Adapting to Heat Extremes with Unequal Access to Cooling: Evidence from India*

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Abstract

The adoption and use of cooling technologies to maintain indoor thermal comfort is a crucial adaptation to rising temperatures. Nonetheless, the access to residential cooling is highly unequal; air conditioning, in particular, remains a luxury good in most developing countries, posing a challenge to heat adaptation. To address this issue, more affordable alternatives, such as evaporative coolers, have been proposed to bridge the cooling disparity. However, the effectiveness of this solution in protecting against extreme heat remains uncertain. This paper examines this heterogeneous technological response of households to heat extremes, and the consequences for heat-related mortality impacts in India for the period 2014-2019. Our empirical results highlight a critical trade-off in heat adaptation. While we find that the expensive air-conditioning proves to be highly effective in reducing temperature-related mortality, its ownership and use remains low, predominantly limited to high-income cities. In contrast, many Indian households, including low-income ones, purchase cheaper evaporative coolers, which we estimate offer reduced protection against heat stress. We then estimate that in our sample period heat adaptation technologies have avoided 27% of heat-related deaths, generating an annual gross welfare gain of 32 billion dollars. Being six times more widespread evaporative coolers have contributed to two-thirds of these benefits. However, if air conditioners had been as widespread as evaporative coolers, air conditioners alone could have prevented 47% of the heat-related deaths. We conclude showing that subsidising air-conditioning is a cost-effective way to reduce heat-related mortality in India.

Keywords: Heat Extremes, Cooling, Mortality, Inequality, India

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

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1 Introduction

As global temperatures rise, the impact of extreme heat on human health and well-being becomes increasingly concerning. High temperatures have been indeed linked to a range of adverse effects.[1] A related literature highlights households' attempts to shield themselves from extreme heat exposures by using cooling technologies, particularly air conditioners (Davis and Gertler, 2015; De Cian et al., 2019; Davis et al., 2021; Pavanello et al., 2021). Air-conditioning provides thermal comfort by moderating indoor temperatures, which has the protective effect of reducing adverse health and well-being effects associated with heat exposures (Barreca et al., 2016; Park et al., 2020; Somanathan et al., 2021; Hua et al., 2022).

Yet, especially in developing countries, credit constraints limit the adoption of expensive cooling appliances such as air-conditioning units, resulting in highly uneven access to cooling and its associated benefits. To address this disparity, more affordable alternatives like evaporative coolers have emerged, offering potential solutions to bridge the cooling gap. However, the level of *perfect substitution* between the two technologies remain unclear. Evaporative coolers do not reduce indoor temperatures to the same degree as air-conditioning units, and they cannot maintain precise temperature control in most climates.[2] The upshot is the potential for technological inequality, whereby poorer households with limited access to effective cooling technologies end up systematically more vulnerable to heat-related threats to health and well-being. Understanding the consequences of this phenomenon is crucial to the design of interventions that can effectively address the challenges of adapting to heat in ways that ensure equitable access to the health-protective benefits of cooling.

This paper provides the first empirical evidence of the trade-offs among the cost and health protection of different technologies for adapting to extreme heat. To do so, we combine a rich high-frequency longitudinal household-level survey data set with district-level mortality data and high-resolution meteorological information in India for the period 2014-2019. The empirical analysis is divided into four parts.

In the first part we employ micro fixed-effects regressions to examine the heterogeneous technological adaptation responses of Indian households to extreme heat. Our findings indicate that the majority of households still lack the means to adapt through access to any form of cooling technology. However, over our sample period we observe rapid increases in the penetration of cooling technologies, driven mainly by economic development, including rising incomes and reliable electricity supplies. Despite this overall trend, important differences exist across households. When we observe such adaptation, only high-income urban households purchase air-conditioning, while low- and middle-income households living in the warmer regions primarily rely on the more affordable coolers.

The second part shows how access to cooling technologies modulates households' electricity consumption behaviour, particularly in response to ambient high temperature extremes. To do so, we test how plausibly exogenous shocks in daily temperature distribution affect household monthly electricity consumption. We estimate that on average, relative to a day with an average temperature of 17-20 °C, an additional $\geq$ 35 °C day is associated with an increase in monthly electricity consumption of 0.46%. Households in the bottom decile of the income distribution exhibit much smaller responses (0.18% and 0.38%, respectively), while the responses of high-income households are more than twice as large, and those of rich urban households are more than three times bigger. Similarly, households equipped with an air-conditioning are almost two

[1] The societal 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] Information on cooling appliances from the U.S. Department of Energy: https://www.energy.gov/energysaver/home-cooling-systems

times more responsive to very hot days compared to those relying on evaporative coolera. This difference persists even when focusing solely on high-income families.

Our intensive margin results corroborate the findings on technology adoption at the extensive margin. Indeed, households that are more likely to own an air conditioner are also more elastic to positive temperature shocks. This is because air conditioners is more energy intensive of evaporative coolers. Moreover, heterogeneous response across income levels then allow us to identify how, even with access to the the same technology, only richer households are really able to respond to extreme heat. Our results are also robust to several specification checks.

The third part quantifies the health protective benefits of air conditioners and coolers, characterising their mediating effects on district-level annual mortality. We initially exploit presumably quasi-random variation in temperature distributions to determine the impact of extreme heat on mortality rates. We find that, relative to a day with average temperatures of 15-20 °C, an additional day at or exceeding 35 °C is associated with an increase in the annual mortality rate by 1%. This effect is amplified during very humid days. Moreover, it is concentrated in rural areas and districts with larger shares of low-income households. This suggests that poorer populations face elevated risk of heat-related mortality. We then augment the regression model interacting temperature with the annual penetration rates of both technologies. When we include adaptation, we estimate that an air-conditioning unit is more than three times more effective than an evaporative cooler at reducing temperature-related mortality. Focusing on days with temperatures at or above 35 °C, we then compute how much of the uninteracted effect of these days is reduced by the interaction terms with the technologies. In our preferred specification we find that, on average, increasing air-conditioning prevalence by 1% reduces the mortality impact of an additional at or above 35 °C day by 1.3%, whereas the same increase in cooler prevalence yields only a 0.4% reduction. Consistent with the different modes of operation of the two technologies, we also find that in humid conditions air-conditioning is even more protective, while coolers produce smaller thermal comfort.

Importantly, although quasi-random variation in air-conditioning and coolers ownership rate is not available for our analysis, several robustness checks corroborate our results. Indeed, we do not find any impact of the cooling appliances on temperature below 30 °C, suggesting that the adoption of these technologies does not relate with factors that determine the overall mortality rate. Moreover, our findings about temperature, mortality and adaptation are robust to a wide variety of specification tests.

In the fourth part, we provide estimates of the number of prevented deaths and monetary benefits associated with these different cooling adaptations. Over our sample period, heat adaptation has avoided 21% of the excess deaths due to temperature at or above 35 °C, generating annually gross welfare gains equal to 32 billion dollars (2.1% of the annual GDP). Most of these benefits (66%) are due to evaporative coolers, being more than five times more widespread than air-conditioning systems. However, if the penetration rate of air conditioners had been equal to that of evaporative coolers, the avoided deaths associated with air conditioners alone would have been 47%, corresponding to a gross economic benefit of 73 billion dollars (4.9% of the annual GDP). We conclude suggesting that the benefits from prevented heat-related deaths are likely greater than subsidising the cost of air conditioners.

Our results contribute to several strands of literature. We provide new evidence about the adaptation opportunities that are available in response to climate change with existing technologies (Barreca et al., 2016; Davis and Gertler, 2015; Auffhammer and Schlenker, 2014; Auffhammer and Mansur, 2014). We also contribute to the literature on inequality in heat adaptation (Davis and Gertler, 2015; Davis et al., 2021; Pavanello et al., 2021; Mastrucci et al., 2019). While income inequality is a key determinant of disparities in access to air-conditioning (Davis and Gertler, 2015; Davis et al., 2021; Pavanello et al., 2021; Romitti et al., 2022), we shed light on the additional technological layer of this issue. The important implication is that when households attempt to adapt to heat exposures, income constraints can limit the scope of feasible actions to those that yield only modest benefit, resulting in an unequal distribution of residual mortality risk. Moreover, differently from what the literature have done so far, our data feature allows to explore not only how the technology are distributed across households — the cross-sectional variation —, but also what determines its adoption — the within-household variation. This provides new insights about what drives the cooling demand in developing countries.

Our paper also estimates temperature-related response functions, which in developing countries are very limited due to data availability and reliability issues.

First, we shed light on the channels through which cooling adaptation drives residential electricity consumption responses to temperature (Deschênes and Greenstone, 2011; Davis and Gertler, 2015; Auffhammer, 2022). Our household-level estimates complement those of Colelli et al. (2023) based on aggregate load data, and we exploit the richness of our micro data to highlight heterogeneity in the relationship. 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 we are not the first to characterise the relationship between heat and mortality in India — Burgess et al. (2017) do so using annual district-level mortality data for 1957-2001 —, we provide updated responses for the period 2014-2019.[3] Moreover, we also introduce humidity as a key driver of mortality in India, showing that most of the deaths due to heat occur during extreme hot and humid days. Finally, whereas Burgess et al. (2017) focuses on bank expansion as a mediator of the impact of temperature on mortality, our paper aims at isolating a different form of adaptation.

Our work also closely relates to the few studies that combine empirical analysis of both the impacts of temperature extreme on mortality and the related-heat adaptation. On the one hand, 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. However, in their study the two dose-responses are only studied separately. This is not the case for our work. On the other hand, Barreca et al. (2016) combines information on adaptation, particularly air-conditioning, daily temperatures, and state-level monthly mortality rates in the United States. They find that the diffusion of residential air conditioning has reduced hot day–related fatalities by 80% in the United States. We mainly differ from this study as (i) we provide a more comprehensive analysis of heat adaptation responses, exploring heterogeneities across margins, income and technologies; (ii) we compare the protective effects of two alternative cooling technologies, shedding light on the trade-offs between them; and (iii) we emphasise how income levels profoundly shape the distribution of the benefits arising from cooling technologies across the population. Notably, Barreca et al. (2016) also proposes a measure of welfare gains coming from heat adaptation, particularly through the adoption of air-conditioning.[4] Our estimates of such welfare improvements align closely with theirs, reinforcing the robustness and relevance of our findings.

Finally, our work has crucial policy implications. Our results unveils an overlooked form of inequality in accessing cooling technologies. The technological inequality exacerbates the challenges faced by policymakers who strive to promote sustainable cooling for all, as it perpetuates a situation where households with limited means must make trade-offs between affordability and the efficacy of cooling technologies.

The remained of the paper is structured as follows. Section 2 provides a background about extreme heat and adaptation in India. 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 discuss the welfare and policy implications of our findings. Last section concludes our work.

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

[4] Barreca et al. (2016) identifies welfare improvement as the surplus gain by computing the area between the demand curves of adopters and non-adopters of air-conditioning. Deschênes and Greenstone (2011) also quantifies a heat-related welfare measure. However, in their work they determine the welfare loss (willingness-to-avoid) associated with a climate change-induced increase in temperatures.

2 Heat Extremes and Residential Cooling in India

Temperatures in India have risen by 0.7 °C between 1901 and 2018, thereby changing the climate in India (Chakraborty et al., 2020). As a consequence, India is also facing unprecedented extreme heat periods. Between March and May 2022 severe heatwaves were recorded in India, with temperature reaching 51 °C. With future global warming, heatwaves like this will become even more common and hotter. At the global mean temperature scenario of +2°C such heatwaves would become an additional factor of 2-20 times more likely and 0.5-1.5°C hotter compared to 2022 Zachariah et al. (2022).

These extreme temperatures are already posing clear and present dangers, particularly in rural areas (Burgess et al., 2017). Deaths caused due to heat in India increased by 55% between 2000-2004 and 2017-2021 (Romanello et al., 2022). For instance, the 2015 heatwave alone claimed more than 2,500 Indian lives.[5] Under a business-as-usual scenario with no mitigation effort (RCP8.5), even with adaptation extreme heat would pose 60 deaths per 100,000 people per year, a rate as high as the death rate from all infectious diseases in India today (Carleton et al., 2022).

In response to the threats posed by extreme heat, Indian households are increasingly turning to cooling energy solutions. High summer temperatures in the north, and high humidity levels in the west and south are driving this growth, along with rapid increase in disposable incomes. The two primary cooling technologies utilised are evaporative coolers and air conditioning systems, each with distinct characteristics.

Evaporative coolers offer a more affordable option compared to air conditioning systems.[6] They work passing outdoor air over water-saturated pads, and as the water in the pads evaporates, it reduces the air temperature. Operating on the basis of a power source and water supply, evaporative coolers do not require complex installation procedures or extensive ductwork. They so consume less electricity and have lower upfront costs. These advantages have contributed to their popularity among Indian households, with an average penetration rate of 33% in 2019.[7] Furthermore, the efforts to improve electricity accessibility in remote locations of the country have further increased their demand, even in rural regions (28%) and among lower-income households (15%). In terms of performance, coolers are effective in dry climates and can provide localised cooling for specific areas or rooms. However, they cannot cool rooms as much as air conditioners, and, critically, they perform badly in regions with high humidity.

On the other hand, air conditioning systems entail higher upfront costs and consume more electricity than coolers. They work through the application of a refrigerant gas and a compressor that cools the surrounding air down in an air-recirculation process. Moreover, they require professional installation, involving indoor and outdoor units, refrigerant piping, electrical connections, and potentially ductwork. In turn, they can reduce air temperature more than evaporative coolers. They offer comprehensive and consistent cooling throughout the day. They enable precise temperature control, dehumidify the air, and are capable of cooling larger spaces. Moreover, they are suitable for various climates, encompassing both dry and humid regions.

The air-conditioning market has also been growing fast at the rate of 15-20% annually (AEEE, 2015), with imports value of air conditioners almost doubled in the last decade (Figure A1). According to IEA, by 2050, around 2/3 of the world's households could have an air conditioner, and India, together with China and Indonesia, will account for half of the total number (IEA, 2018). However, as of today at the household level air-conditioning still remains a luxury good. Its penetration rate is low, reaching on average 6% in the country in 2019. Moreover, access to air-conditioning is highly uneven, indicating that households' ability to adapt to climate change through the use of air-conditioning energy is linked to their socio-economic conditions. Only richer people are indeed currently able to install the good, whereas for poorer people the access

[5] However, in India vital statistics are known to be under-reported (Romanello et al., 2022).

[6] The average purchasing costs of an air conditioner and evaporative cooler are 35 and 6 thousand rupees respectively.

[7] Authors' own calculation.

to the technology remains prohibitive (Davis et al., 2021). Moreover, future increasing income and temperatures are not expected to alone fill the cooling gaps, leaving 29–58 million households unable to properly adapt to extreme heat through air conditioners (Pavanello et al., 2021).

The Indian government has acknowledged this cooling emergency. It has also recognised the importance of meeting this need effectively but in a sustainable manner, so that it does not result in runaway climate change or an energy crisis. In 2019 the government has developed the Indian Cooling Action Plan. This provides a 20-year perspective and outlines actions needed to provide access to sustainable cooling and improve thermal comfort.[8] India has so become the first major country in the world to approve a national cooling policy. However, the plan has not been implemented yet, and it is still not clear how the government concretely intends to pursue its goals.

3 Theoretical Framework

In this section we provide a simple adaptation model, where in response to direct temperature-induced utility damages households simultaneously choose how much cooling energy to consume and own. The results from the maximisation problem are used to first discuss the source of inequality in the cooling adaptation response, and then the potential trade-off between cooling technologies with different investment costs and effectiveness. These model implications then guide the subsequent empirical analysis.

We begin by assuming that a representative household solves the following utility maximisation problem:

$$\max_{q_S, q_N, k, x} \quad \{u = D[T, q_S, k] \cdot z[q_N, x] \mid y \geq p(q_S + q_N) + rk + x\} \tag{1}$$

where z is the net utility from electricity for other uses, q_N and the composite (numeraire) good x. Equation 1 also introduces a direct utility penalty D from exposure to temperatures, T, that exceed the household's optimum temperature, T^*:

$$D = 1 - \delta \left\{ \frac{1}{A[q_S, k]} T - T^* \right\} \tag{2}$$

In Equation 2 the coefficient δ is marginal disutility of higher-than-optimal temperature, and A is a cooling adaptation function that describes the attenuating effects of space conditioning on ambient temperature, T, such that $A^{-1}T \geq T^*$. We assume that A is a Leontieff function that represents the household's decision to adjust the quantities of electricity for cooling (q_S, at price p) or space conditioning capital (k, at rental rate r):

$$A = a^{-1} \min [q_S, k] \tag{3}$$

The parameter a (with units of °C/kWh) represents the amount of electricity consumed for cooling that is not effectively used in reducing the disutility from ambient temperature. Moreover, in our framework, both q_S and k are expressed in kWh as they respectively signify the actual electricity consumption for cooling and the maximum capacity of cooling appliances a household can consume. Consequently, k reflects the upper limit of cooling capacity based on the owned appliances. This has two implications. Firstly, when $q_S < k$, the household consumes less cooling than its cooling appliances' maximum capacity allows. Conversely, when $q_S = k$, the household is operating its cooling appliances at their full capacity. Secondly, any changes in k correspond to adjustments in either the amount or the capacity of the cooling appliances

[8]The Plan seeks to (1) reduce cooling demand across sectors by 20% to 25% by 2037-38; (2) reduce refrigerant demand by 25% to 30% by 2037-38; (3) reduce cooling energy requirements by 25% to 40% by 2037-38; (4) recognise "cooling and related areas" as a thrust area of research under national Science and Technology Programme; (v) training and certification of 100,000 servicing sector technicians by 2022-23 (Cell, 2019).

owned by the household. The piecewise character of adaptation then implies that we can write the indirect utility function in two cases corresponding to the household's adaptation at the intensive margin q_S (i.e., adjusting space conditioning energy use conditional on fixed durable stocks) and the intensive-extensive margin k (i.e., adjusting both cooling appliances' capacity and space conditioning energy use simultaneously).

To solve the model, for simplicity, we assume z is a quasi-linear sub-utility:

$$z = x + \frac{v}{v-1} q_N^{1-\frac{1}{v}} \tag{4}$$

which implies that $\frac{\partial z}{\partial x} = 1$. This simplifies the last FOC, and it leads to the solution of q_N:

$$q_N = p^{(-v)}$$

This trick then allows us to derive closed-form expressions for the responses of q_S and k to temperature at the intensive and extensive margins:

$$q_S^* = \sqrt{\frac{\delta a T \left(y - r\bar{k} - \frac{1}{1-v} p^{1-v}\right)}{p(1+\delta T^*)}} \propto \sqrt{T}\sqrt{y} \tag{5}$$

We can use this expression to back out the maximum intensive-margin space-conditioning energy demand threshold, $q_S^* = \bar{k}$. In the limit,

$$\bar{k} = \frac{-\delta a T r + \sqrt{\delta a T \left(r^2 + 4\left(y - \frac{1}{1-v} p^{1-v}\right) p(1+\delta T^*)\right)}}{2p(1+\delta T^*)} \propto \sqrt{T}\sqrt{y} \tag{6}$$

above this level,

$$q_S^* = k^* = \sqrt{\frac{\delta a T \left(y - \frac{1}{1-v} p^{1-v}\right)}{(p+r)(1+\delta T^*)}} \propto \sqrt{T}\sqrt{y} \tag{7}$$

Equations 5 to 7 show that adaptation responses saturate with temperature and income, suggesting a concave response of cooling, and so reflecting diminishing returns to adaptation. Moreover, the solutions also highlight the importance of temperature-income interactions for determining the cooling adaptation response function.

