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ESSAYS ON ECONOMICS OF ADAPTATION TO CLIMATE CHANGE

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"Believe in the you that believes in yourself!" (Kamina, from "Gurren Lagann")

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Abstract

This PhD thesis consists of three essays in environmental economics, with main focus on the adaptation to climate change.
The first work, "**Air-Conditioning and the Adaptation Cooling Deficit in Emerging Economies**", provides a multi-country, comparative analysis of how income and climate drive air-conditioning adoption in four developing economies, in relation to a comprehensive set of country-specific household characteristics. We then evaluate with a top-down approach how future changes in climate and socio-economic conditions centered around 2040 will influence air-conditioning adoption and electricity. We show that in emerging economies the decision to purchase air-conditioning in response to warmer climatic conditions is strongly anchored to a household's socio-economic conditions and demographic characteristics. Moreover, although the penetration of air-conditioning is expected to increase in the future, we find that an adaptation cooling deficit, characterised by millions of less well-off electrified households that need but cannot obtain air conditioners, will remain.
The results from the first work suggest the need for policymakers to identify resources and policies that may reduce the disparities in access to adaptation in developing economies. The second paper, "**Adaptation to climate change: Air-conditioning and the role of remittances**", then tests whether remittances — a fundamental additional income source for economic development in low-income settings — can relax credit constraints, and so facilitate the heat adaptation process in emerging economies. We rely on household data from 2008 to 2018 for Mexico — the country with the highest percentage of GDP from remittances. Our empirical strategy is based on an instrumental variable approach for dealing with the potential endogeneity of remittance income. We find that remittance income plays a key role in the adaptation process. Then, exploiting climate and income heterogeneity across Mexican households and states, we show that remittances increase the ability of households to purchase air-conditioning (i) mostly in the warmer areas and (ii) especially when families have a relatively low-income level. We conclude underscoring the potential private benefits of this form of adaptation by computing the welfare gain associated with the possession of air-conditioning.
Finally, my third paper, "**Adapting to Heat Extremes with Unequal Access to Cooling: Evidence from India**", investigates the inequality in heat adaptation, examining the effectiveness of alternative cooling technologies in mitigating mortality impacts from extreme heat in India. To do so, we combine rich longitudinal household data with district-level mortality data and high-resolution meteorological information. Our empirical strategy relies on micro-panel fixed-effects regression to identify the effect of temperature as quasi-random assigned. We show that the majority of households lack the means to adapt through access to any form of cooling technology. However, when adaptation is observed, 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 find offering substantially reduced protection against heat stress. This has important implications in terms of (1) number of lives saved, (2) economic benefits, and (3) adaptation policies, since evaporative coolers are usually an important component of sustainable cooling-for-all policies.

Contents

Air-Conditioning and the Adaptation Cooling Deficit in Emerging Economies*

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Abstract

Increasing temperatures will make space cooling a necessity for maintain comfort and protecting human health, and rising income levels will allow more people to purchase and run air conditioners. Here we show that, in Brazil, India, Indonesia, and Mexico income and humidity-adjusted temperature are common determinants for adopting air-conditioning, but their relative contribution varies in relation to household characteristics. Adoption rates are higher among households living in higher quality dwellings in urban areas, and among those with higher levels of education. Air-conditioning is unevenly distributed across income levels, making evident the existence of a disparity in access to cooling devices. Although the adoption of air-conditioning could increase between twofold and sixteen-fold by 2040, from 64 to 100 million families with access to electricity will not be able to adequately satisfy their demand for thermal comfort. The need to sustain electricity expenditure in response to higher temperatures can also create unequal opportunities to adapt.

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1 Introduction

As global temperatures rise, a growing number of people around the world will be exposed to the potential harm caused by heat stress[1]. Adaptation through the use of air-conditioning[2] has been the subject of a recent and growing literature that looks at patterns of potential needs and demand across major cities[3,4], countries[5,6] and world regions[7,8]. Low- and middle-income countries in the tropics or sub-tropics are under the spotlight[9]. About two to four billion people living in those places have no space-cooling devices in their homes and air-conditioning usage is highly concentrated among high-income households[10]. In a warming climate, air-conditioning could contribute to maintain labor productivity[11–13] and to enhance the accumulation of human capital[14] in the long-term. Better understanding how many of those people at risk will or will not be able to adopt air-conditioning remains an important area for future research.

The adoption of air conditioners follows the "S"-shaped pattern that characterizes the uptake of other durable goods, such as automobiles and refrigerators[15,16]. In developing countries, the growth of this curve tends to start off slowly, because of credit constraints, followed by a steeper rise once income levels reach a certain threshold. Stylized "S"-shaped functions have also been used to project future air-conditioning adoption and energy requirements in India[5] and in other low-income countries[17,18]. The expansion of households' air-conditioning will put increasing pressure on future energy demand especially in hot developing countries[19–21], and accounting for this additional driver of energy demand will help improve the aggregate projections and scenarios needed for managing long-term investments[22–24]. Demand-side actions will be an important element in the transition towards net zero emissions over next few decades[25], but most models used to support policy making lack the characterization of adaptation-energy feedback mechanisms. How energy use for adaptation might influence the design of effective mitigation actions remains to be studied[26,27].

Here we provide a multi-country, comparative analysis of how income and climate drive air-conditioning adoption in Brazil, India, Indonesia, and Mexico, in relation to a comprehensive set of country-specific household characteristics, and evaluate with a top-down approach[28] how future changes in climate and socio-economic conditions centered around 2040 will influence air-conditioning adoption and electricity. We show that in emerging economies the decision to purchase air-conditioning in response to warmer climatic conditions is strongly anchored to a household's socio-economic conditions and demographic characteristics. Not explicitly accounting for other characteristics of households can significantly bias the estimates of the marginal contribution of income and climate, which would appear larger. Although the penetration of air-conditioning is expected to increase in the future, an adaptation cooling deficit, characterized by millions of less well-off electrified households that need but cannot obtain air conditioners, will remain. Increasing the use of electricity for residential space cooling is a form of adaptation that helps relieve population from heat stress, but the recurring electricity expenditure required limits the opportunities among the lowest income deciles. In the long run, if left to uncoordinated and autonomous actions, space cooling runs the risk of exacerbating local and global negative externalities and of widening existing inequalities.

2 Results

2.1 An up-to-date database of households and climate

Our results are based on the analysis of a new database that combines the up-to-date household-level survey data covering 2,172 subnational regions in Brazil, Mexico, India, and Indonesia over the 2003-2018 period, with gridded Cooling Degree Days (CDDs). We respond to recent demands to account for the influence of relative humidity[7,8] by using wet-bulb temperature as a more accurate measurement of thermal discomfort that, contrary to dry-bulb temperature, does not overestimate temperature at low humidity levels[29]. To better reflect tropical conditions, we use a higher baseline temperature of 24 °C as opposed to the 18 °C value used in most studies on air temperature impacts and building energy demand[30]. Because temperature set-points can vary across households[4], we also consider a lower temperature threshold of 22 °C as a robustness test. The combination of two temperature thresholds with calculations based on dry-bulb and wet-bulb temperatures makes it possible evaluate the sensitivity of the results for different countries to the climate metric used. For the sake of clarity, in the remainder of this paper, CDDs refer to those computed with wet-bulb temperature and at a base temperature of 24 °C (see section 'Climate Data' in Supplementary Information, where results based on CDDs computed with dry-bulb temperature are also shown). Brazil, Mexico, India, and Indonesia are all tropical countries characterized by relatively high average wet-bulb CDDs, though there is significant variation from one country to another (Supplementary Figure 1). Climate variation remains significant even within each of the four countries considered. The highest long-term average values of wet-bulb temperature are observed in Indonesia and India, although climate heterogeneity between and within countries highlights the presence of high-CDD regions even in Brazil (Figure 1, panel a). The diffusion of air-conditioning units across districts and states closely mirrors patterns of hot climate conditions in the climate maps, though urbanization and access to electricity play a mediating role (see Supplementary Figure 1). In India, for example, the highest CDD values, observed in the states of West Bengal, Assam, Uttar Pradesh, and Orissa, are not associated with the most widespread use of air-conditioning. Households in those regions are mostly rural and often lack access to electricity, as implied by low ownership rates of refrigerators. Fans, which consume less energy and do not require a stable connection, are more widespread throughout the country. In Brazil, the state of Rio de Janeiro shows relatively high adoption rates for air conditioners, despite the lower number of annual CDDs compared to its northern states, where urbanization is low. Although Indonesia has the highest values of CDDs, households rarely own air-conditioning units, except for the districts of Jakarta and the Riau Islands.

Climate is only part of the story, as shown by India and Indonesia. For the same level of total expenditure per capita, air-conditioning ownership rates are the highest in India and the lowest in Indonesia (Figure 1, panel b). In these Asian regions, average annual total expenditure per capita, which we use as an indicator of lifetime income, is below 10,000 USD for nearly all households. The expenditure distribution has a larger variance in Brazil and Mexico where, on average, of at least a quarter of households reports annual total expenditure per capita above 10,000 USD. Across all countries air-conditioning ownership is quite low (12% in India in 2012, 14% in Mexico in 2016), even in Indonesia and Brazil where more recent data are available (8% in Indonesia in 2017, 20% in Brazil 2018). By comparison, fans and refrigerators are more widely used. In India, as early as 2012, fans were owned by 73% of households, even among those with very low-income levels. Refrigerators have the highest adoption rates in Brazil and Mexico (See Supplementary Table 4 for descriptive statistics). Electricity expenditure reflects the ownership patterns of energy-consuming durables. Absolute values are the highest in Brazil and Mexico though, in relative terms, Indian households spend the largest share of their budget on electricity, between 3.4% and 4.5%.

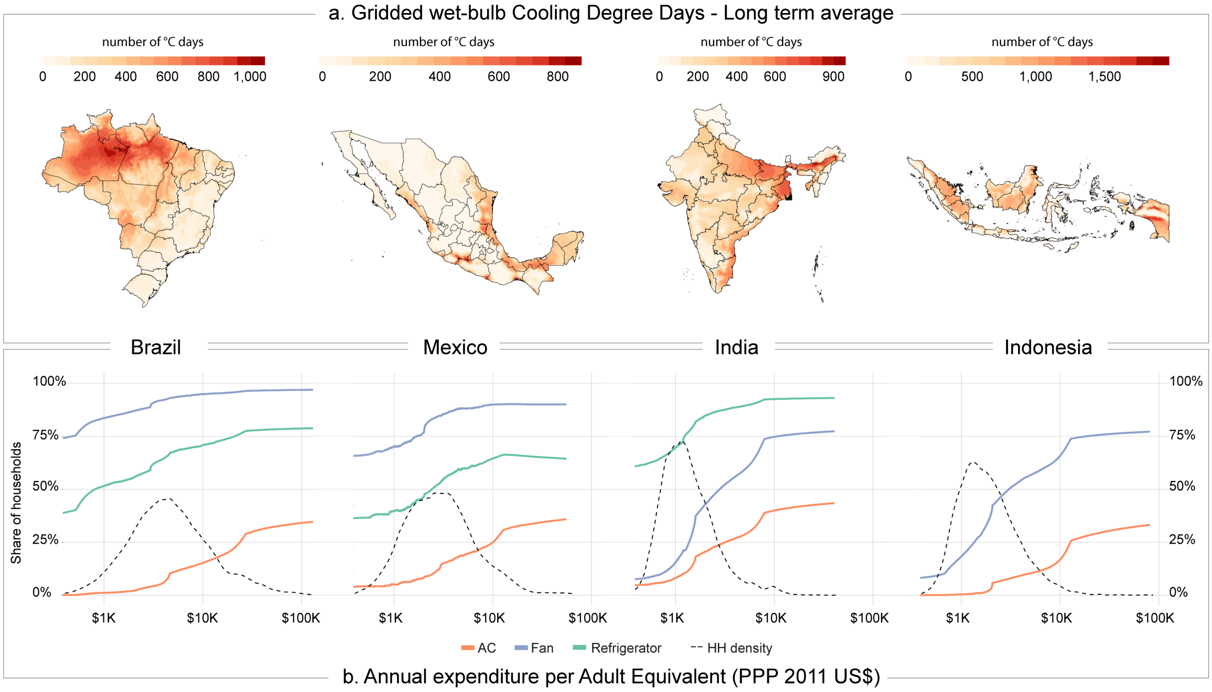

Figure 1: Climate, air-conditioning, and income characteristics in four selected emerging economies. Panel a: A 30-year average of gridded wet-bulb Cooling Degree Days (CDDs), up to the second wave of household data used in the study (2009 for Brazil and 2012 for all other countries). Panel b: Rates of air-conditioning (AC) ownership in relation to per capita total expenditure (2011 US constant dollars at PPP) and comparison to other cooling devices in the second wave of household data. The black dashed line shows the distribution of households (HH) across income levels. Maps are generated using the sp, rgdal, and raster R packages.

2.2 Drivers of air-conditioning adoption

We estimate adoption models for air conditioners for each individual country by using the two most recent survey waves available with a logit model (see Methods). To understand how adoption patterns differ from more commonly owned goods, we also look at the adoption of refrigerators and fans. While fans can substitute air conditioners in the space cooling service they provide, air conditioners are more comparable to refrigerators in terms of the budget required to purchase them. By using two waves, we can control for country-specific, time-varying unobservable trends that affect all households, such as changes in the prices of appliances and country-level regulations.

Income conditions and climate are both important drivers of the decision to adopt air conditioners across all countries (Table 1), but their relative contribution varies in relation to other household characteristics (Supplementary Table 7). The marginal effect of total expenditure is always larger than that of CDDs (except for fans in Mexico), but climate remains an important factor, especially in Brazil and Mexico. Fans, which in the short-term have the lowest costs, are generally more sensitive to CDDs as compared to air-conditioning. Especially in the warmer countries, India and Indonesia, education and the quality of dwellings correlate with a household's wealth and are more strongly related to the adoption of refrigerators and air-conditioning, the most expensive goods. The extent to which climate affects the decision to adopt also depends on a household's average income level. The interaction term between CDDs and total expenditure (Supplementary Table 5) indicates that households respond to rising temperature levels by purchasing a new air-conditioning unit only when their average annual income is sufficiently high (Figure 2, panel a). Moreover, as income increases, households tend to substitute fans with air-conditioning. Refrigerators provide a different service that is desirable across all climates but, as income increases, refrigerators become less sensitive to climate. The adoption of refrigerators responds to CDDs at low-income levels in Brazil and Mexico – where adoption is higher – and at medium income levels in India and Indonesia – where adoption is still quite low.

Demographic and infrastructural characteristics are also important factors in explaining adoption patterns, and their relative contribution, compared to income and climate, varies across countries and the type of good considered (Supplementary Table 6). Urbanization increases the probability of adopting cooling durables, and so does home ownership, though this factor is of less importance in comparison to living in major urban centers. Since for Brazil we lack information on districts, regressions only consider households located in the strata of capital and urban regions because for these strata, the geographical climate information are more accurate. The regressions for Brazil therefore do not include the urbanization variable. Education substantially enhances the propensity to adopt all types of goods considered in all countries. The housing index, which combines information on the quality of roofs, toilet and walls, shows a positive relationship with adoption propensity, indicating that households occupying higher-quality homes are more likely to install an air-conditioning unit. Demographic factors show a robust influence across goods and countries. Household size has a negative sign, whereas the presence of members under 16 years of age has a positive influence. Households with older family heads are more inclined to have a cooling appliance, probably because such persons spend more time at home. Employed household heads, who spend less time at home, are less interested in owning air conditioners. Findings on gender are mixed, and whether having a male head increases or not the propensity to adopt and use of cooling devices varies across countries. Not including this rich set of households' characteristics would significantly bias income and CDD elasticities, which would be estimated to be larger (Supplementary Table 11). Over time, the ability of households to adapt to climate conditions increases. When adoption behaviors are estimated by using only the most recent wave, income and CDD elasticities are significantly larger (Supplementary Table 11), indicating that, for the same income level, climate conditions, as well as all other covariates (*ceteris paribus*), households have a higher probability to adopt air-conditioning in the most recent waves. The higher adaptive capacity of households could also reflect the rapid decline in air-conditioning prices observed over the last twenty years[31], though we cannot formally test this hypothesis with our current data.

While new technologies widen the space of adaptation options available to households, contributing to enhancing their adaptive capacity, actual adaptation depends on behaviors and specifically on how electricity is used. Although we do not observe the specific consumption of electricity for space cooling, we know the total electricity consumption of households. Not only can air-conditioning be reasonably assumed to be more sensitive to changes in temperature than other final usages, but it is also much more energy-intensive compared to fans[32]. Most of the factors that positively influence the adoption of air-conditioning adoption - CDDs, income, urbanization, education, home ownership and housing index - are also positively related to electricity consumption (Supplementary Table 9).

Table 1: Total Marginal Effects for CDDs wet-bulbs and total expenditure from standardized logit models based on the two most recent waves for air-conditioning (AC), fans (FAN), and refrigerators (REF).

