Adaptation technology choice and implications for heat-related health risk*

Filippo Pavanello† Ian Sue Wing‡

Abstract

This paper investigates the consequences of inequality in access to 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 provide robust protection against humid heat. Exploring the mechanisms, 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. Our findings provide the first evidence that income-driven differences in adaptation technology choice translate into unequal health risks under rising heat exposure, potentially reinforcing existing socioeconomic disparities.

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

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†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 technologies in mitigating mortality impacts from extreme heat in India. We shed light on the trade-off between affordability and protective capacity across two widely used adaptation technologies: evaporative coolers and air conditioners.

Evaporative coolers are low-cost, passive, open-loop systems that lower indoor temperatures by drawing hot ambient air across water-saturated media. The resulting evaporation removes thermal energy from the air stream, yielding temperature reductions of up to 4.5 °C relative to outdoor conditions. Their effectiveness, however, may decline in humid environments, and the passive nature of the technology limits the precision with which indoor temperatures can be controlled. By contrast, air conditioning (AC) units are active cooling systems that use closed-loop mechanical vapor compression and expansion to absorb indoor thermal energy and expel it from the building envelope. This physical mode of operation facilitates substantially larger reductions in indoor temperatures below ambient levels—up to 20°C—but at much higher fixed and variable costs (see, e.g., Khosla et al., 2022).[2] As a result, evaporative coolers are poten-

[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] In India, prices of cooling technologies vary widely with type and features, but they constitute a substantial capital expenditure. As of this writing (2025), Amazon (`https://amazon.in`) shows evaporative coolers ranging from under ₹ 1,000 for tabletop misting fans to as much as ₹ 19,000 for commercial-grade floor standing units (median ∼₹ 2,500). For air conditioners, window units range from ₹ 20,000-50,000 while split systems range from ₹ 25,000-80,000 (median ∼₹ 46,000). Central systems cost in excess of ₹ 70,000. Accounting for inflation, acquisition costs as

tially less effective but far more accessible to low-income households, owing to their simple design, modest up-front cost, and substantially lower electricity requirements (e.g., Chatterjee and Lenart, 2007).

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 both technologies grows rapidly. Much of this expansion reflects rising incomes and urbanization rather than changes in local temperatures. 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 income 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. Responses to dry-bulb temperatures are substantially smaller, even at very high thresholds (e.g., dry-bulb temperatures at or above 35°C), underscoring the dominant role of humidity in heat-related mortality.

a fraction of 2019 median annual household income (∼₹ 181,000) range from 0.5-8% for coolers to 10-30% for AC units.

We then augment our baseline specification by interacting wet-bulb temperature with the annual 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 percentage point 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, indicating that AC is substantially more effective in mitigating temperature-related mortality.

Importantly, to mitigate concerns about non-random variation in air conditioning and cooler ownership, our main specification allows the effects of temperature to vary flexibly across states and years. This absorbs annual changes and state-specific temperature–mortality gradients that may be correlated with cooling technology adoption. Moreover, 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, reducing concerns that air conditioning ownership rate simply captures access to better adaptation options in a location.

Finally, we shed light on the mechanisms behind evaporative coolers' small mediating effect. We first draw on novel hourly building data from Tasgaonkar et al. (2022) for three Indian cities to assess how well evaporative coolers reduce indoor temperatures. We show that coolers lower indoor temperatures by up to 4.2 °C, but become largely ineffective when outdoor dry-bulb temperatures exceed 43 °C or when humidity exceeds 66 percent. Next, we examine how different cooling appliances' mitigating effects on temperature-related mortality vary by humidity. Splitting districts into terciles of humidity, we find that both coolers and AC units significantly reduce the mortality effect of high wet-bulb temperatures in drier districts, with no statistically significant difference between them. In more humid districts, however, only air conditioners provide meaningful 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 widely available and actively used in practice (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). While income inequality is a well-documented determinant of disparities in access to air conditioning, our contribution is to highlight a novel and previously unexplored dimension: technology choice. The central implication is that when households face income or credit constraints, the set of feasible adaptation strategies shifts toward cooling appliances that provide only limited protection, thereby generating an unequal distribution of residual heat-related health risk. Distinct from prior research, the longitudinal dimension of our data allows us to examine not only the distribution of cooling technologies across households, but also the determinants of adoption of different alternatives. This enables us to shed new light on the drivers of cooling demand in a developing-country context, and to clarify how resource constraints shape the effectiveness of household-level adaptation.

Second, 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.[3] A key contribution of our study is to isolate humidity as a central driver of mortality risk. High ambient humidity reduces the effectiveness of evaporative cooling from the skin, thereby amplifying heat stress (Barreca, 2012). We show that in India annual mortality rates increase markedly with the number of days that are both extremely hot and humid, whereas similarly hot but drier days have substantially smaller effects.

Third, our work relates to the small set of studies that jointly examine the mortality impacts of temperature extremes and the mitigating role 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 study these responses separately. By contrast, Barreca et al. (2016) combine information on AC ownership, daily temperatures, and state-level

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

monthly mortality rates in the United States, showing that AC diffusion reduced hot-day mortality by roughly 80 percent. We build on this literature by providing a more comprehensive analysis of heat-adaptation responses, exploring heterogeneity across margins, income levels, and technologies. By comparing the protective performance of cooling alternatives, we highlight the cost–performance trade-offs that shape households' adaptation choices and the distribution of health benefits arising from these technologies.

Finally, we demonstrate a novel application of newly available building-level datasets that record indoor and outdoor temperatures at high frequency. These data permit a context-specific characterization of how cooling technologies affect indoor environments—detail 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 leverage 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. 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.

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.[4]

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 period 2000-2020, 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.[5]

Weather data. Household and mortality data are merged with population-weighted 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 data is less prone to station weather bias but might be biased via the meteorological models that

[4] 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.

[5] As a robustness check we compute mortality rates using district-level population counts from LandScan Global (Lebakula et al., 2025).

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.[6] 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, four-monthly, and annual level. These include binned measures of wet bulb and dry bulb temperature, specific humidity,[7] and Cooling Degree Days (CDD), where CDDs are calculated for both wet- and dry- bulb temperatures using a 24°C threshold.[8]

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, reducing indoor heat exposure.

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

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

[8] 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.

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 urbanized states 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, in most states in India, AC still in the process of catching up to the saturation of demand for evaporative coolers.

This phenomenon is highlighted in Figure 2, which illustrates the penetration of cooling technologies with households' income and urban location (cf. Davis et al., 2021). The main finding is that technology choice differs markedly across income levels. Virtually all very poor households lack access to either technology, but adoption of coolers increases rapidly with income, especially in rural areas, while AC prevalence is minimal. Rural and urban districts differ in the patterns saturation of cooler adoption and acceleration of AC adoption. In urban districts, once per capita income exceeds the mode of the distribution for urban residents (₹75,000) the prevalence of households with coolers alone saturates at around 45%, while the prevalence of households with AC takes off, in highest income locations equalling that of coolers. By contrast, in rural districts the threshold for saturation of households with coolers and acceleration of AC adoption is more 50 percent higher, well past the upper quartile of the distribution of rural per-capita income.

Distribution across climatic conditions. Figure 3 divides 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 four-month household income. The key finding is that, controlling for income levels, 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 four-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 backup power supplies can mitigate constraints associated with unreliable electricity service (cf Mugyenyi et al., 2025). 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 (more precipitation) 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. We will return on this topic later in the paper.

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 may worry that this finding could be confounded by non-random sorting of populations across locations with different climatic conditions. 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:

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

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,[9] $g(P_{d(i)w})$ 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., 2025).[10] 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,[11] 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,

[9] In our sample there are 18 waves.
[10] Cohen et al. (2025) finds that in US households mostly rely on expectations about the past 7-8 years.
[11] For example, for the wave January-April 2014, cooling degree days are averaged for the same months over the years 2003-2013.

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 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 effects of medium-run climatic expectations are comparatively modest. 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. Income only moderates the climate response for AC adoption, with no comparable effect for evaporative coolers.

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. In absolute terms, 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 reveals further patterns (Table A4). 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 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 across Indian districts. Second, we introduce cooling adaptation into our analysis, testing whether the uptake of air conditioners and coolers can offset the 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 the 14-24 °C interval as the reference category.[12] For comparison, we estimate the same specification using dry-bulb temperature bins, with 20-25 °C as the omitted interval.

To account for the potentially confounding effects of 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 dry" days (0–3 g/kg) and "very humid" days ($\geq$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 control for unobserved 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 absorb influences on health vary across states and years.[13]

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 Barreca (2012); Burgess et al. (2017). 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 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

[12]We opt for estimating the response function using temperature bins. Extreme high and low temperatures have both harm human health, making it highly likely that the temperature-mortality relationship is nonlinear. Moreover, temperature bins have the attractive property of being able to able to flexibly capture that shape of this exposure response function (see, e.g., Gould et al., 2025).

[13]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.

following interaction model:

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

We define $\mathcal{C}_{dt}^{j}$ as the fraction of households in each district and year who own adaptation technology $j \in \{\text{AC, Coolers}\}$. To distinguish between the two technologies' effects, we avoid overlap in usage attribution and compute cooler shares using only households that own an evaporative cooler but not an air conditioner. This is tantamount to the assumption that owners of air conditioners will prefer air conditioning over evaporative cooling. We also simplify the interaction structure, specifying the term $f(T_{dt}^{WB})$ using only the upper two wet-bulb temperature bins, for which heat mortality risks are expected to be largest. Under the hypothesis that adaptation technologies mitigate heat-related mortality, the coefficients γ_j are expected to be negative.

We share with Barreca et al. (2016) the limitation that adaptation to heat is not identified in a quasi-experimental setting. The potential threat to the validity of our inference is that adaptation may be endogenous to unobserved household or individual characteristics that are correlated with mortality. We address this issue by allowing for fixed differences in the effect of temperature across space and time, which we operationalize by interacting our temperature bins with state and year dummies. The first interaction, $\mu_s f(T_{dt}^{WB})$, captures any time-invariant differences across states in the mortality-temperature relationship that are also correlated with the adoption of the two technologies (e.g., climatic conditions, levels of income and/or education). The second, $\mu_t f(T_{dt}^{WB})$, absorbs time-varying differences across years (e.g., changes in national policies) that could shift 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 effects attributed to adaptation do not merely capture the potential benefit of residing in wealthier districts that may have better access to a variety of public and private coping mechanisms that are not observed by the econometrician.

4.2 Results: the mortality-temperature exposure response

Figure 4 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%. Thus, on average, approximately 6 deaths per 100,000 population can be attributed to a single additional day in the hottest temperature bin.[14]

The magnitude of the foregoing exposure response is consistent with Burgess et al. (2017), who find that an additional 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.