We can also substitute these quantities in the disutility (Equation 2). For instance, for the case $q_S = k$, we get the following optimal disutility chosen by the representative household:

$$D^* = 1 - \delta \left(\sqrt{a} \frac{\sqrt{p+r}}{\sqrt{y - \frac{1}{1-v} p^{1-v}}} \sqrt{\frac{(1+\delta T^*)}{\delta}} \sqrt{T} - T^* \right) \tag{8}$$

Equation 8 suggests that the disutility from ambient temperature is decreasing in income y, and it is increasing in the cost of cooling appliances r, electricity prices p and the share of cooling electricity lost a.

Finally, if we assume that there exists two type of cooling technologies θ, evaporative cooler (C) and air conditioners (AC), this leads to a conditional maximisation problem, where we can re-write the optimal disutility as follows:

$$D_\theta^* = 1 - \delta \left(\sqrt{a_\theta} \frac{\sqrt{p+r_\theta}}{\sqrt{y - \frac{1}{1-v} p^{1-v}}} \sqrt{\frac{(1+\delta T^*)}{\delta}} \sqrt{T} - T^* \right) \tag{9}$$

where we assume that the two technologies may only differ in effectiveness a and cost r. Since we can safely take as given that evaporative cooler are cheaper than air conditioners ($r_C <$

r_{AC}), a household faces a technological trade-off to determine its optimal response to ambient temperature only if evaporative cooler are less effective at bringing thermal comfort ($a_C > a_{AC}$).

In the empirical analysis, the focus is then threefold. First, we aim at identifying which type of households are adapting and through which technology. We explore how the interaction between temperature and income level shape the access and use to the two technologies. Second, we estimate the marginal disutility to temperature, δ, for various level of temperature through the mortality-temperature relationship. Finally, we determine whether the two technologies differ at reducing thermal discomfort, a_θ.

4 Data

This section presents the data utilised in our analysis.[9] To address our research questions, we require data with several features. First, we need a household survey that provides information on ownership of heat adaptation appliances and electricity consumption, 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 its heterogeneity effects across socioeconomic groups, and the mitigation effects of cooling adaptation. All the data sources must provide sufficiently disaggregated geographical information that we can merge with meteorological data sets.

4.1 Household Data

Our primary data to study cooling adaptation is the Consumer Pyramids Household Survey (CPHS) 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 regions × urban status.

CPHS surveys each household every four month, and sampling is staggered so that a representative 25% of all households are sampled each month. The survey provides information on size, origin, and distribution of Indian households' income and expenditures levels. Particularly, we use data on electricity expenditure and income, which are reported at the monthly level. The survey also collects information on households' characteristics, housing, and owned assets at each wave. This makes it possible to determine whether households have air conditioners and evaporative coolers installed in their dwelling every four months.

We enrich the data set with information on electricity prices from the 2011 (67th round) National Sample Survey (NSS). We use these data to compute electricity quantity of the CPHS households, as CHPS only provides electricity expenditure data. NSS indeed provides the electricity prices paid by its interviewed households. We so aggregate these prices at the state $\times$ district $\times$ urban and state $\times$ district $\times$ rural levels, and we assign them to CHPS households.[10] We finally actualise electricity prices to our survey period using a monthly wholesale price index for electricity from the Office of Economic Adviser - Department for Promotion of Industry and Internal Trade.[11]

4.2 Mortality Data

To obtain evidence on the impact of temperature on mortality in India we collect district-level information from the Indian Civil Registration System. Particularly, we digitise their public

[9]Table A1 summarises which data set we use for each analysis.

[10]When the information in NSS was not available in some state $\times$ district $\times$ urban/rural areas surveyed in CHPS, we impute the average prices using state $\times$ urban and state $\times$ rural averages.

[11]The time series of the wholesale price index can be found at the following website: https://eaindustry.nic.in/

reports on "Vital Statistics of India" 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. It also distinguishes between number of deaths occured in rural and urban areas.[12]

For the analysis, we are interested into district-level mortality rates rather than deaths counts. To construct them, we get gridded-level population information from the Gridded Population of the World (GPW), v4 (CIESIN, 2018). This provides estimates of population count for the years 2000, 2005, 2010, 2015, and 2020, consistent with national censuses and population registers. We then aggregate cells at the district, and we exponentially interpolate population counts between each five year-period in each district. Finally, we divide the number of deaths by population in each district to get mortality rates. To get urban and rural populations, we multiply the total populations by the state-level urbanisation rates obtained from 2011 Census.[13]

4.3 Meteorological Data

Household and mortality data are merged with population-weighted[14] meteorological data using the most disaggregated geographical information available, the district.

We compute gridded daily average temperature, specific humidity and total precipitation data from the recently released hourly ERA5-Land data set with a resolution of 0.09°. 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 climate models that are used to generate a gridded product (Auffhammer et al., 2013). Furthermore, this type of data set is increasingly being used in climate econometrics, especially in developing countries, where the quality and quantity of weather data is limited.

We employ the daily information to construct several exposure measures at the monthly, quarterly, and annual level, including temperature and humidity bins, and 24-degree Cooling Degree Days (CDD).[15]

As a robustness, we also collect gridded monthly average temperature and rainfall data at 0.5° resolution from the Climate Research Unit (CRU TS v4.05) of the University of East Anglia (Harris et al., 2014).

4.4 Descriptive Statistics

Heat Adaptation.— Table 1 provides household-level representative descriptive statistics for the whole India and by income quintile across our sample period. Our descriptive evidence reveals that, on average, approximately one-third of Indian households own at least one evaporative cooler, while air conditioners are relatively rare, with an ownership rate of 6%. However, income levels significantly influence the ownership rates of both appliances, with wealthier households showing higher rates of ownership.

Furthermore, the two technologies exhibit different behaviors across the income distribution. Evaporative coolers demonstrate characteristics of a normal good, as they are purchased even by some of the poorest households (11%), and the ownership rate steadily increases — by around 10 percentage points —– across income quintiles. In contrast, air-conditioning resembles a luxury good, as the majority of households do not have air conditioners installed (1-3%), and only high-income households can afford this technology, with an ownership rate of 21%.

[12]Each report also provides the distinction between male and female deaths. However, this information is not always available for all the districts. For this reason, we prefer focusing on all-gender number of deaths.

[13]This means that we are not taking account changes over time of urbanisation rates, as well as differences across districts.

[14]To weigh our climate data we again use gridded-level population information from the Gridded Population of the World (GPW), v4 (CIESIN, 2018).

[15]Cooling Degree Days are defined as the sum of the degree-days above a certain threshold: $CDD = \sum_{i=1}^{n}(T_i - \overline{T})$. As a threshold we impose 24 °C.

Consistently with the distribution of the two technologies, wealthier households also consume 20 to 60 kWh of electricity more per month compared to all other households.

Table 1: Descriptive Statistics at the Household Level - Income Quintiles

	CHPS					
	Air Conditioner (Dummy)	Evaporative Cooler (Dummy)	Electricity Quantity (kWh)	Income (Rupee)	Urban (Dummy)	Power Availability
Total	0.06	0.33	104.85	16021.86	0.33	21.73
	(0.23)	(0.47)	(99.22)	(18849.37)	(0.47)	(3.78)
Income Quintile:						
1st	0.01	0.11	62.53	6866.80	0.14	21.43
	(0.07)	(0.25)	(36.71)	(3209.29)	(0.28)	(3.25)
2nd	0.01	0.24	80.59	9876.61	0.23	21.09
	(0.10)	(0.39)	(56.30)	(5766.23)	(0.38)	(3.76)
3rd	0.02	0.34	97.10	12794.75	0.30	21.67
	(0.13)	(0.46)	(80.48)	(8734.34)	(0.45)	(3.74)
4th	0.03	0.42	117.92	17183.12	0.39	22.08
	(0.19)	(0.52)	(109.06)	(12989.78)	(0.51)	(3.68)
5th	0.21	0.54	166.12	33382.87	0.59	22.35
	(0.49)	(0.60)	(168.85)	(39263.90)	(0.59)	(3.80)
N°Households			210560			

Notes: Means and standard deviations (in parentheses) across the survey period are reported. Air-conditioning, evaporative cooler, urban and power availability are at the four-monthly level. All other variables are at the monthly level. Survey weights for country-level representativeness are applied.

An additional factor that potentially contributes to the disparity in cooling adaptation is whether households reside in urban or rural areas.[16] Within our sample, the majority of households (67%) are situated in rural areas, and these tend to be predominantly lower-income households (70% to 86%). Conversely, wealthier households are more commonly found in urban settings (59%). This discrepancy partly explains the higher prevalence of expensive air conditioners among urban households, particularly in the fifth quintile (31%). In contrast, the more affordable evaporative coolers are consistently purchased, even in rural areas, and both urban and rural families exhibit similar adoption curves along the income distribution (Table A2).

However, it is not solely income that can account for the patterns in cooling adaptation. Significant differences in the quality of electricity supply, as measured by the hours of electric connection availability per day, may emerge as an additional key determinant.[17] The operation of an air conditioner indeed necessitates a reliable grid connection. Since rural areas experience more frequent disconnections (-1.5 hours) compared to urban regions, this disparity may further explain the predominance of air conditioner purchases in cities. Contrary, evaporative coolers do not have the same stringent requirements, and they can operate effectively even with less reliable electricity grid.

Looking at the changes over time, Table A3 indicates the ownership of evaporative cooler rapidly increases over our sample period, moving from 24% to 44%. The spread of air conditioners also grows from 4% to 7%. However, on the one hand, almost only urban households

[16] CMIE uses 2011 Census to define urban and rural areas. Particularly, an area with a population of minimum 5000, population density of at least 400 persons per square km, and at least 75% of the male working population in non-agricultural occupations is defined as urban. The remaining is defined as rural.

[17] In the CHPS data electricity access is about 100%, even in rural areas. This is because CMIE defines access to electricity as given by any means (excluding battery). That is, it does not question whether the connection to the grid is legal or illegal.

purchased air conditioners across the period — from 11% to 17%. On the other hand, the growth in coolers' adoption is almost equally driven by rural (+22 percentage points) and urban areas (+17 percentage points). Increasing income and quality of electricity supply may explain the increasing demand for both appliances, as there are no significant changes in the number of urban and rural households.

Going more in detail on these trends, Figure A2 divide households in nine categories based on long-term temperature conditions — expressed using CDD — and sample average income. Two key findings emerge. First, the prevalence of evaporative coolers appears to be climate sensitive. That is, they are mainly present in areas where temperatures are warmer on average. Contrary, the distribution of air conditioner seems to be independent from the climatic conditions. Second, the graph underlines the differences in the technological choice across income levels. The spread of evaporative coolers is more rapid for low- and middle-income families in warmer areas, whereas in percentage points the demand for air conditioners grows similarly to the demand for coolers in high-income families.

Figure A3 then separates households based on their residence at the state level. The trends across states accentuate the disparities in technological choices along the income distribution. On one hand, high-income urban settings such as Chandigarh and Delhi demonstrate almost full saturation of evaporative cooler ownership at the beginning of the sample period, while the adoption of air conditioners quickly increases over the years, with an upsurge of more than 25 percentage points.[18] Contrary, the other part of India is still in the process of catching up to the saturation of demand for evaporative coolers. This highlights the variations in cooling technology preferences and access to higher-income households and urban areas compared to other regions and income groups.

Mortality and Extreme Weather—. Moving to Table 2, this summarises the mortality rates, extreme temperature variables, and precipitation, for the whole India, across India Zonal Councils, and at the beginning and end of our sample period. The average annual mortality rates across the period 2014-2019 is 2280.401 per 100,000 population, and this rate reaches 2512.532 in 2019. The highest mortality rates are registered in urban areas, and in the Central and Western regions.

Extreme warm days (≥ 35) are on average infrequent (about 5 days per year) in the country. However, they are significantly more frequent in Northern and Eastern areas, where we may expect the identification of this effect. Critically, days with average daily temperature between 30 °C and 35 °C are instead very frequent (about 52 days per year), and more widespread across the whole country. Interestingly, Southern regions, which are characterised by a tropical weather, are significantly much less exposed to warm days, but they more exposed to more days with high level of humidity.

[18]To put it into perspective, in the United States between 1960 and 1970 air-conditioning saturation increased by about 25% (Barreca et al., 2016). In Delhi ownership of air conditioners has increased by 30 percentage points in an even shorter period.

Table 2: Descriptive Statistics at the District Level - Mortality Rates and Extreme Weather

	All-Age Mortality Rates			ERA5					
	Total (per 1,000s)	Rural (per 1,000s)	Urban (per 1,000s)	T(< 10 °C) (N° Days)	T(30 °C - 35 °C) (N° Days)	T(≥ 35 °C) (N° Days)	Precipitation (m)	H(0 - 3 g/kg) (N° Days)	H(≥ 18 g/kg) (N° Days)
Total	5.20	3.96	6.83	3.10	55.48	6.99	1.21	1.47	93.89
	(5.48)	(3.13)	(10.69)	(21.94)	(30.66)	(18.46)	(0.60)	(14.72)	(61.42)
Region:									
Northern	6.05	4.75	7.19.	28.06	59.50	9.02	0.92	9.13	63.01
	(4.83)	(3.37)	(8.13)	(60.75)	(35.35)	(17.11)	(0.48)	(39.81)	(34.51)
Central	7.17	5.70	8.02	0.00	48.09	1.78	1.21	0.00	66.05
	(5.51)	(3.79)	(10.40)	(0.00)	(36.08)	(4.65)	(0.59)	(0.00)	(72.24)
Eastern	3.92	3.07	5.19	1.75	65.98	10.80	1.08	0.78	93.44
	(2.26)	(2.73)	(5.23)	(11.07)	(14.79)	(8.74)	(0.28)	(10.90)	(33.64)
North Eastern	3.93	3.12	5.33	0.00	49.52	1.96	1.48	0.00	148.54
	(3.34)	(2.24)	(8.85)	(0.00)	(18.16)	(3.77)	(0.34)	(0.00)	(34.27)
Western	6.57	4.10	8.07	0.00	57.76	11.18	1.04	0.00	68.60
	(8.99)	(2.73)	(15.55)	(0.00)	(29.65)	(39.97)	(0.45)	(0.00)	(54.45)
Southern	3.82	3.59	9.59	2.41	2.23	0.00	2.76	0.70	115.61
	(5.72)	(2.12)	(16.58)	(31.71)	(6.63)	(0.00)	(1.35)	(16.63)	(113.72)
Year:									
2014	5.03	3.82	6.59	3.26	59.22	6.53	1.11	1.57	81.18
	(5.72)	(3.09)	(10.86)	(23.48)	(30.24)	(18.12)	(0.60)	(15.80)	(58.42)
2019	5.74	4.55	763.12	4.53	59.51	9.53	1.39	1.47	97.51
	(5.38)	(3.02)	(10.98)	(22.34)	(28.95)	(19.36)	(0.59)	(14.17)	(60.65)
N°Districts					657				

Notes: Means and standard deviations (in parentheses) across the analysed period are reported. Population weights for country-level representativeness are applied.

5 Extensive Margin: The Choice of the Cooling Technology

In this section we infer the interplay between temperature and income in the choice of the heat adaptation technology across Indian households. Moreover, we show the role of the other socio-economic and demographic drivers in determining the choice of the technology.

5.1 Empirical Framework

To study the household's investment decision on cooling technologies, we separately estimate the following linear probability model (LPM) for each appliance:

$$\begin{aligned} C_{aiw} = \gamma_0 + \beta_1 \overline{CDD}_{d(i)w} + \beta_2 I_{iw} + \beta_3 (\overline{CDD}_{d(i)w} \times I_{iw}) + \\ + \beta_4 g(P_{d(i)w}) + \lambda X_{iw} + \mu_k + \delta_w + \theta_{s(i)} w + \theta^2_{s(i)} w^2 + \zeta_{iw} \end{aligned} \tag{10}$$

where the outcome variable is a dummy 0 or 1 indicating whether a household i owns at least an unit of the appliance a — either cooler or air conditioner — in wave w; $g(P_d(i)w)$ is a second-degree polynomial of cumulative precipitations experienced by household i in district d during the quarter w; and ζ_{iw} is the error term, which we cluster at the district level.

To measure temperature, we use Cooling Degree Days (CDD) as they are standard measurements designed to reflect the demand for cooling. However, the crucial point is that we do not use contemporaneous CDD. Contrary, $\overline{\text{CDD}}_{d(i)w}$ is a 10-year moving average of quarterly CDD in district d in the decade before the surveyed quarter w,[19] capturing households' medium-term expectations of climatic conditions where they live. The extensive margin — the investment decision — is a slow adjustment process. This is because cooling appliances have long lifetimes, and so households make the investment based on expectations about climatic conditions, i.e., average weather over long periods (Auffhammer and Mansur, 2014; Cohen et al., 2017).[20]

Equation 10 also includes the natural algorithm of household i's income across each wave period, I_{iw}, and an interaction with the moving average of CDD to determine how income levels shape the response of households to changes in climatic conditions.

The specification in Equation 10 also includes unrestricted wave fixed-effects, δ_w. These fixed effects control for time-varying differences in the dependent variable that are common across Indian regions. Since shocks and unobserved time-varying factors may vary across states in India, we also include state-level quadratic trends, $\theta_{s(i)} w$ and $\theta_{s(i)} w^2$.

Furthermore, we control for a vector of time-varying and -invariant households' characteristics, for X_{iw}. This includes a dummy variable indicating whether a household i lives in an urban area, household head's education, age, and gender, roof material of the dwelling, and leave-one-out averages[21] of the power availability[22] (in hours) and ownership of generators in the area[23] where a household i resides.

Importantly, our specification also carefully accounts for unobserved time-invariant heterogeneity μ_k. Unlike existing works, the unique feature of our data set allow us to investigate the influence of climatic conditions not only on the prevalence of cooling appliances — the cross-sectional variation across households, or the stock of appliances —, but also their actual adoption — the within-household variation, or the flows of appliances. Based on how we model the time-invariant unobserved heterogeneity, we can estimate the coefficients for each one of the two dimensions.

[19] That is, for the quarter January-April 2014 cooling degree days are averaged for the same months across the period 2003-2013

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

[21] We prefer to use local leave-one-out averages rather than household-level information to avoid simultaneity.

[22] Each household declares for how many hours per day they have electrical power in the dwelling. We use this information as a proxy of power quality.

[23] We take the averages at the district-urban/rural-wave level.

Critically, the choice about μ_k influences how we then interpret the resulting coefficients for $\overline{\text{CDD}}_{d(i)w}$. When we model prevalence, we make use of state-level fixed effects, $\mu_{s(i)}$. We can so document how the differences in expectations for the climate conditions between households has shaped the distribution of air-conditioning and evaporative cooler in India. Contrary, when the focus is adoption, we use household fixed effects, μ_i, and we capture whether within-household shocks in climatic expectations influences household's investment decision.[24]

In this context, it is however worth noting at the outset the limitations of our data. The ideal data set to shed light on the adoption decision would be a long panel of households spread across different climate regimes that the econometrician was able to observe start out with no cooling, and then progressively acquire various technologies in response to differential long-run heat exposures. By contrast, our panel data set revisits households trimonthly over a comparatively short five-year period, at the beginning of which air conditioners and, particularly evaporative coolers, had already been acquired by a fraction of households. This makes difficult to identify the causal effect of climatic conditions on adoption, as there is not sufficient variation over time in the average weather conditions (Figure A2 and Figure A3).[25]

Given the rapid spread of the two heat technologies in our sample period, we then expect economic development variables, such as income, to have a key role in the adoption of the two technologies. However, for evaporative coolers we expect the effect of economic development to be conditional on climatic conditions. That is, being the appliance already more spread in warmer regions, economic development should drive adoption faster in these areas (Figure A2). We provide a test for this hypothesis.

