality rate. Standard errors are clustered at the district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table A12: Protective effects of heat adaptation appliances (Controlling for income × temperature bins)

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{WB} (24-29)	0.00188	0.00153	0.00195		
	(0.002)	(0.002)	(0.002)		
T^{WB} ($\geq$ 29)	0.00336	0.00830	0.00324		
	(0.015)	(0.014)	(0.015)		
AC × T^{WB} (24-29)	-0.000219		-0.000236	-0.000980	-0.000264
	(0.002)		(0.002)	(0.002)	(0.002)
AC × T^{WB} ($\geq$ 29)	-0.0350***		-0.0350***	-0.0259*	-0.0267**
	(0.010)		(0.010)	(0.013)	(0.013)
Cooler × T^{WB} (24-29)		0.000101	-0.0000331	0.00132	0.00146
		(0.001)	(0.001)	(0.001)	(0.001)
Cooler × T^{WB} ($\geq$ 29)		-0.00108	-0.000855	0.00251	-0.00449
		(0.005)	(0.005)	(0.009)	(0.010)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins × Income	Yes	Yes	Yes	Yes	Yes
Temperature Bins × State	No	No	Yes	Yes	Yes
Temperature Bins × Year	No	No	Yes	Yes	Yes
AC × T^{WB} = Cooler × T^{WB} (pval)			0.001	0.008	0.021
Mean Outcome	0.007	0.007	0.007	0.007	0.007
Observations	2754	2754	2754	2754	2754

Notes: The dependent variable is the natural logarithm of mortality rate. Standard errors are clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table A13: Protective effects of heat adaptation appliances (Climatic region × Trend)

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{WB} (24-29)	0.000737	0.000942	0.000819		
	(0.001)	(0.001)	(0.001)		
T^{WB} (≥ 29)	0.0119***	0.0108***	0.0124***		
	(0.002)	(0.003)	(0.003)		
AC × T^{WB} (24-29)	0.00101		0.000967	-0.000673	-0.000397
	(0.002)		(0.002)	(0.002)	(0.002)
AC × T^{WB} (≥ 29)	-0.0293***		-0.0292***	-0.0223*	-0.0259**
	(0.009)		(0.008)	(0.012)	(0.013)
Cooler × T^{WB} (24-29)		-0.00000246	-0.0000945	0.000972	0.00144
		(0.001)	(0.001)	(0.001)	(0.001)
Cooler × T^{WB} (≥ 29)		-0.00191	-0.00126	0.00370	-0.00454
		(0.005)	(0.005)	(0.009)	(0.010)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Climatic region × Year trend	Yes	Yes	Yes	Yes	Yes
Temperature Bins × State	No	No	Yes	Yes	Yes
Temperature Bins × Year	No	No	Yes	Yes	Yes
AC × T^{WB} = Cooler × T^{WB} (pval)			0.002	0.009	0.028
Mean Outcome	0.007	0.007	0.007	0.007	0.007
Observations	2754	2754	2754	2754	2754

Notes: The dependent variable is the natural logarithm of mortality rate. Standard errors are clustered at the district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table A14: Protective effects of heat adaptation appliances (Rates in levels)

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{WB} (24-29)	0.420	0.238	0.226		
	(0.285)	(0.279)	(0.270)		
T^{WB} ($\geq$ 29)	2.905***	1.870**	2.175***		
	(0.656)	(0.742)	(0.751)		
AC $\times$ T^{WB} (24-29)	-0.0740		0.115	0.115	0.443
	(1.093)		(1.142)	(1.098)	(1.066)
AC $\times$ T^{WB} ($\geq$ 29)	-5.649*		-5.382*	-4.299	-4.857
	(3.011)		(3.069)	(3.654)	(3.801)
Cooler $\times$ T^{WB} (24-29)		0.509	0.479	0.674*	0.995**
		(0.374)	(0.391)	(0.384)	(0.415)
Cooler $\times$ T^{WB} ($\geq$ 29)		1.497	1.597	3.368	1.678
		(1.557)	(1.566)	(2.958)	(3.264)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins $\times$ State	No	No	Yes	Yes	Yes
Temperature Bins $\times$ Year	No	No	Yes	Yes	Yes
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)			0.049	0.027	0.060
Mean Outcome	655.755	655.755	655.755	655.755	655.755
Observations	2756	2756	2756	2756	2756