	Brazil			Mexico			India			Indonesia	
	Ac	Fan	Ref	Ac	Fan	Ref	Ac	Fan	Ref	Ac	Ref
CDDs	0.0565***	0.0880***	-0.0029***	0.023***	0.244***	0.014***	0.017***	0.063***	0.031***	0.0037***	0.073***
	(0.00154)	(0.00359)	(0.00056)	(0.00406)	(0.0126)	(0.00292)	(0.00588)	(0.00783)	(0.00678)	(0.000425)	(0.00750)
Tot. Exp. (in log.)	0.0928***	0.0888***	0.0167***	0.0319***	0.119***	0.0610***	0.0495***	0.0930***	0.247***	0.0123***	0.307***
	(0.00148)	(0.00216)	(0.00053)	(0.00276)	(0.00596)	(0.00251)	(0.00259)	(0.00303)	(0.00517)	(0.000465)	(0.00332)
Observations	75,290	75,290	75,290	78,607	78,607	78,607	167,648	170,470	166,402	524,112	524,112

Clustered standard errors at district level for MEX, IDN, and IND, and robust standard errors for Brazil in parentheses. State- and year-fixed effects for MEX, IDN, and IND and region- and year-fixed effect for BRA. ***p<0.001; **p<0.05; *p<0.1. Notes: Interpretation (Brazil). For a representative household, a 1 Standard Deviation (SD) increases in CDDs raises the probability of adopting AC by 5.65 percentage points on a probability scale 0 to 100. 1 SD increases in the log of income raises the probability of adopting AC by 9.28 percentage points. The total marginal effects include the contribution of the interaction between CDDs and total expenditure and is computed at the mean value of those variables. Full regression results with the full list of covariates are shown in Supplementary Table 7.

As CDDs increase above historical levels, air-conditioning generally rises more rapidly than fans and refrigerators, especially in Brazil (Figure 2, panel b). In India and Indonesia, the speed of diffusion aligns with that of other devices. In Mexico, fans reach a saturation point very rapidly, reflecting the relatively higher correlation with CDDs in a country characterized by very heterogeneous climate conditions.

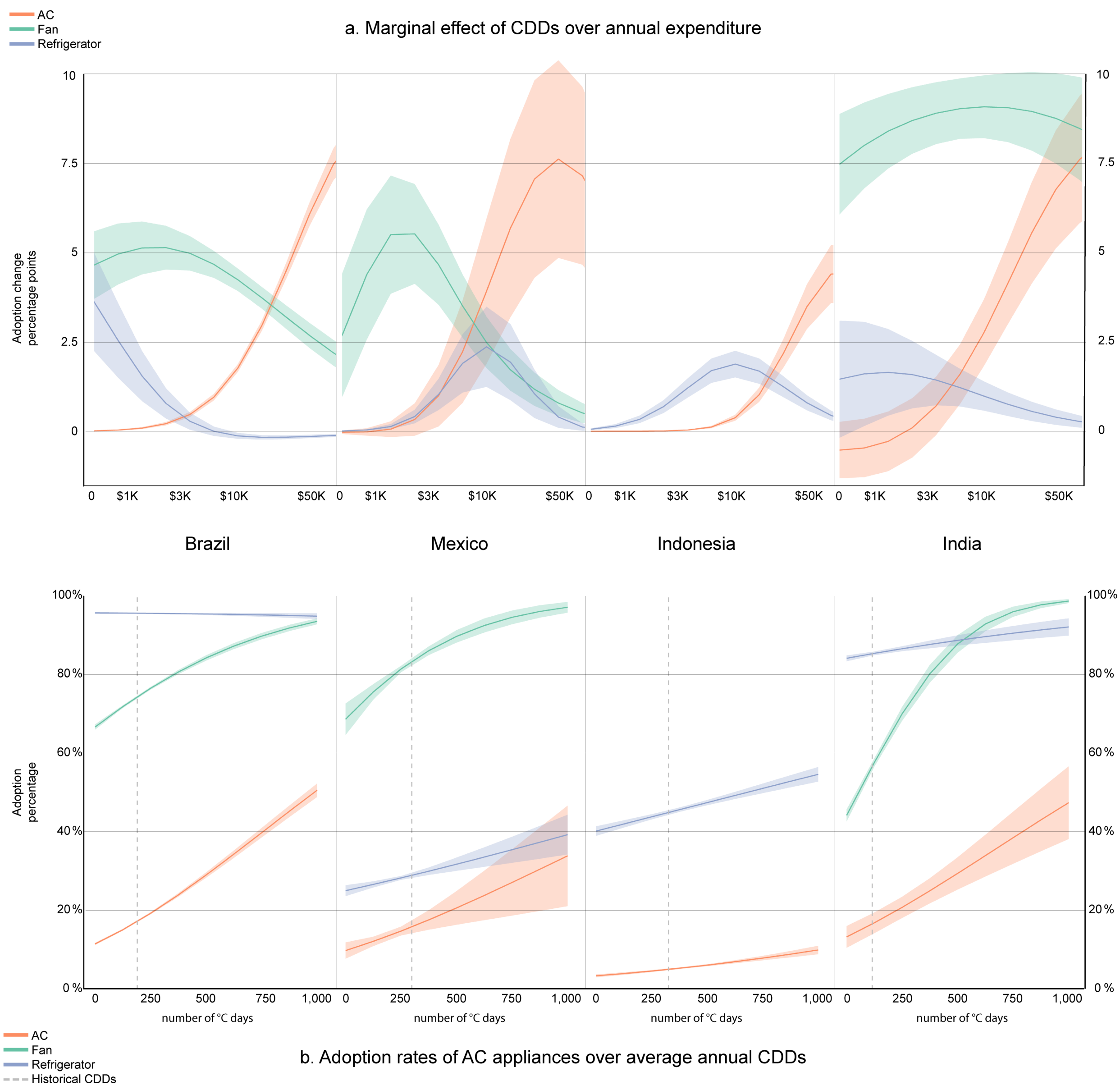

Figure 2: Drivers of air-conditioning adoption. Panel a: Marginal elasticity of air-conditioning adoption to a one-hundred increase in Cooling Degree Days (CDDs) across income levels. Panel b: Predicted adoption rates of air-conditioning (AC) and other cooling devices for varying CDDs wet-bulbs. All other drivers are assumed at their historical mean value (full regression results shown in Supplementary Table 5). The vertical dashed line marks the country-specific, long-term historical average of CDDs. Shaded areas represent the dispersion in predicted adoption levels across households.

Even within tropical regions, temperature measurements based on dry-bulb temperature can over-estimate CDD elasticities, depending on how air-conditioning is distributed across sub-regions with different micro-climates and humidity levels (Supplementary Table 12). If climatic conditions are measured with dry-bulb CDDs, the estimated CDD elasticities are significantly larger in Mexico and India and only slightly so in Brazil. Mexico and India have a high concentration of air-conditioning in the regions characterized by a particularly arid climate (warm arid and very hot dry climate conditions). Overall, our results are robust in relation to the use of different temperature thresholds, as well as to different measurements.

2.3 Future adoption of air-conditioning around mid-century

We simulate how changes in future climate and socio-economic conditions will influence a household's air-conditioning adoption and electricity use around 2040 (see Methods) by combining the change in CDDs simulated under two scenarios of moderate and vigorous warming, as described by the mean climate model Representative Concentration Pathways (RCPs) 4.5[33] and 8.5[34] with changes in income described by five different Shared Socio-economic Pathways[35,36]. In India CDDs increase by a factor of 1.9-2.3, while total expenditure increases by a factor of 4-7 across SSPs. In Indonesia (Brazil), CDDs increase by a factor of 5-9 (6-8) across RCPs while total expenditure by a factor of 3-4 (1.6-2.5) across SSPs. In Mexico CDDs and total expenditure increase by a factor of 1.7-2.5 across SSPs and RCPs.

Increase in the adoption of air-conditioning is substantial (Figure 3 and Supplementary Tables 18-21). In India, the average adoption rate across Indian states increases from 12% in 2012 to 49-69%, across SSPs and RCPs, in 2040; in Indonesia, from 8% in 2017 to 43-61%, in Mexico from 14% in 2016 to 35-42%, and in Brazil from 20% in 2018 to 65-85%. In Brazil, the largest increases are observed in its more affluent states in the southern and southeastern parts of the country, such as São Paulo, where air-conditioning rises from 16% to 78% in SSP5, RCP8.5, and Mato Grosso do Sul, which, starting from 28%, achieves full saturation (90% in SSP5, RCP8.5; results across SSPs and RCPs are available in the Supplementary Material). Brazil's northern states have higher historical ownership rates and therefore see a relatively smaller increase, though they achieve the largest shares by 2040. To mention a few examples, Amazonas, with the contribution of the city of Manaus, Pará, and Tocantins range from 69%, 23% and 29% in 2018, respectively, to full ownership. In Mexico, the average ownership rates in its hotter states are comparatively high already in the historical records, reaching 73% in Sonora or 77% in Sinaloa. The country's average increase in air-conditioning ownership is mediated by the inland regions, which are characterized by very low CDDs and hence no use of air-conditioning. In India, heterogeneous conditions in the access to electricity contribute to determining a more diverse situation across states. We do not model expansion in electricity access and therefore our projections represent households that already have access to electricity at present. This is not an issue for Mexico and Brazil, as they practically coincide with the total survey population (more than 97%). It might lead to an underestimation of AC expansion in Indonesia and India where many households still lack access. The largest increases in air-conditioning are seen in the northeastern part of the country, close to the border with Bangladesh, in states such as Assam, Bihar, Nagaland, and Meghalaya, where CDDs reach the highest values in the country. In India, 6 out of its 35 states, Delhi, Chandigarh, Haryana, Punjab, Rajasthan, and Uttar Pradesh, are expected to achieve full ownership, though only Delhi, Haryana, and Punjab do so across all scenarios. Indonesia exhibits the smallest variation in air-conditioning ownership rates across states. Compared to the other three countries, nearly all states show high CDDs. Still, air-conditioning ownership rates remain relatively low when economic growth is considered. Only Jakarta will come close to full ownership across all scenarios considered in 2040, starting from its 2017 average adoption rates of 30%. Increasing electricity demand also appears to be a ubiquitous form of adaptation (Supplementary Figure 7), and the interquartile range of the estimated growth factor is always positive (Supplementary Tables 14-17).

How temperature is measured and how the comfort setpoint is defined are two important sources of uncertainty that could generate different projections, arising from the interaction between the estimated elasticities and the changes in the temperature variables and the associated degree days. When the estimated elasticities are combined with future CDDs, future projected air-conditioning can be lower when using wet-bulb CDDs (Mexico) because of the lower estimated elasticities, but they can also be higher (Brazil) because only slightly smaller elasticities interact with a larger increase in wet-bulb CDDs relative to the historical period compared to dry-bulb CDDs. Since historical wet-bulb CDDs are much lower than dry-bulb CDDs, their growth rate is higher. Projections based on the 22 °C temperature threshold tend to underestimate projections based on the 24 °C temperature, especially when using wet-bulb measurements (Supplementary Table 12 and Figure 8).

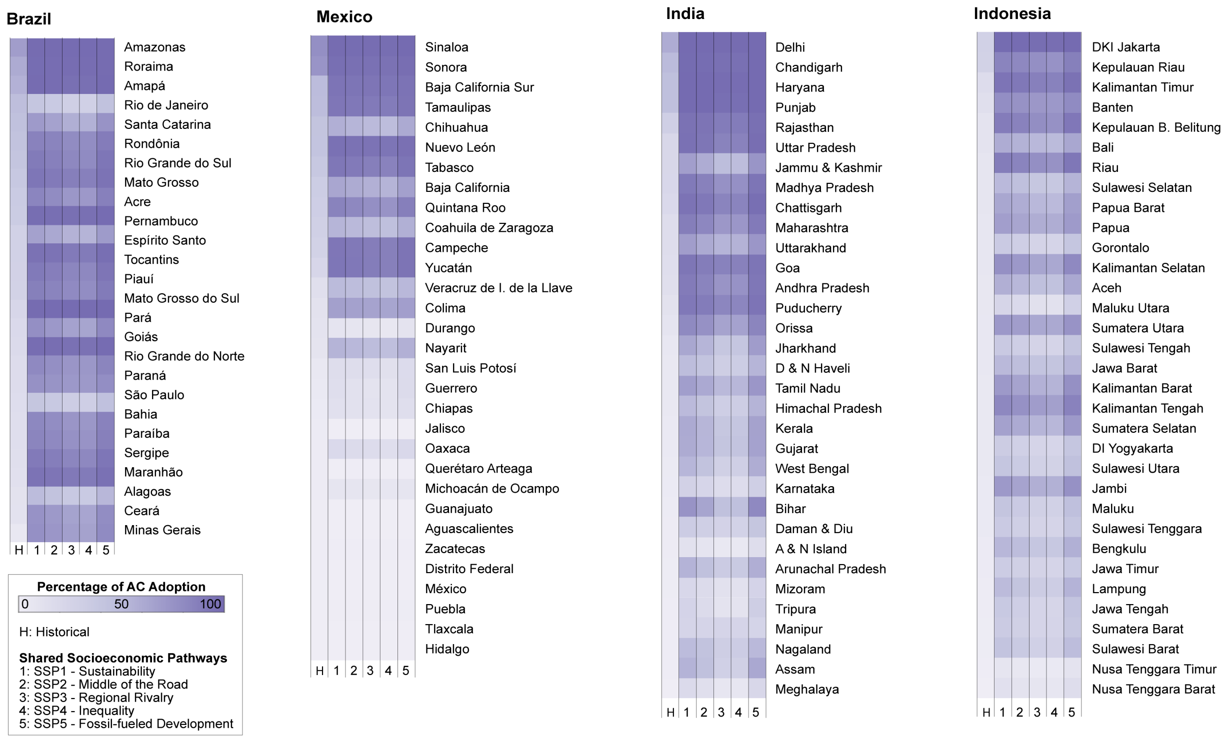

Figure 3: Future average air-conditioning adoption rates across country states in 2040 under RCP8.5-warming. States are ranked from top to bottom, based on historical ownership rates. State-level adoption rates are computed as weighted average of household-level projected adoption rates (see Methods).

2.4 Adaptation cooling deficit

Changes in climate and income conditions will allow more households to have an air conditioning unit by 2040, even when considering the uncertainty characterizing future socio-economic conditions. Yet, a non-negligible fraction of the population will be left behind. Our findings show that in 2040, between 64 and 100 million households (in SSP5-RCP8.5 and SSP3-RCP45, respectively) out of the total number of households living in the four countries considered in the latest waves of 343 million will face an adaptation cooling deficit. These households will face climate conditions warmer than their own country average, measured in terms of a country-specific CDD exposure ratio, and yet they will not be able to protect themselves with air-conditioning, as indicated by an air-conditioning availability ratio. We measure total CDD exposure as in Biardeau et al.[7] by multiplying country- and state-level CDDs by the total number of households. We then compute the CDD exposure ratio for each subnational state across the four countries. When state-level CDD exposure is higher than the country median, the ratio takes a value larger than one and proportional to the distance from the median. This exposure ratio is compared to the AC ratio, which is defined in a similar way. When the state-level average

AC ownership rate is smaller than the country median, the ratio takes a value smaller than one, proportional to the distance from the median. When the state-level average air-conditioning ownership rate is larger than the country respective median, the ratio takes a value greater than one and proportional to the distance from the median.

By combining these two ratios, Figure 4 divides the four countries' states into four groups, for the historical (left panel) and future period (right panel). The imaginary diagonal running from the top-left to the bottom-right quadrant sheds light on the cooling inequality characterizing these countries. States in the top-left quadrant have high adoption rates relative to the country median, despite having lower-than-average CDDs. The state of Rio de Janeiro in Brazil is an example. States in the bottom-right quadrant raise concerns because they have lower-than-average adoption rates despite the higher-than-average exposure to hot climate conditions.

Since socio-economic conditions improve at a faster rate than the increase in CDDs, in comparison with the historical data, the number of states with households experiencing a cooling deficit declines. Brazil and India potentially experience the largest reduction in the adaptation cooling deficit, going from 23 million in 2018 to 8-13 million across the 2040 socio-economic and warming scenarios in Brazil, and from 54 million in 2012 to 29-58 million households in India. In Indonesia, the change is from 26 million households in 2017 to 20-28 million. In Mexico, the historical situation would not change significantly, and it could even worsen (from 5 million in 2016 to 4-6 million households). States with high urbanization levels, hot and humid climate, or with generally poor economic conditions are more likely to face a cooling deficit. Consider, for example, the state of Jharkhand in northeastern India. Because air-conditioning does not keep pace with population and CDDs growth, its position shifts from the top to the bottom-right panel.

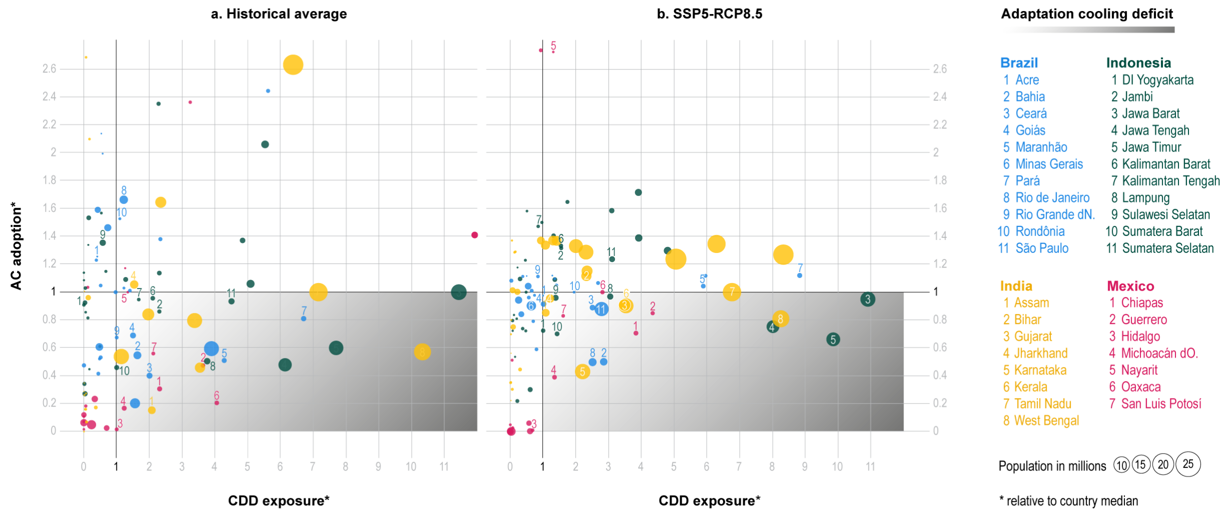

Figure 4: Adaptation cooling deficit. Current situation (Panel a, latest wave available) and future projections in 2040 with RCP8.5 warming and SSP5 (Panel b) computed with Cooling Degree Days (CDDs). Bubble size proportional to the current number of households relative to each country's maximum. For the historical period, the following waves are used: Brazil, 2018 India, 2012, Indonesia, 2017, Mexico, 2016. Colors are used to differentiate the four countries. See http://www.energy-a.eu/cooling-deficit/ for the interactive online version.