Symmetrically, the ideal data set to elucidate the determinants of the prevalence of cooling appliances among Indian families is a large cross section of heterogeneous households spread across different climates, or multiple such cross sections repeated over a long enough interval that the econometrician can observe substantial locational differences in the spread of different cooling technologies (Pavanello et al., 2021; Davis et al., 2021). Our data set well respond to these requirements, and it allows to identify how climate conditions influence the distribution of the cooling appliances across Indian households.

5.2 Results

Prevalence.— Table 3 presents the coefficients of $\overline{\text{CDD}}$ and income, when we model the prevalence of the cooling appliances.

Columns 1 and 2 show the results when the dependent variable does not distinguish the type of cooling appliances that is owned. Columns 2 to 6 depict the same estimates for each specific cooling appliance. Our estimates suggest that the distribution of evaporative cooler is climate sensitive, and families living in warmer areas are more likely to own the appliance. We find that a 100 degree-day increase in CDD is associated with an increase in the probability of having an evaporative cooler by 1.45 percentage points. Column 5 also indicates that this effect of CDD is increasing in income. This means that in warmer, and so more exposed to heat, areas richer families are more likely to have coolers. Contrary, the prevalence of air conditioner does not depend on climatic conditions, as the effect of CDD is small and not precisely estimated. Moreover, the null effect of CDD is common across the income distribution.[26]

Our findings also highlight that household income has a large positive effect for both appliances, with similar elasticities. This suggests the existence of inequality in the access to heat adaptation: the likelihood of owning a cooling appliance is increasing in income. An increase

[24]With household fixed effects, all controls but power availability and ownership of generators are dropped from the regression, as they do not vary over time.

[25]This is especially evident for air conditioners, where the variation we would capture through adoption would mainly come from the cities of Delhi and Chandigarh (Figure A3).

[26]This is in line with anecdotal evidence from Avikal Somvanshi (Urban Lab, Centre for Science and Environment, New Delhi) suggesting that in India air conditioners are mainly considered as a status good.

by 10% in four-month income is associated with an increase in the probability that a household owns an air conditioner by 0.59 percentage points, while in the probability of owning an air cooler by 0.61 percentage points. Our estimates for air-conditioning are consistent with previous cross-sectional works on India (Davis et al., 2021; Pavanello et al., 2021), which suggest a fundamental role of income.

Looking at the other coefficients (Table B1), we estimate statistical significant coefficients of the linear term of precipitation only for coolers, highlighting that households living in more arid regions are more likely to have an evaporative cooler. This is consistent with the technology being more effective in dry conditions. Contrary, we do find large positive effect of urbanisation only for air conditioners. Moving from a rural to an urban area is associated with an increase in the probability of owning an air conditioner by 3.8 percentage points. This is in line with the descriptive analysis suggesting that rural households are catching up urban households in terms of ownership of coolers. In addition, we estimate that one-hour increase in the electricity power available in the dwelling is associated with an increase in the probability of having evaporative cooler by 1.3 percentage points, while the ownership of generators is a positive determinant of the presence of the two appliances. This suggest that even when power is not reliable, having generators may allow to run appliances in the dwelling. Our results also suggest a primary role of demographic characteristics of the household. The saturation of both appliances is increasing with age of the household head. Particularly for air conditioners, education also enhances the probability of owning the technologies, whereas household size diminishes it. Findings on gender instead suggest that the presence of a female family head does not affect the ownership of the two appliances. Finally, estimates for roof materials — a proxy of housing quality — highlight that both appliances are more likely to be find in more insulated houses.

Table 3: Impact of Temperature and Income on the Prevalence of Cooling Appliances

	Both Appliances		Air Conditioner		Evaporative Cooler	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{CDD}}$ (100s)	0.0146***	-0.0373***	0.0000375	-0.0101	0.0145***	-0.0423***
	(0.002)	(0.010)	(0.001)	(0.007)	(0.003)	(0.013)
Log(Income)	0.0863***	0.0637***	0.0592***	0.0547***	0.0611***	0.0363**
	(0.007)	(0.010)	(0.006)	(0.006)	(0.010)	(0.015)
$\overline{\text{CDD}}$ × Log(Income)		0.00548***		0.00107		0.00600***
		(0.001)		(0.001)		(0.002)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.51	0.51	0.21	0.21	0.51	0.51
Observations	2442730	2442730	2442730	2442730	2442730	2442730

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights. Results from the full regression are in Table B1.

Adoption.— The results for the adoption regressions are presented in Table 4. Our results are consistent with our hypothesis that in our sample period the main driver of adoption is economic development. We find that an average India household does not respond to shocks in climatic expectations adopting any of the technology. Even if we estimate that the interaction between income and climate is positive and significant for coolers, the magnitude is very small

— for a high-income household a one-hundred increase in $\overline{\text{CDD}}$ increases the probability of adopting air-conditioning by 0.01 percentage points. Contrary, income keep having a large effect, with a positive shock of 10% in income leading to an increase of the probability of adopting air-conditioning and evaporative cooler by 0.13 and 0.35 percentage points respectively. Moreover, Table B2 shows that a positive shock in the power availability in the area where a household lives positively affects the adoption of evaporative coolers, and the average share of households with a generator remains a key driver for both appliances.

Table 4: Impact of Temperature on the Adoption of Cooling Appliances

	Both Appliances		Air Conditioner		Evaporative Cooler	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{CDD}}$ (100s)	-0.000669	-0.00723**	0.000215	0.00151	-0.000767*	-0.00943***
	(0.000)	(0.003)	(0.000)	(0.001)	(0.000)	(0.003)
Log(Income)	0.0413***	0.0383***	0.0134***	0.0140***	0.0348***	0.0310***
	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
$\overline{\text{CDD}} \times$ Log(Income)		0.000693**		-0.000137		0.000914***
		(0.000)		(0.000)		(0.000)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend × State	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.05	0.02	0.02	0.06	0.06
Observations	2432366	2432366	2432366	2432366	2432366	2432366

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights. Results from the full regression are in Table B2.

Heterogeneity.— The findings from the prevalence regressions identify the drivers of the distribution of cooling appliances across Indian households. Exploring the heterogeneity in the adoption response, we can reconcile the estimates from the prevalence and adoption regressions, showing that in our sample period economic development, especially through incomes, drives the rapid spread across household groups that are more likely to own the good.

First, Table B3 divides households based on whether they live in a rural or an urban setting. We can evince that for air conditioner income elasticity for urban households is 7 times the same elasticity for rural areas. Contrary, for evaporative coolers the income elasticities are similar.

Next, we investigate difference along the distribution of income. We categorise households into three income groups: "Poor," "Middle," and "Rich". The results are presented in Table B4. Critically, based on income level households invest their earnings in different appliances. On the one hand, our estimates suggest only rich families invest household income installing an air conditioner. The income coefficient for wealthiest families is 11 and 6 times greater than for low- and middle-income households. On the other hand, middle-income families are two times more likely than other households to invest their income in evaporative coolers.

Separating households based on both income distribution and urban/rural setting provides additional insights (Table B5). For air conditioners, income elasticity tends to be increasing in income and higher in urban areas. Contrary, income coefficients are more homogeneous across income level for evaporative coolers, with middle-income and urban poor families emerging as the main household groups that invest in the technology.

Finally, Table B6 presents the coefficients for adoption after dividing households in three categories based on temperature levels. It is evincible that in warmer areas households are more likely to invest their income for evaporative cooler, whereas for air conditioners income elasticity is steady across climatic conditions.

Robustness Checks.— Our main estimates remain robust to various robustness tests. For both prevalence and adoption regressions we test alternative fixed-effects specifications (Table B7-B9); clustering standard errors at state level (Table B10); and modelling $\overline{\text{CDD}}$ non-linearly up to degree 3 polynomials (Table B11-B13). Finally, for prevalence we also employ different estimation methodologies, particularly logit (Table B14) and multinomial logit regressions (Table B15).[27] Our results and conclusions remain consistent.

To summarise, our results highlight the importance of considering both cross-sectional and within-household dimensions to comprehend the influence of initial conditions on the adoption of heat adaptation cooling appliances. The extensive margin estimates complement the descriptive evidence presented earlier, revealing two distinct segments in Indian households' cooling technology choices. Evaporative coolers are prevalent in warmer regions, with low- and middle-income families, and rural households increasingly catching up due to rising incomes and improved electricity access. Conversely, air conditioners are predominantly concentrated among high-income, highly educated, urban households, regardless of climatic conditions. Furthermore, the rapid income growth has accelerated adoption only among the wealthiest households, exacerbating disparities in technology access. In the next section, we show how this different distribution of the cooling appliances across households then modulates electricity consumption responses to temperature shocks.

6 Intensive Margin: Electricity Consumption

This section explores the relationship between temperature, income and electricity use. Along the intensive margin temperature impacts electricity quantity through an increasing use of a fixed amount of cooling devices — such as air conditioners and evaporative coolers —, whereas income shocks affect the use of all energy appliances. By then identifying heterogeneous effects of temperature changes along income levels, climatic conditions, and across urban and rural areas, we aim to highlight the unequal distribution of cooling energy use. The findings should be confirmatory of the results obtained in the extensive margin section. That is, we expect to find a higher responsiveness to temperature shocks in urban areas and for high-income households, as it is where air-conditioning, the more energy-intensive appliance, is mostly spread.

6.1 Empirical Framework

To determine the impact of temperature and income on electricity consumption, we estimate the following equation:

$$Q_{imy} = \alpha + \sum_{j=1}^{10} \theta_j T^j_{d(i)my} + g(P_{d(i)my}) + \beta\, I_{imy} + \mu_i + \delta_{my} + \varepsilon_{imy} \tag{11}$$

where Q_{imy} represents the natural logarithm of electricity quantity of household i in month m and year y; $g(P_{d(i)my})$ is a second-degree polynomial of district d's cumulative precipitation in month m and year y; I_{imy} the natural logarithm of household income in month m and year y; μ_i are household fixed-effect; δ_{my} are month-year fixed, absorbing all unobserved time-varying differences in electricity quantity that are common across households; ϵ_{imy} is the stochastic error term. We assume the residuals are heteroskedastic and serially correlated within a district.

Our main interest relies in the relationship between electricity quantity and temperature. In the baseline specification we model temperature using ten 3-degree temperature bins, $T^j_{d(i)my}$.

[27]In the multinomial logit the outcome variable is modelled as a categorical variable with three choices: "No Appliance", "Evaporative Cooler", "Air conditioner".

Particularly, for each district d and month-year my, we count the number of days the mean daily temperature falls into each bin. This non-parametric approach allows to (1) capture potential non-linearities in the relationship electricity-temperature, and (2) is able to capture the response at temperature cold and hot extremes. Each temperature bin's coefficient measures the impact of one more day with a mean temperature falling into the bin on the log of household daily electricity, relative to the reference bin 17-20 °C. As we exploit the plausibly-random variation in weather realisations of $T^{j}_{d(i)my}$ within households and month-year, we interpret these coefficients as short-run effects (Dell et al., 2014; Hsiang, 2016).

To better understand the role of the extensive margin in shaping the dose-response function, we then separately estimate the relationship for different income levels, and across urban and rural areas. We so take into account that the distribution of air-conditioning and air cooler changes as we move along the income distribution and urbanisation levels. We expect richer and urban households to be more responsive to temperature, as they are more likely to have, and so use, the appliances.

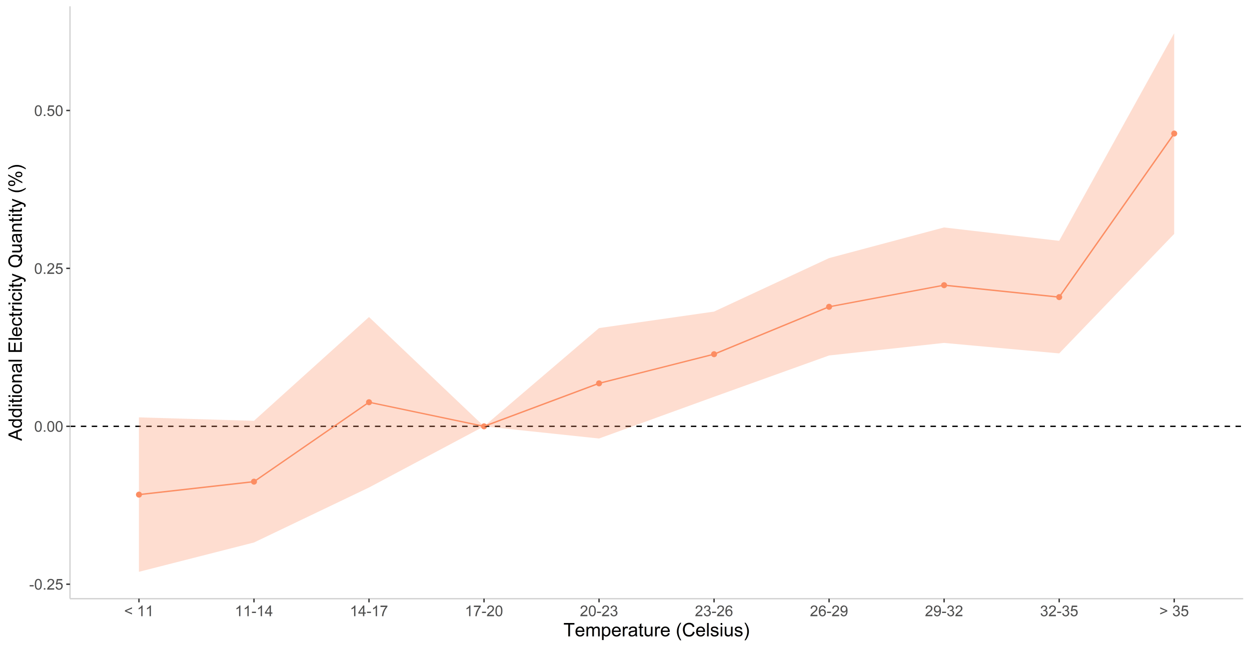
6.2 Results

Main results.— Figure 1 presents the average effects of an additional day in each temperature bin relative to the base range 17-20 °C. We find that with respect to a day between 17-20 °C, an additional day between 32-35 °C increases electricity consumption by 0.21%, while an additional day at or above 35 °C increases annual electricity consumption by 0.46%. Contrariwise, we find evidence of lower use of electricity with cold temperatures. This is mainly because Indian households do not use electric heaters, and so there is no U-shaped response function as in other countries like US (Deschênes and Greenstone, 2011) and Mexico (Davis and Gertler, 2015). [28] As for income shocks[29], we find that a 1%-increase of monthly income induces a 0.08% increase in monthly electricity demand (Table C1).

[28]Remaining in a developing context, Davis and Gertler (2015) estimates the impact of temperature bins on residential monthly electricity quantity in Mexico. Their coefficients are quite greater than ours in the warmer bins. Two factors may explain these differences: 1) the average household in India is much poorer than the average household in Mexico; 2) Mexico has a quite higher penetration of air-conditioning, particularly in warmer areas.

[29]Previous works (Davis et al., 2021; Pavanello et al., 2021) identify income as the main driver of residential electricity demand in India.

Figure 1: Estimated Temperature-electricity Consumption Relationship



Notes: The figure plots the response function between log monthly electricity quantity and average daily temperature bins (Equation 11). The response function is normalised with the 17-20°C category set equal to zero so that each estimate corresponds to the estimated impact of an additional day in bin *j* on the log monthly electricity quantity relative to the electricity quantity associated with a day on which the temperature is between 17°C and 20°C. Full regression results are presented in Table C1. The regression is weighted using survey weights. Standard errors are clustered at the district level.

Heterogeneity.— We test the heterogeneity of the temperature-electricity relationship. Our findings suggest that the effect of temperature on electricity consumption is highly heterogeneous across different types of households, and it mimics the distribution of the appliances.

First, we find that urban households are twice as responsive as rural households for most temperature bins (Table C2). For instance, an additional day above 35 °C, relative to a day between 17-20°C, increases electricity consumption of an urban household by 0.73%, while by 0.32 for a rural household.

Second, dividing again households in three income categories, we find that temperature-semi-elasticity is increasing income (Table C3). This indicates that especially high-income households are able to substantially increase their electricity demand to cope with hot temperatures.

Going more in detail, we split households across both income levels and urban and rural residence (Table C4). Critically, our estimates shows that, independently from income levels, households living in cities tend to have higher semi-elasticity to warmer temperature bins, with high income urban households emerging as the most responsive. Furthermore, Table C4 highlights two potential patterns. On the one hand, in rural areas, where only air coolers are mostly spread, poor households responds more than middle income families, but less than the more wealthy ones. A possible interpretation is that poor households have less efficient air coolers — *technology effect* —, while richer households consume more because either they are less price sensitive — *rebound effect* — or they have higher number of these appliances — *scale effect*. On the other hand, in urban areas the effect of temperature monotonically increases as we move from poor to rich families. Morevoer, even though there is a tiny difference between the coefficients of middle and high income households for the warmer bins, the difference in average electricity consumption in levels is large between the two groups. This means that the similar effect of an additional equal or above 35 °C increases electricity consumption by 0.88 and 1.51 kWh for middle- and rich-income households respectively. This disparity is likely correlated with the different technological choice.

Finally, we also provide a further test where we divide households based on the technology they own. In line with the heterogeneity results, we find that the sample of families with air conditioners consumes two to three times more electricity in response to warmer temperatures than that one with evaporative coolers (Table C5). We find similar results even after restricting these subsamples only to high income households (Table C6).

Robustness checks.— Our main results are robust to: using alternative time fixed-effects (Table C7) and time-varying fixed-effects (Table C8) specifications; expressing electricity quantity in levels (Table C9); exploiting CRU rather than ERA5 climate data (Table C10); clustering standard errors at state level (Table C11); and specifying temperature 5-degree bins (Table C12 and Figure C1). We also test a parametric response function by specifying temperature with up to degree 3 polynomials (Table C13). The results suggest that expressing temperature as linear can be a good approximation. Finally, we employ alternative weather variables (Table C14) to test the relationship, particularly Cooling Degree Days (CDD). The results remain consistent.

Collectively, the results presented in this section suggest the fundamental interrelation between income and temperature for intensive margin response. Furthermore, they underscore the importance of considering urbanisation in shaping households' electricity production frontier. All of these results are confirmatory of what we find for the investment decision. That is, technology modulates the responsiveness to temperature shocks, with households more likely to own an air conditioner that consume more electricity during warmer days. Next, after exploring who is adapting and how, in the next section we identify the benefits of heat adaptation and how they are distributed across the population. Critically, we test whether the disparities in technological choice lead to consequences for health of Indian household.

7 Temperature, Mortality and the Benefit of Cooling

This section examines the impact of extreme temperatures on mortality, and how cooling technologies may mediate it. First, we analyse the relationship between annual mortality rates and temperature distribution in India districts. Next, we demonstrate that the negative impact of extreme temperatures disproportionately affects low-income and rural populations, where cooling appliances are less available. Finally, we introduce cooling adaptation into our analysis, testing whether the uptake of air conditioning and cooler can offset the negative impact of temperature, and how the appliances differ in effectiveness.