Replicating our analysis using dry-bulb temperatures (Table A9) yields results that differ in important ways.[15] 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 imprecisely estimated, while the interaction terms are large, positive and highly significant. These results suggest that adverse 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

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

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

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 we model 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. By comparison, the protective effect of evaporative coolers is an order of magnitude smaller and not significant.

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 effects of the two technologies are significantly different (pval = 0.001). Estimates are largely unchanged controlling for state- and year-level trends in temperature-mortality relationship, with air conditioning's effect diminishing slightly relative to prior specifications (columns 4-5).

To put these results in context, we focus on our preferred and most conservative specification (column 5). The 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 similar hot days in the absence of adaptation. Air conditioners' effect size is in line with Barreca et al. (2016), who find that a 10 percentage point increase in AC penetration reduces the effect of a day above 32 °C (90 °F) by 10%.

Likewise, the faster the penetration of these cooling technologies, the larger 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%.[16]

We test the robustness of our findings by estimating several additional models. First, in Table A10 we interact the two shares with all wet-bulb temperature bins. The results are slightly less precisely estimated, but of similar sign and magnitude. Importantly, we do not find interactions with cold temperatures to be statistically significant. Second, we introduce income as control, on its own as well as interacted with temperature bins (Table A11 and Table A12). The estimated coefficients are the same order of magnitude, and in the latter test are even better

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

identified, suggesting 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); unweighted estimates (Table A16); and using LandScan for district-level population counts (Table A17).

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, they appear to 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 shown that the prevalence of space-conditioning technologies moderates the relationship between exposure to humid heat and mortality. The finding that evaporative coolers do not have a significant mortality reduction benefit raises the question of their effectiveness in cooling indoor environments. As discussed in the Introduction, the physics of evaporative cooling limits the achievable indoor–outdoor temperature differential under high humidity. In this section, we assess the implications of this limitation for low-income households in India, leveraging granular measurements of indoor temperature and humidity from Tasgaonkar et al. (2022).

A major challenge in rigorously quantifying the health benefits of cooling is the scarcity of data on indoor thermal environments—the conditions households actually face. Outdoor heat does not translate to indoor exposures in a one-to-one fashion: buildings provide passive protection through shading and insulation, and households can further modify their environment using cooling appliances such as AC units, coolers or fans. The implication is that the deaths documented in the previous sections actually result from indoor temperatures that could over- or understate the 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 in 2016-18. They use sensors and data loggers to record 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.[17] 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 analytical approach is the following reduced-form specification:

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

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 month-year shocks.

The results, shown in Figure 5, suggest that the insulating effects of the structure alone lower temperatures monotonically by an average of 0.45 °C per degree of ambient temperature above 24 °C, reducing indoor air temperatures during extremely hot hours (>45 °C) by as much as 12 °C relative to outdoors. Beyond this, fans do not have a significant cooling effect, corroborating prior findings of their limited effectiveness (Malik et al., 2022), and during the hottest hours could actually further warm indoor spaces by up to 2.5 °C. Conversely, the presence of an evap-

[17] 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.

orative cooler is 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 sample sites, 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, almost entirely below the sample median.

To generalize this finding, we first identify building-hour observations in our sample that match the high temperature and moderate relative humidity intervals over which evaporative coolers significantly contribute to the indoor-outdoor temperature gap. Figure 6 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 Evaporative cooler prevalence and macro-scale heat exposure mitigation potential

In this section we elaborate the macro-scale implications of the foregoing building-level results. While we cannot directly map our estimates into health outcomes, we can assess the extent to which the geographic distribution of evaporative coolers mitigates exposure to dry heat. Our analysis proceeds in three steps. First, we use ERA5 hourly temperature and humidity to compute, first, hourly wet-bulb globe temperature (WBGT), and, then, cumulating over hours with WBGT $\geq$24°C, monthly wet bulb globe cooling degree hours ($WBGCDH_{24}$) at the district level. The latter is a measure of cumulative ambient humid heat exposure. Next, we 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 5). The result is a measure of humid heat exposure that could potentially be mitigated with 100% cooler prevalence. Finally, we scale the potential values in step 2 by the annual average rates of household prevalence of evaporative coolers observed in CPHS, to estimate the heat exposure that is actually mitigated by evaporative coolers.[18]

The results generally corroborate our findings drawn from observations of a small sample of buildings. Figure 7 shows the district-level intersection between ambient exposure and exposure

[18]The results 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 their constituent households members' activity patterns, none of which we observe.

that is actually mitigated. On average, slightly more than half of annual $WBGCDH_{24}$ exposures have the potential to be mitigated by coolers. This fraction is much larger early in the year (70% in March) and declines sharply as humidity spikes with the onset of the monsoon (37% in June). However, due the geography of cooler penetration, the fraction of $WBGCDH_{24}$ 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 exposures that go unmitigated. These temporal and spatial gradients become much less steep in the second half of the year, when ambient $WBGCDH_{24}$ is much lower.

Figure 8 collapses these results over districts, multiplying by the number of residents to obtain aggregate population heat exposure implications (Colelli et al., 2023; Popp et al., 2025). March, April and May account for 60% of the nearly 6.9 trillion annual person cooling degree hours of exposure ($PCDH_{24}$). Overall, $PCDH_{24}$ 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 massively increasing the penetration evaporative cooling could potentially result in significantly expanded indoor temperature moderation benefits. Yet 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 further, developing insights into what the benefits of evaporative cooling-driven indoor temperature moderation might be.

5.3 The role of humidity in evaporative coolers' mortality reduction benefits

The previous section highlights a potential explanation for the low protective effect of evaporative coolers that stems from their mechanism of operation: the effectiveness of evaporation depends critically on ambient humidity. Elevated ambient humidity reduces evaporative potential, limiting coolers' ability to decrease air temperature. Since our main results demonstrate the heightened mortality risks of extreme heat under humid conditions, this mechanism not only explains coolers' limited overall mortality reduction potential, it indicates ambient conditions under which they could potentially be effective.

Key to this insight is the correlation between humid heat exposures at the daily scale of our mortality analysis and the hourly scale of our building-level analysis (Figure A1). On average, an additional day with $T^{WB} \geq 29$°C is associated with 51 additional $WBGCDH_{24}$. If we restrict the sample to those hours with ambient conditions within the meteorological envelope of coolers' effectiveness, the relationship weakens markedly on average (31 $WBGCDH_{24}$ per $T^{WB} \geq 29$), but actually *strengthens* for districts in the lowest tercile of average annual specific humidity (65 WBGCDH_{24} per $T^{WB} \geq 29$). This result suggests that in arid areas, ambient humidity levels that coincide with extreme moist heat exposures may not be so high as to render evaporative cooling ineffective.

We provide two empirical tests of this hypothesis. First, we re-estimate our main specification (Equation 3) separately by terciles of average specific humidity (Table 4). In the driest tercile (Panel A), the interaction between cooler prevalence and high wet-bulb temperature days yield 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 use bins of dry-bulb rather than wet-bulb temperature as the measure of heat exposure. Results, reported in Table 5, show that 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 suggests that the apparent effectiveness of coolers is largely confined to low-humidity environments.

Taken together, these findings provide a nuanced picture of evaporative cooling as a widespread adaptation strategy that is subject to opportunities as well as limitations, particularly in locations and periods where high temperature and low to moderate humidity coincide.

5.4 Beyond mortality: assessing the implications for morbidity reductions

We close by circling back to critically consider our main mortality results. Taken in isolation, these findings raise a natural question: what would motivate Indian households to purchase evaporative coolers, and the electricity to operate them, if they on average conveyed no significant mortality reduction benefits? Our subsequent analyses conclusively demonstrate that significant benefits do indeed arise, but in low-humidity locations and seasons of the year. Still, the interesting question raised by this line of reasoning is what *other* benefits evaporative coolers could potentially provide. One such benefit, especially among poor households, may be status—the psychological satisfaction of owning an appliance. This motivation is likely more applicable to air conditioners, ownership of which is still considered a luxury in India (Phore and Singh, 2022). More tangibly, evaporative coolers may improve thermal comfort and reduce non-fatal heat-related morbidity.

Although scarcity of data precludes rigorous tests of the latter hypothesis, the CPHS survey nonetheless provides an opportunity to examine whether evaporative coolers offer health benefits along non-fatal margins, through questions 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:

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

where H_{iw} is a binary indicator equal to 1 if individual i, 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 $j \in \{\text{AC, cooler}\}$. The specification includes district-quarter (μ_{dq}) and wave (μ_w) fixed effects.[19] 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, AC ownership is associated with significantly lower likelihood of poor self-reported health, particularly among older adults. Evaporative coolers also appear protective, but only under moderate moist heat exposures (wet-bulb temperatures of 24-29°C). Even in this 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 humid heat exposures the interaction term between cooler use and heat becomes significantly positive, which could indicate that evaporative coolers actively exacerbate thermal discomfort and perceived ill-health, or are not used at all, leaving the household exposed to ambient conditions. Results are invariant to the use of specifications with more restrictive fixed effects (Table A18).

We emphasize that these estimates should be interpreted with caution. In particular, they do not account for selection into ownership of different 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 across India and the persistence of mortality risks during extreme heat events.

[19] 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.

6 Discussion and Conclusion

Our study contributes to the understanding of the critical nexus of climate adaptation, household technology choices, and health outcomes in the context of developing economies experiencing intensifying heat exposures.

We highlight the pivotal role of economic development in shaping cooling technology adoption. Rising incomes are associated with increasing household adoption of heat mitigation appliances. Our results underscore the fact that such increases in adaptive capacity are not uniform: low- and middle-income households predominantly adopt low-cost evaporative coolers that are less effective in moderating indoor temperatures, whereas wealthier households invest in high-cost air conditioners that are highly effective at cooling indoor environments.