The greatest increase in the adoption of air conditioners will be among middle-class and wealthy families, though actual electricity use will rise especially among the wealthiest households (Figure 5). Electricity use increases with income (Supplementary Table 9 and 10), though families sharing similar socio-economic conditions might still have very different usage patterns due to building characteristics, appliance efficiency, climate, and infrastructure conditions, which we can only imperfectly account for. The adaptation cooling deficit persists, especially within the lowest income groups. In 2040, median adoption rates in the first total expenditure decile vary between about 1% (SSP3, RCP4.5) and 27% (SSP5, RCP8.5) in India, between less than 0.1% and 40% in Brazil, between in 0% and 3% in Mexico, and between less than 0.1% and 5% in Indonesia. The wealthiest households drive the aggregate implications in terms of energy use, which are substantial. Electricity increases by about two to three times in Indonesia and India, while the increase is less dramatic in the Latin American countries (Supplementary Tables 14-17). Results show a higher sensitivity to socio-economic scenarios. The distribution of projected air-conditioning and electricity growth rates are not statistically different across climate scenarios, whereas they are across SSPs.

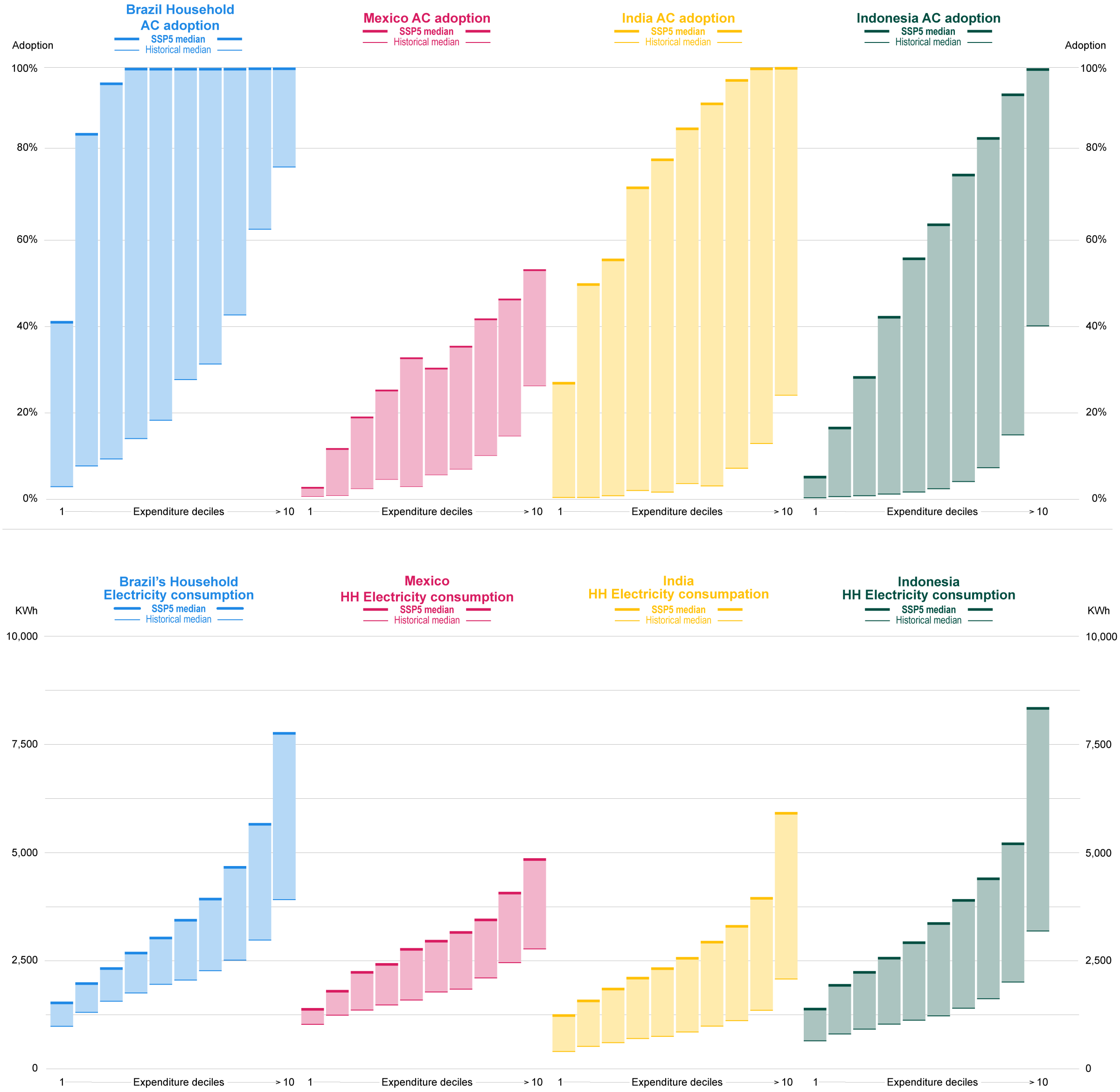

Figure 5: Future increase in air-conditioning and electricity use. Air-conditioning adoption rates (panel a) and total final electricity use (panel b) by income decile in the SSP5 RCP8.5 scenario (historical values refer to the latest available wave, Brazil, 2018; India, 2012; Indonesia, 2017; Mexico, 2016). Horizontal lines show the historical (thin line) and future (thick line) median share across states, as influenced by changes in total expenditure and CDDs. Colors are used to differentiate the four countries and shaded areas highlight the increase between today and 2040.

3 Discussion

While rising temperature and increasing income are likely to exert a positive pressure on the adoption and use of air-conditioning, here we show that the dynamics of air-conditioning are country-specific and relate to demographic and infrastructural characteristics, including education and housing conditions. Access to air-conditioning is highly uneven, indicating that households' ability to adapt to climate change through the use of energy is linked to their socio-economic conditions.

The empirical evidence obtained for Brazil, India, Indonesia, and Mexico contrasts in three key respects with the result from the more studied wealthier countries. First, income has a comparatively more important role than climate in explaining the adoption of air-conditioning, and income critically determines a household's ability to respond to increased exposure to CDDs. By contrast, findings from more developed countries suggest that climatic conditions play a relatively larger role in comparison to income[37–39] since, on average, industrialized countries are above the income threshold at which CDD elasticities rise. Second, better educated heads of households have a consistently stronger propensity to adopt and use air-conditioning. This finding may suggest that the influence of better education goes hand in hand with income and is not associated with a greater awareness of the environmental implications of using air-conditioning, which is in contrast with what is found in richer countries. Third, the relative role of urbanization is an important factor in air-conditioning use, though it plays a smaller role in Brazil, India, Indonesia, and Mexico than in the OECD countries.

With respect to the role of relative humidity, we show that projections based on CDDs computed with the 24 °C wet-bulb temperature threshold lead to higher adoption rates and increases in electricity demand compared to simulations based on lower temperature thresholds or dry-bulb-temperature (Supplementary Figure 8). India and Mexico are two exceptions. We conclude that whether temperature measurements based on dry-bulb-temperature lead to larger or smaller elasticities and projections depends on how air-conditioning is distributed across sub-regions with different micro-climates and humidity levels, and therefore is country-specific. Moreover, the higher density of wet-bulb CDD distribution around small values, especially in Brazil and Mexico, contributes to determining a wider dispersion in the simulated rates of future adoption and electricity consumption.

Aggregate results are in line with the evidence provided by recent single-country studies, such as Gertler and Davis[6] for Mexico. We extend to India, Indonesia, and Brazil concerns regarding a potentially enormous impact from air-conditioning. Over the next twenty years, demand for air-conditioning could rise rapidly with income and CDDs, if households will adjust as they have been doing in the recent past, and so will their demand for electricity. Average electricity growth factors vary across SSPs and RCPs: between 1.3 and 1.8 in Brazil, 2.4 and 3.5 in India, 2.3 and 3.2 in Indonesia, and 1.4 and 1.9 in Mexico, with most of the variation driven by differences across socio-economic scenarios (SSPs), and not so much by differences across climate scenarios (RCPs). Urbanization, education, housing conditions, and electrification, which are taken as given in the simulations, can only further amplify these trends, unless structural changes modify their relationship with mechanical space cooling.

We emphasize that these countries have a vast unmet demand for air-conditioning, and that the uneven distribution of economic resources prevents less affluent households from acceding to this means of adaptation. In 2040, these four countries taken together will face a cooling deficit of up to almost 100 million households, considering only those that already have access to electricity. Not only will the cooling deficit persist for a non-negligible fraction of the population, but even those with air-conditioning will be exposed to a new condition of vulnerability related to supply shortage in the power sector[40] or degraded power stability[41]. It is therefore imperative to manage the growing appetite for residential space cooling by using a mix of technology-oriented and behavioral or social measures and policies[42,43]. Multiple sources of uncertainties will play out over the next twenty years, layered on top of climate and socio-economic uncertainties, and we account for them by utilizing combinations of models and scenarios (see Methods). Behavioral adaptive responses themselves can change, as suggested by the way our estimated elasticities vary not only across countries, but also over time. These differences can reflect changes in technology, characteristics of infrastructure, and market conditions, all of which contribute to propagating uncertainty. Although our database makes it possible to check for a wide set of a household's characteristics, unobserved elements, such as culture, institutions, can always bias cross-sectional estimates. Electricity costs, as well as appliance costs, certainly play a role in a household's decisions concerning adoption and utilization. Our estimates can only include fixed effects that are meant to capture the influence of a state's fixed characteristics, as well as time varying factors common to all states within each country. Higher elasticities obtained when estimating results only with the latest waves could indeed suggest that unobserved declining costs of appliances have made adoption easier over time.

Our simulations for the future focus on the potential influence of CDDs and income without considering the further adjustments that could be induced by the evolution of prices, technology, and by structural changes. Our estimates for air-conditioning adoption and electricity demand can be used as inputs by quantitative system models to analyze the macroeconomic consequences induced by the simultaneous adjustments across multiple sectors. Integrated Assessment Models (IAMs) or Computable General Equilibrium models (CGEs) can also be used to examine the tension between adaptation and mitigation in terms of economic costs, welfare implications, policy effectiveness and design.

Methods

Empirical Analysis

McFadden's basic utility framework (1974, 1982)[44,45] provides the theoretical framework describing the adoption behavior of households. The utility of household i is modelled as a function of expenditure and ownership of goods under the budget constraint given by the household's resources. We distinguish between a vector of cooling durables, k_i with price p and expenditure on all other items c_i:

$$\begin{aligned} & U_i = U(c_i, \mathbf{k}_i) \\ \text{s.t.} \quad & c_i + \mathbf{p}^{'}\mathbf{k}_i = y_i \end{aligned} \tag{1}$$

A household's preferences with respect to the decision to purchase a cooling durable goods are revealed by the latent variable k_{ij}^* with $\in AC, FANS, REF$, which can be modelled as a function of a vector of explanatory variables $\mathbf{X}_i\beta$ and a random independent error term, ϵ_j:

$$k_{ij}^* = \mathbf{X}_i\beta + \epsilon_j \tag{2}$$

The latent variable is revealed once adoption of a given technology is observed.

We model the decision to adopt a cooling durable as a dichotomous variable, k_j, determined by the following decision rule:

$$k_{ij} = \begin{cases} 1 & \text{if } k_{ij}^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

and the probability of a household's purchasing device j as a logistic function:

$$P(k_{ij} = 1|\mathbf{X}) = \frac{\exp(\mathbf{X}_i\beta)}{1 + \exp(\mathbf{X}_i\beta)})) = \Lambda(\mathbf{X}_i\beta) \tag{4}$$

where $\Lambda()$ is the logistic cumulative distribution function.

In our specification we want to focus on the relative contribution of climate and income, proxied by total expenditure and their interaction. Following a number of studies evaluating the electricity-temperature response function in Brazil[46] and India[47], as well as that of AC ownership[5] showing how adjustments in electricity demand to climate change vary with income, we assume that the marginal effect of CDDs on the adoption of cooling assets depends on the level of income (y). The marginal effect of income, approximated by total household expenditure, also depends on climatic conditions:

$$P(k_{ij} = 1|CDD, y_i, \mathbf{X}_i) = \Lambda(\beta_1 CDD + \beta_2 y_i + \beta_3 CDD\, y_i + \mathbf{X}_i\beta) \tag{5}$$

$$\frac{\partial P(k_{ij} = 1|CDD, y_i, \mathbf{X}_i)}{\partial CDD} = \Lambda(.)'[\beta_1 + \beta_3\, y_i] \tag{6}$$

$$\frac{\partial P(k_{ij} = 1|CDD, y_i, \mathbf{X}_i)}{\partial y_i} = \Lambda(.)'[\beta_2 + \beta_3\, CDD] \tag{7}$$

This specification implies that the marginal effects of climate and income are not constant.

The CDD-response function of electricity consumption is estimated for each individual country by applying Ordinary Least Squares (OLS) with a sandwich cluster estimator to the most recent wave available for each country. We model electricity use in average annual kilowatt-hours for each household, q_i, as a function of CDDs, income, y_i, and a set of control variables, $\mathbf{X}_i$:

$$\ln(q_i) = \beta_1 CDD + \beta_2 y_i + \beta_3 CDD\, y_i + \mathbf{X}_i\beta + \epsilon_i \tag{8}$$

By omitting the ownership of air-conditioning and other energy-using appliances, the model captures the long-term response of electricity use to climate and income, as discussed in Depaula and Mendelsohn[46]. Not including air-conditioning, fans, and other appliances means that we are assuming they can change over time, and the effect of the changes in these variables is implicitly captured by the coefficient of the CDD variable. The energy demand literature has long made a distinction between the so-called intensive margin, i.e. how electricity demand varies with temperature for a given stock of equipment, and the extensive margin, namely how the adoption of appliances changes with temperature, income, and other covariates. Earlier studies discuss how the two decisions are jointly related, and how not accounting for common determinants can lead to biased estimates[48]. Unfortunately, the data gathered for the four countries do not make it possible to develop a two-stage approach that accounts for the short-term effect of air-conditioning on electricity consumption, as in Randazzo et al.[38]. We can therefore only evaluate the long-term responses.

Data

We build a household-level database using survey data over the 2003-2018 period for four emerging and developing countries - Brazil, India, Indonesia and Mexico. Three waves are available for Brazil, Indonesia and Mexico, including the most recent years (2016-2018), whereas only two waves are available for India. In Table 1, we estimate adoption models for air conditioners, fans, and refrigerators for each individual country by using the two most recent survey waves available. The use of two waves makes it possible to include time dummies that check for country-specific, time-varying unobservable variables. However, our projections, as shown in Figures 3-5 for both air-conditioning and electricity, are based on regression results that only use the most recent wave, since it better reflects the most recent conditions of these fast-growing countries. Supplementary Table 11 shows the sensitivity of CDDs and total expenditure elasticities when different waves are used.

Validation

We evaluate the predictive power of our logit models by using the Area under the Receiver Operating Characteristic curve (AUC and ROC)[49]. The most important component of our model is the AC adoption model, which is based on a logistic regression that studies determinants of a dichotomic outcome, such as having or not having air-conditioning. Validation techniques for approaches based on logistic regressions exploit a classifier algorithm. Predicted probabilities are computed for all observations, and then the classifier algorithm assigns each predicted probability to class 0 or 1, based on a threshold (usually 0.5). If the predicted probability is larger than 0.5 the observation is classified in class 1, namely as having air-conditioning. If the predicted probability is smaller than 0.5 the observation is classified in class 0, namely as not having air-conditioning. The results are predicted classes for all the observations that are subsequently compared with the truly observed classed, in order to check the accuracy of the model. The justness of a logistic regression is evaluated by building a confusion matrix, a table of fitted versus observed observation classes that makes it possible to identify, after choosing the classification threshold, the number of false positives and negatives that the model predicts. Since the threshold choice for classification is arbitrary, the validation practice computes such a confusion matrix for multiple thresholds and visualizes the results by using a ROC curve displaying the two types of errors for all possible thresholds. The overall performance of the logistic regression is evaluated over an infinite number of thresholds by computing the area under the ROC curve, called AUC. The AUC has a value of between 0.5 and 1. The larger the AUC the better the performance of the logistic regression. We first train our logistic regression on a training dataset defined as a random subsample of our dataset – containing 3/5 of total observations - and then we predict households with air-conditioning in the test dataset, as the remaining subsample of 2/5 of total observations. For three countries, the ROC exhibits an area under the curve (AUC) of more than 0.9 (it is 0.83 which is still very good in Brazil) for air-conditioning, and more than 0.8 for both fans and refrigerators (Supplementary Figure 2). This suggests a good performance of our models in predicting owners of a cooling asset.