7.1 Empirical Framework

We describe the regression model used to estimate the relationship between mortality and temperature for the period 2014-2019. Similarly to Burgess et al. (2017), we specify our regression equation as follows:

$$M_{dt} = \alpha_0 + \sum_j \theta_j T_{dtj} + \sum_k \delta_k P_{dtk} + \sum_h \beta_h H_{dth} + \mu_d + \rho_t + \lambda_{r(d)} t + \lambda^2_{r(d)} t^2 + \epsilon_{dt} \tag{12}$$

where M_{dt} is the natural logarithm of all-age all-cause mortality rate in district d in year t. The variable T_{dtj} denotes the number of days in district d and year t on which the daily mean temperature fell in the jth of temperature bins. Particularly, for our baseline specification we use 5-degree temperature bins,[30] and the omitted bin category is 15-20. We so estimate separate coefficients δ_j for each of these temperature bin regressors. We again opt for estimating the response function using temperature bins, since (1) as too-high and too-low temperatures can both

[30]Having annual mortality rates for few years we prefer to employ 5-degree rather 3-degree temperature bins to avoid losing too much variability.

harm human health, it is likely that the temperature-mortality relationship is nonlinear; (2) the nice property of temperature bins is that they are more able to capture response to temperature extremes.

Because it is possible that temperature variation is correlated with precipitation variation, the inclusion of precipitation is important. We then control for total precipitation P_{dtk} using a categorical variable indicating whether a district d belongs to the k precipitation tercile in year t.

In our specification we also include humidity, which has been shown to have relevant effect on mortality (Barreca, 2012). We divide daily specific humidity in three-grams-of-water-vapour per kg bins, with the interval 9 g/kg to 12 g/kg of water vapour as omitted category. We also specify further regressions where we enrich the covariates with interactions between temperature and humidity. We so aim to capture the impact of days with extreme hot and humid/arid weather conditions.

Our specification also incorporate district fixed-effects μ_d, which absorb all unobserved region-specific time invariant determinants of the outcomes, and year fixed-effects δ_t, which instead absorb for time-varying differences in the dependent variable that are common across regions. Finally, we control for climatic region-level quadratic time trends, $\lambda_{r(d)}t$ and $\lambda^2_{r(d)}$, that take account shocks or time-varying factors that affect health may not be common across state in India.[31]

To estimate Equation 12 we employ Weighted Least Squares (WLS), where the weights are the square root of total population in the district. The reasons are (1) the estimates of mortality rates from large population districts are more precise, so this weighting corrects for heteroskedasticity associated with these differences in precision; (2) the results reveal the impact on the average person rather than on the average district, which we believe to be more meaningful.

Equation 12 estimates average population mortality-temperature responses. However, we may expect the effect of temperature to vary based on the income distribution within each district, generating so unequal exposure. We then test whether extreme temperatures unevenly affects low-income populations. Specifically, we first estimate Equation 12 differentiating between urban and rural mortality rates.[32] In addition, we estimate the heterogeneous effects of temperature, differentiating between districts with a higher share of poor population. Specifically, for each district we define the share of individuals that are below the third income deciles as poor, and we compute the share relative to the district population. Finally, we create two subsamples of districts based on the median level of the share.

Finally, we introduce heat adaptation in the analysis. We first restrict the numbers of districts to the CHPS sample for the years 2014-2019. We so match our mortality data with district-level information on air-conditioning and evaporative cooler penetration shares, which we obtain by aggregating the household data using the survey weights. We exploit this information to test the hypothesis that cooling adaptation can serve as a critical mediator in mitigating the negative effects of temperature extremes. We then specify our augmented equation such that we can separate the protective effects of evaporative cooler and air conditioners:

$$\begin{aligned} M_{dt} = \alpha_0 + \sum_j \theta_j T_{dtj} + \sum_{l=1}^{2} \phi_l C_{dtl} + \sum_{l=1}^{2} \gamma_l (T_{dt}^{\geq 35} \times C_{dtl}) + \\ + \sum_k \delta_k P_{dtk} + \sum_h \beta_h H_{dth} + \mu_d + \rho_t + \lambda_{r(d)} t + \lambda^2_{r(d)} t^2 + \epsilon_{dt} \end{aligned} \tag{13}$$

We hypothesise that if cooling appliances are indeed a mediator of the negative effects of temperature extremes, then we would expect γ_l to be negative at the warmer temperature bins. Heat adaptation C_{dtl} is a vector including air-conditioning and cooler shares at the district-year

[31]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.

[32]Burgess et al. (2017) suggests that most heat-related deaths in India occurred in rural areas.

level. In further regressions we also test for the role of humidity in determining the protective effect of cooling appliances.

As in Barreca et al. (2016), a drawback of our analysis is that to identify the role of heat adaptation we do not employ a quasi-experimental setting. The risk is then to capture through the interaction coefficients correlation between the two appliances and other unobserved causes of mortality. To rule out this possibility, we run a robustness check where we interact the two shares with all the temperature bins. We so verify that the interactions are statistically significant only for the warmer bins — that is, when the appliances are used. Additionally, we provide specifications where we include the natural logarithm of income per capita and its interactions with the bins of temperature.

7.2 Results

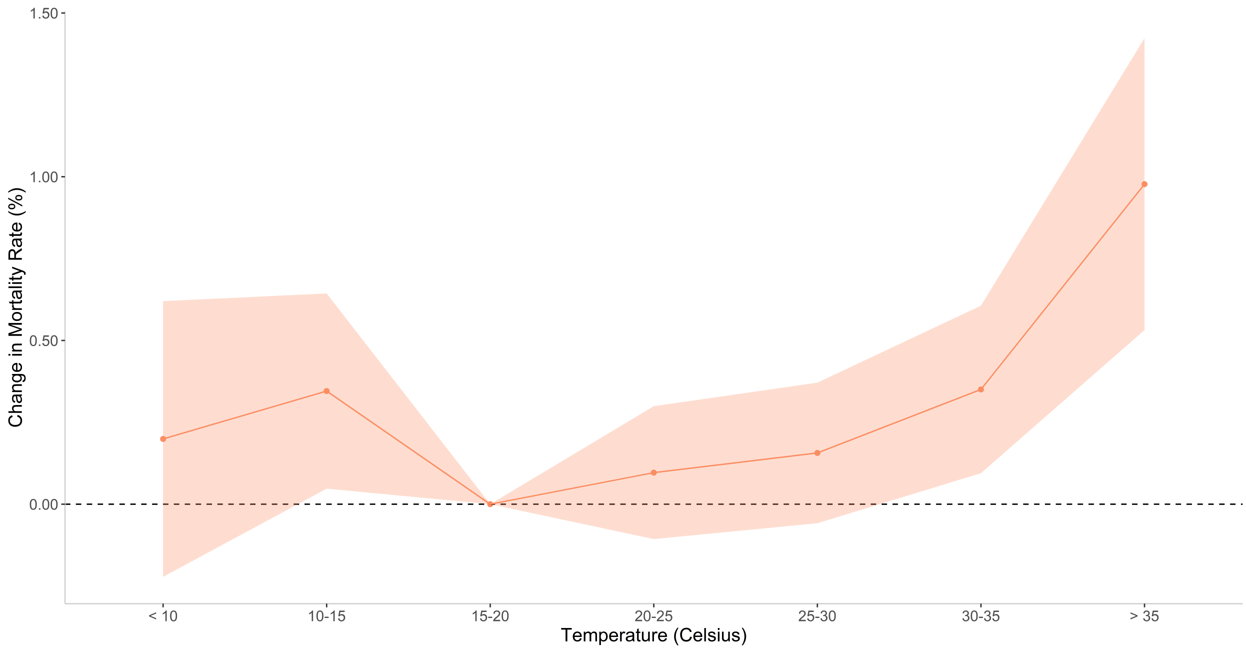
Main results.— Figure 2 presents the effects of an additional day in each temperature bin relative to the base range of 15-20°C. Our findings indicate that extreme warm temperatures have significant clinical implications and may lead to potentially fatal outcomes. It is however worthy to mention that, since we cannot distinguish the cause of death, the effect we identify includes both the direct — such as heat strokes — and indirect impacts on individual health — that is, through other illnesses, such as cardiovascular or renal diseases.

We observe that an additional day between 30 and 35 °C is associated with a 0.30% increase in the annual mortality rate. However, while this effect is noteworthy and statistically significant, the majority of heat-induced deaths occur on days within the most extreme warm bin. Comparing to a day in the range of 15-20 °C, an additional day at or above 35 °C is linked to a 1% increase in the annual mortality rate. This implies that, across our sample, about 6 deaths per 100,000 population can be attributed to an additional day in the extreme temperature bin.[33]

Our results align to the estimates from Burgess et al. (2017), who find that an additional day above 35 °C increases annual mortality rate by 0.74%. Similarly to their findings, our estimates for the association between mortality and colder temperatures are imprecise. However, cold temperatures are quite rare in India, as the country's average temperature hovers around 25 °C.

[33] This is obtained multiplying $0.00996 \times \overline{\mathrm{T}(\geq 35)} \times 100,000$

Figure 2: Estimated Temperature-mortality Relationship



Notes: The figure plots the response function between log annual mortality rate and average daily temperature bins (Equation 12) for the period 2014-2019. The response function is normalised with the 15-20°C category set equal to zero so that each estimate corresponds to the estimated impact of an additional day in bin j on the log annual mortality rate relative to the mortality rate associated with a day on which the temperature is between 15°C and 20°C. Full regression results are presented in Table D1. All regressions are weighted by the square root of district population. Standard errors are clustered at the district level.

Table D1 also provides the estimated coefficients for humidity and precipitation. We highlight two key findings from the analysis.

First, Columns 2 to 4 show that precipitation does not directly affect mortality. Second, Column 3 indicate that humidity alone is not significantly associated with mortality in India. This differs from the findings of Barreca (2012) for the United States, where humidity demonstrates a U-shaped pattern of influence on mortality. However, Column 4 suggest that controlling for humidity proves to be important in obtaining unbiased estimates of the impact of temperature. When controlling for humidity, the estimates for the effects of temperature bins increase compared to the specification in Columns 1 and 2.

In Table D2, we extend our analysis to include several types of interactions between temperature and humidity. In Column 2, we introduce an interaction term between average annual specific humidity and temperature bins. Similar to findings by Barreca (2012), our results suggest that heat-related deaths are more prevalent during humid conditions. This is evident as the non-interacted terms, particularly for temperatures $\geq$ 35 °C, become small and statistically insignificant. Moving on to Columns 3 to 5, we incorporate interactions between the warmest temperature bin and the two extreme humidity bins. These outcomes further validate the role of humid conditions. Notably, we observe no statistically significant effect of the interaction term with arid conditions ($0 - 3$ kg/g). In contrast, we estimate that the interaction with very humid conditions ($\geq$ 18 kg/g) significantly influences the impact of extreme heat. Specifically, under these conditions, an additional day is associated with 6.43 deaths per 100,000 population.

All our main results are robust to various alternative specifications. This includes restricting districts and years to the CHPS sample (Table D6-Table D7); imposing alternative fixed effects' specifications (Table D8); controlling for income per capita (Table D9); clustering standard errors at the state level (Table D10); and altering the temperature bins' interval to 3 degrees (Table D11).

Heterogeneity.— Our data also allows us to explore the hypothesis that weather vulnerability is correlated with differences in income. This is because credit constraints limit the possibility of individuals to respond to extreme temperature. We explore this relationship in two dimensions.

First, we estimate the temperature-mortality relationship function distinguishing between urban and rural mortality rates. The separate regressions are reported in Table D3. Consistent with the findings of Burgess et al. (2017), we find that majority of heat-related deaths occurs in rural areas. An additional day at or above 35 °C is associated with a 0.9-1% increase in the annual rural mortality rate, while with a 0.5-0.6% increase in annual urban mortality rate. Furthermore, warm and humid days are associated with increased deaths only in rural areas.

Second, in Table D4 we examine the differential responses between districts with a high and low share of individuals living in poverty. The results indicate that districts with a higher poverty share are also more affected by temperature extremes. An additional day at or above 35 °C is associated with a 1.7% increase in the annual mortality rate — equivalent to 8.31 deaths per 100,000 population. Conversely, areas where wealthier individuals reside exhibit a weaker temperature-mortality relationship. Even after accounting for humidity, the results remain robust.

Lastly, in Table D5, we combine both dimensions of heterogeneity. Again, we find that the most vulnerable individuals are those living in rural areas within districts with a higher share of poverty.

Heat Adaptation.— Table 5 presents the results of estimating Equation 13 to examine the protective effect of heat adaptation. We highlight four key findings.

First, Columns 1-3 show the coefficients of our preferred specification, where we model the interaction between the warmest temperature bin and the two technologies. We find strong evidence that cooling adaptation is associated with a significant decrease in mortality due to hot days. Notably, the protective effect of evaporative cooler is less precisely estimated, and once we control for air-conditioning ownership rate it becomes non-significant. Moreover, the effect of air-conditioning is more than three times as large as that of evaporative coolers. Specifically, a 1 percentage points increase in residential air-conditioning and cooler ownership is associated with a decrease in the mortality effect of a day at or above 35 °C by 0.021-0.027% and 0.006-0.007%, respectively. This corresponds to approximately 1.3% and 0.4% of the mortality effect of such hot days when no adaptation is taking place. The effect for air conditioners is in line with the one found by Barreca et al. (2016). They find that a 10 percentage points increase in the penetration rate of air-conditioning reduces by 10% the effect of a day above 32 °C (90 °F).

Second, we examine whether heat adaptation reduces the mortality effect of very humid days (Columns 4-6). Consistent with the finding of no significant effect of humidity on mortality, we do not observe any significant reduction in mortality from air conditioners and coolers in humid conditions. However, the mitigation effect of air conditioner remains larger in absolute value, and with the correct sign, with respect to the coefficient of cooler.

Third, in the last specification (Columns 7-9), we test whether the two technologies can protect households from extreme warm and humid days. We find that air conditioners are three times more effective than air coolers. These results align with the functioning of the two technologies, as air coolers perform well in dry conditions but poorly in very humid conditions, while air conditioners are effective in all weather conditions.

Lastly, we observe that the higher the penetration of these cooling technologies, the greater the reduction in the impact of extreme hot days. For example, in Delhi, where air-conditioning penetration increased by 20 percentage points between 2014 and 2019, the mortality effect of days at or above 35 °C (Table D1) was reduced by a further 41%.

Table 5: Protective Effect of Heat Adaptation

	Temperature			Humidity			Temperature $\times$ Humidity		
	Air Conditioner	Cooler	Both	Air Conditioner	Cooler	Both	Air Conditioner	Cooler	Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AC $\times$ T ($\geq$ 35)	-0.0270***		-0.0206**						
	(0.009)		(0.009)						
Cooler $\times$ T ($\geq$ 35)		-0.00769*	-0.00629						
		(0.004)	(0.005)						
AC $\times$ H ($\geq$ 18)				-0.000662		-0.000685			
				(0.002)		(0.002)			
Cooler $\times$ H ($\geq$ 18)					0.000507	0.000538			
					(0.001)	(0.001)			
AC $\times$ T ($\geq$ 35) $\times$ H ($\geq$ 18)							-0.000422***		-0.000384***
							(0.000)		(0.000)
Cooler $\times$ T ($\geq$ 35) $\times$ H ($\geq$ 18)								-0.0000512	-0.0000238
								(0.000)	(0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend $\times$ Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Observations	2753	2753	2753	2753	2753	2753	2753	2753	2753

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Regressions also include all the temperature and humidity bins, and precipitation terciles. Reference category for temperature is bin 15-20 ° C. Reference category for humidity is bin 9-12 g/kg. (1)-(9) clustered standard errors 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.

We test the robustness of our findings. First, we substitute the district-level ownership shares with state-level penetration shares. This is because CHPS are not perfectly representative at the district level, while they are at the state level (Table D12). The results remain consistent. Second, in Table D13 we interact the two shares with all the temperature bins. The results are more imprecisely estimated as we introduce many variables. However, sign and magnitude of the interaction with the warmest bins remain consistent. In addition, we do not find that coefficients at colder temperatures are statistically significant. Third, we introduce income and its interactions with all temperature bins as further controls (Table D14). The coefficients remain in the same order of magnitude. These robustness checks suggest that it is unlikely that our estimates of the protective effect of heat adaptation are correlated with unobserved determinants of mortality.

In summary, our findings demonstrate that high-temperature days lead to additional deaths in India, particularly during extremely warm days. Furthermore, given the correlation between income and access to cooling appliances, the benefits of heat adaptation are primarily experienced by a few. We find that most heat-related deaths occur in rural and poorer regions. Finally, despite the wider spread of evaporative coolers due to their lower cost, they are less effective in protecting individuals from extremely warm conditions compared to air-conditioning.

8 Discussion

To illustrate the economic significance of our findings, we provide a back-to-the-envelope calculation of the gross welfare gains related to the number of prevented deaths from heat adaptation, with particular attention to the differential performance of air conditioners and coolers. We also discuss the policy implications of our results, analysing the cost of policies aiming at subsidising heat adaptation technologies for households.

8.1 Benefits from Avoided Deaths

The estimates obtained in previous section allow to provide simple back-to-the-envelope calculations of the benefits from heat adaptation.

We begin by estimating the number of heat-induced deaths for in India. To do so, we use the estimated coefficients from the specification specified in Equation 13 (Column 3, Table 5).[34] For this exercise, we only consider the extreme bin ≥ 35 °C. Firstly, we calculate the number of deaths in India across the years 2014-2019 under the assumption of no adaptation as follows:

$$\text{Deaths}_{NoAdapt} = \hat{\theta}_{\geq 35} \times \overline{T}_{\geq 35} \times \overline{TPOP} \times \overline{M}$$

where both air conditioning and evaporative cooler ownership rates are set to zero, and we use the average country population in the period (country population ($\overline{TPOP}$), and the sample averages of mortality rate ($\overline{M}$) and number of days in the warmest bin ($\overline{T}_{\geq 35}$). Secondly, we compute the number of deaths when adaptation takes place:

$$\text{Deaths}_{Adapt} = \hat{\theta}_{\geq 35} \times \overline{T}_{\geq 35} \times \text{TPOP} \times \overline{M} - \sum_{l=1}^{2} \hat{\gamma}_{l\geq 35} \times \overline{T}_{\geq 35} \times \overline{C}_l \times \overline{TPOP} \times \overline{M}$$

This provides the percentage of lives saved in each adaptation scenario. Finally, to estimate the gross welfare gains related to the avoided deaths, we multiply by the estimated Indian Value of a Statistical Life (VSL) from Madheswaran (2007), which is 0.18 million dollars (15 million rupees).[35]

[34] We provide alternative results using the specification expressed in Column 9 of Table 5.

[35] Other estimates of the VSL for India have been used. For instance, Jack et al. (2022) uses 1 billion dollars. We prefer opting for a more conservative estimate.

Based on our estimates, during the period 2014-2019, approximately 0.865 million people in India would have died as a result of extreme heat if no adaptation technologies had been available. However, thanks to the use of air conditioners and evaporative coolers, about 21% of these excess deaths were avoided. This translates to a significant annual gross welfare gain of 32 billion dollars. This is equivalent to 2.1% of the average annual GDP in India in the period 2014-2019.

The largest contribution to the economic benefits comes from evaporative coolers (66%). This is because they are five times more spread than air conditioners. Indeed, if air conditioning had been as widely adopted as evaporative coolers, air conditioners alone would have avoided around 47% of heat-induced deaths, resulting in a larger annual gross welfare gain, 73 billion dollars. This corresponds to 4.9% of the average annual GDP. These estimates are similar to the ones obtained from Barreca (2012) for the United States in 1980 — 85-185 billion dollars.[36] Contrariwise, if evaporative coolers had been as prevalent as air conditioners, they would have avoided only around 2% of heat-related deaths. Critically, this shows the large disparities in terms of economic benefits that two technologies can provide.