Notes: The dependent variable is mortality rate per 100,000 people. Standard errors are clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table A15: Protective effects of heat adaptation appliances (State-level clustered standard errors)

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{WB} (24-29)	-0.000104	-0.0000459	-0.0000211		
	(0.001)	(0.001)	(0.001)		
T^{WB} (≥ 29)	0.0119***	0.0101**	0.0121**		
	(0.004)	(0.005)	(0.005)		
AC $\times$ T^{WB} (24-29)	-0.000699		-0.000732	-0.00155	-0.000500
	(0.002)		(0.002)	(0.002)	(0.002)
AC $\times$ T^{WB} (≥ 29)	-0.0340***		-0.0340***	-0.0248***	-0.0276***
	(0.010)		(0.010)	(0.009)	(0.005)
Cooler $\times$ T^{WB} (24-29)		0.0000146	-0.000165	0.000998	0.00147
		(0.001)	(0.001)	(0.001)	(0.001)
Cooler $\times$ T^{WB} (≥ 29)		-0.000877	-0.000291	0.00422	-0.00481
		(0.007)	(0.007)	(0.004)	(0.003)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins $\times$ State	No	No	Yes	Yes	Yes
Temperature Bins $\times$ Year	No	No	Yes	Yes	Yes
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)			0.026	0.025	0.004
Mean Outcome	0.007	0.007	0.007	0.007	0.007
Observations	2754	2754	2754	2754	2754

Notes: The dependent variable is the natural logarithm of mortality rate. Standard errors are clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table A16: Protective effects of heat adaptation appliances (Unweighted)

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{WB} (24-29)	-0.000165	-0.000185	-0.000154		
	(0.001)	(0.001)	(0.001)		
T^{WB} ($\geq$ 29)	0.0114***	0.00979***	0.0118***		
	(0.002)	(0.003)	(0.003)		
AC $\times$ T^{WB} (24-29)	-0.00111		-0.00114	-0.00299	-0.00178
	(0.002)		(0.002)	(0.002)	(0.002)
AC $\times$ T^{WB} ($\geq$ 29)	-0.0319***		-0.0318***	-0.0210**	-0.0227**
	(0.008)		(0.008)	(0.011)	(0.011)
Cooler $\times$ T^{WB} (24-29)		0.000212	0.0000583	0.000774	0.00146
		(0.001)	(0.001)	(0.002)	(0.002)
Cooler $\times$ T^{WB} ($\geq$ 29)		-0.00139	-0.00111	0.00489	-0.00307
		(0.005)	(0.004)	(0.008)	(0.009)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins $\times$ State	No	No	Yes	Yes	Yes
Temperature Bins $\times$ Year	No	No	Yes	Yes	Yes
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)			0.001	0.004	0.023
Mean Outcome	0.007	0.007	0.007	0.007	0.007
Observations	2754	2754	2754	2754	2754

Notes: The dependent variable is the natural logarithm of mortality rate. Standard errors are clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Wet-bulb temperature, health status, and heat adaptation (Alternative fixed effects)

	Full	< 5 yro.	5-64 yro.	≥ 65 yro.	Full	< 5 yro.	5-64 yro.	≥ 65 yro.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T^{WB} (24-29)	0.0000117	-0.0000652	0.00000904	0.0000112	0.00000691	-0.0000603	0.00000391	-0.0000254
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T^{WB} ($\geq$ 29)	0.0000456	-0.00000581	0.0000658	0.000105	0.0000432	-0.0000781	0.0000781	-0.0000521
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)
AC $\times$ T^{WB} (24-29)	-0.0000433**	0.0000278	-0.0000190	-0.000133	-0.0000359**	-0.00000368	-0.0000149	-0.000153*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AC $\times$ T^{WB} ($\geq$ 29)	0.000208	-0.000327	0.000128	-0.00171**	0.000218	-0.000328	0.000155	-0.00161*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Cooler $\times$ T^{WB} (24-29)	-0.0000666***	-0.0000278	-0.0000441**	-0.000489***	-0.0000644***	-0.0000301	-0.0000410**	-0.000487***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cooler $\times$ T^{WB} ($\geq$ 29)	0.000659**	0.000261	0.000334*	0.00593***	0.000594**	0.000309	0.000264	0.00576***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)
Household-Quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Individual-Quarter FE	No	No	No	No	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AC $\times$ T^{WB} = Cooler $\times$ T^{WB} (pval)	0.175	0.085	0.365	0.000	0.254	0.059	0.608	0.000
Mean Outcome	0.027	0.015	0.018	0.176	0.027	0.014	0.018	0.177
Observations	10105549	308925	9206094	493242	9533122	260273	8652586	465327