These divergent technology choices have important health consequences. We find a marked difference in the ability of the two technologies to mitigate the mortality risk associated with exposure to extreme hot and humid days. Prevalence of residential air conditioning is associated with substantially lower rates of heat-attributable deaths over the full range of exposures. By contrast, the moderating effect of evaporative coolers is much more modest on average. Yet, our results document the striking phenomenon that evaporative coolers can be nearly as effective as air conditioners in mitigating heat-related mortality, but only in the locations and seasons where humidity is low enough to enable them to substantially reduce indoor temperatures below ambient extremes.[20] As well, coolers appear to mitigate less severe adverse health outcomes associated with moderate humid heat exposures. Notwithstanding these patterns, adaptation among low-income households remains incomplete and is often accompanied by substantial residual exposure to extreme heat. By the end of our sample period more than 640 million people in 165 million households still lacked access to either technology. The majority of these individuals lived in the 52% of districts in which over half the population was without cooling. The latter finding should motivate consideration of cooling policies that explicitly focus on adaptation, and interventions to address disparities therein, with the goal of ensuring that the economic benefits of cooling are not merely accessible to a small, well-resourced segment of the society.[21]

What could such interventions look like, and how effective might they be? As an illustration

[20] Over the sample period India experienced 35.9 million deaths, for an average crude death rate of 5.4 per thousand. In-sample predictions with the model in Table 4 suggest that, of these, nearly 1.6 million (4.4%) were attributable to heat exposures, net of cooling adaptation. In the absence of the levels of evaporative cooling and air conditioning observed in CPHS, there would have been more than 432,000 (17%) additional heat-attributable deaths. At national scale these avoided deaths are mostly attributable to AC, but the lowest humidity tercile districts account for the majority of this mortality reduction, which is split 2:1 between coolers and air conditioning.

[21] Twenty three countries have developed national cooling action plans. These focus overwhelmingly on mitigating climate change, through policies such as establishing minimum energy performance standards and support for transition to energy efficient cooling equipment (see, e.g., UNDP, 2023). India's plan stands out for explicitly considering thermal comfort, but its main objective is nonetheless to moderate the projected 4.5-fold increase in future consumption of primary energy for cooling (Government of India, 2019).

we consider a hypothetical appliance giveaway policy, whose costs and benefits can be estimated using back-of-the-envelope calculations that leverage our results in Table 4. We focus on low-cost evaporative coolers, assessing the scale, capital cost and mortality-reduction benefits of a hypothetical one-time increase in the prevalence of cooling units by 2.5, 5 and 10 percentage points in districts where the fraction of households lacking access to cooling exceeded these target levels in 2014. We further assume that the policy targets districts in the lowest humidity tercile where coolers have demonstrated health benefits. Two features of such a program merit emphasis. First, because coolers are a durable good, initial investment in additional units translates into continued mortality reductions over the sample period, conditional on continued utilization. Second, among poor and energy-insecure households, the common coping strategy of limiting expenditures on space conditioning (Siegel et al., 2024) may substantially constrain utilization. Effective implementation would therefore likely require complementary subsidies for electricity consumption to offset operating costs (e.g., Nayak, 2024).

The results are summarized in Table A19. The main finding is that, despite coolers' generally low effectiveness and the scheme's diminishing marginal returns (increasing penetration requires distribution of 262-314 coolers to avoid a single death), capital costs are moderate, operating costs (i.e., electricity) are substantial, and total costs are exceeded by the benefits of avoided mortality for high values of a statistical life (2015 US $256,000, Cropper et al., 2019), with benefit cost ratios in the range 1.5-1.9.

The external validity of our findings is an important topic for further study, but it is challenging to understand whether the technological inequality in heat adaptation we observe is a distinctive feature of India, or if it is shared by other countries. The rapid diffusion of evaporative coolers in India raises broader questions about how climate-adaptive capacity may expand with economic development. One possibility is that India's experience foreshadows the widespread adoption of low-cost, moderately effective cooling technologies in other low-income, moderate-humidity regions.

Studies across multiple related literatures suggest that many of the necessary ingredients may already be in place. Climates with aridity levels similar to the Indian subcontinent are shared by several developing regions, e.g., western South America, northeast Brazil, eastern and southern Africa (Zomer et al., 2022). Large swaths of these areas (especially in sub-Saharan Africa) have per capita GDP levels at or below the Indian districts with the highest cooler prevalence (Kummu et al., 2025). These locations are also expanding access to electricity rapidly, but unevenly (Falchetta et al., 2020). Notwithstanding, poor households' uptake of the more reliable but high-cost grid electricity necessary to power coolers (to say nothing of AC units) remains low (Blimpo et al., 2020; Sievert and Steinbuks, 2020), which is likely to be a limiting factor in cooling appliance adoption (Cisse, 2025).

Additional uncertainties make it difficult to establish the broader applicability of our findings beyond the Indian context. Perhaps the most intractable is assembling data with comparable observations of cooling technologies across countries and time periods. The CPHS survey's major limitation is that it does not record ownership of fans. Although this technology is the lowest rung on the cooling ladder, its use is widespread. By contrast, it is rare for household surveys to record evaporative cooling, despite anecdotal evidence of its availability (Table A20).[22] Symmetrically, surveys in Africa that measure appliance aspirations or ownership record very limited adoption of high-energy cooling technologies (Lee et al., 2016; Richmond and Urpelainen, 2019). This complicates efforts to refine projections of cooling access in the world's poorest regions: it is very difficult to infer what trajectories of evaporative cooler adoption, and competition with AC among high-income households, might look like as incomes rise with economic development. For example, Falchetta et al. (2024) estimate that, by 2050 up to 41% of the world's population could lack residential air conditioning. It remains open how many of these households, in which regions, could instead purchase, operate and benefit from evaporative coolers as an adaptation to heat. In sum, while it is tempting to think of evaporative cooling as a "missing middle" along the development path, data limitations make it very difficult to definitively say whether this is in fact the case.

A more subtle uncertainty is how environmental conditions favourable to low-cost evaporative cooling might themselves shift as climate change intensifies. Ambient humidity depends on the balance over space and time between the physical forces of the atmosphere's evaporative demand and the quantity moisture supplied by precipitation. With climate change-driven increases in air temperatures, the former effect is expected to become increasingly dominant, resulting in widespread continental drying (Douville and Willett, 2023; Sardans et al., 2024). Holding trajectories of income constant, such changes could increase the feasibility of evaporative cooler adoption by expanding the meteorological envelope of the technology's potential effectiveness.

These and other considerations suggest multiple avenues for future work. First, our study illustrates how competing adaptation technologies may contribute to inequality in residual exposure to the impacts of climate change, a framework that could be applied to other adaptation domains (e.g., agriculture). Second, while our empirical estimates might not easily translate to other countries, investigating their implications for India's potential to meet its future cooling needs could yield valuable insights. Over the coming decades India is expected to experience

[22] Trade and online shopping websites in various countries list evaporative coolers for sale, but the extent of their household prevalence remains unknown.

intensifying heat exposures due to climate change as well as rapid increases in income. The latter trend is likely to lead to relaxation of credit constraints that could accelerate low income households' purchases of coolers, in addition to middle income households' adoption of air conditioners. Future trends in the cost of cooling appliances will critically influence this process (Davis and Gertler, 2025). Moreover, rising income alone will not be able to solve cooling inequality (Pavanello et al., 2021; Davis et al., 2021)—we expect a fraction of the population to lack access to cooling and remain exposed to extreme heat.[23] Exploring structural simulations of interventions aimed at expanding cooling's health benefits and alleviating inequality, that build on our back-of-the-envelope analysis, could be highly informative.

We close with a discussion of caveats to our study. First, we attribute cooling technologies' mortality-reduction benefits to extensive-margin adoption as opposed to intensive-margin utilization. A key limitation of household surveys including CPHS is that they do not record appliance-specific electricity use. This is relevant for our mortality estimates, since ownership is unlikely to capture systematic differences across households in utilization. Additionally, our mortality records lack the granularity to distinguish differences in deaths by age categories and diseases, which could help to characterize the mechanisms at work in further depth. Similarly, the relatively short time span and annual frequency of our data limit the variation we are able to exploit to identify the effect of temperature and adaptation. Finally, the building data we employ are devoid of linkages to household behaviour and/or attributes, which strictly limits our ability to characterize the association between indoor temperature reductions and health outcomes. Likewise, the measurement campaign's focus on slum dwellings directly translates into a lack of observation of air conditioner ownership, which would allow for a more direct comparison with coolers within the econometric framework. Notwithstanding these limitations, the present study paints a multifaceted portrait of the dynamics of residential cooling in the world's most populous country.

[23]Even in high per-capita incomes, there is still substantial use of evaporative cooling for low-cost space conditioning in arid areas. By the mid-1990s "swamp coolers" were still used by 46 percent of homes the US desert city of Phoenix, Arizona (Karpiscak et al., 1998), and the EIA Residential Energy Consumption Survey indicates that as late as 2020 almost one million US households (0.8%) still used the technology.