There are however important drawbacks in our estimates. On the one hand, these estimates represent an upper bound. Our mortality data do not allow to estimate age-specific temperature-mortality responses. This means that we are assuming the same life expectancy for all individuals who would have died without heat adaptation. On the other hand, we might also underestimate the true economic benefits coming from heat-related adaptation. To obtain a monetary value, we use the VSL, which may not fully capture the value of preventing non-fatal risks for health.

8.2 Policy Implications

Our results have several policy implications. First, our findings highlight the potential public health benefits of using more effective cooling technologies in mitigating heat-related health risks. Whereas evaporative coolers are cheaper and more sustainable, they appear as a stop-gap solution to reduce the cooling gap. However, as heatwaves and extreme heat events are becoming more frequent and severe due to climate change, not increasing the access to the most effective technology may have significant health threats.

Second, we show that air conditioners are still not affordable most of the population in developing countries. In this sense, incentives, subsidies, or support programs are fundamental make air conditioners more accessible to vulnerable populations. Even though these policies may be expensive due to the price of air conditioners, the costs are likely to be lower than the benefits. To illustrate this, we can conduct a simple back-of-the-envelope calculation. We start assuming that the average annualised upfront cost for an air conditioner is about 3083 rupees, and the total number of households in India is about 302.4 million.[37] Subsidising 100% of the total cost to increase the penetration rate of air conditioner from 6% to the same level of evaporative cooler (33%) would cost about 3 billion dollars. In addition to upfront costs, we must consider the additional electricity expenses for each new household with air conditioning following the policy. This can be estimated by multiplying the coefficient for the bin $\geq$ 35 °C in Column 1 of Table C6 by i) the average annual number of days in the extreme temperature bin, ii) the average annual electricity consumption of a household with air conditioning, iii) electricity prices, and iv) the number of households with air conditioning post-policy. This calculation suggests an estimated additional electricity expenditure during days with temperature at or above 35°C equal to 0.56 billion dollars. Finally, this increased electricity usage would result in additional emissions, incurring a social cost for Indian society. We can estimate this emission-related social cost by multiplying the previously calculated additional electricity consumption (kWh) by i) Indian car-

[36]Critically, the average level of Indian GDP in our sample period is quite near to the GDP of the United States in 1980.

[37]The durability is assumed equal to ten years.

bon intensity (0.28), ii) the mean estimate (185 $/$tCO_2$) of the Social Cost of Carbon from Rennert et al. (2022), and once again, iii) the number of the new households with air-conditioning. This computation yields a social cost from emissions during days with temperature at or above 35°C equal to 3.7 million dollars. Thus, In conclusion, the estimated cost associated with subsidising air conditioners is notably smaller than the economic benefit such a policy would generate.

9 Conclusions

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

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

Critically, this technological disparity have important consequences for households' health. Our estimate indicate a clear difference in the protective effect of the two technologies against extreme heat. Air conditioners prove to highly effective at reducing heat-related deaths, accentuating the role of more advanced technologies. In contrast, evaporative coolers, while more accessible to credit constrained households, exhibit a comparatively modest effect. As a result, even when lower income households adapt, they remain exposed to the health effect of extreme heat. This disparity in outcomes underscores the pressing need for equitable technology dissemination, ensuring that economic benefits from lives saved are not prerogative of few.

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

Yet, it is important to acknowledge relevant limitations of our study. First, due to variations in the timing of the questions, in the household data we cannot directly isolate the impact of air conditioners and evaporative coolers on electricity demand. This would have allowed to estimate appliance-specific electricity consumption to employ in the mortality analysis. Owning an electric appliance is indeed not necessarily a synonym of utilising it. Additionally, our mortality data lack the granularity to differentiate across age categories, which impacts our back-of-the-envelope calculations for the economic benefits of heat adaptation. Moreover, the relatively short time span and annual frequency of our data limit the variation we can exploit to identify the effect of temperature and adaptation.

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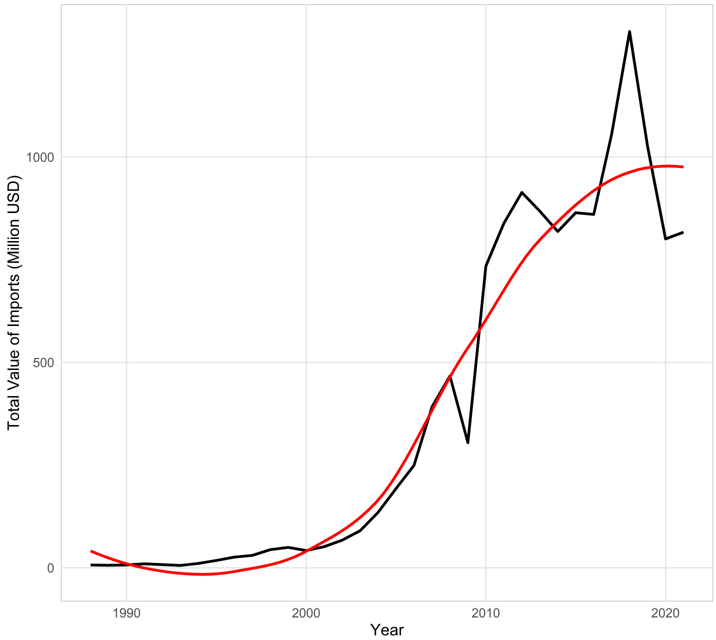
Appendix

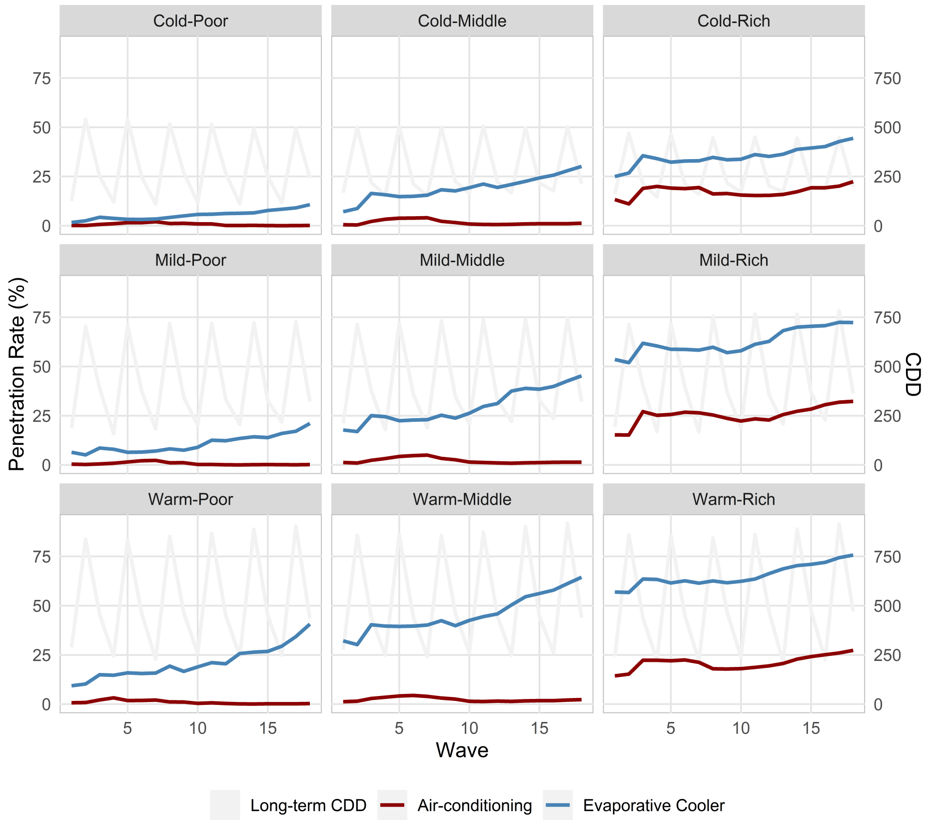
A. Data: Additional Statistics

Figure A1: Total Value (USD Millions) of Air-Conditioning Imports in India (1987-2021)



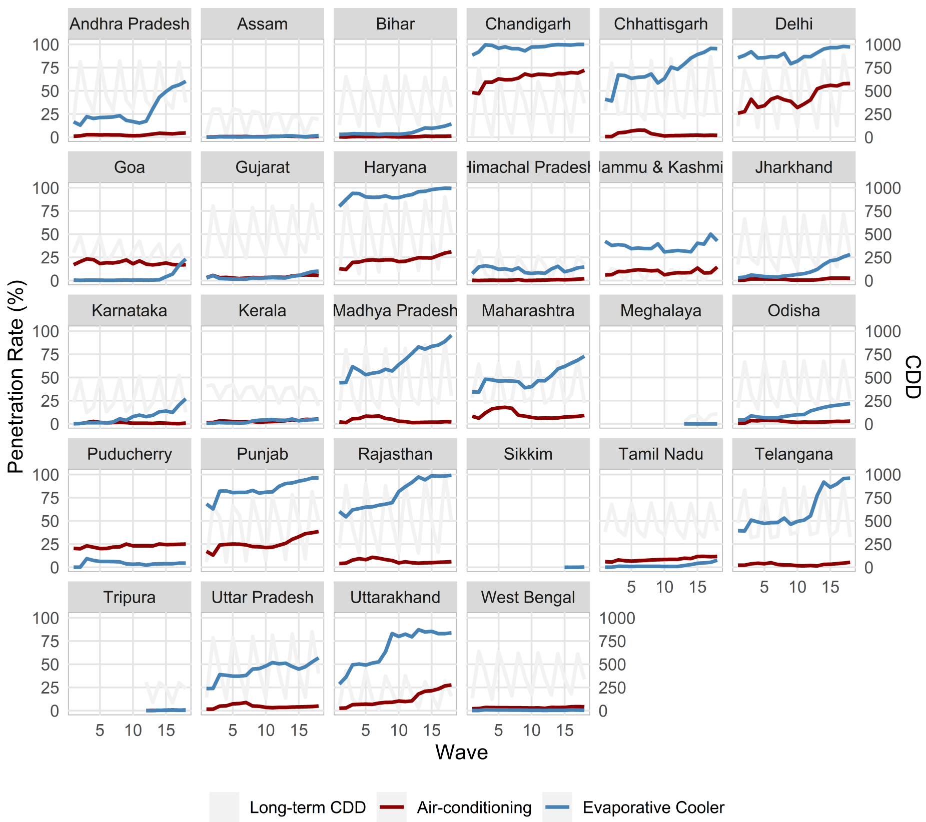
Notes: The black line represents the observed total value of air-conditioning imports in India. The red line is a locally weighted regression to capture the trend.

Figure A2: Air-conditioning and Evaporative Coolers Penetration Rates by Income Level and Climatic Conditions (2014-2019)



Notes: Red and blue lines: the trends in household ownership rate of the two appliances across our sample period. Grey line: a 10-year moving average of quarterly CDD in the previous decade. 'Poor', 'Middle' and 'Rich' respectively refer to households between the 1st and 2nd decile, between the 3rd and 8th decile, and between the 9th and 10th decile. 'Cold', 'Mild' and 'Warm' are terciles of a 30-year average of annual CDD.

Figure A3: Air-conditioning and Evaporative Coolers Penetration Rates by Indian State (2014-2019)



Notes: Red and blue lines: the trends in household ownership rate of the two appliances across our sample period. Grey line: a 10-year moving average of quarterly CDD in the previous decade.

Table A1: Data Sources for Each Analysis

Source	Type	Unit	Frequency	Years	Variables
			Extensive Margin		
CHPS	Panel	Household	Four-monthly	2014-2019	Air-conditioning, Evaporative Cooler, Household Income, Household characteristics
GLDAS	Panel	Grid	Daily	1981-2019	Cooling Degree Days
ERA5-Land	Panel	Grid	Daily	1981-2019	Precipitation
			Intensive Margin		
CHPS	Panel	Household	Monthly	2014-2019	Electricity Consumption, Household Income
ERA5-Land	Panel	Grid	Daily	1981-2019	Temperature Precipitation
NSS	Cross-sectional	Household	Yearly	2011	Electricity Price
			Mortality		
CRS	Panel	District	Annual	2014-2019	Mortality Rates
CHPS	Panel	Household	(Four-)Monthly	2014-2019	Household Income, Air-conditioning, Evaporative Cooler
ERA5-Land	Panel	Grid	Daily	1957-2019	Temperature Precipitation Humidity

Table A2: Descriptive Statistics at the Household Level - Urban vs Rural Areas and Income Quintiles

	Rural						Urban					
	Total	1st	2nd	3rd	4th	5th	Total	1st	2nd	3rd	4th	5th
CHPS:												
Air-conditioning (Dummy)	0.02	0.01	0.01	0.01	0.02	0.07	0.13	0.01	0.02	0.03	0.06	0.31
	(0.09)	(0.05)	(0.07)	(0.08)	(0.10)	(0.20)	(0.49)	(0.15)	(0.20)	(0.22)	(0.33)	(0.65)
Evaporative Cooler (Dummy)	0.29	0.10	0.21	0.33	0.42	0.56	0.42	0.20	0.33	0.37	0.41	0.52
	(0.31)	(0.18)	(0.27)	(0.33)	(0.36)	(0.40)	(0.70)	(0.57)	(0.69)	(0.69)	(0.70)	(0.70)
Electricity Quantity (kWh)	89.28	60.49	76.82	91.78	109.88	138.06	137.09	75.35	93.00	109.63	130.61	85.94
	(57.51)	(27.62)	(39.17)	(53.45)	(70.77)	(104.21)	(173.22)	(81.73)	(104.01)	(132.65)	(158.72)	(205.30)
Income (Rupee)	13406.28	6822.23	9817.41	12702.13	16981.04	29796.09	21435.13	7146.55	10087.13	13013.10	17501.73	35917.25
	(11867.20)	(2615.27)	(4541.54)	(6863.16)	(10294.84)	(30454.94)	(30286.02)	(4403.73)	(6267.55)	(8648.15)	(12414.11)	(40270.70)
Power Availability	21.24	21.22	20.69	21.23	21.66	21.69	22.70	22.65	22.45	22.67	22.73	22.80
	(2.84)	(2.62)	(2.86)	(2.83)	(2.79)	(3.03)	(4.01)	(4.43)	(4.58)	(4.15)	(3.93)	(3.67)
N°Households	71232						139328					

Notes: Means and standard deviations (in parentheses) across the survey period are reported. Air-conditioning, air cooler, and power availability are at the four-monthly level. All other variables are at the monthly level. Weights for country-level representativeness are applied.

Table A3: Descriptive Statistics at the Household Level across Years - Urban vs Rural Areas and Income Quintiles

	Total		Rural		Urban	
	2014	2019	2014	2019	2014	2019
CHPS:						
Air-conditioning (Dummy)	0.04	0.07	0.01	0.02	0.11	0.17
	(0.21)	(0.25)	(0.07)	(0.09)	(0.46)	(0.52)
Evaporative Cooler (Dummy)	0.24	0.44	0.19	0.41	0.34	0.51
	(0.45)	(0.49)	(0.27)	(0.35)	(0.71)	(0.70)
Electricity Quantity (kWh)	92.35	113.56	76.19	99.65	125.94	142.04
	(95.47)	(100.83)	(50.14)	(61.20)	(176.61)	(173.05)
Income (Rupee)	13251.31	20313.84	10949.97	17460.70	18035.89	26157.00
	(16556.57)	(23917.88)	(10575.25)	(16877.12)	(24602.18)	(33885.25)
Urban	0.34	0.33	-	-	-	-
	(0.49)	(0.47)	-	-	-	-
Power Availability	20.61	22.67	19.88	22.35	22.03	23.31
	(4.95)	(2.45)	(3.47)	(1.92)	(5.58)	(2.50)
N° Households			210560			

Notes: Means and standard deviations (in parentheses) across the survey period are reported. Air-conditioning, air cooler, and power availability are at the four-monthly level. All other variables are at the monthly level. Weights for country-level representativeness are applied.

B.1 Extensive Margin: Main Results

Table B1: Impact of Temperature on the Prevalence of Cooling Appliances

	Both Appliances		Air Conditioner		Evaporative Cooler	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{CDD}}$ (100s)	0.0146***	-0.0373***	0.0000375	-0.0101	0.0145***	-0.0423***
	(0.002)	(0.010)	(0.001)	(0.007)	(0.003)	(0.013)
Log(Income)	0.0863***	0.0637***	0.0592***	0.0547***	0.0611***	0.0363**
	(0.007)	(0.010)	(0.006)	(0.006)	(0.010)	(0.015)
$\overline{\text{CDD}}$ $\times$ Log(Income)		0.00548***		0.00107		0.00600***
		(0.001)		(0.001)		(0.002)
Urban (Yes = 1)	0.0143	0.0149	0.0380***	0.0381***	-0.00945	-0.00878
	(0.014)	(0.014)	(0.006)	(0.006)	(0.016)	(0.016)
Precipitation	-0.0517***	-0.0488***	0.000392	0.000959	-0.0556***	-0.0524***
	(0.017)	(0.017)	(0.005)	(0.005)	(0.019)	(0.019)
Precipitation^2	0.00709	0.00654	0.000998	0.000891	0.00693	0.00633
	(0.013)	(0.013)	(0.002)	(0.002)	(0.014)	(0.014)
Power Availability	0.0107***	0.0107***	-0.000245	-0.000245	0.0126***	0.0126***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
Generators (%)	0.610***	0.609***	0.129***	0.129***	0.643***	0.641***
	(0.048)	(0.047)	(0.022)	(0.022)	(0.052)	(0.051)
Head Age	0.00119***	0.00119***	0.00104***	0.00104***	0.000871***	0.000879***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Head Gender (Female = 1)	-0.00138	-0.00138	-0.00100	-0.00101	-0.00138	-0.00138
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Primary	0.0451***	0.0452***	0.0118***	0.0118***	0.0382***	0.0383***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)
Secondary	0.0846***	0.0847***	0.0321***	0.0322***	0.0721***	0.0723***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)
Post-secondary	0.144***	0.143***	0.152***	0.152***	0.0976***	0.0974***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.008)	(0.008)
2-5 Members	0.00722	0.00632	-0.0371***	-0.0372***	0.0273**	0.0263**
	(0.011)	(0.011)	(0.005)	(0.005)	(0.012)	(0.012)
5-10 Members	-0.0115	-0.0123	-0.0606***	-0.0608***	0.0175	0.0165
	(0.013)	(0.012)	(0.007)	(0.007)	(0.015)	(0.015)
$\geq$ 11 Members	-0.0138	-0.0145	-0.0865***	-0.0867***	0.0255	0.0248
	(0.021)	(0.020)	(0.013)	(0.013)	(0.023)	(0.023)
Plastics	-0.0473***	-0.0480***	-0.00942**	-0.00957**	-0.0355**	-0.0363**
	(0.014)	(0.014)	(0.005)	(0.005)	(0.016)	(0.016)
Wood and Grass	-0.106***	-0.106***	0.00127	0.00130	-0.102***	-0.102***
	(0.014)	(0.014)	(0.003)	(0.003)	(0.014)	(0.014)
Stone	0.0760***	0.0759***	-0.0350***	-0.0350***	0.0792***	0.0791***
	(0.025)	(0.025)	(0.011)	(0.011)	(0.025)	(0.025)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State $\times$ Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.51	0.51	0.21	0.21	0.51	0.51
Observations	2442730	2442730	2442730	2442730	2442730	2442730

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'. (1)-(3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B2: Impact of Temperature on the Adoption of Cooling Appliances