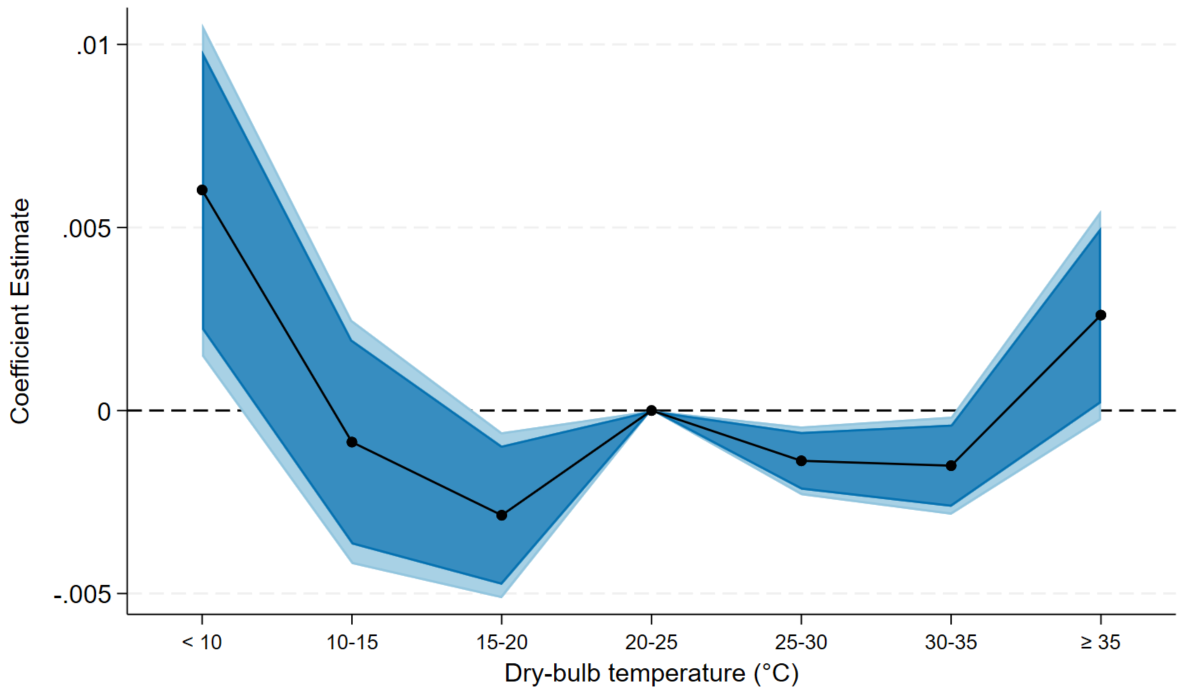
Notes: The dependent variable is a dummy variable for self-reported health status (= 1 if negative). Reference category for temperature is bin 14-24 °C. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by individual survey weights.

Supplementary information (not for publication)