Projections

We use the Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs), a set of five socioeconomic and GHG emission scenarios that have been developed by the research community to make scenario-based mitigation and impact studies more comparable across the literature[36]. The socio-economic scenarios (SSPs) describe five plausible and internally consistent storylines, named SSP1 to SSP5, that narrate how socio-economic variables might unfold over the century[35]. Representative Concentration Pathways (RCPs) are trajectories of total future radiative forcing that have been used as input by climate models that generate projections of temperature and other climate variables[36].

We use nationwide growth rates of per capita Gross Domestic Product (GDP), considering a long-term average GDP per capita between 2020 and 2060, and assuming that household expenditure will increase at the same rate. In all countries, per capita GDP grows the most in SSP1 and SSP5, followed by SSP2, which is the continuation of historical trends. Growth rates are particularly high for India (between 289% and 528% compared to 2010) and Indonesia (263%-409%), whereas in Mexico and Brazil GDP per capita approximately doubles. Projections of future dry-bulb (CDDdb) and wet-bulb (CDDwb) cooling degree-days are obtained by using two different sources of meteorological variables from climate model simulations. Data for bias-corrected daily mean temperature dry-bulb (Tdb) for 2021-2060 mid-century are from NEX-GDDP. NEX-GDDP is a broad combination of downscaled and biased-corrected 0.25 gridded daily meteorological fields from 21 Global Climate Models (GCMs) that simulate vigorous (RCP 8.5) and moderate (RCP 4.5) warming under the Coupled Model Intercomparison, Phase V (CMIP5) climate modelling exercise. Because the NEX-GDDP does not include projections of humidity, CDDwb are computed by using variables from the ISIMIP2b scenarios[50], which include bias-corrected data[51] from four CMIP5-models over the same period and for the same two RCP scenarios (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC5). The multi-model median CDDwb of the four GCMs (21 GCMs in the case of CDDdb) are then utilized for the subsequent aggregation to sub-national levels in each country. The projections of the subnational-level population weighted degree-days for the four countries use population data from Jones and O'Neill[52], who provide decadal population (2020-2100) at 0.125° gridded resolution, for the five SSPs. We utilize projected populations for the year 2040 in each SSP as being representative of the midpoint of our mid-century projections. The 0.125° gridded population are matched to the gridded degree-days by using CDO remapping operators, with a prior weighting of the degree-days by population to the district level boundaries in R[53].

To predict the percentage of households with air-conditioning we estimate a logit model by using the latest available wave for each country. We then replace each household's current total expenditure and CDDs with the projected CDDs and expenditure around the year 2040. Projected CDDs are computed by applying state-level growth rates to the historical (as simulated by climate models 1986-2005) district-level CDDs. Projected household-level expenditure is computed by scaling up household expenditure with the country-level income growth projected by different SSPs. We use the fitted equation from the logit model to calculate the adoption probability for each household. In Figure 4, to estimate the future number of households with air-conditioning, we used the 0.5 probability cutoff. Figure 5 shows state-level averages in air-conditioning ownership rates by expenditure decile computed from the household-level adoption rates. To predict future household-level electricity demand, we have fitted the estimated OLS equations with updated income and CDD values, keeping all other covariates to their historical value. The increase in electricity demand shown in Figure 5 and in Supplementary Tables 9-10 has been computed at the household level, and then aggregated to the state level by taking the mean value.

Data availability

The output data generated in this study are available in the Github repository: [https://github.com/Energy-a/Comparative_paper_NatComms]. No access code is required and the following DOI can be used for citation: https://zenodo.org/badge/latestdoi/363125121. This repository also contains R-scripts to regenerate all figures in this paper. An interactive visualization of the adaptation cooling deficit is available at [http://www.energy-a.eu/cooling-deficit/]. The input data used in this analysis are available at in the Data Mendeley repository: [https://data.mendeley.com/datasets/ws7cmwbnfg/1] and can be cited using the following [https://doi.org/10.17632/ws7cmwbnfg.1]. Additional raw input data used in this analysis are available at the following public locations: NASA/NOAA GLDAS: [https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_3H_2.0/summary?keywords=GLDAS_NOAH025_3H_2.0]; CMIP5-NASA NEX GDDP climate data: [https://www.nccs.nasa.gov/services/data-collections/land-based-products/nexgddp]; ISMIP: [https://esg.pik-potsdam.de/projects/isimip2b/]; GDP and population for the Shared Socioeconomic Pathways: [https://tntcat.iiasa.ac.at/SspDb]. Spatial population data for the historical period: [https://beta.sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-rev10]; Spatial population projections for the SSPs: [https://doi.org/10.7927/H4RF5S0P]. The raw data for Indonesia are protected and are not available due to data privacy laws.

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Supplementary Information

Table of Contents

1 Data overview

We have built a household-level database using survey data over the period 2002-2018 for four emerging and developing countries - Brazil, India, Indonesia, and Mexico. The aim is to create a homogeneous database, where variables of interest are constructed in a uniform way across four different consumption expenditure surveys. These data have then been combined with sub-national regional climate data.

These four countries have a long tradition in collecting data on household characteristics and behaviors, and conduct expenditure surveys on a regular basis. In Brazil, since 1987, the IBGE (the Brazilian Institute of Geography and Statistics) has conducted household expenditure surveys covering the entire national territory every six or seven years. In India, since 1972-73, the National Sample Survey Office (NSSO) has conducted broad surveys every five years on household expenditures by. The Indonesian Government fields the National Socioeconomic Survey (SUSENAS), a set of large-scale multi-purpose socioeconomic surveys that were initiated in 1963-1964 and have been fielded every year or two since 1993 on a nationally representative level. In Mexico the National Institute of Geography and Statistics (INEGI) has conducted a household survey on income and expenditure every two years since 1992 (less regularly even since 1984).

In every country, surveys run over different years and periods. Supplementary Table 1 summarizes the data availability and the reference period across the four countries considered in this study. The information regarding the period of implementation is important when merging surveys with climate information. As of now, three waves are available for Brazil, Indonesia, and Mexico, including the most recent years (2016-2018), whereas only two waves are available for India.

Two levels of administrative units are included in the database. Level 1 includes administrative units such as States or Union Territories (these are similar to states but managed by the central government). These can be very large, such as Amazonas in Brazil, which has a territorial area of 1,559,000 square kilometers. Level 2 provides the level of administrative division and includes districts or municipalities (Supplementary Table 2). It is available for India, Indonesia, and Mexico. The survey on Brazil does not give information regarding the municipality or district where the households are located, as they want to preserve the identity of the families. States can be further stratified into stratum units: one for rural locations and three for urban locations - the capital of the State, the metropolitan region or other urban municipalities.

The weight variables available in the survey datasets have been used to obtain population-representative descriptive statistics. We have omitted strata and primary sampling unit (PSU) variables, given strong the incompatibilities and missing values among countries and across waves (e.g. in ENIGH 2004 and in all POF waves there are no PSU and strata variables).

The database has been broken down into six main sections describing, respectively, demographics and household characteristics, house features, income and expenditure patterns, energy use, durables ownership, and climate indicators.

For the first two sections, we have selected and harmonized basic information on the households. These include the number of total members and the number of members divided by gender and age. We have considered as adults individuals aged 16 and above, and as infants from newborns to 5 years of age.

To make information on the household heads coherent across surveys, we have elaborated common variables on education level, gender, literacy, and occupation's type and sector. Education level is based on school attainment data divided among 1) primary, 2) secondary or 3) higher educational levels. We have assumed 0) no education for no or incomplete primary schooling. We have not used data on years of education because none are available for India and Mexico. For the occupation sector we have distinguished between employees in the agricultural sector, including forestry, fishing, livestock, and those not. We have also gathered data on the living area and characteristics of dwellings. These include dummy variables to classify households dwelling in an urban area or not, as well as whether they own the house they live in or not and whether they have electricity access. Common categories across the different countries are identified to homogenize information on energy sources for cooking and lighting, sources of drinking water and types of toilet facilities (Supplementary Table 3).

To compare and summarize information on the characteristics of dwellings across countries and waves, we have created a set of categorical variables and used them to build a housing index. The housing index is a composite measure of a household's living conditions. It is calculated by using data about assets related to housing construction materials (walls and roof), as well as about the type of toilet facilities and access to drinking water. Each household is assigned a standardized score for each asset, depending on the type and quality of the selected asset. These scores are summed by household, and the final score is then ranked according to three categories, namely Low, Middle and High housing quality. The housing index sets a minimum value of 1 for low quality dwelling conditions, and a maximum value of 3 for high dwelling conditions.

We have gathered data on household income and expenditure. As figures about income are only available for Brazil and Mexico, we have used the total expenditure as a measurement of a household's economic level. Single survey expenditure values are reported in local currency units (LCU) by different reference periods. For each of them, we compute annual values and convert them into constant (2011) purchasing-power-parity (PPP) US dollars. To convert LCU to current USD PPP we have used the World Bank's PPP conversion factor for private consumption[1]. For converting from current USD PPP to 2011 constant USD PPP we have used the CPI Inflation Calculator from the U.S. Bureau of Labor Statistics[2].

Our final dataset includes five expenditure categories (Supplementary Table 4): total expenditure, energy expenditure, electricity expenditure, food expenditure and medical expenditure. Total expenditure is based on aggregate reported values, except for Mexico, for which we noted some inconsistencies affecting the computation of non-monetary expenses across waves (see section on Mexico). To ensure consistency across years, Mexico's total expenditure comprises only its monetary expenditure. We have used total household expenditure in USD2011 PPP to compute total expenditure per adult equivalent (i.e. divided by the number of household members, imposing a weight of 1 for adults and a weight of 0.5 for minors).

Household ownership of a broad number of appliances (including air-conditioning, fans and

[1] https://data.worldbank.org/indicator/ PA.NUS.PRVT.PP
[2] https://www.bls.gov/data/inflation_calculator.htm

refrigerators) and other devices (e.g. car, tv, radio) is reported through a set of dummy variables, where 0 = "Not owned" and 1 = "Owned". For each country, we have constructed two variants of climate variables – annual Cooling Degree Days (CDDs), Units: °C days– by using daily dry-bulb and wet-bulb temperature. We have merged climate and survey data at the district level, since it is the most pinpointed disaggregated geographical information available for India, Indonesia, and Mexico, except for Brazil, whose data have been merged at the state level (Federal Unit), by stratum type. To do so, first the climate data are aggregated from the grid-cell level to the district (or state) levels utilizing (i) within country administrative boundaries (from geo-spatial shape files) at the respective admin level[3]; and (ii) routines in R (R Core Team, 2018) made available by open-source packages sp, rgdal, raster and spatialEco.

The remainder of this section provides a detailed description of the survey dataset for each country and its climate data.

[3]Admin levels 2 and 3 are for States and Districts, respectively.

Brazil - POF

Survey Name	Consumer Expenditure Survey (Pesquisa de Orçamentos Familiares - POF)
Institution	Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatistica - IBGE)
Frequency	Every six or seven years
Survey Waves	2002-2003, 2008-2009, 2017-2018
Period of observation	POF 2002-2003: July 2002 to June 2003. POF 2008-2009: May 2008 to May 2009. POF 2017-2018: June 2017 to July 2018
Type	Cross-Sectional
Coverage	Occupied permanent private housing units and their residents in the area covered by the survey in both urban and rural areas
Geographic Information	National, federation units and stratum (1 rural, 3 urban)
Observation-Level	Household members
Weight	Each household of the subsample is associated with a sample weight or expansion factor that, attributed to the characteristics investigated by the POF, makes it possible to estimate the quantities of interest for the entire population
Total Observations	162,363 (2002-2003: 48,473; 2008-2009: 55,970; 2017-2018: 57,920)
Data URL	`https://www.ibge.gov.br/estatisticas/sociais/trabalho/9050-pesquisa-de-orcamentos-familiares.html?=&t=downloads`

We have concatenated *NÚMERO SEQUENCIAL*[4] (the sequential number for each of the Sample Sectors), *DV DO SEQUENCIAL* (one-digit code that verifies the sequential number assigned to the Sector Sample) and *NÚMERO DO DOMICÍLIO* (two-digit code, identifying the domicile, assigned sequentially to each household selected in each sector) in order to obtain a unique identifier for each household (*hhid*).

To elaborate descriptive statistics that are population-representative, we have used a weight variable available in the survey. For both waves POF reports two weight variables: *FATOR DE EXPANSÃO 1* and *FATOR DE EXPANSÃO 2*. Both variables identify the expansion factor attributed to the household. The former is the weight used for the survey design; the latter, which is the one we have opted for, is the adjusted weight that should be used to calculate estimates from the survey data.

In the first two waves we have created the dummy variable, *urban*, starting from *ESTRATO GEOGRÁFICO*, to identify whether the household lives in an urban or rural settlement. The variable consists of a sequence of two numbers that identify either the municipality of the capital, or the rest of the metropolitan region or the rest of the federative units or a rural area. Thus,

[4]Where not otherwise specified we report the original name of the variables common to the greatest number of waves. In some cases, small differences may emerge between waves.

we associate the first three categories with living in an urban area, while the latter category with dwelling in a rural area. In the 2017-2018 wave we have used the available specific variable *TIPO_SITUAÇÃO_REG*, which takes a value of 1 for urban households and a value of 2 for rural ones.

Aggregate (*total*, *energy*, *electricity* and *food*) expenditures are reported on a monthly basis in local currency (Brazilian real).

In POF waves revenues are reported on monthly basis in local currency. Among the different income variables available in the survey we have opted for *RENDA TOTAL MENSAL DA UC*. This corresponds to the value of the gross monthly gross income of the consumption unit (family), and it is obtained through the sum of the gross monetary income of all residents of the unit of consumption, obtained through labor, transfers, other income and the positive balance of the financial transaction, plus the portion related to the non-monetary income of the unit of consumption. Then, we compute it on an annual basis in $2011 PPP.

POF survey considers only employed respondents, without considering those that are inactive or unemployed. *POSIÇÃO NA OCUPAÇÃO* identifies a detailed range of possible positions as principal occupation. We have distributed them among our unique five occupation categories defining the household head's employment status (see Supplementary Table 3).

For the other categorical variables we have adopted *SEXO* for a household head's gender; *CÓDIGO DE ATIVIDADE PRINCIPAL* for the household head's occupation sector; *CONDIÇÃO DE OCUPAÇÃO* for housing ownership; *MATERIAL QUE PREDOMINA NAS PAREDES EXTERNAS* for house walls; *MATERIAL QUE PREDOMINA NA COBERTURA* for house roof; *PROVENIÊNCIA DA ÁGUA* (*TIPO DE ABASTECIMENTO DE ÁGUA* in 2004) for drinking water; *ESCOADOURO SANITÁRIO* for toilet facilities.

For cooking fuel we combine the following POF variables:

- *FOGÃO A GÁS*
- *FOGÃO A LENHA*
- *FOGÃO A CARVÃO*
- *FOGÃO A ENERGIA ELÉTRICA*
- *FOGÃO COM OUTRA FONTE*

For electricity access and lighting energy source we combine the following POF variables:

- *REDE GERAL DE ENERGIA ELÉTRICA*
- *FONTE PRÓPRIA PARA ENERGIA ELÉTRICA*
- *DIESEL/GASOLINA/GÁS PARA ENERGIA ELÉTRICA*
- *ENERGIA SOLAR PARA ENERGIA ELÉTRICA*
- *ENERGIA EÓLICA PARA ENERGIA ELÉTRICA*
- *ÁGUA PARA ENERGIA ELÉTRICA*
- *BIODIESEL PARA ENERGIA ELÉTRICA*
- *SISTEMA MISTO PARA ENERGIA ELÉTRICA*
- *OUTRA FONTE PARA ENERGIA ELÉTRICA*

In POF 2002 there are no information on house walls and roof materials and toilet type

India - NSS

Survey Name	Household Consumer Expenditure, National Sample Survey (NSS)
Institution	National Sample Survey Office (NSSO), Ministry of Statistics and Programme Implementation, Government of India
Frequency	Quinquennial from 1972-73[5]
Survey Waves	2004-2005, 2011-2012
Period of observation	Over 12 months, from July through June
Type	Cross-Sectional
Coverage	Randomly selected households based on sampling procedure
Geographic Information	The whole Indian Union except (i) Leh (Ladakh) and Kargil districts of Jammuand Kashmir (in 2004-2005), (ii) interior villages of Nagaland situated beyond five kilometres of the bus route and villages in Andaman and Nicobar Islands inaccessible throughout the year (in 2004-2005 and 2011-2012)
Observation-Level	Household members
Weight	The level sample size of State/Union Territories (UT) is allocated between two sectors (urban and rural) in proportion to population as per census 2001
Total Observations	226,306 (2004-2005: 124,644; 2011-2012: 101,662)
Data URL	`http://microdata.gov.in/nada43/index.php/catalog/central/about`

A unique household identification number (*HHID*) is provided across the different waves. It is a 9 digit sequence, composed by concatenating First Stage Unit Serial number of the village/urban block (FSU), Hamlet Group Sub Stratum number, Second stage stratum number and Sample household number.

Double weighting is applied to an urban sector subject, provided that urban sample size for larger states not exceed the rural sample size. A variable reporting weights (or multipliers) is given at the end of each record (combined multiplier), and is used to compute population-representative statistics.