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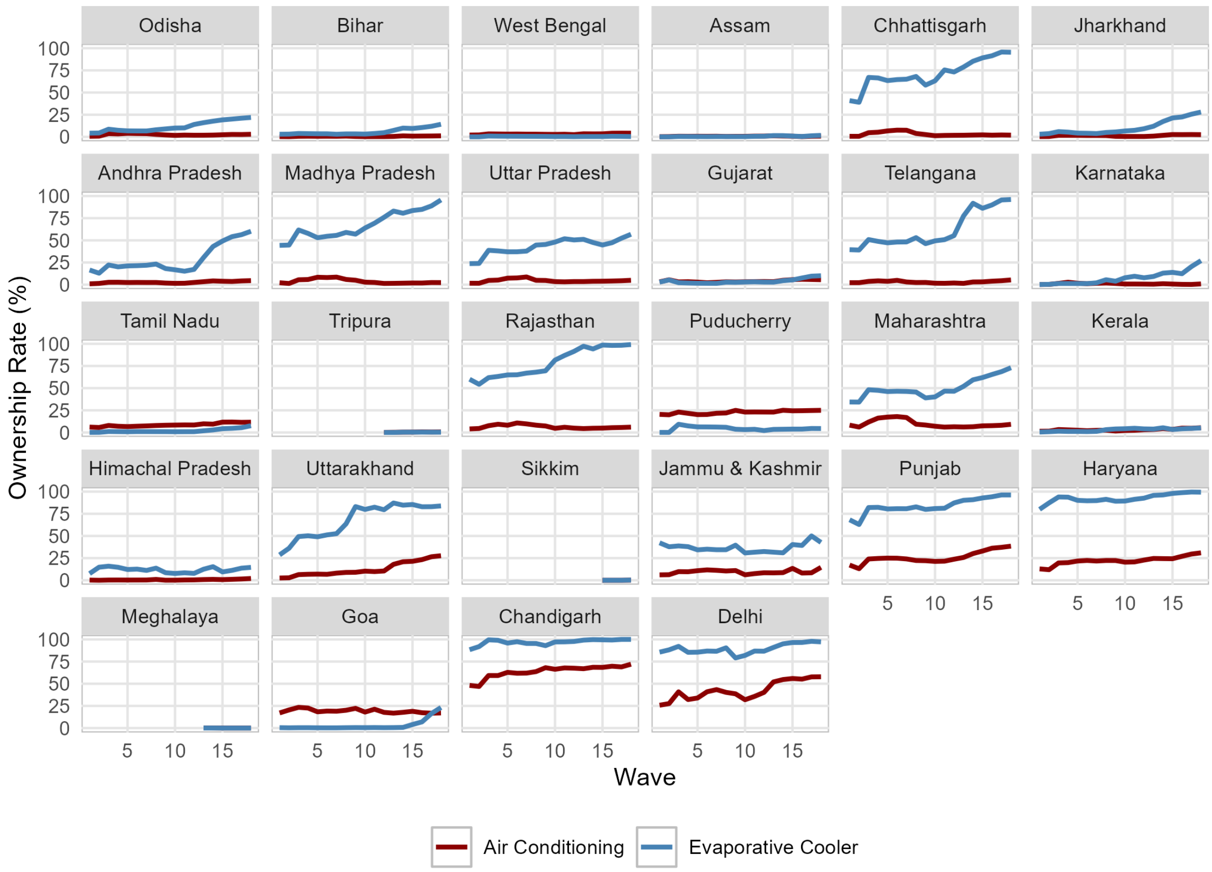
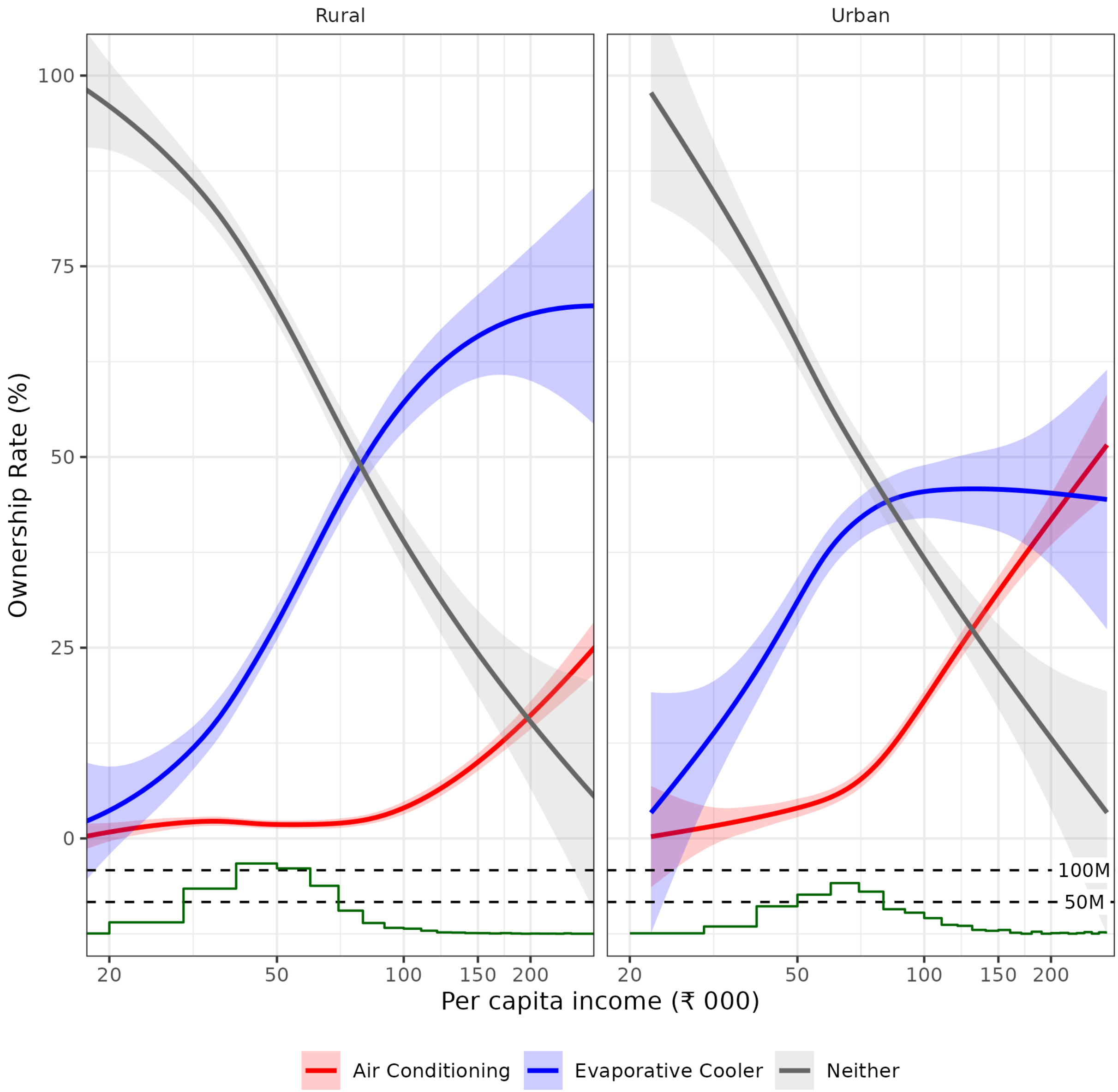
Tables and Figures

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



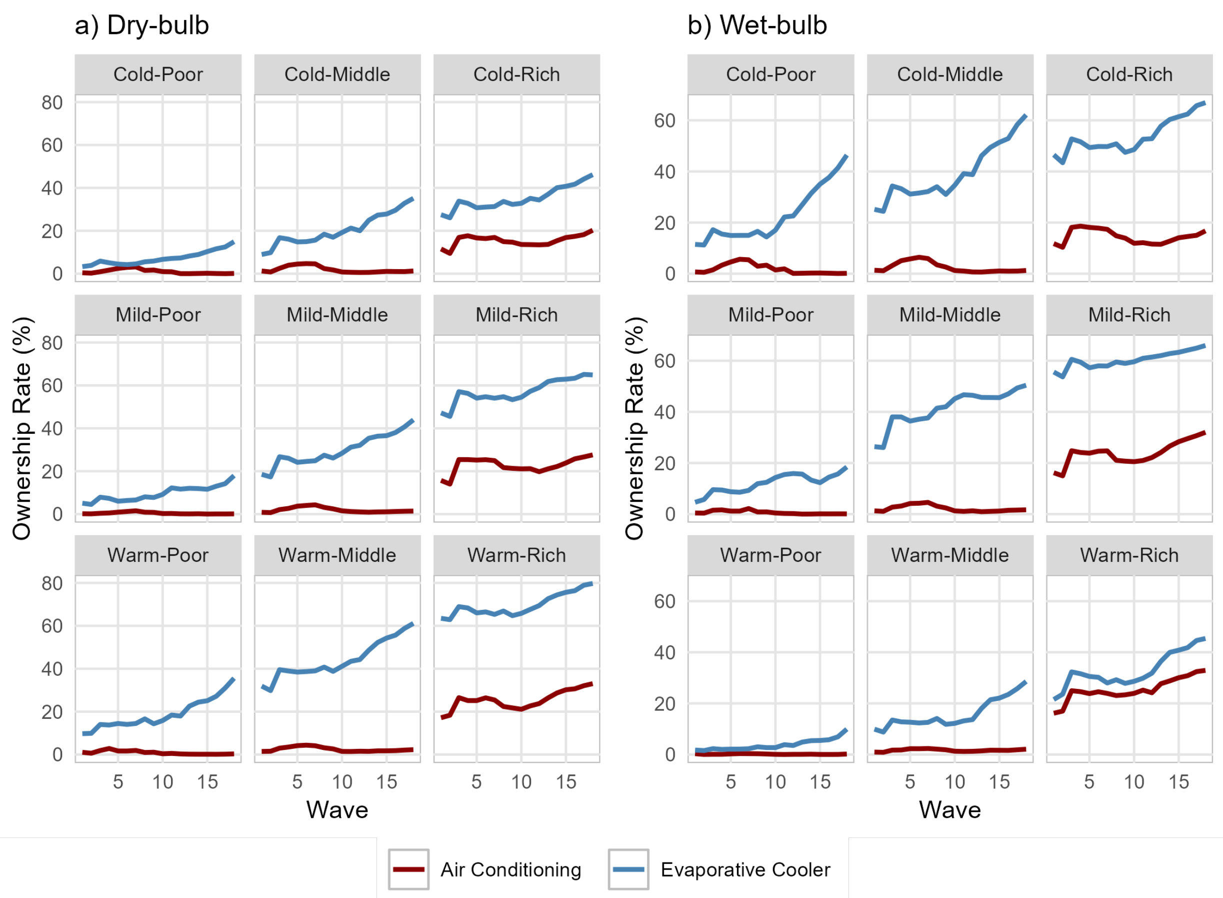
Notes: The figure plots the trends in the ownership of air conditioning and evaporative coolers across CPHS waves, obtained applying sample weights. Indian states are ordered based on quarterly household income.

Figure 2: Trends in ownership of air conditioning and evaporative coolers, and lack of access to cooling, with income, for rural and urban districts



Notes: The figure shows univariate generalized additive model trends in district-level prevalence of households with air conditioning, evaporative cooling only, and access to neither technology with per capita income, calculated from CPHS. Income distribution of the district population is shown in green. Urban districts are so classified if the within-district faction of households identified as urban in CPHS exceeds the sample mean (26.4%).