Table S1: Data sources for each analysis

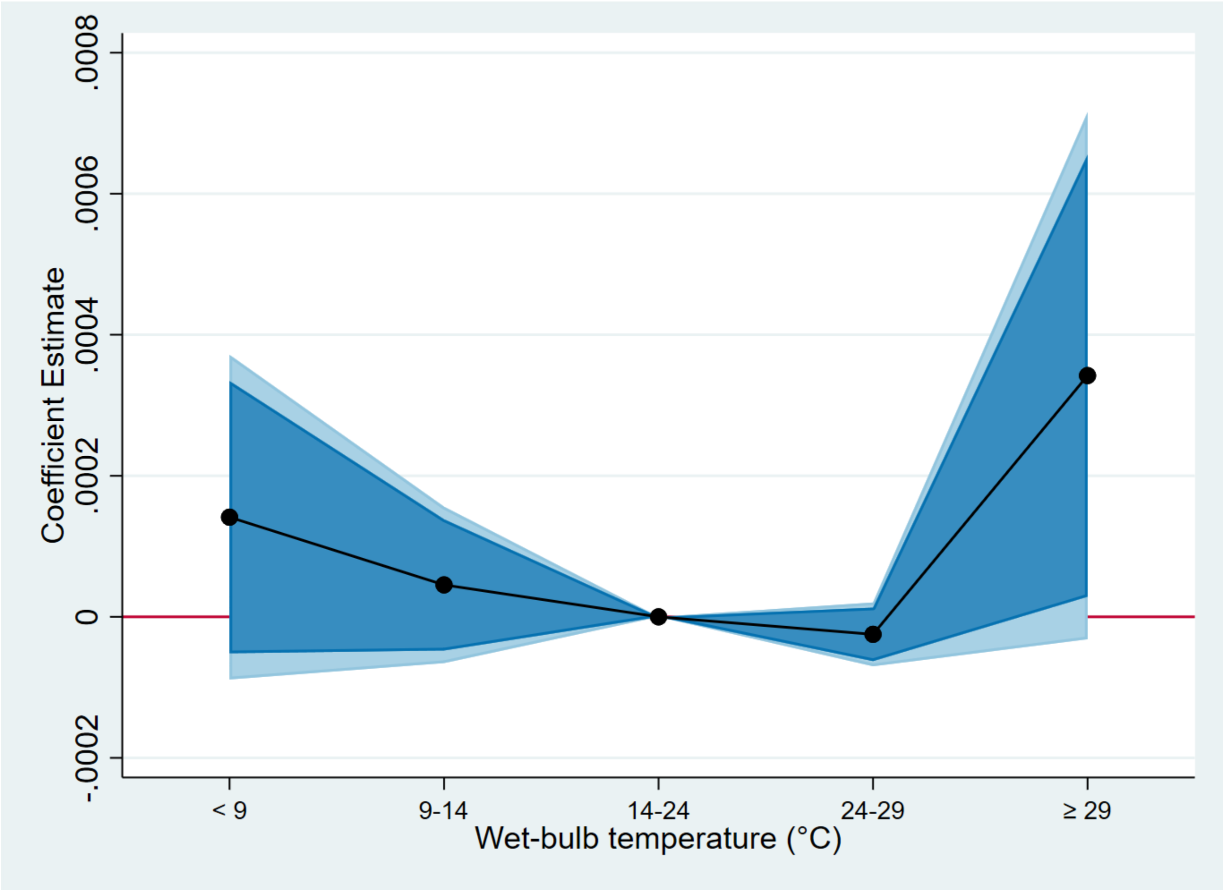
Source	Type	Unit	Frequency	Years	Variables
CHPS	Panel	Household	Four-monthly	2014-2019	Air conditioning, Evaporative cooler, Household income, Health status, Household characteristics
ERA5	Panel	Grid	Daily	1981-2019	Cooling Degree Days, Temperature, Precipitation, Humidity
CRS	Panel	District	Annual	2014-2019	Mortality