	Both Appliances		Air Conditioner		Evaporative Cooler	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{CDD}}$	-0.000669	-0.00723**	0.000215	0.00151	-0.000767*	-0.00943***
	(0.000)	(0.003)	(0.000)	(0.001)	(0.000)	(0.003)
Log(Income)	0.0413***	0.0383***	0.0134***	0.0140***	0.0348***	0.0310***
	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
$\overline{\text{CDD}} \times$ Log(Income)		0.000693**		-0.000137		0.000914***
		(0.000)		(0.000)		(0.000)
Power Availability	0.00429**	0.00430**	-0.000902*	-0.000903*	0.00384**	0.00384**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Generators (%)	0.358***	0.358***	0.126***	0.126***	0.351***	0.351***
	(0.057)	(0.057)	(0.019)	(0.019)	(0.057)	(0.057)
Precipitation	-0.00374	-0.00345	-0.00350	-0.00355	-0.00179	-0.00141
	(0.005)	(0.005)	(0.002)	(0.002)	(0.005)	(0.005)
Precipitation^2	0.0000601	0.0000564	0.00215*	0.00215*	-0.00155	-0.00156
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend $\times$ State	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.05	0.02	0.02	0.06	0.06
Observations	2432366	2432366	2432366	2432366	2432366	2432366

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights

Table B3: Impact of Temperature on the Adoption of Cooling Appliances — Urban and Rural

	Air Conditioner		Evaporative Cooler	
	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)
$\overline{\text{CDD}}$ (100s)	0.000512	0.000903	-0.0130***	-0.00288
	(0.001)	(0.002)	(0.004)	(0.003)
Log(Income)	0.00554***	0.0342***	0.0316***	0.0284***
	(0.001)	(0.003)	(0.003)	(0.004)
$\overline{\text{CDD}} \times$ Log(Income)	-0.0000104	-0.0000845	0.00128***	0.000225
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitations Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Quadratic Trend $\times$ State	Yes	Yes	Yes	Yes
R^2	0.50	0.72	0.75	0.80
Observations	786354	1646012	786354	1646012

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(4) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B4: Impact of Temperature on the Adoption of Cooling Appliances — Income Level

	Air Conditioner			Evaporative Cooler		
	Poor	Middle	Rich	Poor	Middle	Rich
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{CDD}}$ (100s)	0.00105	-0.000831	0.000590	-0.0310***	-0.0250***	0.0000605
	(0.001)	(0.001)	(0.006)	(0.005)	(0.006)	(0.004)
Log(Income)	0.00320***	0.00752***	0.0437***	0.0184***	0.0324***	0.0159***
	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)	(0.004)
$\overline{\text{CDD}} \times$ Log(Income)	-0.000115	0.000104	-0.0000134	0.00346***	0.00256***	-0.0000619
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend $\times$ State	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.47	0.47	0.72	0.68	0.74	0.84
Observations	485084	1219147	485420	485084	1219147	485420

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B5: Impact of Temperature on the Adoption of Cooling Appliances — Income Level and Urban and Rural

	Air Conditioner						Evaporative Cooler					
	Rural			Urban			Rural			Urban		
	Poor	Middle	Rich	Poor	Middle	Rich	Poor	Middle	Rich	Poor	Middle	Rich
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\overline{\text{CDD}}$ (100s)	0.00194	0.00131	0.00768	-0.00438**	-0.00698**	-0.00896	-0.0315***	-0.0287***	-0.000432	-0.0230***	-0.0139**	0.00206
	(0.001)	(0.002)	(0.007)	(0.002)	(0.003)	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)	(0.004)
Log(Income)	0.00305***	0.00449***	0.0237***	0.00391***	0.0156***	0.0631***	0.0163***	0.0312***	0.0226***	0.0327***	0.0363***	0.0103**
	(0.001)	(0.001)	(0.005)	(0.001)	(0.002)	(0.005)	(0.004)	(0.005)	(0.006)	(0.008)	(0.005)	(0.004)
$\overline{\text{CDD}} \times$ Log(Income)	-0.000208	-0.000109	-0.000629	0.000470**	0.000719**	0.000880	0.00353***	0.00291***	-0.0000609	0.00249***	0.00142**	-0.000266
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend $\times$ State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.48	0.43	0.59	0.46	0.51	0.72	0.65	0.73	0.81	0.73	0.78	0.85
Observations	243703	407412	79366	241381	811735	406054	243703	407412	79366	241381	811735	406054

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(12) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B6: Impact of Temperature on the Adoption of Cooling Appliances — Climate

	Air Conditioner			Evaporative Cooler		
	Cold	Mild	Warm	Cold	Mild	Warm
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{CDD}}$ (100s)	0.00306	0.000877	0.000374	-0.0156***	-0.000243	-0.00156
	(0.003)	(0.001)	(0.001)	(0.006)	(0.004)	(0.004)
Log(Income)	0.0152***	0.0134***	0.0128***	0.0122***	0.0370***	0.0435***
	(0.003)	(0.002)	(0.002)	(0.005)	(0.004)	(0.005)
$\overline{\text{CDD}}$ × Log(Income)	-0.000353	-0.0000251	-0.0000400	0.00159***	-0.0000936	0.0000270
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend × State	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.68	0.70	0.66	0.76	0.77	0.76
Observations	829670	739207	863489	829670	739207	863489

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

B.2 Extensive Margin: Robustness Checks

Table B7: Impact of Temperature on the Prevalence of Cooling Appliances — Alternative Fixed-effects Specification

	FE	FE	FE	FE	FE
	(1)	(2)	(3)	(4)	(5)
$\overline{\text{CDD}}$ (100s)	0.00638***	-0.000320	0.000334	-0.000642	-0.000494
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Log(Income)	0.0923***	0.101***	0.0925***	0.0936***	0.0933***
	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No	No
District FE	No	Yes	Yes	Yes	Yes
Wave FE	No	No	Yes	Yes	Yes
Linear State × Year Trend	No	No	No	Yes	No
Quadratic State × Year Trend	No	No	No	No	Yes
R^2	0.49	0.57	0.57	0.58	0.59
Observations	2442730	2442730	2442730	2442730	2442730

Notes: Column (5) shows the main specification. The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(5) clustered standard errors at state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights

Table B8: Impact of Temperature on the Prevalence of Air-conditioning — Alternative Fixed-effects Specification

	FE (1)	FE (2)	FE (3)	FE (4)	FE (5)
$\overline{\text{CDD}}$ (100s)	-0.000627**	-0.000548***	0.000207	0.000400*	0.000405*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Income)	0.0558***	0.0537***	0.0583***	0.0581***	0.0582***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No	No
District FE	No	Yes	Yes	Yes	Yes
Wave FE	No	No	Yes	Yes	Yes
Linear State × Year Trend	No	No	No	Yes	No
Quadratic State × Year Trend	No	No	No	No	Yes
R^2	0.20	0.24	0.25	0.25	0.25
Observations	2442730	2442730	2442730	2442730	2442730

Notes: Column (5) shows the main specification. The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(5) clustered standard errors at state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights

Table B9: Impact of Temperature on the Prevalence of Cooler — Alternative Fixed-effects Specification

	FE (1)	FE (2)	FE (3)	FE (4)	FE (5)
$\overline{\text{CDD}}$ (100s)	0.00680***	-0.00000788	0.000354	-0.000847*	-0.000725*
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Log(Income)	0.0695***	0.0829***	0.0718***	0.0726***	0.0722***
	(0.010)	(0.005)	(0.004)	(0.004)	(0.004)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No	No
District FE	No	Yes	Yes	Yes	Yes
Wave FE	No	No	Yes	Yes	Yes
Linear State × Year Trend	No	No	No	Yes	No
Quadratic State × Year Trend	No	No	No	No	Yes
R^2	0.49	0.58	0.58	0.60	0.60
Observations	2442730	2442730	2442730	2442730	2442730

Notes: Column (5) shows the main specification. The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(5) clustered standard errors at state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights

Table B10: Impact of Temperature and Income on the Prevalence of Cooling Appliances — Alternative Standard Errors Specifications

	All	Air-conditioning	Evaporative Cooler
	(1)	(2)	(3)
$\overline{\text{CDD}}$ (100s)	-0.000494	0.000405*	-0.000725
	(0.000)	(0.000)	(0.000)
Log(Income)	0.0933***	0.0582***	0.0722***
	(0.007)	(0.007)	(0.012)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes
R^2	0.59	0.25	0.60
Observations	2442730	2442730	2442730

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(3) clustered standard errors at state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B11: Impact of Temperature on the Prevalence of Cooling Appliances — Nonlinear Specification

	FE	FE	FE
	(1)	(2)	(3)
$\overline{\text{CDD}}$ (100s)	0.0146***	0.00237	0.00935
	(0.002)	(0.004)	(0.010)
$\overline{\text{CDD}}^2$		0.00125***	-0.000477
		(0.000)	(0.002)
$\overline{\text{CDD}}^3$			0.000109
			(0.000)
Log(Income)	0.0863***	0.0863***	0.0862***
	(0.007)	(0.007)	(0.007)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes
R^2	0.51	0.51	0.51
Observations	2442730	2442730	2442730

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B12: Impact of Temperature on the Prevalence of Air-conditioning — Nonlinear Specification

	FE (1)	FE (2)	FE (3)
$\overline{\text{CDD}}$ (100s)	0.0000375	0.00369***	-0.000971
	(0.001)	(0.001)	(0.004)
$\overline{\text{CDD}}^2$		-0.000372**	0.000780
		(0.000)	(0.001)
$\overline{\text{CDD}}^3$			-0.0000730
			(0.000)
Log(Income)	0.0592***	0.0592***	0.0592***
	(0.006)	(0.006)	(0.006)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes
R^2	0.21	0.21	0.21
Observations	2442730	2442730	2442730

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B13: Impact of Temperature on the Prevalence of Coolers — Nonlinear Specification

	FE (1)	FE (2)	FE (3)
$\overline{\text{CDD}}$ (100s)	0.0145***	0.000153	0.00619
	(0.003)	(0.004)	(0.010)
$\overline{\text{CDD}}^2$		0.00147***	-0.0000261
		(0.000)	(0.002)
$\overline{\text{CDD}}^3$			0.0000945
			(0.000)
Log(Income)	0.0611***	0.0610***	0.0610***
	(0.010)	(0.010)	(0.010)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes
R^2	0.60	0.60	0.60
Observations	2442730	2442730	2442730

Notes: The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B14: Impact of Temperature on the Prevalence of Cooling Appliances — Logit

	Both Appliances		Air Conditioner		Evaporative Cooler	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{CDD}}$ (100s)	0.0162***	-0.0509***	0.0000764	0.00233	0.0160***	-0.0537***
	(0.002)	(0.011)	(0.000)	(0.004)	(0.002)	(0.013)
Log(Income)	0.0826***	0.0529***	0.0460***	0.0469***	0.0587***	0.0283*
	(0.008)	(0.012)	(0.002)	(0.002)	(0.010)	(0.015)
$\overline{\text{CDD}} \times$ Log(Income)		0.00715***		-0.000223		0.00743***
		(0.001)		(0.000)		(0.002)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State $\times$ Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2442730	2442730	2442730	2442730	2442730	2442730

Notes: Average marginal effects (AMEs) are reported. The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B15: Impact of Temperature on the Prevalence of Cooling Appliances — Multinomial Logit

	Multinomial Logit (1)	Multinomial Logit (2)
$\overline{\text{CDD}}$ (100s) $\times$		
Evaporative Cooler	0.0168***	-0.0483***
	(0.002)	(0.012)
Air Conditioner	0.00105**	-0.00887**
	(0.000)	(0.003)
Log(Income) $\times$		
Evaporative Cooler	0.0388***	0.0100
	(0.008)	(0.013)
Air Conditioner	0.0484***	0.0442***
	(0.002)	(0.002)
($\overline{\text{CDD}}$ $\times$ Log(Income)) $\times$		
Evaporative Cooler		0.00696***
		(0.001)
Air Conditioner		0.00103***
		(0.000)
Precipitations Controls	Yes	Yes
Household Controls	Yes	Yes
Wave FE	Yes	Yes
State FE	Yes	Yes
Quadratic State $\times$ Year Trend	Yes	Yes
Observations	2442958	2442958

Notes: Average marginal effects (AMEs) are reported. The dependent variable is a dummy variable (0,1) indicating the ownership of the appliance. (1)-(2) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

C.1 Intensive Margin: Main Results

Table C1: Impact of Temperature on Electricity Quantity using Temperature Bins

	FE (1)	FE (2)	FE (3)
< 11	-0.000772	-0.00116*	-0.00108*
	(0.001)	(0.001)	(0.001)
$11 - 14$	-0.000679	-0.000857*	-0.000877*
	(0.000)	(0.000)	(0.000)
$14 - 17$	0.000486	0.000375	0.000380
	(0.001)	(0.001)	(0.001)
$20 - 23$	0.000768*	0.000708	0.000681
	(0.000)	(0.000)	(0.000)
$23 - 26$	0.00125***	0.00119***	0.00114***
	(0.000)	(0.000)	(0.000)
$26 - 29$	0.00202***	0.00195***	0.00189***
	(0.000)	(0.000)	(0.000)
$29 - 32$	0.00211***	0.00225***	0.00223***
	(0.000)	(0.000)	(0.000)
$32 - 35$	0.00192***	0.00210***	0.00205***
	(0.000)	(0.000)	(0.000)
≥ 35	0.00432***	0.00463***	0.00464***
	(0.001)	(0.001)	(0.001)
Log(Income)			0.0770***
			(0.006)
Precipitations Controls	No	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.001	0.001	0.018
Observations	7950694	7950694	7950694

Notes: The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. (1), (2) and (3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C2: Heterogeneous Impact of Temperature on Electricity Quantity using Temperature Bins — Urban and Rural Areas

	Rural	Urban
	(1)	(2)
< 11	-0.00120*	-0.0000935
	(0.001)	(0.001)
$11-14$	-0.000725	-0.00104*
	(0.001)	(0.001)
$14-17$	0.000438	0.000525
	(0.001)	(0.001)
$20-23$	0.000497	0.00126*
	(0.000)	(0.001)
$23-26$	0.000873**	0.00181***
	(0.000)	(0.001)
$26-29$	0.00147***	0.00294***
	(0.000)	(0.001)
$29-32$	0.00163***	0.00350***
	(0.001)	(0.001)
$32-35$	0.00149***	0.00337***
	(0.001)	(0.001)
≥ 35	0.00318***	0.00736***
	(0.001)	(0.001)
Log(Income)	0.0518***	0.206***
	(0.004)	(0.013)
Precipitations Controls	Yes	Yes
Household FE	Yes	Yes
Month-Year FE	Yes	Yes
R^2	0.011	0.056
Observations	2498975	5451719

Notes: The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. (1) and (2) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C3: Heterogeneous Impact of Temperature on Electricity Quantity using Temperature Bins — Income Levels

	Poor	Middle	Rich
	(1)	(2)	(3)
< 11	-0.000598	-0.000910	-0.00230**
	(0.001)	(0.001)	(0.001)
$11 - 14$	0.000705	-0.00185***	0.000194
	(0.001)	(0.001)	(0.001)
$14 - 17$	0.000480	0.000874	-0.00148
	(0.001)	(0.001)	(0.002)
$20 - 23$	0.000959*	0.000751	-0.000209
	(0.001)	(0.000)	(0.001)
$23 - 26$	0.00121***	0.00112***	0.000895*
	(0.000)	(0.000)	(0.001)
$26 - 29$	0.00194***	0.00185***	0.00192***
	(0.001)	(0.000)	(0.001)
$29 - 32$	0.00195***	0.00217***	0.00275***
	(0.001)	(0.001)	(0.001)
$32 - 35$	0.00178***	0.00170***	0.00370***
	(0.001)	(0.001)	(0.001)
≥ 35	0.00381***	0.00419***	0.00693***
	(0.001)	(0.001)	(0.001)
Log(Income)	0.0917***	0.0594***	0.123***
	(0.009)	(0.004)	(0.016)
Precipitations Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.019	0.013	0.041
Observations	1646801	3991330	1534166

Notes: The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. "Poor", "Middle" and "Rich" respectively refers to households between the 1st and 2nd decile, between the 3rd and 8th decile, and between the 9th and 10th decile. (1), (2) and (3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C4: Impact of Temperature on Electricity Quantity using Temperature Bins — Income Levels and Urban and Rural Areas

	Rural			Urban		
	Poor	Middle	Rich	Poor	Middle	Rich
	(1)	(2)	(3)	(4)	(5)	(6)
< 11	-0.000857	-0.00125*	-0.00192*	0.00130	0.000505	-0.00179
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$11 - 14$	0.00128	-0.00171**	-0.000120	-0.00153*	-0.00201***	-0.000506
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$14 - 17$	0.000317	0.000333	-0.0000656	0.00193*	0.00230**	-0.00291
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$20 - 23$	0.000782	0.000234	-0.000216	0.00234***	0.00203***	-0.000319
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$23 - 26$	0.00112**	0.000607	0.000665	0.00206***	0.00236***	0.000764
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$26 - 29$	0.00164***	0.00113**	0.00179**	0.00381***	0.00353***	0.00175**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$29 - 32$	0.00162***	0.00134**	0.00203***	0.00379***	0.00404***	0.00268***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$32 - 35$	0.00148**	0.00102*	0.00280***	0.00363***	0.00339***	0.00362***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
≥ 35	0.00345***	0.00271***	0.00422***	0.00566***	0.00748***	0.00779***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Log(Income)	0.0822***	0.0421***	0.0454***	0.196***	0.177***	0.252***
	(0.008)	(0.004)	(0.006)	(0.013)	(0.012)	(0.019)
Precipitations Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.017	0.008	0.013	0.041	0.041	0.088
Observations	791899	1293061	236447	854902	2698269	1297719

Notes: The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. 'Poor', 'Middle' and 'Rich' respectively refer to households between the 1st and 2nd decile, between the 3rd and 8th decile, and between the 9th and 10th decile. (1) to (6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C5: Heterogeneous Impact of Temperature on Electricity Quantity using Temperature Bins — Air Conditioner and Evaporative Cooler

	Air Conditioner	Evaporative Cooler
	(1)	(2)
< 11	-0.00181	-0.00280*
	(0.001)	(0.001)
$11 - 14$	0.000532	-0.00293***
	(0.001)	(0.001)
$14 - 17$	-0.00214	-0.00144
	(0.002)	(0.001)
$20 - 23$	0.000126	-0.00112
	(0.001)	(0.001)
$23 - 26$	0.00105*	-0.000308
	(0.001)	(0.001)
$26 - 29$	0.00169**	0.000758
	(0.001)	(0.001)
$29 - 32$	0.00315***	0.00153**
	(0.001)	(0.001)
$32 - 35$	0.00425***	0.00169**
	(0.001)	(0.001)
≥ 35	0.00726***	0.00429***
	(0.002)	(0.001)
Log(Income)	0.138***	0.0465***
	(0.016)	(0.004)
Precipitations Controls	Yes	Yes
Household FE	Yes	Yes
Month-Year FE	Yes	Yes
R^2	0.036	0.011
Observations	724127	3648335

Notes: The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. (1) and (2) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