Figure 3: 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 CPHS 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

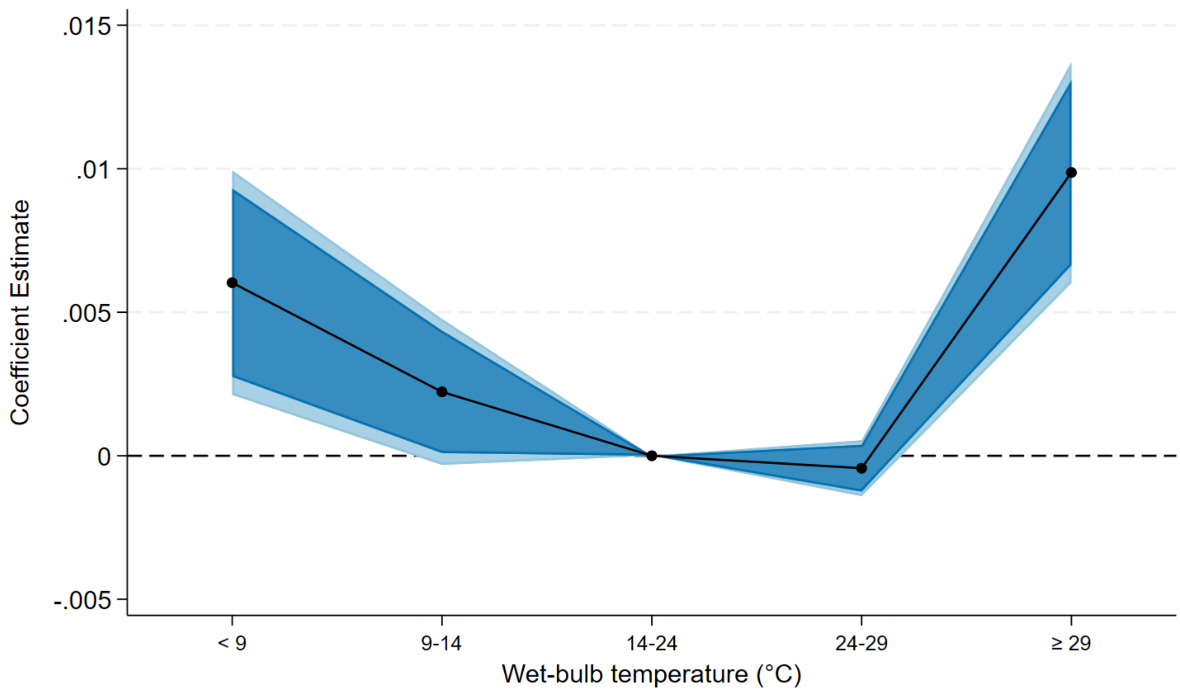
Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. For the categorical variables the omitted categories are: 'No Education', '1 Member', and 'Tile'. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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 4: Mortality and wet-bulb temperature



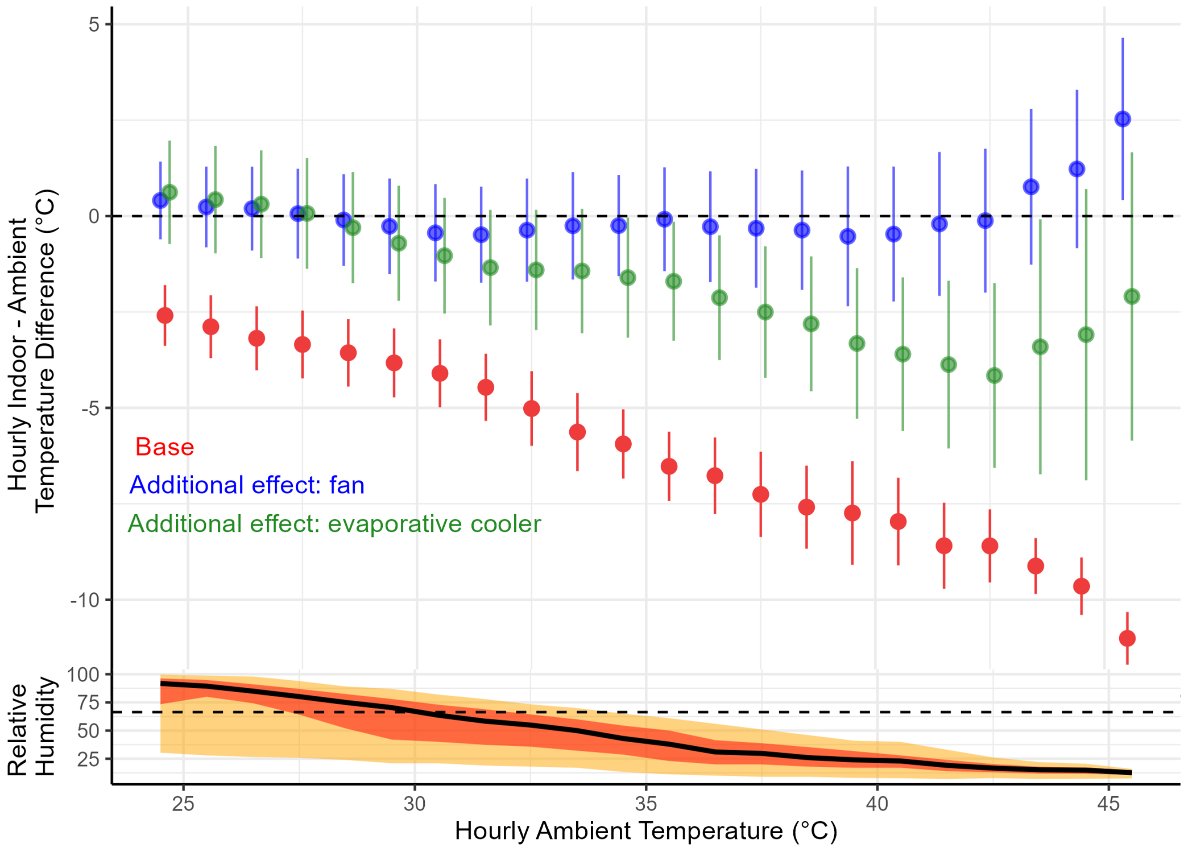
Notes: The figure plots the relationship between all-age mortality (in logs) and wet-bulb daily average temperature (in bins). Light blue areas are 95% confidence intervals; dark blue areas are 90% confidence intervals.

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
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.001	0.003	0.015
Mean Outcome	0.007	0.007	0.007	0.007	0.007
Observations	2754	2754	2754	2754	2754

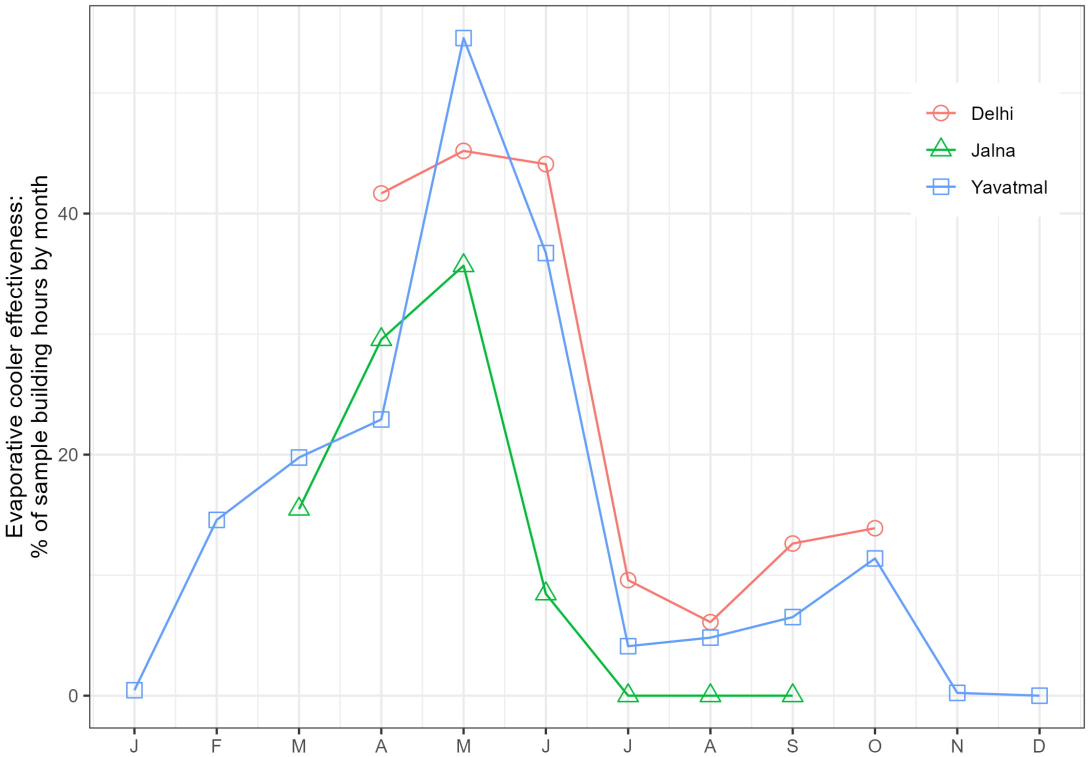
Notes: The dependent variable is the natural logarithm of mortality rate. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Figure 5: Indoor-outdoor temperature differential: low-income dwellings in three locations



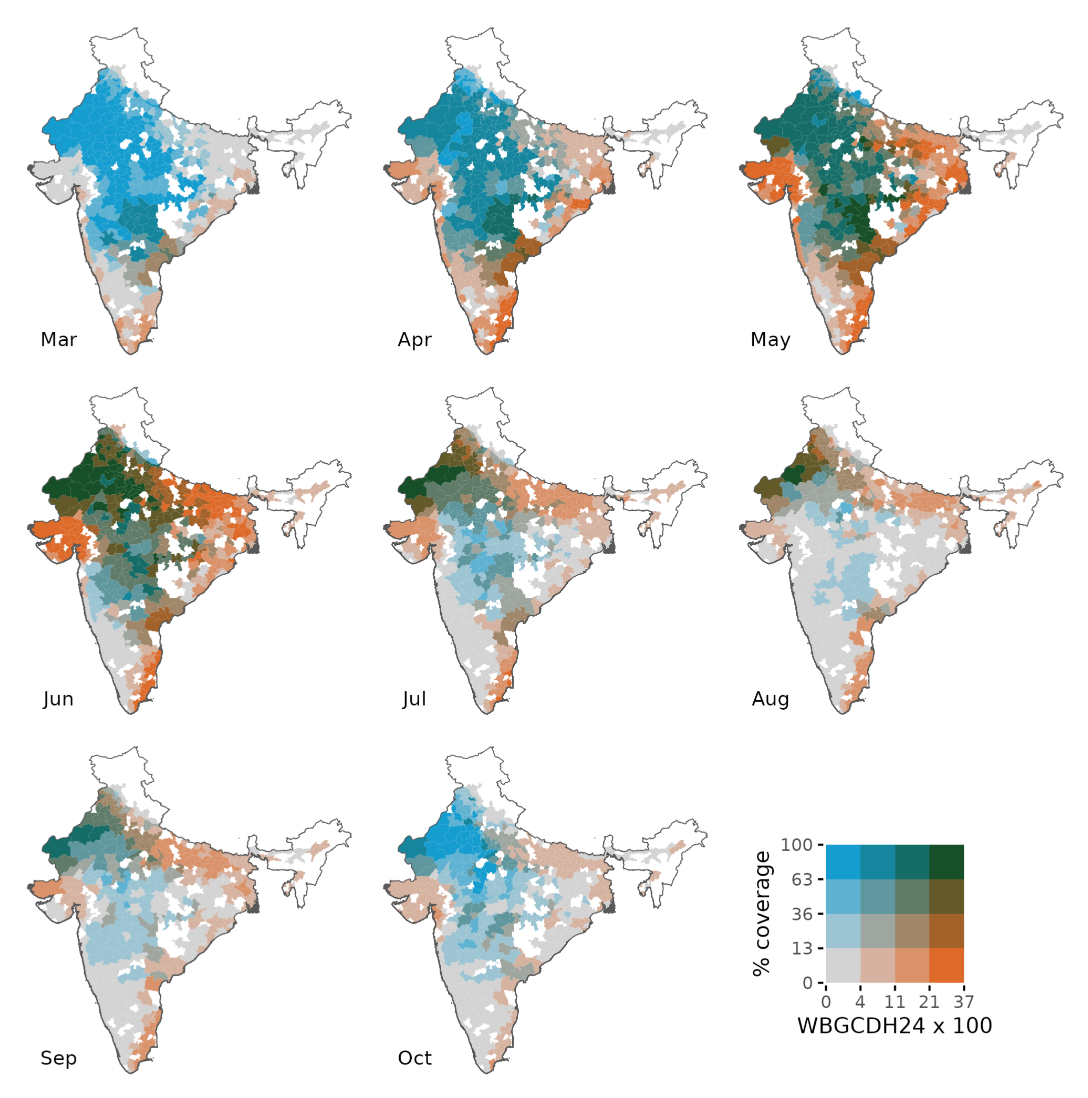
Notes: The figure plots the estimated coefficients of Equation 4 along with their 95% confidence intervals (for standard errors clustered at the building level), showing across the ambient temperature distribution the average indoor-outdoor temperature differential (base: $\hat{\beta}$) as well as the additional effects of cooling equipment (fans and evaporative coolers: $\hat{\gamma}$). 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 6: The meteorological window of opportunity for effective evaporative cooling