Figure S1: Mortality and dry-bulb temperature



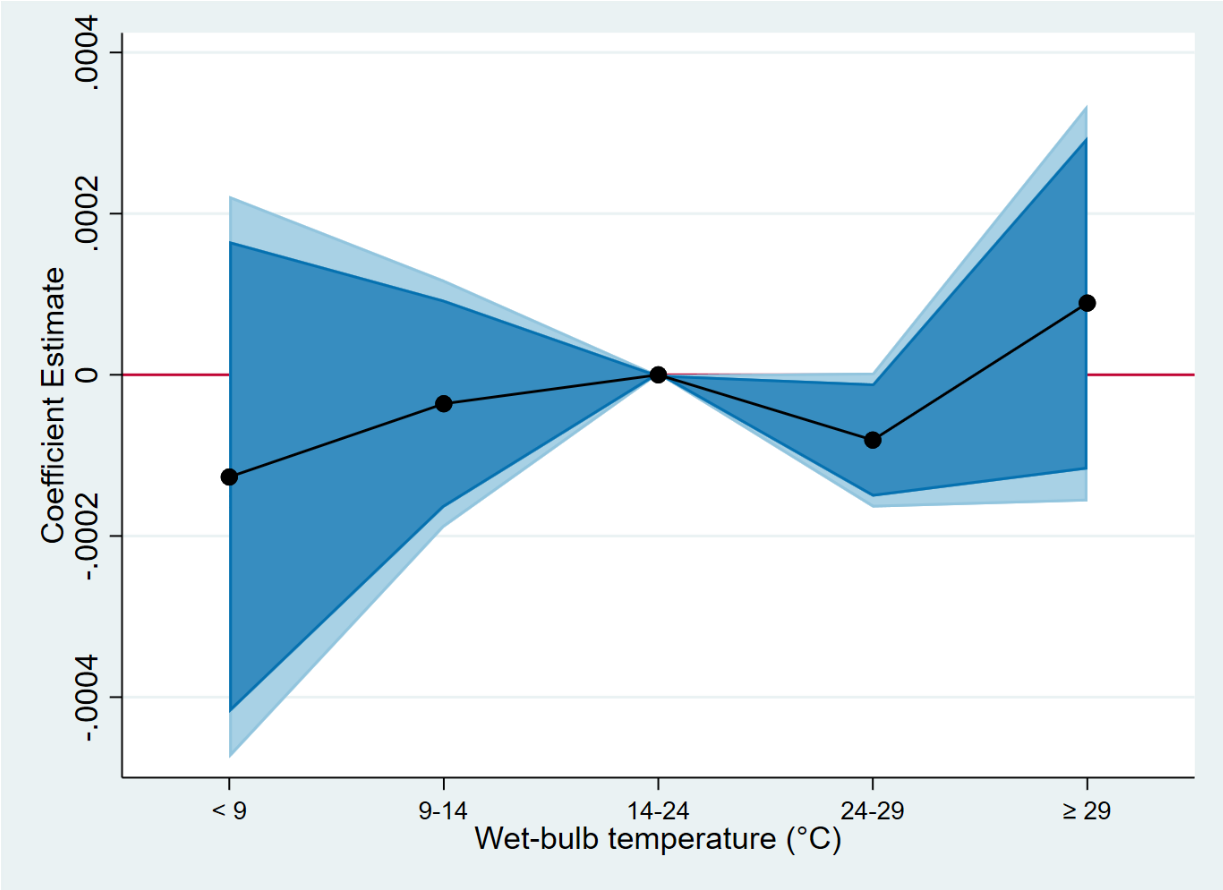
Notes: The figure plots the relationship between all-age mortality (in logs) and dry-bulb daily average temperature (in bins). Light blue areas are 95% confidence intervals; dark blue areas are 90% confidence intervals.

Figure S2: Health status and wet-bulb temperature (Full sample)