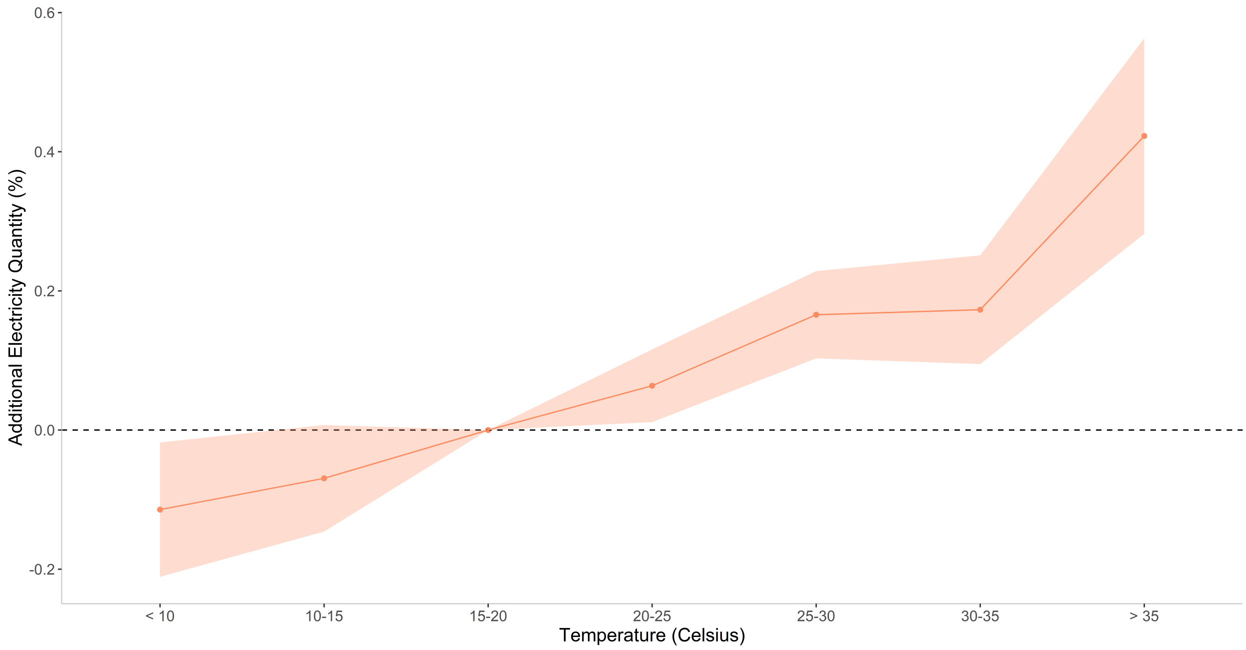
Table C6: Heterogeneous Impact of Temperature on Electricity Quantity using Temperature Bins — Air Conditioner and Evaporative Cooler, only Rich Households

	Air Conditioner	Evaporative Cooler
	(1)	(2)
< 11	-0.00260	-0.00313*
	(0.002)	(0.002)
$11 - 14$	0.000662	-0.000643
	(0.001)	(0.001)
$14 - 17$	-0.00293	-0.00267
	(0.002)	(0.002)
$20 - 23$	0.000407	-0.000354
	(0.001)	(0.001)
$23 - 26$	0.00115	-0.0000127
	(0.001)	(0.001)
$26 - 29$	0.00196**	0.00104
	(0.001)	(0.001)
$29 - 32$	0.00416***	0.00288***
	(0.001)	(0.001)
$32 - 35$	0.00518***	0.00344***
	(0.001)	(0.001)
≥ 35	0.00939***	0.00677***
	(0.002)	(0.001)
Log(Income)	0.167***	0.0769***
	(0.021)	(0.010)
Precipitations Controls	Yes	Yes
Household FE	Yes	Yes
Month-Year FE	Yes	Yes
R^2	0.048	0.021
Observations	490613	995301

Notes: The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. (1) and (2) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

C.2 Intensive Margin: Additional Figures

Figure C1: Electricity-temperature Response Function — 5-degree Temperature Bins



C.3 Intensive Margin: Robustness Checks

Table C7: Impact of Temperature on Monthly Electricity Quantity — Alternative Time Fixed Effects

	FE (1)	FE (2)	FE (3)	FE (4)
< 11	-0.00205***	-0.00108*	-0.00145**	-0.000719
	(0.001)	(0.001)	(0.001)	(0.001)
$11 - 14$	-0.00185***	-0.000877*	-0.00107**	-0.000283
	(0.001)	(0.000)	(0.000)	(0.000)
$14 - 17$	0.000470	0.000380	0.000555	0.000163
	(0.001)	(0.001)	(0.001)	(0.001)
$20 - 23$	0.000476	0.000681	0.000670	0.000626
	(0.000)	(0.000)	(0.000)	(0.000)
$23 - 26$	0.00145***	0.00114***	0.00145***	0.000929***
	(0.000)	(0.000)	(0.000)	(0.000)
$26 - 29$	0.00231***	0.00189***	0.00246***	0.00176***
	(0.000)	(0.000)	(0.000)	(0.000)
$29 - 32$	0.00294***	0.00223***	0.00266***	0.00186***
	(0.000)	(0.000)	(0.000)	(0.000)
$32 - 35$	0.00279***	0.00205***	0.00275***	0.00192***
	(0.000)	(0.000)	(0.000)	(0.000)
≥ 35	0.00599***	0.00464***	0.00471***	0.00413***
	(0.001)	(0.001)	(0.001)	(0.001)
Log(Income)	0.0925***	0.0770***	0.0769***	0.0776***
	(0.007)	(0.006)	(0.006)	(0.006)
Precipitations Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	No	No
Month-Year FE	No	Yes	No	Yes
Month-Year Trend	No	No	Yes	No
Quadratic State $\times$ Year Trend	No	No	No	Yes
R^2	0.027	0.018	0.018	0.019
Observations	7950694	7950694	7950694	7950694

Notes: Column (2) shows main specification results. The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. (1), (2), (3) and (4) clustered std. errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C8: Impact of Temperature on Electricity Quantity — Alternative Time-Invariant Fixed Effects

	FE (1)	FE (2)	FE (3)
< 11	-0.00108*	-0.000779	-0.00325*
	(0.001)	(0.001)	(0.002)
$11 - 14$	-0.000877*	-0.000834	0.00143
	(0.000)	(0.001)	(0.001)
$14 - 17$	0.000380	0.000766	-0.00152
	(0.001)	(0.001)	(0.001)
$20 - 23$	0.000681	0.000783*	-0.000936
	(0.000)	(0.000)	(0.001)
$23 - 26$	0.00114***	0.00126***	0.00116
	(0.000)	(0.000)	(0.001)
$26 - 29$	0.00189***	0.00195***	0.00392***
	(0.000)	(0.000)	(0.001)
$29 - 32$	0.00223***	0.00239***	0.00627***
	(0.000)	(0.000)	(0.002)
$32 - 35$	0.00205***	0.00202***	0.00282*
	(0.000)	(0.000)	(0.002)
≥ 35	0.00464***	0.00480***	0.00893***
	(0.001)	(0.001)	(0.002)
Log(Income)	0.0770***	0.182***	0.226***
	(0.006)	(0.010)	(0.014)
Precipitations Controls	Yes	Yes	Yes
Household FE	Yes	No	No
District FE	No	Yes	No
State FE	No	No	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.018	0.095	0.130
Observations	7950694	7953221	7953221

Notes: Column (1) shows main specification results. The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. (1), (2) and (3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C9: Impact of Temperature on Monthly Electricity Quantity — Electricity in Level

	FE (1)	FE (2)	FE (3)
< 11	-0.395***	-0.452***	-0.441***
	(0.117)	(0.117)	(0.113)
$11 - 14$	-0.380***	-0.407***	-0.409***
	(0.084)	(0.086)	(0.085)
$14 - 17$	0.0250	0.00843	0.00914
	(0.105)	(0.104)	(0.104)
$20 - 23$	0.00239	-0.00764	-0.0115
	(0.057)	(0.057)	(0.057)
$23 - 26$	0.0887**	0.0779*	0.0714*
	(0.044)	(0.044)	(0.043)
$26 - 29$	0.171***	0.161***	0.152***
	(0.050)	(0.049)	(0.049)
$29 - 32$	0.182***	0.205***	0.203***
	(0.061)	(0.061)	(0.061)
$32 - 35$	0.187***	0.213***	0.205***
	(0.058)	(0.060)	(0.060)
≥ 35	0.578***	0.623***	0.624***
	(0.133)	(0.134)	(0.133)
Log(Income)			10.88***
			(1.001)
Precipitations Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.001	0.001	0.016
Observations	7950694	7950694	7950694

Notes: The dependent variable is monthly electricity quantity (in kWh). Reference category is bin 17-20. (1), (2) and (3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C10: Impact of Temperature on Electricity Quantity — CRU Weather Data

	FE (1)	FE (2)	FE (3)
T (°C)	0.00426***	0.00454***	0.00439***
	(0.001)	(0.001)	(0.001)
Log(Income)			0.0751***
			(0.005)
Precipitations Controls	No	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.001	0.001	0.017
Observations	7902147	7902147	7902147

Notes: The dependent variable is log of monthly electricity quantity (in kWh). (1), (2) and (3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C11: Impact of Temperature on Electricity Quantity — Alternative Standard Errors Specifications

	District (1)	State (2)
< 11	-0.00108*	-0.00108
	(0.001)	(0.001)
$11 - 14$	-0.000877*	-0.000877
	(0.000)	(0.001)
$14 - 17$	0.000380	0.000380
	(0.001)	(0.001)
$20 - 23$	0.000681	0.000681
	(0.000)	(0.001)
$23 - 26$	0.00114***	0.00114*
	(0.000)	(0.001)
$26 - 29$	0.00189***	0.00189***
	(0.000)	(0.001)
$29 - 32$	0.00223***	0.00223***
	(0.000)	(0.001)
$32 - 35$	0.00205***	0.00205***
	(0.000)	(0.001)
≥ 35	0.00464***	0.00464***
	(0.001)	(0.001)
Log(Income)	0.0770***	0.0770***
	(0.006)	(0.020)
Precipitations Controls	Yes	Yes
Household FE	Yes	Yes
Month-Year FE	Yes	Yes
R^2	0.018	0.018
Observations	7950694	7950694

Notes: Column (1) shows main specification results. The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. (1) clustered standard errors at district level in parentheses. (2) clustered standard errors at state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C12: Impact of Temperature on Electricity Quantity — 5-degree Temperature Bins

	FE (1)	FE (2)	FE (3)
< 10	-0.000868*	-0.00118**	-0.00114**
	(0.000)	(0.001)	(0.000)
$10-15$	-0.000516	-0.000652*	-0.000694*
	(0.000)	(0.000)	(0.000)
$20-25$	0.000711***	0.000688**	0.000636**
	(0.000)	(0.000)	(0.000)
$25-30$	0.00173***	0.00171***	0.00166***
	(0.000)	(0.000)	(0.000)
$30-35$	0.00160***	0.00176***	0.00173***
	(0.000)	(0.000)	(0.000)
≥ 35	0.00400***	0.00425***	0.00423***
	(0.001)	(0.001)	(0.001)
Log(Income)			0.0770***
			(0.006)
Precipitations Controls	No	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.001	0.001	0.018
Observations	7950694	7950694	7950694

Notes: The dependent variable is log of monthly electricity quantity (in kWh). Reference category is bin 15-20. (1), (2) and (3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C13: Impact of Temperature on Monthly Electricity Quantity — Non-linearities

	FE (1)	FE (2)	FE (3)
T (°C)	0.00454***	0.00284**	0.00361***
	(0.001)	(0.001)	(0.001)
T^2		0.0000433*	-0.00000680
		(0.000)	(0.000)
T^3			0.000000948
			(0.000)
Log(Income)	0.0769***	0.0769***	0.0769***
	(0.006)	(0.006)	(0.006)
Precipitations Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.018	0.018	0.018
Observations	7927651	7927651	7927651

Notes: The dependent variable is log of monthly electricity quantity (in kWh). (1), (2) and (3) clustered std. errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table C14: Impact of Temperature on Electricity Quantity — Cooling Degree Days

	FE (1)	FE (2)	FE (3)
CDD (in 100s)	0.0149***	0.0183***	0.0174***
	(0.003)	(0.003)	(0.003)
Log(Income)			0.0766***
			(0.006)
Precipitations Controls	No	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.000	0.001	0.017
Observations	7854909	7854909	7854909

Notes: The dependent variable is log of monthly electricity quantity (in kWh). CDDs are constructed using 24 °C as threshold. (1), (2) and (3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

D.1 Mortality: Main Results

Table D1: Impact of Temperature on Mortality Rate

	FE (1)	FE (2)	FE (3)	FE (4)
T (< 10)	0.00272	0.00275		0.00304
	(0.002)	(0.002)		(0.002)
T (10 − 15)	0.00241*	0.00249*		0.00276**
	(0.001)	(0.001)		(0.001)
T (20 − 25)	0.00202*	0.00211*		0.00211**
	(0.001)	(0.001)		(0.001)
T (25 − 30)	0.00161	0.00179		0.00202*
	(0.001)	(0.001)		(0.001)
T (30 − 35)	0.00247**	0.00263**		0.00307**
	(0.001)	(0.001)		(0.001)
T (≥ 35)	0.00932***	0.00944***		0.00997***
	(0.002)	(0.002)		(0.002)
P (2^{nd})		-0.00645	0.00263	-0.00458
		(0.025)	(0.024)	(0.025)
P (3^{rd})		0.0448	0.0560*	0.0469
		(0.035)	(0.033)	(0.036)
H (0 − 3)			0.000660	-0.000503
			(0.003)	(0.003)
H (3 − 6)			-0.00195*	-0.00255**
			(0.001)	(0.001)
H (6 − 9)			0.000907*	0.000412
			(0.001)	(0.001)
H (12 − 15)			0.000170	0.000190
			(0.001)	(0.001)
H (15 − 18)			0.000436	0.000914
			(0.001)	(0.001)
H (≥ 18)			-0.000102	0.000755
			(0.001)	(0.001)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quadratic Trend × Region	Yes	Yes	Yes	Yes
R^2	0.03	0.03	0.02	0.03
Observations	3908	3908	3908	3908

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category for temperature is bin 15-20 °C. Reference category for humidity is bin 9-12 g/kg. (1)-(4) clustered standard errors 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 D2: Impact of Temperature and Humidity Interactions on Mortality Rate

	FE (1)	FE (2)	FE (3)	FE (4)	FE (5)
T (< 10)	0.00305	0.00544	0.00306	0.00294	0.00297
	(0.002)	(0.006)	(0.002)	(0.002)	(0.002)
T (10 – 15)	0.00276**	0.00151	0.00276**	0.00279**	0.00279**
	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)
T (20 – 25)	0.00211**	-0.00547	0.00210**	0.00199*	0.00199*
	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
T (25 – 30)	0.00202*	-0.00348	0.00202*	0.00187	0.00186
	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
T (30 – 35)	0.00307**	0.00642	0.00306**	0.00302**	0.00301**
	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)
T (≥ 35)	0.00996***	-0.0101	0.00994***	0.000320	0.000195
	(0.002)	(0.011)	(0.002)	(0.003)	(0.003)
Humidity × T (< 10)		-0.000428			
		(0.001)			
Humidity × T (10 – 15)		0.0000728			
		(0.000)			
Humidity × T (20 – 25)		0.000585**			
		(0.000)			
Humidity × T (25 – 30)		0.000439**			
		(0.000)			
Humidity × T (30 – 35)		-0.000197			
		(0.000)			
Humidity × T (≥ 35)		0.00162*			
		(0.001)			
T (≥ 35) × H (0 – 3)			0.000500		0.00109
			(0.001)		(0.001)
T (≥ 35) × H (≥ 18)				0.000123***	0.000124***
				(0.000)	(0.000)
Precipitation Terciles	Yes	Yes	Yes	Yes	Yes
Humidity Bins	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Quadratic Trend × Region	Yes	Yes	Yes	Yes	Yes
R^2	0.03	0.03	0.03	0.04	0.04
Observations	3908	3908	3908	3908	3908

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category for temperature is bin 15-20 °C. Reference category for humidity is bin 9-12 g/kg. (1)-(4) clustered standard errors 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 D3: Impact of Temperature and Humidity on Mortality Rate — Urban and Rural Deaths

	Rural			Urban		
	(1)	(2)	(3)	(4)	(5)	(6)
T (< 10)	-0.00326	-0.00285	-0.00304	-0.00130	-0.00106	-0.00113
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
T (10 − 15)	0.00592*	0.00602*	0.00586*	0.00222	0.00261	0.00259
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
T (20 − 25)	0.000624	0.000549	0.000230	0.000751	0.000902	0.000851
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
T (25 − 30)	0.000420	0.000623	0.000200	0.00176	0.00209	0.00203
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
T (30 − 35)	0.00178	0.00230	0.00204	0.00230	0.00276	0.00279
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
T (≥ 35)	0.00909**	0.00993***	-0.00191	0.00549*	0.00622**	0.00229
	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)
P (2^{nd})	0.0563	0.0594	0.0632	0.0429	0.0416	0.0434
	(0.061)	(0.061)	(0.061)	(0.043)	(0.044)	(0.045)
P (3^{rd})	0.102	0.104	0.103	0.107**	0.105*	0.105*
	(0.086)	(0.087)	(0.087)	(0.053)	(0.054)	(0.054)
H (0 − 3)		-0.00230	-0.00123		-0.000814	-0.000762
		(0.006)	(0.006)		(0.006)	(0.006)
H (3 − 6)		-0.00406**	-0.00304		-0.00113	-0.000847
		(0.002)	(0.002)		(0.002)	(0.002)
H (6 − 9)		0.000427	0.000222		-0.000838	-0.000915
		(0.001)	(0.001)		(0.001)	(0.001)
H (12 − 15)		0.00104	0.000933		-0.000723	-0.000746
		(0.001)	(0.001)		(0.001)	(0.001)
H (15 − 18)		0.00136	0.00150		-0.0000322	0.0000330
		(0.001)	(0.001)		(0.001)	(0.001)
H (≥ 18)		0.00130	0.000335		0.000143	-0.000109
		(0.002)	(0.002)		(0.001)	(0.001)
T (≥ 35) × H (≥ 18)			0.000153**			0.0000533
			(0.000)			(0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend × Region	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.03	0.03	0.04	0.02	0.02	0.02
Observations	2520	2520	2520	1549	1549	1549

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category for temperature is bin 15-20 °C. Reference category for humidity is bin 9-12 g/kg. (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district rural and urban population.