Sector is the variable that in the surveys identifies households living in a rural or urban area. We use it to create the dummy variable *urban* across all waves.

Information about household members and composition were derivable from demographic variables available in the survey, including *Sex*, *Age*, *HH_Size* (respectively *B4_q4, B4_q5, B3_q1* in 2004-2005). We have used them to construct variables on a household head's gender and age, as well as the number of members, adults, children and infants within the household.

No variables reporting income values are available in the survey.

Two reference periods are reported for monthly per capita consumer expenditure (MPCE): a Uniform Reference Period (URP) based on data collected with a 30-day reference period for all items, a Mixed Reference Period (MRP) based on data with a 365-day reference period wherever available, and a 30-day reference period for other items. For the purpose of this work we have used the MRP estimate of per capita consumption (*MPCE_MRP*). Expenditure amounts include the sum total of monetary values of all the items (i.e. goods and services) consumed by the household on domestic account during the reference period. It is provided on a per capita basis (divided by the household size) and in local currency units (Rs).

Monthly household expenditure values are available for energy and electricity. As for food expenditure, values are provided in sub-categories (e.g. cereals, pulses, milk and milk products, etc.) that need to be aggregated. Medical expenditure includes figures on institutional (incurred as an in-patient of a medical institution) and non-institutional expenses.

Categorical variables are constructed starting from the following variables:

- *Education* (*B4_q7* in 2004-2005) for the household head's education level (*edu_head_2*);
- *HH_Type_code* (*B3_q4* in 2004-2005) for the household head's occupation (*occupation_head*);
- *NIC_2008* (*NIC_1998* in 2004-2005) for the occupation sector of the household head (*sector_head*). NIC codes are provided for each economic activity according to the National Industrial Classification. We use them to distinguish households working in the agriculture, forestry and fishing sectors (codes starting with 01, 02, 03) from those involved in other economic sectors;
- *Dwelling_unit_Code* (*B3_q16* in 2004-2005) for the house ownership (*ownership*); Information on other characteristics of the house (i.e. size, walls, roofs) are not available;
- *Lighting_Code* (*B3_q18* in 2004-2005) to determine whether household has access to electricity (*ely_access*) and the lighting source (*lighting*);
- *Cooking_Code* (*B3_q17* in 2004-2005) for the energy sources used for cooking (*cooking*);
- Information on sources of drinking water and type of toilet facility are not available;
- Ownership of durables and the respective expenditure are reported for a large number of items (*Whether_Possesses and Expenditure_Durables* in 2011-2012, *B11_q3, B11_q14* in 2004-2005).

Indonesia - SUSENAS

Survey Name	National Socio-Economic Survey (Survei Sosial Ekonomi Nasional - SUSENAS)
Institution	Indonesian Central Statistics Agency (Badan Pusat Statistik - BPS)
Frequency	Irregular since 1963, nationally representative since 1993
Survey Waves	2004, 2012, 2017
Period of observation	July (2004), March to December (2012), March (2017)
Type	Cross-Sectional
Coverage	Covers a large representative sample of households across Indonesia
Geographic Information	National, province, regency/city (district), sub-district and village levels. Sub-district and village identification not available after 2012
Observation-Level	Household members
Weight	Frequency weights computed within each stratum (census block which is an administrative/geographical unit) as the inverse of the sampling fraction
Total Observations	648,643 (2004: 65,254; 2012: 286,113; 2017: 297,276)
Data URL	`https://mikrodata.bps.go.id/mikrodata/index.php/catalog/SUSENAS`

To uniquely identify SUSENAS households across waves (*hhid*), we have used the available variable *urut*. As of 2017, there are 34 provinces (*povinsi*) and 514 districts (*kabupaten/kota*) in Indonesia. However, the number of states and districts has changed in the period 2004-2017. The number of provinces has increased from 30 to 34 and the number of districts from 373 to 514.

To make descriptive statistics that are population-representative, we have used weights available in the survey, namely *wert*.

The variable *b1r5* identifies households dwelling in a rural or urban settlement. We use it to create the dummy variable *urban* across all waves.

In SUSENAS there is no information about income. Total expenditure at monthly level in local currency is reported in the variable *expend*.

There is no total energy expenditure, but single fuel expenditures are available (tri-monthly). They are identified by different codes (*kode*) in variable *b42k6* (*electricity = 238*, *lpg = 242*, *city gas = 244*, *kerosene = 246*, *generator fuel = 248*, *charcoal= 253*, *firewood = 254*).

For the categorical variables we adopt *jk* for the household head's gender; *b6r3* for housing ownership; *b6r6* for house walls; *b6r5* for house roof; *b6r14a* for electricity access and lighting energy source; *b6r15* for cooking fuel; b6r9a for drinking water; *b6r13b* for toilet facilities.

Information on education is available as number of years attended in school. Both education and occupation of the household head are created by using a combination of different variables (*b5r14* to *b5r17* for education, *b5r24a1*, *b5r25*, *b5r26*, *b5r31* for occupation).

Information on the ownership of a wide range of goods is provided under variable *b7r4*. Ownership of air conditioning is not available in the 2004 wave, whereas ownership of fans is unavailable in all waves.

Mexico - ENIGH

Survey Name	Household Income and Expenditure Survey (Encuesta Nacional de Ingresos y Gastos de los Hogares - ENIGH)
Institution	Instituto Nacional de Estadistica, Geografia e Informatica
Frequency	Bilennial (since 1992)
Survey Waves	2004, 2012, 2016
Period of observation	August to November
Type	Cross-Sectional
Coverage	It is constituted by households of national or foreign people, who habitually reside in private housing units within the national territory.
Geographic Information	National, federal entity and municipality levels
Observation-level	Household members
Weight	Probability survey weights. Taking account of the weights, the sample is representative at both the national level and subnational levels (urban vs rural)
Total observations	101,907 (2004: 22,595; 2012: 9002; 2016: 70,310)
Data URL	https://www.inegi.org.mx/programas/enigh/nc/2016/

There are two versions of the ENIGH survey: the traditional and the new construction. In 2008, INEGI started to publish the results of the survey under a new construction methodology. The main difference among the two versions relies on how revenues are aggregated in reported income variables. For the new construction, the aggregation rules are in accordance with UN recommendations. In our analysis, we have opted for the traditional version for the 2004 wave (since it was the only one available), while we have used the new construction for both the 2012 and the 2016 waves.

There are two identifiers of the respondent, one associated with the house, *folio_viv*, and another associated with the household, *folio_hog*. We concatenate the two in order to obtain a unique identifier for each household (*hhid*).

In 2004 INEGI collected households and dwellings variables in the same dataset, and these have a unique identifier *FOLIO* - a sequence of 11 digits. The first 10 digits are associated with the dwelling. The last one identifies the household living in that house. If the eleventh digit of *FOLIO* is equal to 0, this refers to the main household; while, if *FOLIO* ends with a digit greater than 0, this refers to the other households dwelling in the same house. Since INEGI reports data about dwellings' characteristics - e.g. having an air conditioner, house wall materials - only for the main household, we assume that they also apply to the secondary families.

To elaborate descriptive statistics that are population-representative, we have used the weight variable *factor* in the ENIGH survey 2016. In 2012 and in 2004 there were two factor of expansion, *factor_viv* and *factor_hog* (*HOG* in 2004). Since our analysis is at the household level, we use *factor_hog* as weighting variable.

In all the three waves we have created the dummy variable *urban* starting from *tam_loc* (*ESTRATO* in 2004) to identify whether the household dwells in an urban or a rural settlement. This variable identifies urban areas as localities of 2500 or more inhabitants, while rural areas as localities with fewer than 2500 inhabitants.

Aggregate (*total*, *energy*, *electricity* and *food*) expenditures are reported at tri-monthly basis in local currency (pesos).

As *income* we use the total current income (*ingcor*), which corresponds to the sum of both monetary and non-monetary revenues. Other revenues are reported on a tri-monthly basisin local currency. Thus, we compute annual income and converted it in $2010 PPP through the same procedure for expenditure.

We construct *occupation head* variable through the following procedure:

- Using *id_trabajo* (*COD_TRAB* in 2004), we only focus on the household-head's primary job occupation;
- We have divided household-heads between those that worked in the previous month and those that did not (*trabajo_mp* in 2012-2016; *TRABAJO* in 2004). From inactive respondents, we have removed household-heads who declared to be looking for a job, identifying them as "unemployed" (*act_buscot* in 2012-2016; *BUS_TRAB* in 2004). Based on their contract, we have distinguished workers between the self-employed, employees and seasonal workers (*indep*, *subor*, *tipocontr* in 2012-2016; *POSICION09*, *CONTR171* in 2004).

For the other categorical variables we adopt *sexo_jefe* (*SEXO* in 2004) for the household head's gender; *educa_jefe* (*ED_FORMAL* in 2004) for the household head's education level; *scian* (*SCIAN151* in 2004) for the household head's occupation sector; *tenencia* (*TENENCIA12* 2004) for housing ownership; *mat_pared* (*MUROS01* in 2004) for house walls; *mat_techos* (*TECHOS02* in 2004) for house roof; *disp_elect* (*LUZ21* in 2004) for electricity access and lighting energy source; *combustible* (*COMBUS11* in 2004) for cooking fuel; *disp_agua* (*AGUA15* in 2004) for drinking water; *sanit_agua* (*BANO17* in 2004) for toilet facilities.

There is no information on household energy and electricity consumption in kWh. Hence, we have gathered state-level electricity price information from INEGI's Consumer Price Index.[6] We have then divided households' electricity expenditure by prices to get electricity demand.

For most goods, ENIGH waves provide the number of durables owned. We use this number to generate the ownership dummy variables.

[6]https://www.inegi.org.mx/programas/inpc/2010/

Climate Data

Data Type	'DegDays 0p25 1970-2018'
Raw Data	3-hourly temperature (°C) (GLDAS, Rodell et al., 2004) aggregated to daily timesteps
Climate variable	Long-term average Dry (CDD_{db}) and Wet Bulb (CDD_{wb}) Cooling Degree Days
Frequency	Annual
Resolution	State and District level
Period of observation	1970-2016
Data source	Mistry M.N., 2019a; Mistry M.N., 2019b

Two climate variables (annual CDD dry-bulb and CDD wet-bulb - *CDDdb* and *CDDwb*) have been computed at the grid-cell level before being spatially aggregated to the district or state/stratum level. Our preferred variable, *CDD wet-bulb*, takes into account the influence of relative humidity on evaporative cooling, which can have an important role in the countries in our study, as they are tropical countries that feature not only spatial heterogeneity in relative humidity, but also coastal regions with high relative humidity. When relative humidity is 100%, dry-bulb and wet-bulb temperature measurements coincide; otherwise wet-bulb temperature (and therefore also CDD *wet-bulb*), are always lower.

Both variants of the CDDs, measured in annual °C days, are assembled by using the input meteorological fields at a high-spatial resolution (0.25°gridded, about 27 km x 27 km at the equator) from the Global Land Data Assimilation System (GLDAS), covering the 1970-2016 period. At each grid-cell the CDDs are calculated by using the American Society of Heating, Refrigerating and Air-Conditioning (ASHRAE) method, and by fixing the baseline temperature at 24 °C, as opposed to the more commonly used threshold of 18 °C, which works better for temperate countries. As sensitivity checks, we also use a baseline temperature of 22 °C for both dry- and wet- bulb CDDs.

We have computed long-term climatological averages of degree-days at the administrative level in two ways: 1) starting in 1970 up to the year the survey was conducted, 2) considering the ten years preceding the individual survey years. Since for Brazil and India the survey was carried out over two years, we have opted for the year the wave started - namely, 2002, 2008 and 2017 for Brazil, and 2004, 2011 for India.

We have merged climate and survey data at the district level for India, Indonesia, and Mexico, while for Brazil at the lowest administrative unit at which we can locate households, which is the state (Federal Unit). Within each state, we have been able to distinguish household locations across four strata: rural, capital, metropolitan region, and other urban areas. Gridded CDDs are subsequently aggregated to subnational boundaries in each of the four countries. Subnational population weighted degree-days for the four countries have been assembled by using population data from CIESIN[7]. The 1°gridded populations are matched to the gridded degree-days by

[7]Center for International Earth Science Information Network - CIESIN - Columbia University. 2017. Gridded Population of the World, Version 4 (GPWv4): Population Count, Revision 10. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H4PG1PPM

using CDO[8] remapping operators, with prior weighting of the degree-days by population to the district level boundaries.

[8]Schulzweida, Uwe (Max Planck Institute for Meteorologie). 2018. “Climate Data Operators (CDO) User Guide, Version 1.9.0.

Supplementary Table 1: Overview of data availability

	Brazil	India	Indonesia	Mexico
Wave 1	July 2002 - June 2003	July 2004 - June 2005	July 2004	Aug - Nov 2004
Wave 2	May 2008 - May 2009	July 2011 - June 2012	March - Dec 2012	Aug - Nov 2012
Wave 3	June 2017 - July 2018	n.a.	March 2017	Aug - Nov 2016

Supplementary Table 2: Administrative divisions

	Brazil	India	Indonesia	Mexico
Level 1	Federation Units	States & Union Territories	Provinces	Provinces
	27	35/35	30/33/33	32
Level 2	Stratum	Districts	Regencies	Municipalities
	4x27	577/583	360/497/491	490/369/919

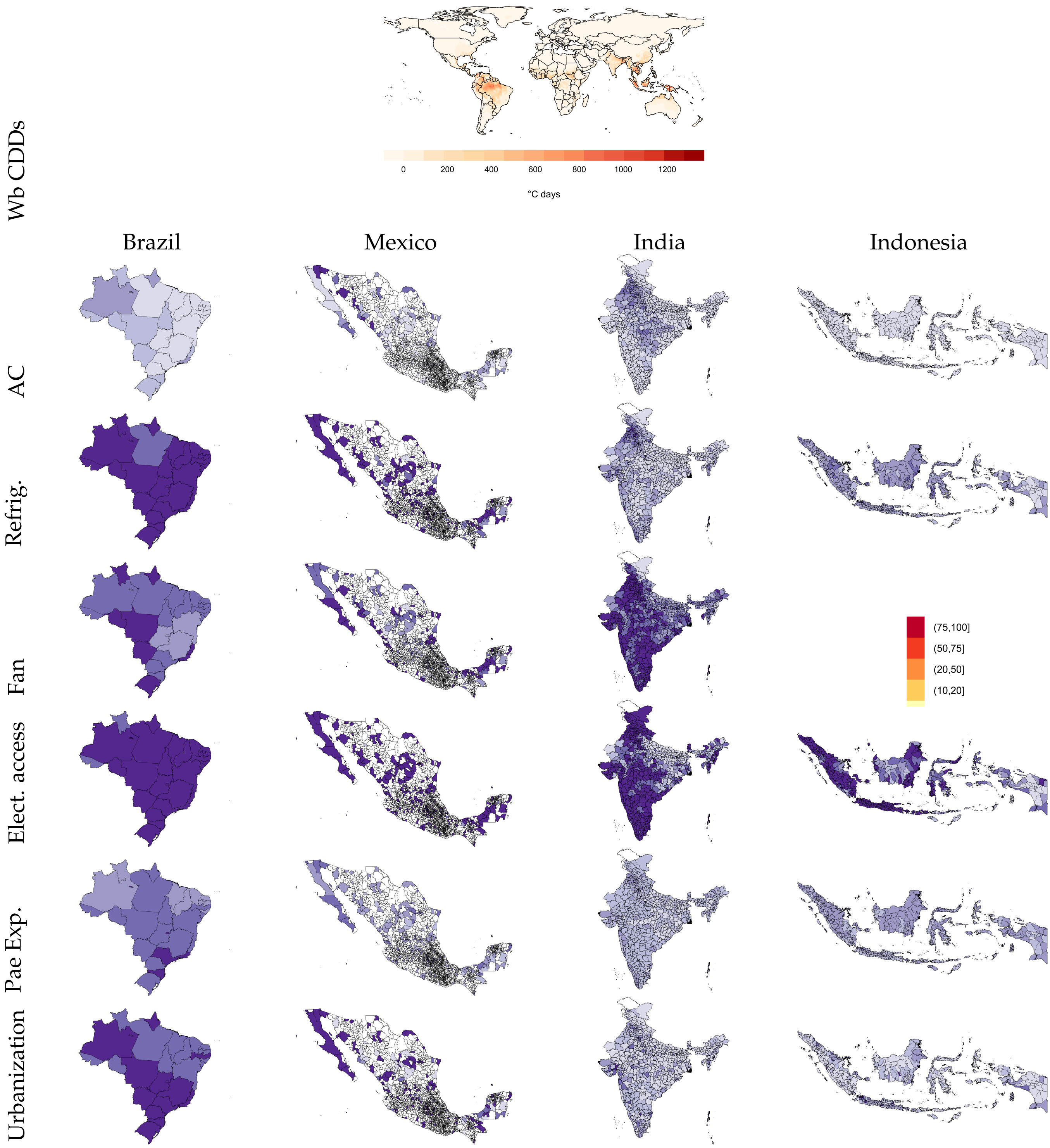
Supplementary Table 3: Categorical variables