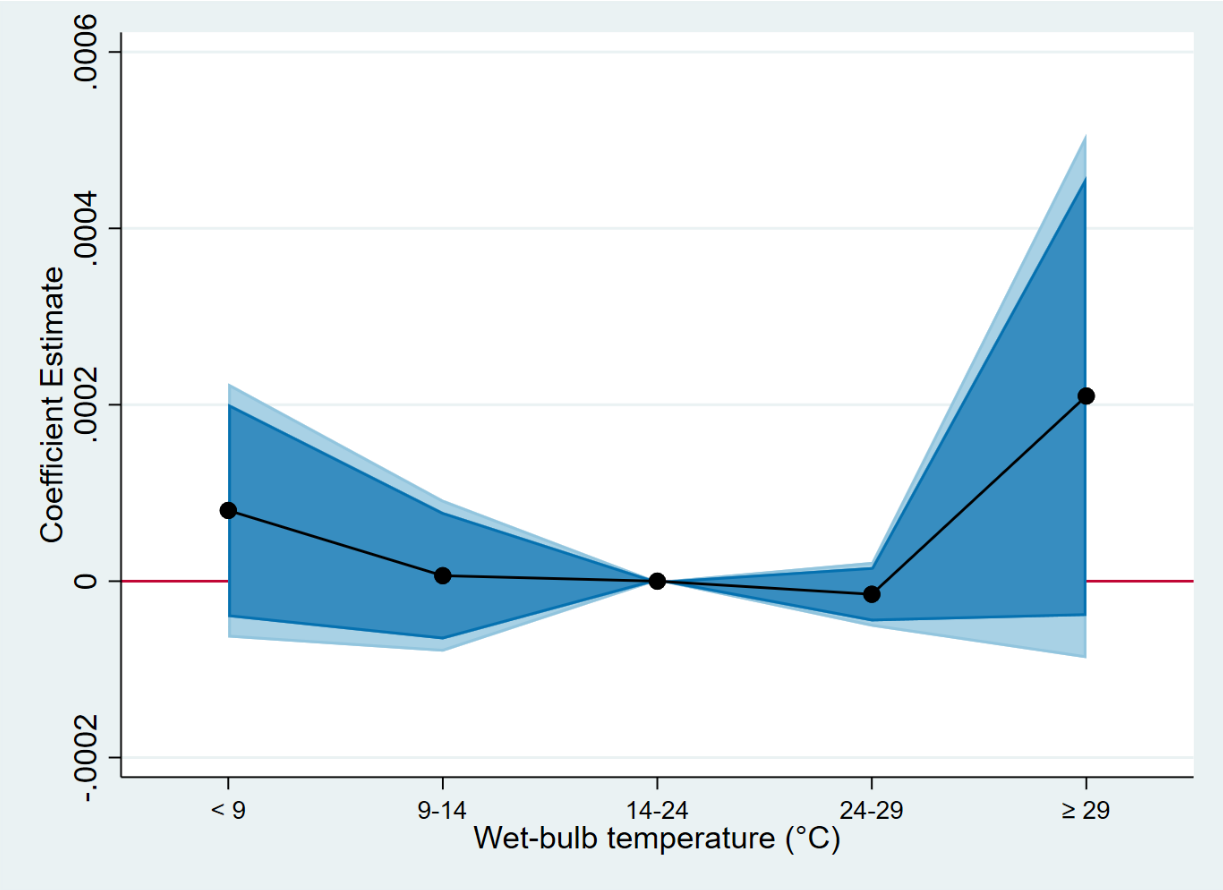
Notes: The figure plots the relationship between all-age mortality (in logs) and dry-bulb daily average temperature (in bins). Light blue areas are 95% confidence intervals; dark blue areas are 90% confidence intervals.

Figure S3: Health status and wet-bulb temperature (< 5)



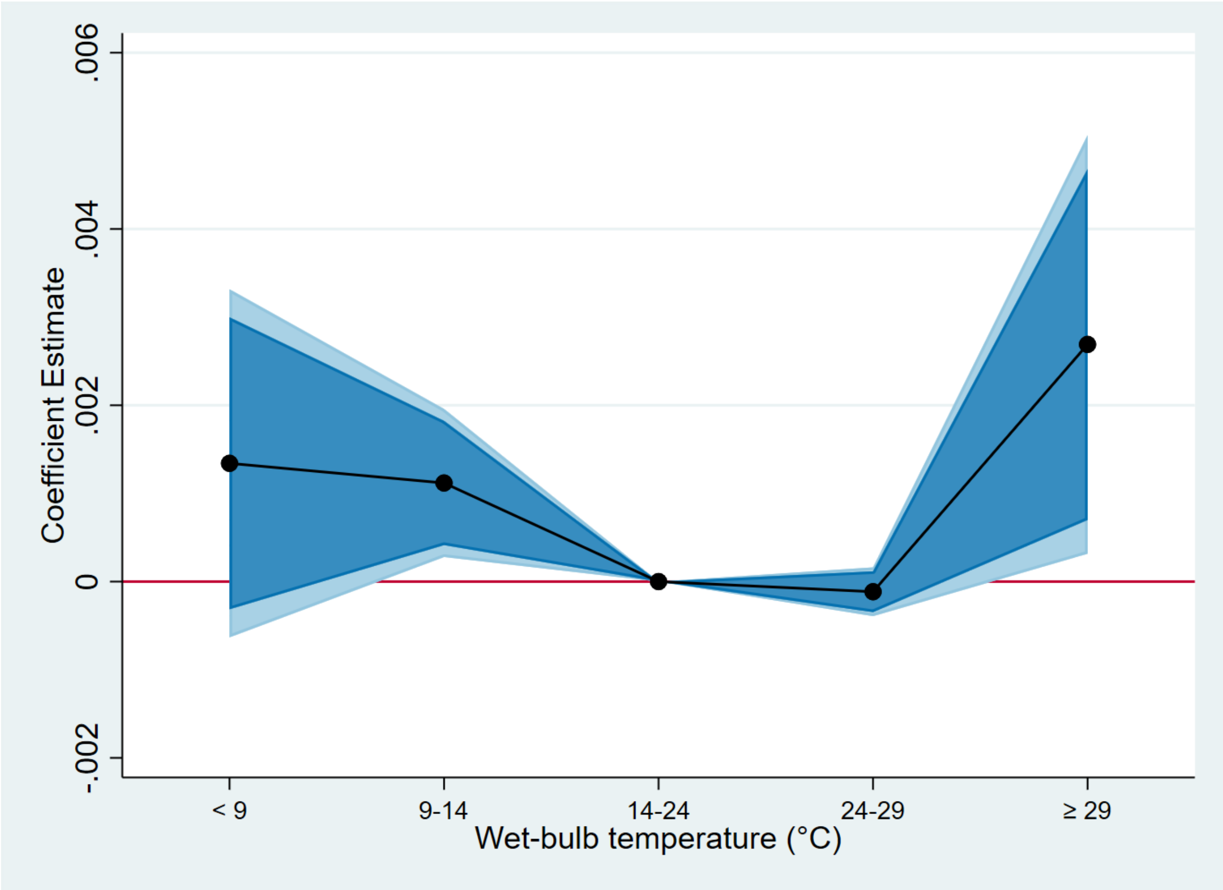
Notes: The figure plots the relationship between self-reported health status and wet-bulb daily average temperature (in bins). Light blue areas are 95% confidence intervals; dark blue areas are 90% confidence intervals.