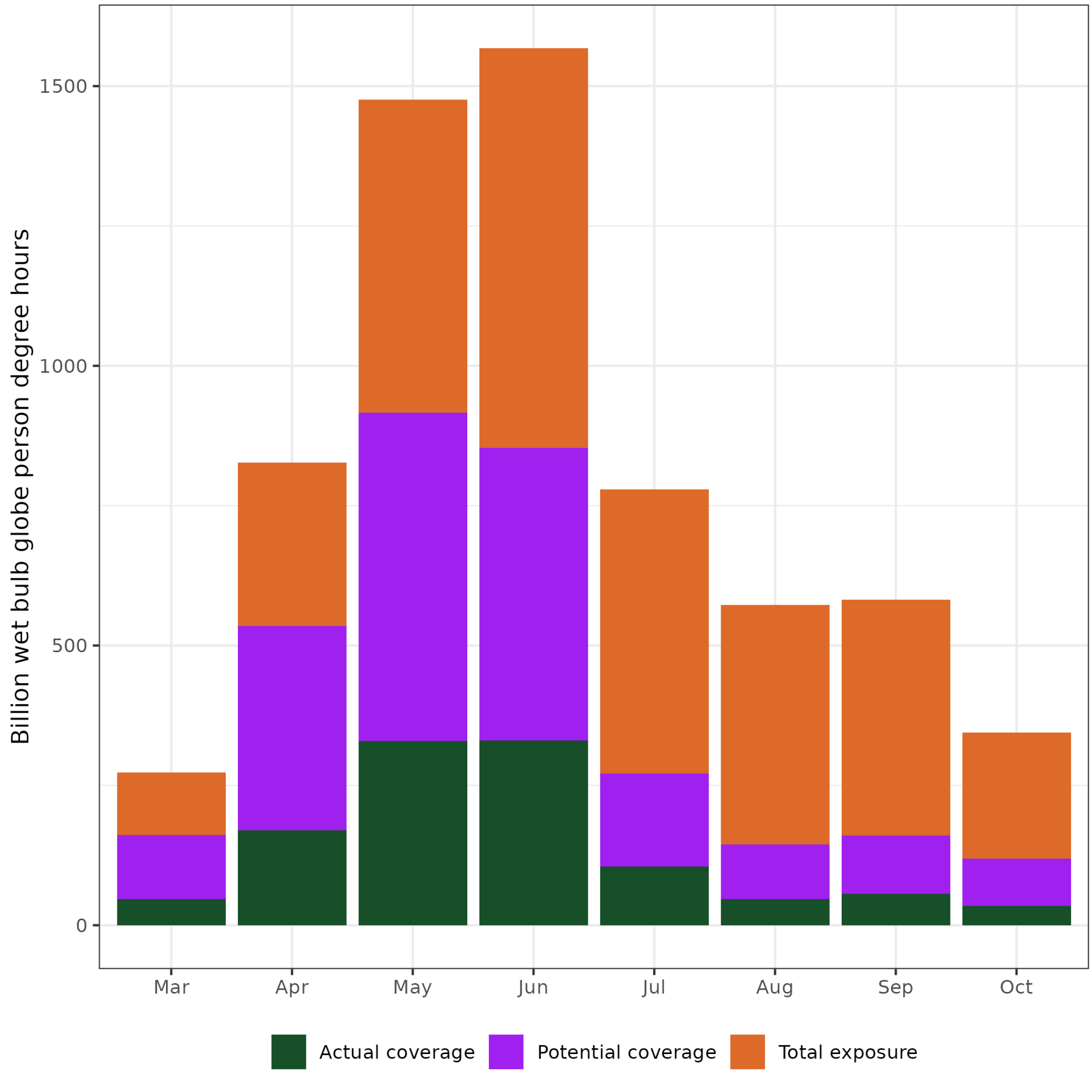
Notes: The figure plots the fraction of building hours surveyed by Tasgaonkar et al. (2022) that in each month correspond to the ranges of ambient temperature and humidity for which the estimated coefficients of Equation 4 show evaporative coolers significantly reduce indoor temperatures relative to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

Figure 7: 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 8: Evaporative coolers and the adaptation cooling deficit



Notes: The figure aggregates Figure 7 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).

Table 4: Protective effect of heat adaptation appliances (Specific 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)
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.215	0.080	0.078
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)
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.041	0.062	0.327
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)
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.000	0.003	0.001
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
$\sum$ AC $\times$ T^{DB} = $\sum$ Cooler $\times$ T^{DB} (pval)			0.001	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 (1)	<5 yro. (2)	5-64 yro. (3)	≥ 65 yro. (4)
T^{WB} (24-29)	-0.0000121	-0.0000752*	-0.000000591	-0.0000961
	(0.000)	(0.000)	(0.000)	(0.000)
T^{WB} (≥ 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} (≥ 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} (≥ 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.

Appendix

Table A1: Descriptive statistics (CHPS)

	Mean	SD
Air conditioning (Yes = 1)	0.056	0.230
Evaporative cooler (Yes = 1)	0.325	0.468
$\widetilde{\text{CDD}}^{24}_{WB}$	143.186	140.750
$\widetilde{\text{CDD}}^{24}_{DB}$	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 $\times$ 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 × 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 $\times$ 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_{18}^{WB} (1)	CDD_{21}^{WB} (2)	CDD_{18}^{DB} (3)	CDD_{21}^{DB} (4)	CDD_{24}^{DB} (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)
$\widetilde{CDD_{18}^{WB}}$ (100s)	0.000246									
	(0.000)									
$\widetilde{CDD_{21}^{WB}}$ (100s)		0.000364								
		(0.000)								
$\widetilde{CDD_{18}^{DB}}$ (100s)			0.000154							
			(0.000)							
$\widetilde{CDD_{21}^{DB}}$ (100s)				0.000171						
				(0.000)						
$\widetilde{CDD_{24}^{DB}}$ (100s)					0.000231					
					(0.000)					
CDD_{24}^{WB} (100s)						0.000297				
						(0.000)				
CDD_{24}^{DB} (100s)							0.000230			
							(0.000)			
$\widetilde{CDD_{24}^{WB}}$ (100s)								0.000577	-0.00247	0.000562
								(0.001)	(0.002)	(0.000)
$(\widetilde{CDD_{24}^{WB}})^2$								-0.00000313	0.00181	
								(0.000)	(0.001)	
$(\widetilde{CDD_{24}^{WB}})^3$									-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 $\times$ 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} ($\geq$ 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 ($\geq$ 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} ($\geq$ 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
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.002	0.022	0.017
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
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.001	0.004	0.016
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
$\sum$ AC × T^{WB} = $\sum$ Cooler × T^{WB} (pval)			0.001	0.005	0.017
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} ($\geq$ 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} ($\geq$ 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} ($\geq$ 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
$\sum$ AC × T^{WB} = $\sum$ Cooler × T^{WB} (pval)			0.003	0.006	0.020
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
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.064	0.027	0.056
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} ($\geq$ 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} ($\geq$ 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} ($\geq$ 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
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.017	0.013	0.002
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} (≥ 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} (≥ 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} (≥ 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
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.001	0.002	0.012
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: Protective effects of heat adaptation appliances (LandScan population counts)

	AC	Cooler	Both appliances		
	(1)	(2)	(3)	(4)	(5)
T^{WB} (24-29)	0.0000453	0.0000172	0.0000767		
	(0.001)	(0.001)	(0.001)		
T^{WB} ($\geq$ 29)	0.0109***	0.00944***	0.0113***		
	(0.002)	(0.003)	(0.003)		
AC $\times$ T^{WB} (24-29)	-0.00110		-0.00108	-0.00168	-0.000843
	(0.002)		(0.002)	(0.002)	(0.002)
AC $\times$ T^{WB} ($\geq$ 29)	-0.0298***		-0.0296***	-0.0197	-0.0226*
	(0.009)		(0.009)	(0.012)	(0.012)
Cooler $\times$ T^{WB} (24-29)		0.000311	0.000135	0.00135	0.00165
		(0.001)	(0.001)	(0.001)	(0.001)
Cooler $\times$ T^{WB} ($\geq$ 29)		-0.00138	-0.00106	0.00279	-0.00511
		(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	Yes	Yes	Yes
Temperature Bins $\times$ Year	No	No	Yes	Yes	Yes
$\sum$ AC $\times$ T^{WB} = $\sum$ Cooler $\times$ T^{WB} (pval)			0.003	0.018	0.052
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 A18: Wet-bulb temperature, health status, and heat adaptation (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} (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
$\sum$ AC $\times$ T^{WB} = $\sum$ 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.