Variables	Var. Code	Description	Categories
Urban	*urban*	Living or not in an urban area	0 = Rural ; 1 = Urban
Gender Head	*sex_head*	Household head's gender	1 = Male; 2 = Female
Education Head	*edu_head_2*	Household head's education level	0 = No education; 1 = Primary; 2 = Secondary; 3 = Above
Occupation Head	*occupation_head*	Household head's employment status	0 = Inactive; 1 = Unemployed; 2 = Self-employed; 3 = Regular wage earning; 4 = Casual worker; 5 = Other
Sector Head	*sector_head*	Household head's occupation sector	0 = Other sectors; 1 = Agriculture (including forestry, fishing, livestock)
Dwelling Ownership	*ownership_d*	Whether household owns the dwelling where it lives	0 = No; 1 = Yes
House Walls	*house_walls*	Materials of the dwelling's walls	1 = Masonry; 2 = Wood; 3 = Earth structures; 4 = Metal and asbestos; 5 = Waste materials 6 = Other
House Roof	*house_roof*	Materials of the dwelling's roof	1 = Tile; 2 = Concrete; 3 = Wood; 4 = Metal and asbestos; 5 = Earth structure; 6 = Waste materials; 7 = Other
Electricity Access	*ely_access*	Access to electricity	0 = No; 1 = Yes
Lighting Energy Source	*lighting_source*	Energy source for lighting in the dwelling	0 = No lighting; 1 = Public supply/electric utilities; 2 = Renewable plant; 3 = Fossil fuels; 4 = Other
Cooking Energy Source	*cooking_source*	Energy source for cooking	0 = No arrangements; 1 = Electricity; 2 = Gas; 3 = Coal; 4 = Firewood; 5 = Other
Drinking Water Source	*drinking_water*	Source of fresh and drinking water	1 = Piped water; 2 = bottled water; 3 = Wells and springs (including lakes, river); 4 = other
Toilet	*toilet*	Toilet type	0 = No toilet; 1 = Flush; 2 = Pit and latrine; 3 = Other
Housing Index	*housing_index_lab*	Synthesis measure of dwelling conditions	1 = Low quality; 2 = Medium quality; 3 = High quality

Supplementary Table 4: Descriptive statistics. Selected variables in the database

	Brazil 2003		Brazil 2009		Brazil 2018		Mexico 2004		Mexico 2012		Mexico 2016	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AC	0.01	0.09	0.09	0.28	0.20	0.40	0.04	0.19	0.12	0.33	0.14	0.35
Fan	0.60	0.49	0.62	0.49	0.76	0.43	0.54	0.50	0.47	0.50	0.48	0.50
Refrigerator	0.86	0.35	0.92	0.28	0.98	0.14	0.79	0.41	0.82	0.39	0.86	0.35
Urban	0.85	0.36	0.85	0.35	0.86	0.35	0.77	0.42	0.78	0.41	0.78	0.41
Total exp (USD2011 PPP)	14644.32	22198.35	19344.54	29309.79	22879.01	31150.79	8941.12	10964.58	11309.29	12866.61	12502.30	12813.61
Exp pae (USD2011 PPP)	5550.61	9400.03	7815.43	13358.90	9747.70	14383.69	3031.42	4585.54	4162.75	6021.74	4631.66	5772.92
Energy exp (USD2011 PPP)	506.75	398.59	626.98	555.28	824.58	574.54	468.06	591.98	472.84	597.29	520.85	541.54
Ely exp (USD2011 PPP)	360.08	360.94	465.89	514.86	607.50	528.09	375.11	519.55	274.61	455.34	281.71	422.10
Medical exp (USD2011 PPP)	1243.15	7074.99	1345.80	3168.54	2862.72	4295.45	343.61	1810.12	281.62	1366.05	337.52	1644.36
Food exp (USD2011 PPP)	2745.60	2852.61	3261.98	3234.13	3631.78	3726.63	2730.26	3335.88	3810.63	2789.03	4375.67	3286.14
Electricity consump (kWh)	1766.52	1323.02	1956.01	1551.76	1953.88	1556.37	n/a	n/a	2071.65	2002.14	2098.60	2023.17
N. members	3.63	1.83	3.30	1.65	3.01	1.49	4.04	1.99	3.72	1.88	3.67	1.83
Share under 16	0.24	0.23	0.21	0.23	0.16	0.21	0.28	0.24	0.23	0.23	0.23	0.23
Share infants	0.09	0.15	0.07	0.13	0.06	0.12	0.10	0.15	0.09	0.15	0.08	0.14
Literacy head	0.77	0.42	0.90	0.29	0.85	0.36	0.89	0.31	0.90	0.29	0.92	0.26
House ownership	0.72	0.45	0.73	0.45	0.73	0.45	0.73	0.45	0.68	0.46	0.69	0.46
Electricity access	0.96	0.20	0.98	0.13	0.99	0.07	0.99	0.12	0.99	0.09	1.00	0.07
Housing index	1.48	0.50	2.81	0.43	2.85	0.37	2.81	0.47	2.85	0.42	2.89	0.35
Car	0.30	0.46	0.33	0.47	0.46	0.50	0.27	0.44	0.27	0.44	0.28	0.45
TV	0.89	0.31	0.94	0.23	0.97	0.18	0.92	0.27	0.92	0.27	0.94	0.25
CDDs dry-bulb (24 deg)	529.17	380.66	500.21	391.90	492.15	402.52	343.35	393.56	373.10	414.55	388.31	412.46
CDDs wet-bulb (24 deg)	193.79	203.71	189.03	213.09	187.36	226.64	102.61	158.41	124.80	177.02	118.48	170.27
CDDs dry-bulb (22 deg)	1053.49	583.21	1001.31	598.01	979.50	617.42	593.06	622.46	651.18	652.12	675.89	638.38
CDDs wet-bulb (22 deg)	482.45	339.81	463.06	351.58	452.84	366.18	217.87	292.81	250.09	317.14	240.15	305.29

	Indonesia 2004		Indonesia 2012		Indonesia 2017		India 2005		India 2012	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AC	n/a	n/a	0.05	0.21	0.08	0.27	0.08	0.26	0.12	0.32
Fan	n/a	n/a	n/a	n/a	n/a	n/a	0.52	0.50	0.73	0.45
Refrigerator	0.21	0.41	0.36	0.48	0.54	0.50	0.12	0.33	0.20	0.40
Urban	0.48	0.50	0.50	0.50	0.53	0.50	0.27	0.44	0.32	0.46
Total exp (USD2011 PPP)	3058.30	3820.84	7388.83	9531.56	10058.63	9810.02	3332.24	2810.94	5514.13	5098.54
Exp pae (USD2011 PPP)	969.04	1025.58	2389.18	2843.42	3310.71	3045.11	927.70	822.38	1642.18	1611.93
Energy exp (USD2011 PPP)	312.37	345.24	272.08	247.60	390.86	499.21	323.29	229.89	464.04	307.27
Ely exp (USD2011 PPP)	144.82	180.17	118.79	186.81	248.66	449.01	149.09	183.83	185.62	243.81
Medical exp (USD2011 PPP)	n/a	n/a	210.66	1514.16	425.65	1947.33	308.87	734.28	468.14	1242.36
Food exp (USD2011 PPP)	n/a	n/a	3673.80	2458.50	5120.81	3364.60	1626.25	1025.58	2410.25	1564.59
Electricity consump (kWh)	957.94	1061.26	890.37	8649.57	1392.84	1740.10	798.41	1427.65	931.76	975.85
N. members	3.93	1.69	3.87	1.68	3.76	1.65	4.74	2.41	4.43	2.21
Share under 16	0.27	0.22	0.27	0.21	0.24	0.21	0.31	0.25	0.27	0.24
Share infants	0.10	0.14	0.10	0.14	0.09	0.14	0.11	0.16	0.09	0.14
Literacy head	0.89	0.31	0.92	0.27	0.94	0.23	0.62	0.49	0.68	0.47
House ownership	0.80	0.40	0.80	0.40	0.80	0.40	0.85	0.36	0.84	0.37
Electricity access	0.91	0.29	0.96	0.20	0.98	0.13	0.65	0.48	0.80	0.40
Housing index	2.51	0.57	2.64	0.54	2.79	0.44	n/a	n/a	n/a	n/a
Car	0.05	0.22	0.08	0.27	0.11	0.31	0.02	0.14	0.04	0.20
TV	0.68	0.47	0.09	0.29	0.13	0.34	0.39	0.49	0.59	0.49
CDDs dry-bulb (24 deg)	705.58	472.68	663.42	446.09	658.39	428.99	1037.23	439.16	1045.07	448.12
CDDs wet-bulb (24 deg)	318.59	315.16	327.01	326.62	328.20	327.47	297.15	196.23	299.49	197.71
CDDs dry-bulb (22 deg)	1299.55	630.89	1247.22	607.76	1248.98	585.56	1547.99	567.49	1552.28	577.83
CDDs wet-bulb (22 deg)	678.71	511.54	676.47	515.02	671.57	511.16	527.54	271.48	523.48	271.46



Supplementary Figure 1: Spatial distribution of ownership of AC, fans, refrigerators, per adult equivalent (pae) expenditure, electricity access, urbanization in 2012 (Brazil 2009). Maps are generated using the sp, rgdal, and raster R packages.

2 Empirical results

Supplementary Table 5: Logit models with state fixed effects using CDD wet-bulbs. Marginal Effects

	Brazil			India			Indonesia		Mexico		
	AC	FAN	REF	AC	FAN	REF	AC	REF	AC	FAN	REF
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mean CDD wet-bulb	-0.000277***	0.000455***	0.000111***	-0.000373***	-0.000322*	0.000168	-2.58e-05***	5.20e-05	-0.000609***	0.000929**	9.62e-06
	(0.00006)	(0.00013)	(0.00002)	(8.68e-05)	(0.000173)	(0.000195)	(6.84e-06)	(0.000108)	(0.000223)	(0.000428)	(9.09e-05)
Total Expenditure (Log)	0.0930***	0.102***	0.0212***	0.0558***	0.113***	0.356***	0.0162***	0.423***	0.0277***	0.135***	0.0717***
	(0.00184)	(0.00314)	(0.00072)	(0.00456)	(0.00766)	(0.00946)	(0.000650)	(0.00655)	(0.00341)	(0.00838)	(0.00335)
CDD wb x Log Exp	5.49e-05***	-7.78e-06	-1.31e-05***	5.56e-05***	7.92e-05***	-1.36e-08	4.26e-06***	1.97e-05	8.23e-05***	5.52e-05	7.87e-06
	(0.00001)	(0.00001)	(1.99e-06)	(1.06e-05)	(2.27e-05)	(2.35e-05)	(7.67e-07)	(1.23e-05)	(2.55e-05)	(4.91e-05)	(1.03e-05)
Urban (Yes = 1)				0.0318***	0.0588***	0.129***	0.0145***	0.178***	0.0202***	0.0794***	0.0257***
				(0.00293)	(0.00361)	(0.00485)	(0.000712)	(0.00640)	(0.00467)	(0.0116)	(0.00383)
HH size	-0.0130***	-0.00573***	8.79e-05	-0.00457***	-0.00895***	-0.0284***	-0.00179***	-0.0208***	-0.00695***	-0.0138***	0.00162*
	(0.00079)	(0.00127)	(0.00033)	(0.000404)	(0.000665)	(0.000985)	(0.000101)	(0.00114)	(0.000786)	(0.00219)	(0.000880)
Share < 16	0.0176***	-0.0264***	0.00189	-0.00293	-0.00904*	0.000631	0.00565***	0.166***	0.0182***	-0.0110	0.00255
	(0.00564)	(0.00937)	(0.00212)	(0.00245)	(0.00468)	(0.00721)	(0.000500)	(0.00987)	(0.00377)	(0.0144)	(0.00633)
House Ownership (Yes = 1)	0.0243***	-0.000467	0.00856***	0.0183***	0.0399***	0.0913***	0.00323***	0.127***	0.0186***	0.0328***	0.0403***
	(0.00211)	(0.00364)	(0.00097)	(0.00157)	(0.00465)	(0.00396)	(0.000227)	(0.00559)	(0.00251)	(0.00718)	(0.00342)
Education Head (Primary)	0.0321***	0.0668***	0.00788***	0.0162***	0.0449***	0.0629***	-0.000503**	0.0584***	0.0114***	0.0932***	0.0596***
	(0.00261)	(0.00487)	(0.00127)	(0.00126)	(0.00289)	(0.00250)	(0.000254)	(0.00315)	(0.00131)	(0.00746)	(0.00403)
Education Head (Secondary)	0.0750***	0.0796***	0.0117***	0.0313***	0.0662***	0.151***	0.00572***	0.183***	0.0209***	0.112***	0.0856***
	(0.00309)	(0.00498)	(0.00126)	(0.00205)	(0.00358)	(0.00496)	(0.000354)	(0.00387)	(0.00257)	(0.00837)	(0.00437)
Education Head (Above)	0.133***	0.0228***	0.0117***	0.0527***	0.0669***	0.226***	0.0180***	0.168***	0.0468***	0.148***	0.106***
	(0.00479)	(0.00671)	(0.00175)	(0.00355)	(0.00455)	(0.00569)	(0.000857)	(0.00709)	(0.00481)	(0.0102)	(0.00470)
Age Head	0.000747***	-0.000189	0.000184***	0.000584***	0.000706***	0.00346***	0.000101***	0.00370***	0.000351***	0.00248***	0.00297***
	(0.00007)	(0.00012)	(0.00003)	(5.20e-05)	(9.30e-05)	(0.000149)	(9.09e-06)	(0.000205)	(8.90e-05)	(0.000252)	(0.000113)
Gender Head (Female = 1)	-0.0130***	0.00487	0.00275***	0.0141***	0.0169***	0.0784***	0.000267	-0.00413	-0.00133	-0.00209	0.0148***
	(0.00194)	(0.00328)	(0.00077)	(0.00213)	(0.00251)	(0.00566)	(0.000214)	(0.00383)	(0.00120)	(0.00628)	(0.00220)
House Quality (Medium)	0.0567***	0.285***	0.0377***				0.00267***	0.108***	0.00779***	0.00528	0.0696***
	(0.01128)	(0.03591)	(0.00922)				(0.000604)	(0.00766)	(0.00245)	(0.0284)	(0.0153)
House Quality (High)	0.0661***	0.302***	0.0461***				0.00900***	0.380***	0.0361***	0.0818**	0.133***
	(0.01087)	(0.03557)	(0.00921)				(0.000682)	(0.00887)	(0.00291)	(0.0340)	(0.0162)
Observations	75,290	75,290	75,290	167,648	170,470	166,402	524,112	524,112	78,607	78,607	78,607

Clustered standard errors at district level for MEX, IDN and IND, and robust standard errors for Brazil in parentheses
State fixed effects for India, Indonesia and Brazil. Region fixed effects for Brazil
*** p<0.01, ** p<0.05, * p<0.1
We have also included (but not above-reported) occupation of the household head in MEX and IND regressions

Supplementary Table 6: Logit models with state fixed effects using CDD wet-bulbs. Total Marginal Effects

	Brazil			India			Indonesia		Mexico		
	AC	FAN	REF	AC	FAN	REF	AC	REF	AC	FAN	REF
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mean CDD wet-bulb	0.000245***	0.000381***	-1.27e-05***	9.31e-05***	0.000340***	0.000168***	1.14e-05***	0.000225***	0.000135***	0.00143***	8.05e-05***
	(0.00001)	(0.00002)	(2.41e-06)	(3.19e-05)	(4.22e-05)	(3.67e-05)	(1.30e-06)	(2.30e-05)	(2.37e-05)	(7.35e-05)	(1.70e-05)
Total Expenditure (Log)	0.105***	0.100***	0.0188***	0.0713***	0.134***	0.356***	0.0173***	0.429***	0.0379***	0.142***	0.0726***
	(0.00167)	(0.00245)	(0.00060)	(0.00374)	(0.00438)	(0.00745)	(0.000650)	(0.00465)	(0.00329)	(0.00709)	(0.00299)
Urban (Yes = 1)				0.0320***	0.0586***	0.129***	0.0142***	0.177***	0.0205***	0.0794***	0.0257***
				(0.00294)	(0.00361)	(0.00485)	(0.000700)	(0.00640)	(0.00470)	(0.0116)	(0.00383)
HH size	-0.0131***	-0.00573***	8.91e-05	-0.00459***	-0.00891***	-0.0284***	-0.00175***	-0.0208***	-0.00703***	-0.0138***	0.00161*
	(0.00080)	(0.00127)	(0.00033)	(0.000406)	(0.000663)	(0.000986)	(9.75e-05)	(0.00114)	(0.000797)	(0.00219)	(0.000880)
Share < 16	0.0178***	-0.0264***	0.00192	-0.00295	-0.00900*	0.000631	0.00553***	0.166***	0.0184***	-0.0110	0.00255
	(0.00570)	(0.00938)	(0.00215)	(0.00247)	(0.00467)	(0.00721)	(0.000487)	(0.00987)	(0.00382)	(0.0144)	(0.00632)
House Ownership (Yes = 1)	0.0246***	-0.000467	0.00867***	0.0184***	0.0397***	0.0913***	0.00317***	0.127***	0.0188***	0.0327***	0.0403***
	(0.00214)	(0.00364)	(0.00098)	(0.00158)	(0.00464)	(0.00396)	(0.000222)	(0.00558)	(0.00257)	(0.00718)	(0.00342)
Education Head (Primary)	0.0324***	0.0669***	0.00799***	0.0163***	0.0447***	0.0629***	-0.000493**	0.0584***	0.0115***	0.0932***	0.0596***
	(0.00264)	(0.00488)	(0.00128)	(0.00127)	(0.00289)	(0.00250)	(0.000249)	(0.00315)	(0.00134)	(0.00746)	(0.00404)
Education Head (Secondary)	0.0758***	0.0796***	0.0118***	0.0315***	0.0659***	0.151***	0.00560***	0.183***	0.0212***	0.112***	0.0855***
	(0.00313)	(0.00499)	(0.00127)	(0.00206)	(0.00358)	(0.00495)	(0.000345)	(0.00387)	(0.00263)	(0.00837)	(0.00437)
Education Head (Above)	0.134***	0.0228***	0.0119***	0.0530***	0.0667***	0.226***	0.0176***	0.167***	0.0473***	0.148***	0.105***
	(0.00485)	(0.00671)	(0.00178)	(0.00357)	(0.00455)	(0.00568)	(0.000834)	(0.00709)	(0.00487)	(0.0102)	(0.00471)
Age Head	0.000755***	-0.000189	0.000186***	0.000588***	0.000703***	0.00346***	9.91e-05***	0.00370***	0.000355***	0.00248***	0.00297***
	(0.00007)	(0.00012)	(0.00003)	(5.24e-05)	(9.27e-05)	(0.000149)	(8.85e-06)	(0.000205)	(9.03e-05)	(0.000251)	(0.000113)
Gender Head (Female = 1)	-0.0131***	0.00487	0.00279***	0.0142***	0.0169***	0.0784***	0.000261	-0.00413	-0.00135	-0.00209	0.0148***
	(0.00197)	(0.00328)	(0.00078)	(0.00214)	(0.00251)	(0.00566)	(0.000210)	(0.00383)	(0.00122)	(0.00628)	(0.00220)
House Quality (Medium)	0.0573***	0.285***	0.0381***				0.00262***	0.108***	0.00789***	0.00528	0.0695***
	(0.01142)	(0.03592)	(0.00934)				(0.000591)	(0.00765)	(0.00248)	(0.0284)	(0.0153)
House Quality (High)	0.0669***	0.302***	0.0467***				0.00881***	0.380***	0.0365***	0.0818**	0.133***
	(0.01101)	(0.03557)	(0.00932)				(0.000668)	(0.00887)	(0.00293)	(0.0340)	(0.0162)
Observations	75,290	75,290	75,290	167,648	170,470	166,402	524,112	524,112	78,607	78,607	78,607