Table D4: Impact of Temperature and Humidity on Mortality Rate — Share of Poverty

	Below Median		Above Median	
	(1)	(2)	(3)	(4)
T (< 10)	0.000192	-0.000254	0.0354	0.0315
	(0.002)	(0.003)	(0.027)	(0.025)
T (10 – 15)	0.00241	0.00312*	0.00462	0.00433
	(0.002)	(0.002)	(0.004)	(0.004)
T (20 – 25)	0.000549	0.000314	0.00315**	0.00255
	(0.001)	(0.001)	(0.002)	(0.002)
T (25 – 30)	0.000667	0.000827	0.00416**	0.00342*
	(0.002)	(0.002)	(0.002)	(0.002)
T (30 – 35)	0.00204	0.00262	0.00625***	0.00558***
	(0.002)	(0.002)	(0.002)	(0.002)
T (≥ 35)	0.00430*	0.00410	0.0173***	0.00147
	(0.003)	(0.003)	(0.004)	(0.006)
P (2^{nd})	0.0272	0.0274	0.0915	0.100*
	(0.023)	(0.024)	(0.056)	(0.057)
P (3^{rd})	0.0245	0.0176	0.196***	0.201***
	(0.033)	(0.034)	(0.068)	(0.069)
H (0 – 3)		0.00463		0.0479
		(0.007)		(0.031)
H (3 – 6)		-0.00203		-0.00253
		(0.002)		(0.003)
H (6 – 9)		-0.000357		0.000601
		(0.001)		(0.001)
H (12 – 15)		-0.000987		0.000670
		(0.001)		(0.001)
H (15 – 18)		0.000440		0.00133
		(0.001)		(0.001)
H (≥ 18)		0.000790		-0.000446
		(0.001)		(0.002)
T (≥ 35) × H (≥ 18)		0.0000199		0.000168**
		(0.000)		(0.000)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quadratic Trend × Region	Yes	Yes	Yes	Yes
R^2	0.04	0.04	0.06	0.07
Observations	1369	1369	1384	1384

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category is bin 15-20 °C. Reference category for humidity is bin 9-12 g/kg. (1)-(4) clustered standard errors 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 D5: Impact of Temperature and Humidity on Mortality Rate — Share of Poverty and Urban and Rural Deaths

	Rural				Urban			
	Below		Above		Below		Above	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T (< 10)	-0.00501	-0.00420	0.0619	0.0539	0.000282	0.000651	-0.0213	-0.0177
	(0.005)	(0.005)	(0.049)	(0.047)	(0.005)	(0.006)	(0.023)	(0.023)
T (10 – 15)	0.00417	0.00521	0.00984	0.00981	0.00241	0.00253	0.00586**	0.00591*
	(0.003)	(0.003)	(0.007)	(0.007)	(0.002)	(0.003)	(0.003)	(0.003)
T (20 – 25)	-0.00191	-0.00281	0.00201	0.000751	0.000855	0.00160	0.00126	0.00234
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
T (25 – 30)	-0.00193	-0.00242	0.00115	-0.0000706	0.00129	0.00220	0.00418	0.00538**
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
T (30 – 35)	-0.000230	0.000530	0.00290	0.00192	0.00242	0.00314	0.00422	0.00501
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)
T (≥ 35)	0.00450	0.00427	0.0146**	-0.00494	0.00435	0.00367	0.0109**	0.00932
	(0.005)	(0.005)	(0.006)	(0.009)	(0.004)	(0.005)	(0.005)	(0.009)
P (2^{nd})	0.0253	0.0152	0.112	0.140	0.0363	0.0450	0.0834	0.0785
	(0.037)	(0.041)	(0.113)	(0.117)	(0.051)	(0.053)	(0.075)	(0.080)
P (3^{rd})	0.0214	0.00198	0.203	0.230*	0.0823	0.0935*	0.197*	0.186*
	(0.061)	(0.063)	(0.135)	(0.139)	(0.052)	(0.056)	(0.110)	(0.108)
H (0 – 3)		-0.00115		0.0399		-0.00123		—
		(0.006)		(0.047)		(0.006)		(—)
H (3 – 6)		-0.00203		-0.00321		0.0000841		-0.00893
		(0.002)		(0.004)		(0.002)		(0.006)
H (6 – 9)		0.00202		-0.000896		-0.00282**		0.00149
		(0.001)		(0.002)		(0.001)		(0.002)
H (12 – 15)		0.000118		0.00158		-0.000873		-0.00120
		(0.002)		(0.002)		(0.001)		(0.002)
H (15 – 18)		0.00251		0.00132		-0.000898		0.00102
		(0.002)		(0.002)		(0.001)		(0.002)
H (≥ 18)		0.00367		-0.00167		-0.00115		0.000536
		(0.002)		(0.002)		(0.002)		(0.003)
T (≥ 35) × H (≥ 18)		0.0000170		0.000208**		0.0000296		0.0000268
		(0.000)		(0.000)		(0.000)		(0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend × Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.07	0.03	0.04	0.02	0.03	0.04	0.05
Observations	1208	1208	1312	1312	856	856	693	693

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category is bin 15-20 °C. Reference category for humidity is bin 9-12 g/kg. (1)-(8) clustered standard errors 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.

D.2 Mortality: Robustness

Table D6: Impact of Temperature on Mortality Rate — CHPS Sample

	FE (1)	FE (2)	FE (3)	FE (4)
T (<10)	0.00566**	0.00240	-0.000651	-0.000167
	(0.003)	(0.002)	(0.002)	(0.002)
T ($10-15$)	0.0111***	0.00286**	0.00250	0.00291*
	(0.004)	(0.001)	(0.002)	(0.002)
T ($20-25$)	0.00849***	0.00121	0.00214**	0.00210**
	(0.002)	(0.001)	(0.001)	(0.001)
T ($25-30$)	0.00854***	0.00119	0.00234**	0.00290**
	(0.002)	(0.001)	(0.001)	(0.001)
T ($30-35$)	0.00580**	0.00301**	0.00376***	0.00457***
	(0.003)	(0.001)	(0.001)	(0.001)
T (≥ 35)	0.0129***	0.00971***	0.00973***	0.0101***
	(0.004)	(0.002)	(0.002)	(0.002)
P (2^{nd})				0.0543*
				(0.029)
P (3^{rd})				0.113***
				(0.038)
District FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Quadratic Trend $\times$ Region	No	No	Yes	Yes
R^2	0.15	0.02	0.04	0.02
Observations	2758	2753	2753	2753

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category is bin 15-20 °C. (1)-(4) clustered standard errors 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 D7: Impact of Temperature and Humidity on Mortality Rate — CHPS Sample

	FE (1)	FE (2)	FE (3)	FE (4)
T ($<$ 10)	-0.000167		-0.000757	-0.000937
	(0.002)		(0.003)	(0.003)
T (10 – 15)	0.00291*		0.00302*	0.00293*
	(0.002)		(0.002)	(0.002)
T (20 – 25)	0.00210**		0.00219**	0.00199**
	(0.001)		(0.001)	(0.001)
T (25 – 30)	0.00290**		0.00315***	0.00288***
	(0.001)		(0.001)	(0.001)
T (30 – 35)	0.00457***		0.00493***	0.00480***
	(0.001)		(0.001)	(0.001)
T ($\geq$ 35)	0.0101***		0.0105***	0.000885
	(0.002)		(0.002)	(0.003)
P (2^{nd})	0.0543*	0.0495*	0.0551*	0.0580*
	(0.029)	(0.029)	(0.030)	(0.030)
P (3^{rd})	0.113***	0.106***	0.112***	0.111***
	(0.038)	(0.036)	(0.039)	(0.038)
H (0 – 3)		0.00348	0.00379	0.00447
		(0.006)	(0.007)	(0.007)
H (3 – 6)		-0.00225*	-0.00307**	-0.00231*
		(0.001)	(0.001)	(0.001)
H (6 – 9)		0.00117**	0.000528	0.000359
		(0.001)	(0.001)	(0.001)
H (12 – 15)		-0.0000303	-0.0000257	-0.0000989
		(0.001)	(0.001)	(0.001)
H (15 – 18)		-0.000202	0.000436	0.000566
		(0.001)	(0.001)	(0.001)
H ($\geq$ 18)		-0.000666	0.000450	-0.000270
		(0.001)	(0.001)	(0.001)
T ($\geq$ 35) $\times$ H ($\geq$ 18)				0.000126**
				(0.000)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quadratic Trend $\times$ Region	Yes	Yes	Yes	Yes
R^2	0.04	0.03	0.05	0.05
Observations	2753	2753	2753	2753

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category is bin 15-20 °C. Reference category for humidity is bin 9-12 g/kg. (1)-(4) clustered standard errors 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 D8: Impact of Temperature on Mortality Rate — Alternative Fixed Effects

	FE (1)	FE (2)	FE (3)	FE (4)	FE (5)	FE (6)
T (< 10)	0.000827	0.00376*	0.00293	0.00327	0.00355*	0.00305
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
T (10 – 15)	0.0113**	0.00261**	0.00250*	0.00288**	0.00304**	0.00276**
	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T (20 – 25)	0.0107***	0.00187*	0.00237**	0.00169	0.000173	0.00211**
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T (25 – 30)	0.0100***	0.00151	0.00235*	0.00141	-0.000250	0.00202*
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T (30 – 35)	0.00884***	0.00256**	0.00329**	0.00238*	0.000195	0.00307**
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T (≥ 35)	0.0160***	0.00955***	0.0107***	0.00960***	0.00893***	0.00996***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
P (2^{nd})	-0.178***	-0.000990	-0.00400	-0.00977	-0.0151	-0.00458
	(0.064)	(0.025)	(0.026)	(0.025)	(0.023)	(0.025)
P (3^{rd})	-0.0479	0.0601*	0.0493	0.0448	0.0103	0.0469
	(0.122)	(0.036)	(0.038)	(0.036)	(0.035)	(0.036)
H (0 – 3)	0.00509**	0.0000676	-0.00393	-0.0000155	0.000683	-0.000505
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
H (3 – 6)	0.00879***	-0.00230**	-0.00373***	-0.00265**	-0.00199*	-0.00255**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
H (6 – 9)	-0.00220*	0.000505	0.000527	0.000472	0.000265	0.000412
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
H (12 – 15)	-0.00232**	-0.0000733	0.000179	-0.000329	-0.000420	0.000190
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
H (15 – 18)	0.000658	0.000175	0.00102	0.000286	0.000119	0.000915
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
H (≥ 18)	0.000680	-0.000351	0.000909	-0.000119	0.000326	0.000756
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
District FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Year × Region	No	No	Yes	No	No	No
Linear Trend × Region	No	No	No	Yes	No	No
Linear Trend × State	No	No	No	No	Yes	No
Quadratic Trend × Region	No	No	No	No	No	Yes
R^2	0.23	0.02	0.03	0.03	0.10	0.03
Observations	3911	3908	3908	3908	3908	3908

Notes: Column (6) shows main specification results. The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category for temperature is bin 15-20 ° C. Reference category for humidity is bin 9-12 g/kg. (1)-(6) clustered standard errors 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 D9: Impact of Temperature on Mortality Rate — Controlling for Income per capita

	FE (1)	FE (2)
T (< 10)	-0.000757	-0.000829
	(0.003)	(0.003)
T ($10 - 15$)	0.00302*	0.00300*
	(0.002)	(0.002)
T ($20 - 25$)	0.00219**	0.00219**
	(0.001)	(0.001)
T ($25 - 30$)	0.00315***	0.00316***
	(0.001)	(0.001)
T ($30 - 35$)	0.00493***	0.00494***
	(0.001)	(0.001)
T (≥ 35)	0.0105***	0.0105***
	(0.002)	(0.002)
P (2^{nd})	0.0551*	0.0553*
	(0.030)	(0.030)
P (3^{rd})	0.112***	0.112***
	(0.039)	(0.039)
H ($0 - 3$)	0.00379	0.00365
	(0.007)	(0.007)
H ($3 - 6$)	-0.00307**	-0.00313**
	(0.001)	(0.001)
H ($6 - 9$)	0.000528	0.000526
	(0.001)	(0.001)
H ($12 - 15$)	-0.0000257	-0.0000399
	(0.001)	(0.001)
H ($15 - 18$)	0.000436	0.000406
	(0.001)	(0.001)
H (≥ 18)	0.000450	0.000418
	(0.001)	(0.001)
Income per capita	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Quadratic Trend $\times$ State	Yes	Yes
R^2	0.05	0.05
Observations	2753	2753

Notes: The dependent variable is the natural logarithm of mortality rate. The estimated period is 2014-2019. Reference category for temperature is bin 15-20 °C. Reference category for humidity is bin 9-12 g/kg. (1) and (2) clustered standard errors at district level in parentheses respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Table D10: Impact of Temperature on Mortality Rate — State-level Clustered Standard Errors

	FE (1)	FE (2)
T (<10)	0.00305	0.00305
	(0.002)	(0.003)
T ($10-15$)	0.00276**	0.00276
	(0.001)	(0.003)
T ($20-25$)	0.00211**	0.00211
	(0.001)	(0.001)
T ($25-30$)	0.00202*	0.00202
	(0.001)	(0.001)
T ($30-35$)	0.00307**	0.00307**
	(0.001)	(0.001)
T (≥ 35)	0.00996***	0.00996*
	(0.002)	(0.005)
P (2^{nd})	-0.00458	-0.00458
	(0.025)	(0.018)
P (3^{rd})	0.0469	0.0469
	(0.036)	(0.041)
H ($0-3$)	-0.000505	-0.000505
	(0.003)	(0.003)
H ($3-6$)	-0.00255**	-0.00255
	(0.001)	(0.002)
H ($6-9$)	0.000412	0.000412
	(0.001)	(0.001)
H ($12-15$)	0.000190	0.000190
	(0.001)	(0.002)
H ($15-18$)	0.000915	0.000915
	(0.001)	(0.001)
H (≥ 18)	0.000756	0.000756
	(0.001)	(0.001)
District FE	Yes	Yes
Year FE	Yes	Yes
Quadratic Trend × Region	Yes	Yes
R^2	0.03	0.03
Observations	3908	3908

Notes: Column (1) shows main specification results. The dependent variable is the natural logarithm of mortality rate. The estimated period is 2014-2019. Reference category for temperature is bin 15-20 °C . Reference category for humidity is bin 9-12 g/kg. (1) clustered standard errors at district level in parentheses. (2) clustered standard errors at 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 D11: Impact of Temperature on Mortality Rate — 3-degree Bins

	FE	FE	FE	FE
	(1)	(2)	(3)	(4)
T ($<$ 11)	-0.0000731	0.00124	0.000274	0.000274
	(0.001)	(0.001)	(0.002)	(0.002)
T (11 $-$ 14)	0.0159***	0.000365	0.0000645	0.0000645
	(0.003)	(0.001)	(0.002)	(0.002)
T (14 $-$ 17)	-0.0126***	-0.00269**	-0.00315**	-0.00315**
	(0.003)	(0.001)	(0.001)	(0.001)
T (20 $-$ 23)	0.00437*	0.000784	0.00115	0.00115
	(0.002)	(0.001)	(0.001)	(0.001)
T (23 $-$ 26)	0.00688***	0.000453	0.000512	0.000512
	(0.002)	(0.001)	(0.001)	(0.001)
T (26 $-$ 29)	0.00433**	-0.000400	0.000172	0.000172
	(0.002)	(0.001)	(0.001)	(0.001)
T (29 $-$ 32)	0.00525**	-0.000259	0.000205	0.000205
	(0.002)	(0.001)	(0.001)	(0.001)
T (32 $-$ 35)	0.00217	-0.000636	0.0000182	0.0000182
	(0.002)	(0.002)	(0.002)	(0.002)
T ($\geq$ 35)	0.0129***	0.00629***	0.00691***	0.00691***
	(0.003)	(0.002)	(0.002)	(0.002)
P (2^{nd})	-0.178***	-0.0146	-0.0164	-0.0164
	(0.044)	(0.025)	(0.025)	(0.025)
P (3^{rd})	-0.0868	0.0387	0.0286	0.0286
	(0.075)	(0.036)	(0.035)	(0.035)
H (0 $-$ 3)	0.00121	0.000491	-0.0000610	-0.0000610
	(0.002)	(0.003)	(0.003)	(0.003)
H (3 $-$ 6)	0.00624***	-0.00205*	-0.00210*	-0.00210*
	(0.001)	(0.001)	(0.001)	(0.001)
H (6 $-$ 9)	-0.00141	0.000720	0.000717	0.000717
	(0.001)	(0.001)	(0.001)	(0.001)
H (12 $-$ 15)	-0.00206**	-0.000322	0.0000720	0.0000720
	(0.001)	(0.001)	(0.001)	(0.001)
H (15 $-$ 18)	-0.000258	-0.000425	0.000373	0.000373
	(0.001)	(0.001)	(0.001)	(0.001)
H ($\geq$ 18)	0.000740	-0.00120	-0.0000892	-0.0000892
	(0.001)	(0.001)	(0.001)	(0.001)
District FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Quadratic Trend $\times$ Region	No	No	Yes	Yes
R^2	0.27	0.02	0.03	0.03
Observations	3911	3908	3908	3908

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category for temperature is bin 17-20 °C. Reference category for humidity is bin 9-12 g/kg. (1)-(4) clustered standard errors 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 D12: Protective Effect of Heat Adaptation — State-level Penetration Rates

	Temperature			Humidity			Temperature × Humidity		
	Air Conditioner	Cooler	Both	Air Conditioner	Cooler	Both	Air Conditioner	Cooler	Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AC × T (≥ 35)	-0.0444***		-0.0373***						
	(0.013)		(0.014)						
Cooler × T (≥ 35)		-0.0109**	-0.00770						
		(0.005)	(0.005)						
AC × H (≥ 18)				-0.00228		-0.00521			
				(0.005)		(0.005)			
Cooler × H (≥ 18)					-0.000857	-0.000746			
					(0.002)	(0.002)			
AC × T (≥ 35) × H (≥ 18)							-0.000390**		-0.000397**
							(0.000)		(0.000)
Cooler × T (≥ 35) × H (≥ 18)								-0.0000427	-0.00000122
								(0.000)	(0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend × Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.06	0.06	0.05	0.06	0.07	0.05	0.06	0.06
Observations	2753	2753	2753	2753	2753	2753	2753	2753	2753

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category is bin 15-20 °C. Reference category for humidity is bin 9-12 g/kg. (1)-(9) clustered standard errors 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 D13: Protective Effect of Heat Adaptation — Interactions with All Temperature Bins

	Air Conditioner	Evaporative Cooler	Both
	(1)	(2)	(3)
AC $\times$ T (≤ 10)	0.00109		-0.000206
	(0.009)		(0.009)
Cooler $\times$ T (≤ 10)		0.0000828	0.000279
		(0.003)	(0.003)
AC $\times$ T ($10-15$)	-0.0114*		-0.0102
	(0.006)		(0.007)
Cooler $\times$ T ($10-15$)		-0.00219	-0.000694
		(0.004)	(0.004)
AC $\times$ T ($20-25$)	-0.00499		-0.00523
	(0.004)		(0.004)
Cooler $\times$ T ($20-25$)		-0.00195	-0.00153
		(0.002)	(0.002)
AC $\times$ T ($25-30$)	-0.00293		-0.00278
	(0.005)		(0.005)
Cooler $\times$ T ($25-30$)		0.000724	0.00104
		(0.002)	(0.002)
AC $\times$ T ($30-35$)	-0.00903		-0.0101
	(0.006)		(0.006)
Cooler $\times$ T ($30-35$)		0.00309	0.00365*
		(0.002)	(0.002)
AC $\times$ T (≥ 35)	-0.0246**		-0.0155
	(0.010)		(0.011)
Cooler $\times$ T (≥ 35)		-0.00752	-0.00646
		(0.005)	(0.005)
Precipiation Terciles	Yes	Yes	Yes
Humdity Bins	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quadratic Trend $\times$ Region	Yes	Yes	Yes
R^2	0.05	0.06	0.06
Observations	2753	2753	2753

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category for temperature is bin 15-20 ° C. Reference category for humidity is bin 9-12 g/kg. (1)-(3) clustered standard errors 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 D14: Protective Effect of Heat Adaptation — Controlling for Income

	FE	FE
	(1)	(2)
AC $\times$ T ($\geq$ 35)	-0.0208**	-0.0178*
	(0.009)	(0.010)
Cooler $\times$ T ($\geq$ 35)	-0.00636	-0.00629
	(0.005)	(0.005)
Income Per Capita	Yes	Yes
Income $\times$ Temperature Bins	No	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Quadratic Trend $\times$ Region	Yes	Yes
R^2	0.05	0.06
Observations	2753	2753

Notes: The dependent variable is the natural logarithm of mortality rate. Estimated period is 2014-2019. Reference category for temperature is bin 15-20 ° C. Reference category for humidity is bin 9-12 g/kg. (1)-(3) clustered standard errors 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.