Table A19: Costs and benefits of a hypothetical evaporative cooler giveaway policy

Increase over 2014 cooler prevalence (%)	2.5	5	10
Districts targeted	167	675	612
Additional coolers (million)[a]	2.0	3.9	7.0
Capital costs (Bn ₹)[b]	9	18	33
Operating costs (Bn ₹)[c]	119	231	418
Total costs (Bn ₹)	128	249	451
Avoided deaths	7,583	13,159	22,111
Total benefits (Bn ₹)[d]	80-244	139-423	233-711

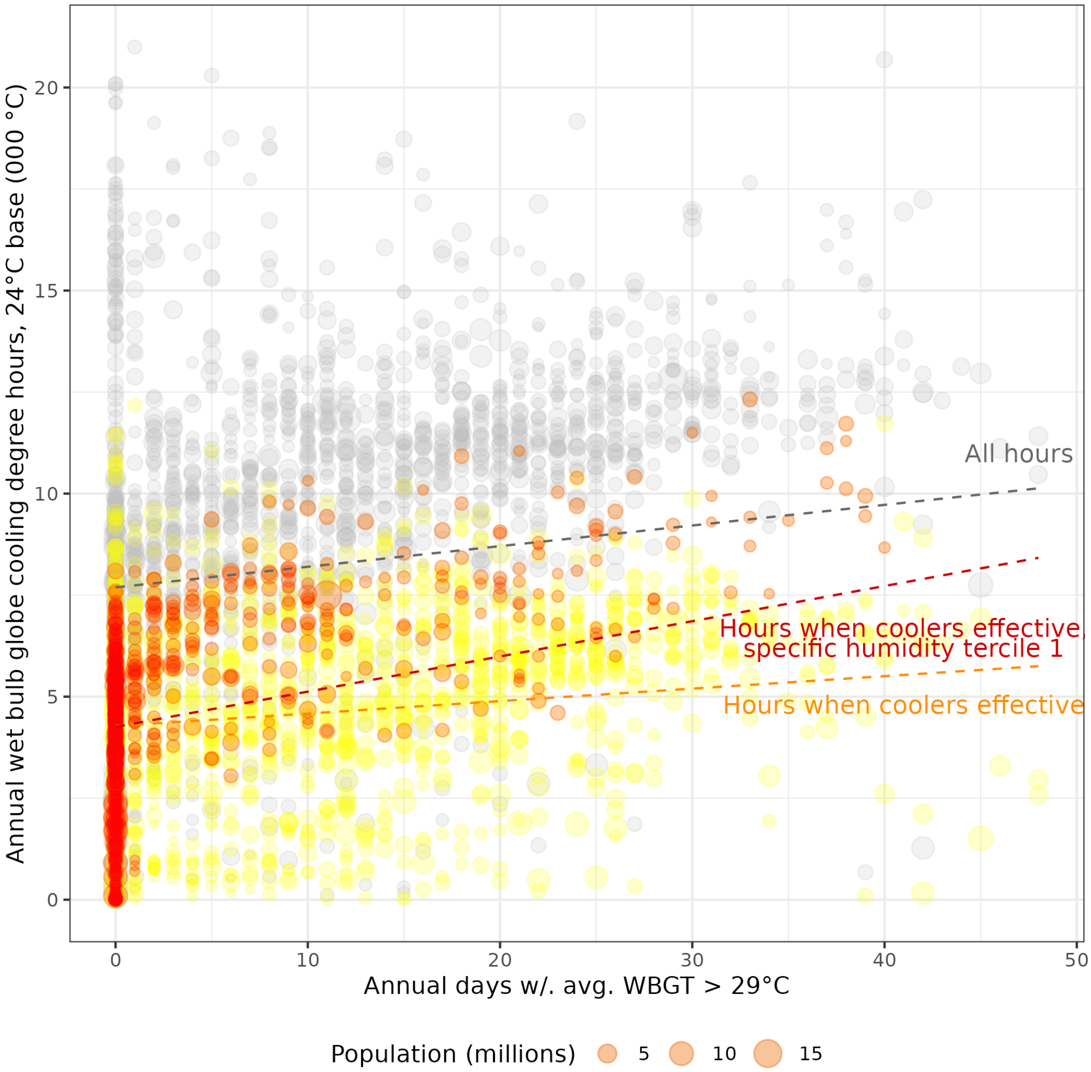
Notes:
[a] Total number of cooling units assumed to be distributed in 2014 and used over the 2014-2019 sample period.
[b] Mean cooler price (₹4776) from https://amazon.in.
[c] Assuming an electricity price of ₹10/kWh and average monthly utilization of 250 kWh (Chatterjee and Lenart, 2007) over the March-June pre-monsoon season (cf Figure 7).
[d] Calculated using value of statistical life range from Cropper et al. (2019), translated to ₹ using the 2015-2025 change in the US CPI and market exchange rates (90.4 ₹/$).

Table A20: Residential cooling technology choice represented in household surveys

Country	Survey year	Major Koppen climate classes[a]	Adm. 2 income per capita[b]	Prevalence (%)		
				Fan	AC	Cooler
Togo	2010	Aw	780-3,952	19.0	1.3	
South Sudan	2008	Aw	843-2,840	0.4	0.1[c]	
Benin	2013	Aw	1,063-5,886	17.0	1.2	
Nigeria[d]	2018	Aw/BSh	1,206-16,728	52.0	3.3	
Cameroon[d]	2018	Aw/Am	1,315-6,832	24.0	1.5	
Senegal	2013	BSh/BWh	1,471-6,532	65.9	2.9	
Sudan	2008	BWh	1,548-9,736	10.0	2.2[c]	
Gabon[d]	2012	Aw/Am	6,405-23,668	55.6	7.5	
Colombia	2005	Af/Am	1,023-30,092	26.0	1.9	
Nicaragua	2005	Af/Am/Aw	1,356-12,168	35.8	1.5	
Panama	2010	Am	2,624-66,944	70.8	15.5	
Myanmar[d]	2015	Cwa/Aw/Am	1,600-11,933	26.5	2.7	
Cambodia	2019	Am	2,092-12,456	79.3	7.3	
Laos	2015	Cwa/Aw/Am	2,563-20,576	67.3	7.7	
Thailand	2000	Aw/Am	1,231-70,757	92.1	10.4	
Pakistan[d]	2017	BWh	1,753-8,077		11.6	18.0
Egypt	2006	BWh	2,166-23,870	83.8	4.0	
Jordan[d]	2017	BWh	3,371-29,624	90.6	30.1	

Notes:
[a] Aw: equatorial savannah with dry winter; BSh: arid steppe hot; BWh: arid desert hot; Af: equatorial rainforest, fully humid; Am: equatorial monsoon; Cwa: warm temperate with dry winter and hot summer. For reference, the lowest humidity tercile Indian districts in the present study are mostly Aw climate.
[b] Current US $ (Kummu et al., 2025).
[c] Includes evaporative coolers.
[d] USAID Development and Health Surveys.

Figure A1: Wet bulb globe cooling degree hours and daily average temperatures



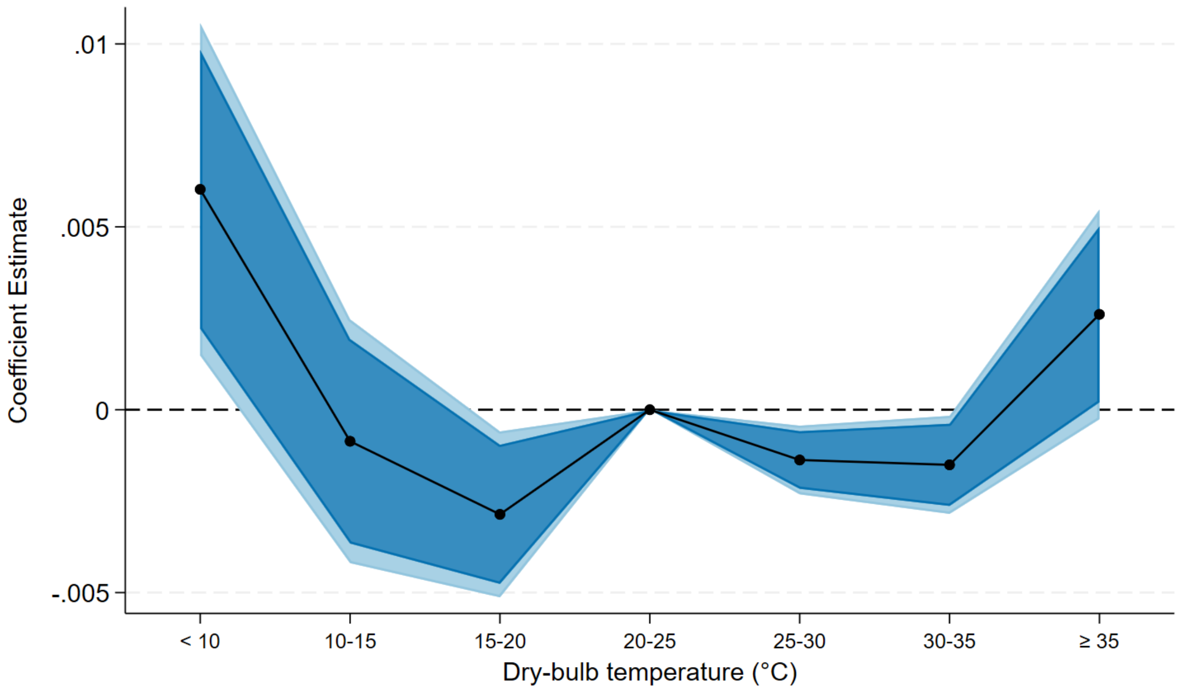
Notes: The figure aggregates Figure 7 over time, plotting the 2014-2019 district-level variation in wet bulb globe cooling degree hours, 24°C base ($WBGCDH_{24}$) with days with wet bulb globe temperature exceeding 29°C. Gray: $WBGCDH_{24}$ aggregated over all annual hours, yellow: only those hours with temperature and humidity corresponding to effective evaporative cooling are shown in yellow, red: effective evaporative cooling hours in the sample's lowest tercile of specific humidity.