Clustered standard errors at district level for MEX, IDN and IND, and robust standard errors for Brazil in parentheses

State fixed effects for India, Indonesia and Brazil. Region fixed effects for Brazil

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

We have also included (but not above-reported) occupation of the household head in MEX and IND regressions

Supplementary Table 7: Standardised logit models with state fixed effects using CDD wet-bulbs. Marginal Effects

	Brazil			India			Indonesia		Mexico		
	AC	FAN	REF	AC	FAN	REF	AC	REF	AC	FAN	REF
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Std. Mean CDD wet-bulb	0.0558***	0.0880***	-0.00290***	0.0171***	0.0633***	0.0311***	0.00381***	0.0735***	0.0228***	0.244***	0.0138***
	(0.00152)	(0.00362)	(0.00055)	(0.00585)	(0.00790)	(0.00677)	(0.000434)	(0.00750)	(0.00399)	(0.0126)	(0.00292)
Std. Total Expenditure (Log)	0.0918***	0.0888***	0.0165***	0.0492***	0.0933***	0.247***	0.0126***	0.307***	0.0315***	0.119***	0.0610***
	(0.00145)	(0.00218)	(0.00053)	(0.00258)	(0.00303)	(0.00516)	(0.000475)	(0.00331)	(0.00272)	(0.00596)	(0.00251)
Std. CDD wb x Log Exp	0.0112***	-0.00159	-0.00268***	0.00712***	0.0102***	-1.74e-06	0.000992***	0.00459	0.0118***	0.00793	0.00113
	(0.00121)	(0.00285)	(0.00041)	(0.00136)	(0.00292)	(0.00301)	(0.000179)	(0.00286)	(0.00366)	(0.00706)	(0.00148)
Urban (Yes = 1)				0.0318***	0.0588***	0.129***	0.0145***	0.178***	0.0202***	0.0794***	0.0257***
				(0.00293)	(0.00361)	(0.00485)	(0.000712)	(0.00640)	(0.00467)	(0.0116)	(0.00383)
Std. HH size	-0.0209***	-0.00924***	0.000142	-0.0108***	-0.0212***	-0.0674***	-0.00305***	-0.0354***	-0.0129***	-0.0256***	0.00299*
	(0.00127)	(0.00205)	(0.00053)	(0.000958)	(0.00158)	(0.00233)	(0.000172)	(0.00194)	(0.00145)	(0.00404)	(0.00163)
Share < 16	0.00389***	-0.00583***	0.000419	-0.000674	-0.00208*	0.000145	0.00123***	0.0361***	0.00424***	-0.00256	0.000594
	(0.00125)	(0.00207)	(0.00047)	(0.000564)	(0.00108)	(0.00166)	(0.000109)	(0.00214)	(0.000880)	(0.00336)	(0.00148)
House Ownership (Yes = 1)	0.0243***	-0.000467	0.00856***	0.0183***	0.0399***	0.0913***	0.00323***	0.127***	0.0186***	0.0328***	0.0403***
	(0.00211)	(0.00364)	(0.00097)	(0.00157)	(0.00465)	(0.00396)	(0.000227)	(0.00559)	(0.00251)	(0.00718)	(0.00342)
Education Head (Primary)	0.0321***	0.0668***	0.00788***	0.0162***	0.0449***	0.0629***	-0.000503**	0.0584***	0.0114***	0.0932***	0.0596***
	(0.00261)	(0.00487)	(0.00127)	(0.00126)	(0.00289)	(0.00250)	(0.000254)	(0.00315)	(0.00131)	(0.00746)	(0.00403)
Education Head (Secondary)	0.0750***	0.0796***	0.0117***	0.0313***	0.0662***	0.151***	0.00572***	0.183***	0.0209***	0.112***	0.0856***
	(0.00309)	(0.00498)	(0.00126)	(0.00205)	(0.00358)	(0.00496)	(0.000354)	(0.00387)	(0.00257)	(0.00837)	(0.00437)
Education Head (Above)	0.133***	0.0228***	0.0117***	0.0527***	0.0669***	0.226***	0.0180***	0.168***	0.0468***	0.148***	0.106***
	(0.00479)	(0.00671)	(0.00175)	(0.00355)	(0.00455)	(0.00569)	(0.000857)	(0.00709)	(0.00481)	(0.0102)	(0.00470)
Std. Age Head	0.0119***	-0.00301	0.00292***	0.00793***	0.00958***	0.0469***	0.00137***	0.0502***	0.00562***	0.0397***	0.0476***
	(0.00117)	(0.00193)	(0.00047)	(0.000706)	(0.00126)	(0.00202)	(0.000123)	(0.00278)	(0.00142)	(0.00403)	(0.00181)
Gender Head (Female = 1)	-0.0130***	0.00487	0.00275***	0.0141***	0.0169***	0.0784***	0.000267	-0.00413	-0.00133	-0.00209	0.0148***
	(0.00194)	(0.00328)	(0.00077)	(0.00213)	(0.00251)	(0.00566)	(0.000214)	(0.00383)	(0.00120)	(0.00628)	(0.00220)
House Quality (Medium)	0.0567***	0.285***	0.0377***				0.00267***	0.108***	0.00779***	0.00528	0.0696***
	(0.01128)	(0.03591)	(0.00922)				(0.000604)	(0.00766)	(0.00245)	(0.0284)	(0.0153)
House Quality (High)	0.0661***	0.302***	0.0461***				0.00900***	0.380***	0.0361***	0.0818**	0.133***
	(0.01087)	(0.03557)	(0.00921)				(0.000682)	(0.00887)	(0.00291)	(0.0340)	(0.0162)
Observations	75,290	75,290	75,290	167,648	170,470	166,402	524,112	524,112	78,607	78,607	78,607

Clustered standard errors at district level for MEX, IDN and IND, and robust standard errors for Brazil in parentheses
State fixed effects for India, Indonesia and Brazil. Region fixed effects for Brazil
*** p<0.01, ** p<0.05, * p<0.1
We have also included (but not above-reported) occupation of the household head in MEX and IND regressions

Supplementary Table 8: Logit models with state fixed effects using dry-bulb CDDs. Marginal effects

	Brazil			India			Indonesia		Mexico		
	AC	FAN	REF	AC	FAN	REF	AC	REF	AC	FAN	REF
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mean CDD dry-bulb	-0.000277***	-0.0000410	0.0000345***	-0.000105***	-0.000268***	7.29e-06	-2.61e-05***	-0.000265***	5.97e-07	0.00128***	7.19e-05*
	(0.00003)	(0.00006)	(0.00001)	(3.73e-05)	(5.96e-05)	(8.49e-05)	(5.28e-06)	(7.95e-05)	(2.94e-05)	(0.000140)	(3.97e-05)
Total Expenditure (Log)	0.0794***	0.0858***	0.0206***	0.0396***	0.0790***	0.347***	0.0150***	0.401***	0.0260***	0.168***	0.0731***
	(0.00201)	(0.00337)	(0.00093)	(0.00561)	(0.00938)	(0.0130)	(0.000636)	(0.00807)	(0.00274)	(0.00780)	(0.00311)
CDD db x Log Exp	4.45e-05***	4.07e-05***	-3.46e-06**	2.42e-05***	5.10e-05***	8.98e-06	3.86e-06***	4.61e-05***	1.42e-05***	-8.07e-05***	-2.42e-06
	(3.13e-06)	(0.00001)	(1.39e-06)	(4.29e-06)	(7.79e-06)	(1.02e-05)	(5.85e-07)	(9.12e-06)	(2.87e-06)	(2.01e-05)	(4.30e-06)
Urban (Yes = 1)				0.0310***	0.0548***	0.129***	0.0142***	0.177***	0.0168***	0.0733***	0.0253***
				(0.00243)	(0.00365)	(0.00486)	(0.000670)	(0.00643)	(0.00274)	(0.0110)	(0.00374)
HH size	-0.0123***	-0.00627***	2.72e-06	-0.00449***	-0.00884***	-0.0286***	-0.00182***	-0.0211***	-0.00586***	-0.0143***	0.00167*
	(0.00076)	(0.00126)	(0.00033)	(0.000337)	(0.000637)	(0.000986)	(9.95e-05)	(0.00115)	(0.000620)	(0.00203)	(0.000877)
Share < 16	0.0176***	-0.0210**	0.00220	-0.00229	-0.0105**	8.37e-05	0.00586***	0.168***	0.0147***	-0.00327	0.00253
	(0.00549)	(0.00932)	(0.00217)	(0.00219)	(0.00436)	(0.00716)	(0.000485)	(0.00982)	(0.00279)	(0.0141)	(0.00630)
House Ownership (Yes = 1)	0.0242***	-0.00162	0.00848***	0.0173***	0.0356***	0.0910***	0.00329***	0.128***	0.0142***	0.0308***	0.0401***
	(0.00205)	(0.00361)	(0.00099)	(0.00142)	(0.00444)	(0.00401)	(0.000215)	(0.00563)	(0.00138)	(0.00687)	(0.00337)
Education Head (Primary)	0.0310***	0.0660***	0.00795***	0.0156***	0.0438***	0.0634***	-0.000500**	0.0585***	0.00906***	0.0915***	0.0595***
	(0.00251)	(0.00486)	(0.00128)	(0.00107)	(0.00284)	(0.00253)	(0.000250)	(0.00313)	(0.00110)	(0.00774)	(0.00405)
Education Head (Secondary)	0.0752***	0.0797***	0.0116***	0.0306***	0.0640***	0.151***	0.00566***	0.183***	0.0157***	0.108***	0.0853***
	(0.00301)	(0.00496)	(0.00127)	(0.00192)	(0.00348)	(0.00494)	(0.000340)	(0.00380)	(0.00156)	(0.00874)	(0.00434)
Education Head (Above)	0.131***	0.0253***	0.0115***	0.0516***	0.0656***	0.226***	0.0179***	0.167***	0.0428***	0.143***	0.105***
	(0.00470)	(0.00670)	(0.00178)	(0.00284)	(0.00439)	(0.00567)	(0.000835)	(0.00713)	(0.00380)	(0.0102)	(0.00464)
Age Head	0.000725***	-0.000165	0.000188***	0.000576***	0.000745***	0.00347***	0.000101***	0.00369***	0.000287***	0.00240***	0.00296***
	(0.00007)	(0.00012)	(0.00003)	(4.53e-05)	(8.53e-05)	(0.000149)	(8.86e-06)	(0.000205)	(4.75e-05)	(0.000248)	(0.000111)
Gender Head	-0.0128***	0.00431	0.00274***	0.0146***	0.0178***	0.0789***	0.000222	-0.00464	-0.000300	-0.00144	0.0148***
	(0.00189)	(0.00326)	(0.00078)	(0.00200)	(0.00229)	(0.00561)	(0.000210)	(0.00386)	(0.000973)	(0.00639)	(0.00219)
House Quality (Medium)	0.0539***	0.286***	0.0412***				0.00273***	0.110***	0.00524***	0.0226	0.0694***
	(0.01052)	(0.03704)	(0.00979)				(0.000596)	(0.00751)	(0.00176)	(0.0256)	(0.0153)
House Quality (High)	0.0637***	0.301***	0.0498***				0.00906***	0.381***	0.0259***	0.0934***	0.133***
	(0.01012)	(0.03670)	(0.00978)				(0.000671)	(0.00863)	(0.00332)	(0.0304)	(0.0162)
Observations	75,290	75,290	75,290	167,648	170,470	166,402	525,918	525,918	78,607	78,607	78,607

Clustered standard errors at district level for MEX, IDN and IND, and robust standard errors for Brazil in parentheses
State fixed effects for India, Indonesia and Brazil. Region fixed effects for Brazil
*** p<0.01, ** p<0.05, * p<0.1
We have also included (but not above-reported) occupation of the household head in MEX and IND regressions

Supplementary Table 9: OLS regression models for electricity quantity with state fixed effects using wet-bulb CDDs.

Variables	Brazil (1)	India (2)	Indonesia (3)	Mexico (4)
Mean CDD wet-bulb	-0.00220***	-4.24e-05	-0.000549**	-0.00240***
	(0.000181)	(0.000480)	(0.000275)	(0.000326)
Total Expenditure (Log)	0.270***	0.582***	0.490***	0.262***
	(0.00520)	(0.0211)	(0.0107)	(0.00819)
CDD wb x Log Exp	0.000246***	3.26e-05	9.42e-05***	0.000328***
	(1.88e-05)	(5.62e-05)	(2.86e-05)	(3.72e-05)
Urban (Yes = 1)		0.286***	0.266***	0.123***
		(0.0115)	(0.0119)	(0.0140)
HH size	0.0891***	-0.00953***	0.00527***	0.0465***
	(0.00273)	(0.00217)	(0.00189)	(0.00219)
Share < 16	-0.0735***	0.00286	0.126***	-0.0441***
	(0.0182)	(0.0143)	(0.0134)	(0.0152)
House Ownership (Yes = 1)	0.0421***	0.237***	0.119***	0.0710***
	(0.00681)	(0.0103)	(0.00954)	(0.00845)
Education Head (Primary)	0.114***	0.0724***	0.0276***	0.0824***
	(0.0124)	(0.00620)	(0.00627)	(0.00748)
Education Head (Secondary)	0.190***	0.136***	0.104***	0.114***
	(0.0132)	(0.00813)	(0.00733)	(0.00820)
Education Head (Above)	0.261***	0.199***	0.135***	0.160***
	(0.0151)	(0.00938)	(0.0115)	(0.0106)
Age Head	0.00331***	0.00541***	0.00541***	0.00560***
	(0.00023)	(0.000276)	(0.000296)	(0.000261)
Gender Head (Female = 1)	-0.00117	0.0695***	-0.0130**	0.0180***
	(0.00593)	(0.00770)	(0.00546)	(0.00530)
House Quality (Medium)	0.107		0.180***	0.0927***
	(0.127)		(0.0264)	(0.0249)
House Quality (High)	0.0993		0.437***	0.224***
	(0.126)		(0.0301)	(0.0281)
Observations	34,459	85,371	268,310	61,421
R-squared	0.325	0.523	0.395	0.503

Clustered standard errors at district level for MEX, IDN and IND, and robust standard errors for Brazil in parentheses
State fixed effects for India, Indonesia and Brazil. Region fixed effects for Brazil
*** p<0.01, ** p<0.05, * p<0.1
We have also included (but not above-reported) occupation of the household head in MEX and IND regressions

Supplementary Table 10: OLS regression models for electricity quantity with state fixed effects using dry-bulb CDDs.