Figure S4: Health status and wet-bulb temperature (5-64)



Notes: The figure plots the relationship between self-reported health status and wet-bulb daily average temperature (in bins). Light blue areas are 95% confidence intervals; dark blue areas are 90% confidence intervals.

Figure S5: Health status and wet-bulb temperature (≥ 65)



Notes: The figure plots the relationship between self-reported health status and wet-bulb daily average temperature (in bins). Light blue areas are 95% confidence intervals; dark blue areas are 90% confidence intervals.

Table S2: Impact of wet-bulb temperature on health status

	Full (1)	< 5 yro. (2)	5-64 yro. (3)	$\geq$ 65 yro. (4)
T (< 9)	0.000141	-0.000127	0.0000802	0.00134
	(0.000)	(0.000)	(0.000)	(0.001)
T (9-14)	0.0000453	-0.0000359	0.00000620	0.00112***
	(0.000)	(0.000)	(0.000)	(0.000)
T (24-29)	-0.0000248	-0.0000810*	-0.0000149	-0.000115
	(0.000)	(0.000)	(0.000)	(0.000)
T ($\geq$ 29)	0.000342*	0.0000890	0.000210	0.00269**
	(0.000)	(0.000)	(0.000)	(0.001)
District-Quarter FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Mean Outcome	0.027	0.015	0.018	0.175
Observations	10106841	361399	9210234	535203

Notes: The dependent variable is a dummy variable for self-reported health status (= 1 if negative). Reference category for temperature is bin 14-24 °C. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by individual survey weights.

Table S3: Impact of wet-bulb temperature on health status (Alternative fixed effects)

	Full (1)	< 5 yro. (2)	5-64 yro. (3)	$\geq$ 65 yro. (4)	Full (5)	< 5 yro. (6)	5-64 yro. (7)	$\geq$ 65 yro. (8)
T^{WB} (< 9)	0.000378	-0.000105	0.000208	0.00379	0.000411	-0.0000832	0.000224	0.00377
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)
T^{WB} (9-14)	0.0000795	-0.000114	0.0000255	0.00140**	0.0000662	-0.000140	0.0000204	0.00147**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
T^{WB} (24-29)	-0.0000149	-0.0000849*	-0.0000116	-0.0000594	-0.0000193	-0.0000837	-0.0000154	-0.0000941
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T^{WB} ($\geq$ 29)	0.000412**	0.0000596	0.000252*	0.00280**	0.000374*	0.00000157	0.000230	0.00256**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Household-Quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Individual-Quarter FE	No	No	No	No	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.027	0.015	0.018	0.176	0.027	0.014	0.018	0.177
Observations	10105549	308925	9206094	493242	9533122	260273	8652586	465327

Notes: The dependent variable is a dummy variable for self-reported health status (= 1 if negative). Reference category for temperature is bin 14-24 °C. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by individual survey weights.