Supplementary information (not for publication)

Table S1: Data sources for each analysis

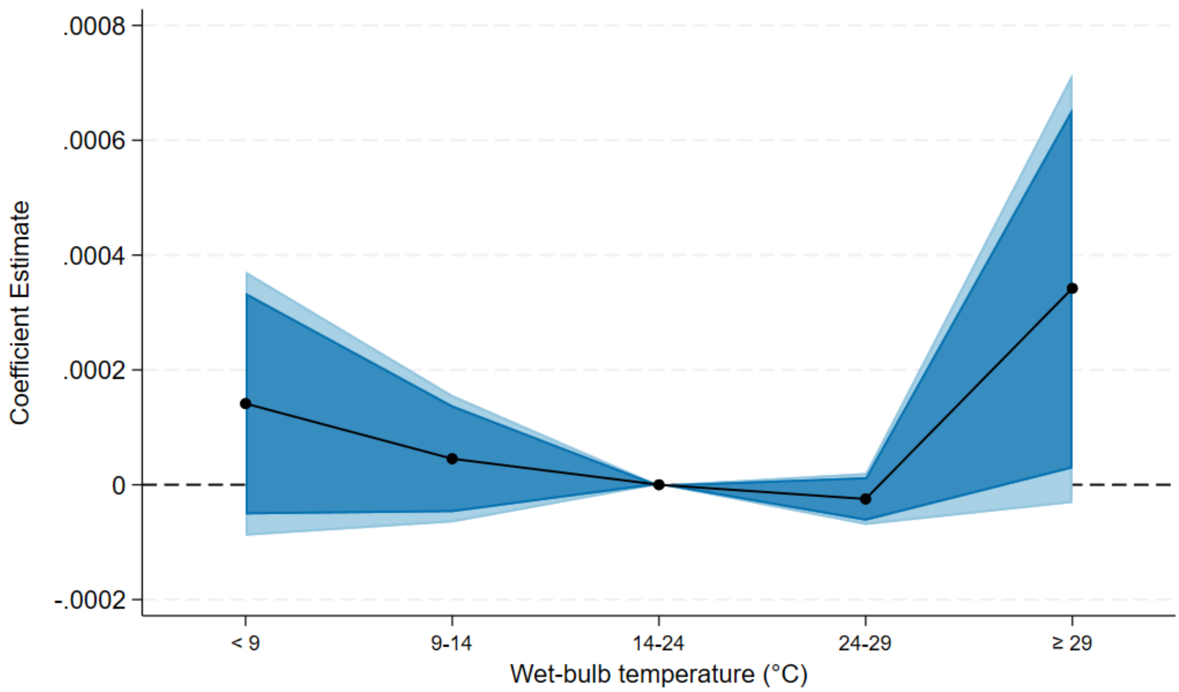
Dataset	Type	Unit	Frequency	Years	Source
CHPS	Panel	Household	Four-monthly	2014-2019	Link
ERA5	Panel	Grid	Daily	1981-2019	Link
CRS	Panel	District	Annual	2014-2019	Link

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)



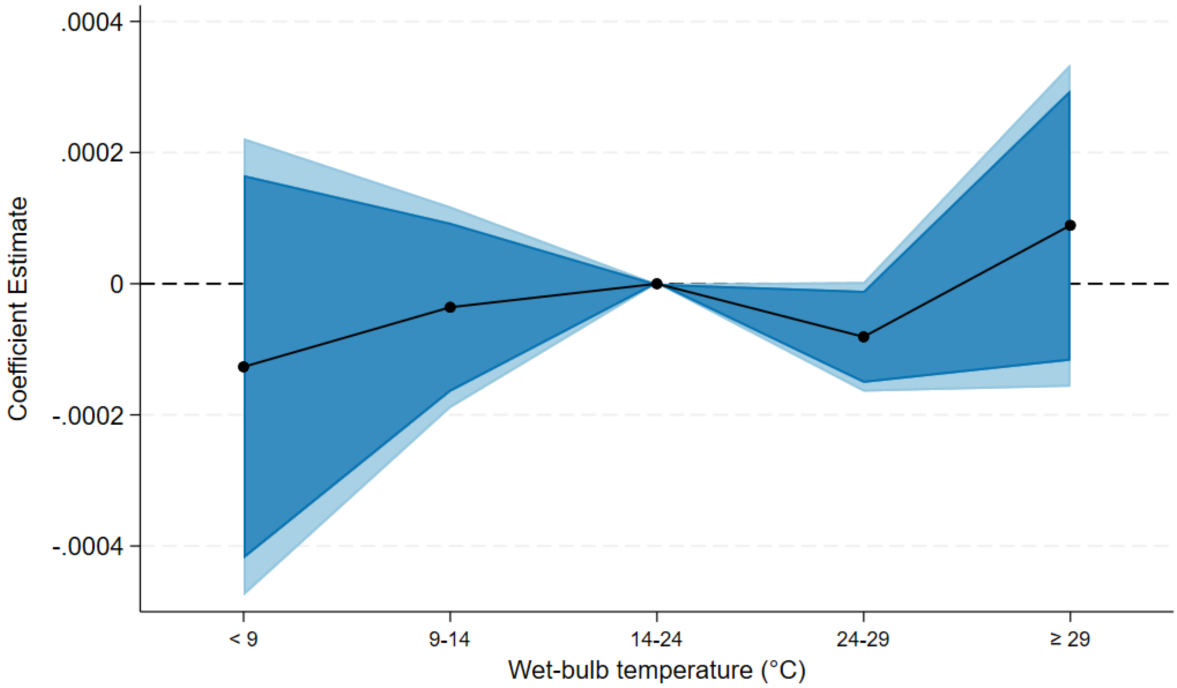
Notes: The figure plots the relationship between all-age mortality (in logs) and dry-bulb daily average temperature (in bins). Light blue areas are 95% confidence intervals; dark blue areas are 90% confidence intervals.

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

	Full (1)	<5 yro. (2)	5-64 yro. (3)	≥ 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 (≥ 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.

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



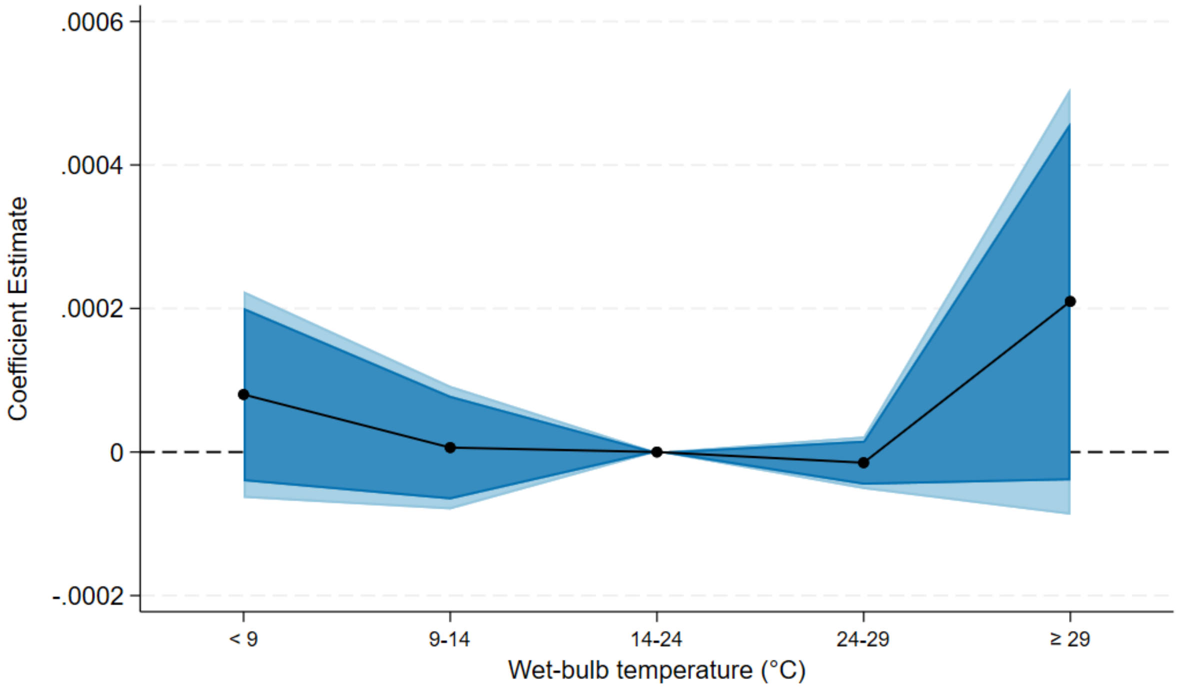
Notes: The figure plots the relationship between self-reported health status and wet-bulb daily average temperature (in bins). Light blue areas are 95% confidence intervals; dark blue areas are 90% confidence intervals.

Table S3: Impact of wet-bulb temperature on health status (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} (<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} (≥ 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

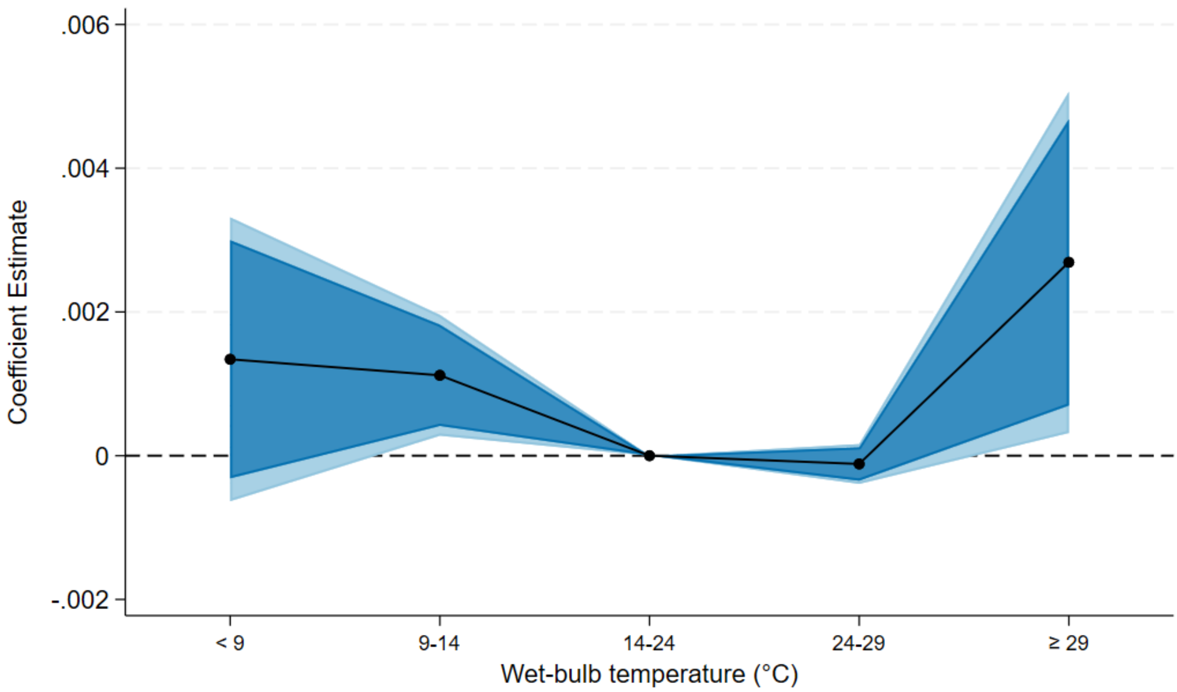
Notes: The dependent variable is a dummy variable for self-reported health status (= 1 if negative). Reference category for temperature is bin 14-24 °C. Standard errors are clustered at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by individual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

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.