Variables	Brazil (1)	India (2)	Indonesia (3)	Mexico (4)
Mean CDD dry-bulb	-0.00108***	-0.000600***	-0.000459**	-0.00121***
	(8.74e-05)	(0.000198)	(0.000188)	(0.000106)
Total Expenditure (Log)	0.254***	0.498***	0.469***	0.228***
	(0.00584)	(0.0301)	(0.0138)	(0.00682)
CDD wb x Log Exp	0.000127***	8.72e-05***	7.47e-05***	0.000188***
	(9.06e-06)	(2.35e-05)	(2.07e-05)	(1.20e-05)
Urban (Yes = 1)		0.285***	0.263***	0.121***
		(0.0117)	(0.0116)	(0.0114)
HH size	0.0883***	-0.00955***	0.00545***	0.0470***
	(0.00272)	(0.00214)	(0.00186)	(0.00213)
Share < 16	-0.0690***	0.00365	0.128***	-0.0475***
	(0.0182)	(0.0141)	(0.0133)	(0.0147)
House Ownership (Yes = 1)	0.0424***	0.237***	0.120***	0.0670***
	(0.00680)	(0.0102)	(0.00955)	(0.00743)
Education Head (Primary)	0.109***	0.0724***	0.0279***	0.0862***
	(0.0125)	(0.00617)	(0.00614)	(0.00710)
Education Head (Secondary)	0.185***	0.136***	0.103***	0.115***
	(0.0133)	(0.00812)	(0.00724)	(0.00756)
Education Head (Above)	0.258***	0.199***	0.134***	0.167***
	(0.0151)	(0.00945)	(0.0115)	(0.00974)
Age Head	0.00330***	0.00548***	0.00540***	0.00560***
	(0.000228)	(0.000270)	(0.000296)	(0.000257)
Gender Head (Female = 1)	-0.000698	0.0707***	-0.0146***	0.0186***
	(0.00593)	(0.00768)	(0.00539)	(0.00504)
House Quality (Medium)	0.117		0.183***	0.0897***
	(0.125)		(0.0258)	(0.0221)
House Quality (High)	0.106		0.441***	0.218***
	(0.124)		(0.0293)	(0.0244)
Observations	34,459	85,371	269,277	61,421
R-squared	0.326	0.525	0.398	0.525

Clustered standard errors at district level for MEX, IDN and IND, and robust standard errors for Brazil in parentheses
State fixed effects for India, Indonesia and Brazil. Region fixed effects for Brazil
*** p<0.01, ** p<0.05, * p<0.1
We have also included (but not above-reported) occupation of the household head in MEX and IND regressions

Supplementary Table 11: Logit models: sensitivity to omitted variables and waves

	AC-Brazil	AC-Brazil	AC-Brazil	AC-Mexico	AC-Mexico	AC-Mexico	AC-India	AC-India	AC-India	AC-Indonesia	AC-Indonesia	AC-Indonesia
CDD wb	0.000480***	0.000491***	0.000245***	0.000150***	0.000145***	0.000135***	0.000133**	0.000126***	0.0000931***	0.0000303***	0.0000161***	0.0000114***
	(0.00002)	(0.00002)	(0.00001)	(0.00003)	(0.00003)	(0.00002)	(0.00005)	(0.00004)	(0.00003)	(0.00000)	(0.00000)	(0.00000)
Log Tot. exp.	0.220***	0.186***	0.105***	0.0559***	0.0395***	0.0379***	0.134***	0.0995***	0.0713***	0.0485***	0.0253***	0.0173***
	(0.00314)	(0.00364)	(0.00167)	(0.00468)	(0.00348)	(0.00329)	(0.00545)	(0.00496)	(0.00374)	(0.00202)	(0.00094)	(0.00065)
Other vars.	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
Two waves	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Clustered standard errors at district level for MEX, IDN and IND, and robust standard errors for Brazil in parentheses

State fixed effects for India, Indonesia and Brazil. Region fixed effects for Brazil

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

We have also included (but not above-reported) occupation of the household head in MEX and IND regressions.

The specifications that do not use the two waves only use the latest wave.

Supplementary Table 12: Marginal elasticity of air-conditioning to CDDs across temperature measurements and temperature thresholds

	24 deg - wb				**24 deg - db**			
	AC-Brazil	AC-Mexico	AC-India	AC-Indonesia	AC-Brazil	AC-Mexico	AC-India	AC-Indonesia
CDDs	0.0565***	0.0230***	0.0172***	0.00373***	0.0608***	0.0533***	0.0444***	0.00339***
	(0.00154)	(0.00406)	(0.00588)	(0.00042)	(0.00194)	(0.00556)	(0.00440)	(0.00034)
Log Tot. exp.	0.0928***	0.0319***	0.0495***	0.0123***	0.0930***	0.0265***	0.0456***	0.0123***
	(0.00148)	(0.00276)	(0.00259)	(0.00046)	(0.00151)	(0.00216)	(0.00247)	(0.00045)
	22 deg - wb				**22 deg - db**			
	AC-Brazil	AC-Mexico	AC-India	AC-Indonesia	AC-Brazil	AC-Mexico	AC-India	AC-Indonesia
CDDs	0.0696***	0.0366***	0.0158**	0.00408***	0.0774***	0.0578***	0.0469***	0.00350***
	(0.00177)	(0.00680)	(0.00636)	(0.00040)	(0.00222)	(0.00511)	(0.00469)	(0.00032)
Log Tot. exp.	0.0928***	0.0299***	0.0493***	0.0120***	0.0935***	0.0236***	0.0450***	0.0120***
	(0.00148)	(0.00261)	(0.00262)	(0.00044)	(0.00149)	(0.00238)	(0.00252)	(0.00042)

Clustered standard errors at district level for MEX, IDN and IND, and robust standard errors for Brazil in parentheses

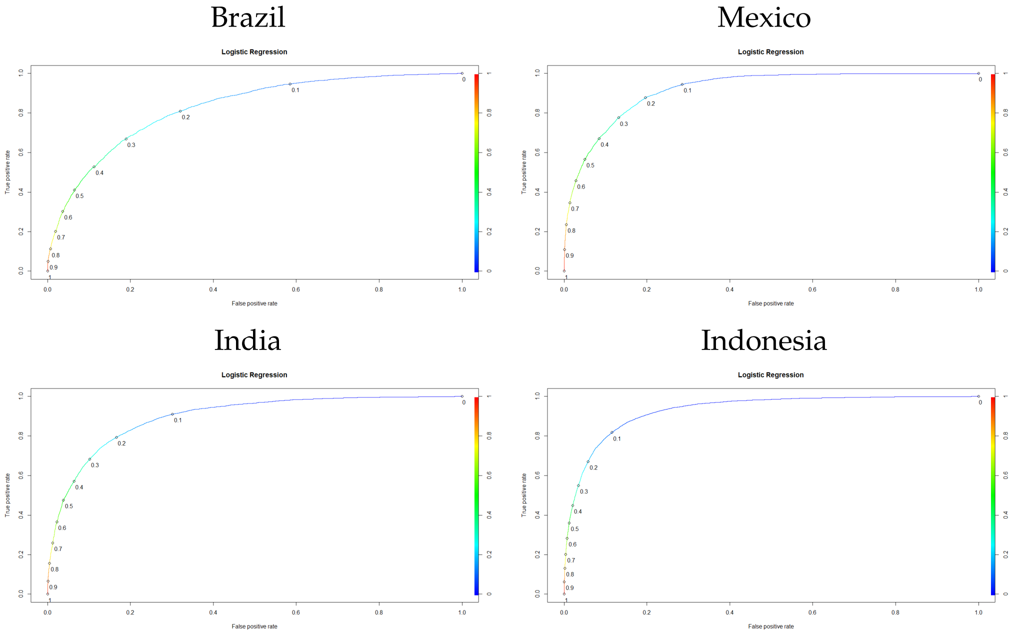
State fixed effects for India, Indonesia and Brazil. Region fixed effects for Brazil

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

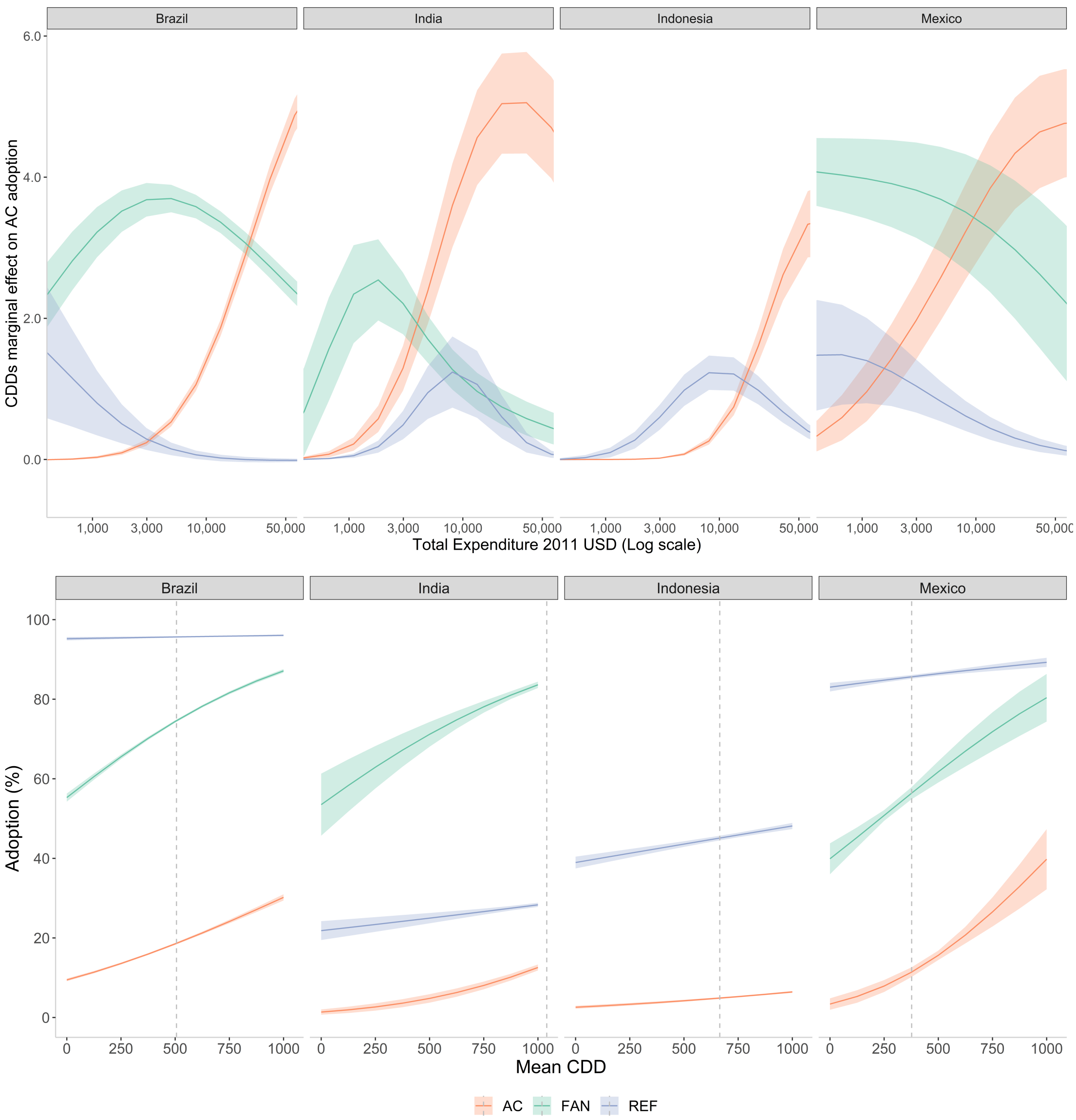
We have also included (but not above-reported) occupation of the household head in MEX and IND regressions.

Supplementary Table 13: Total number of households with at least one AC unit around 2040 under different climate change scenarios (in million)

	Historical	RCP4.5	RCP8.5
Brazil	10.931	[29.591-36.197]	[35.099-40.377]
India	28.904	[142.004-183.668]	[151.822-190.327]
Indonesia	5.498	[29.597-40.809]	[31.584-42.564]
Mexico	4.795	[9.924-12.300]	[10.536-13.012]

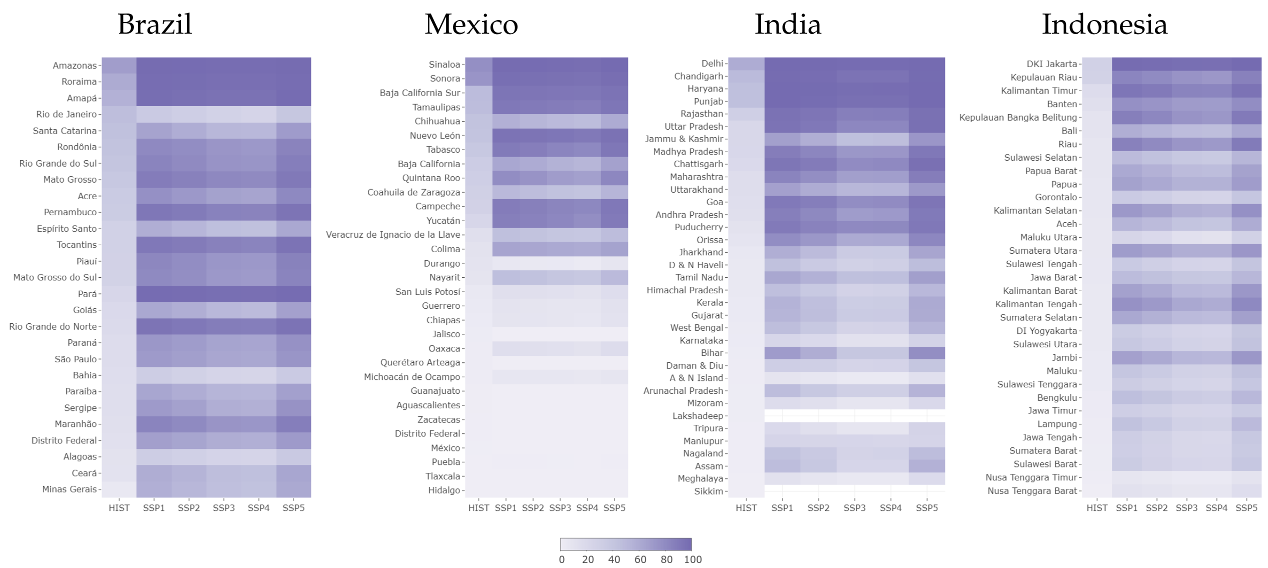


Supplementary Figure 2: Diagnostic of air conditioning logit model performance through the inspection of the Area Under the Receiver Operating Characteristic (ROC) curve.

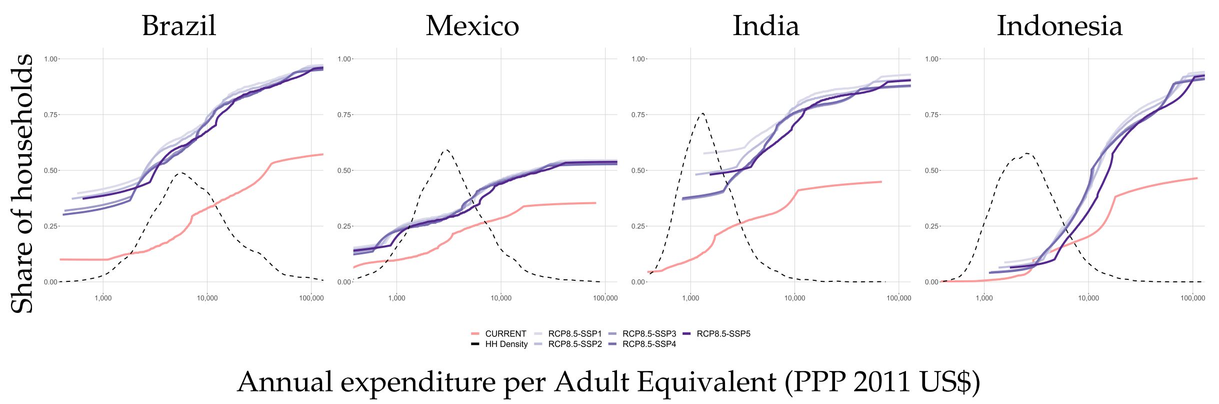


Supplementary Figure 3: Top: Average marginal effect (in percentage points) of dry-bulb CDDs on air conditioner, fan and refrigerator adoption for different levels of total expenditure. Bottom: Predicted adoption rates of air-conditioning and other durable goods used for cooling across different levels of dry-bulb CDDs.

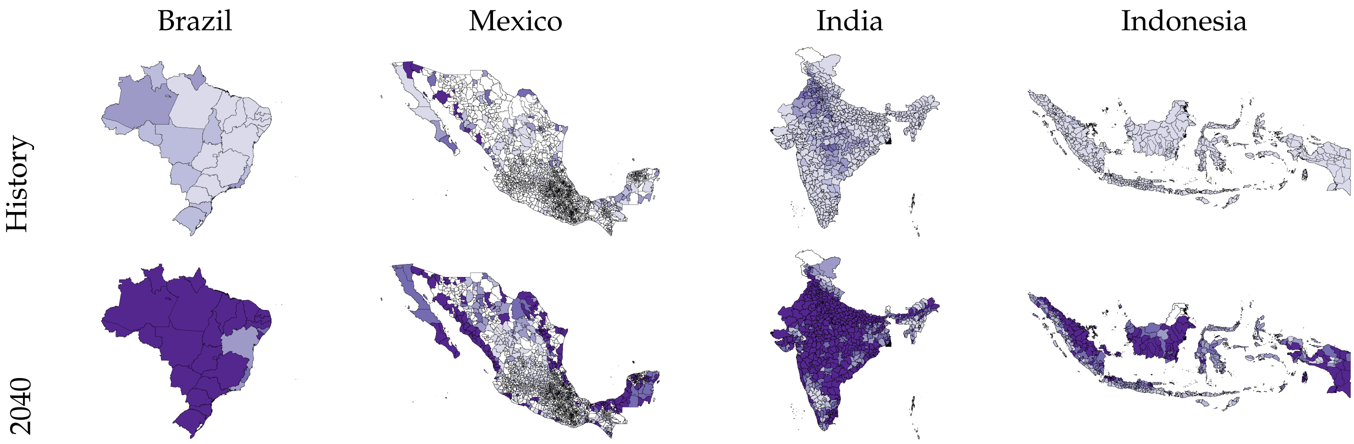
3 Projected changes in air-conditioning adoption and electricity use



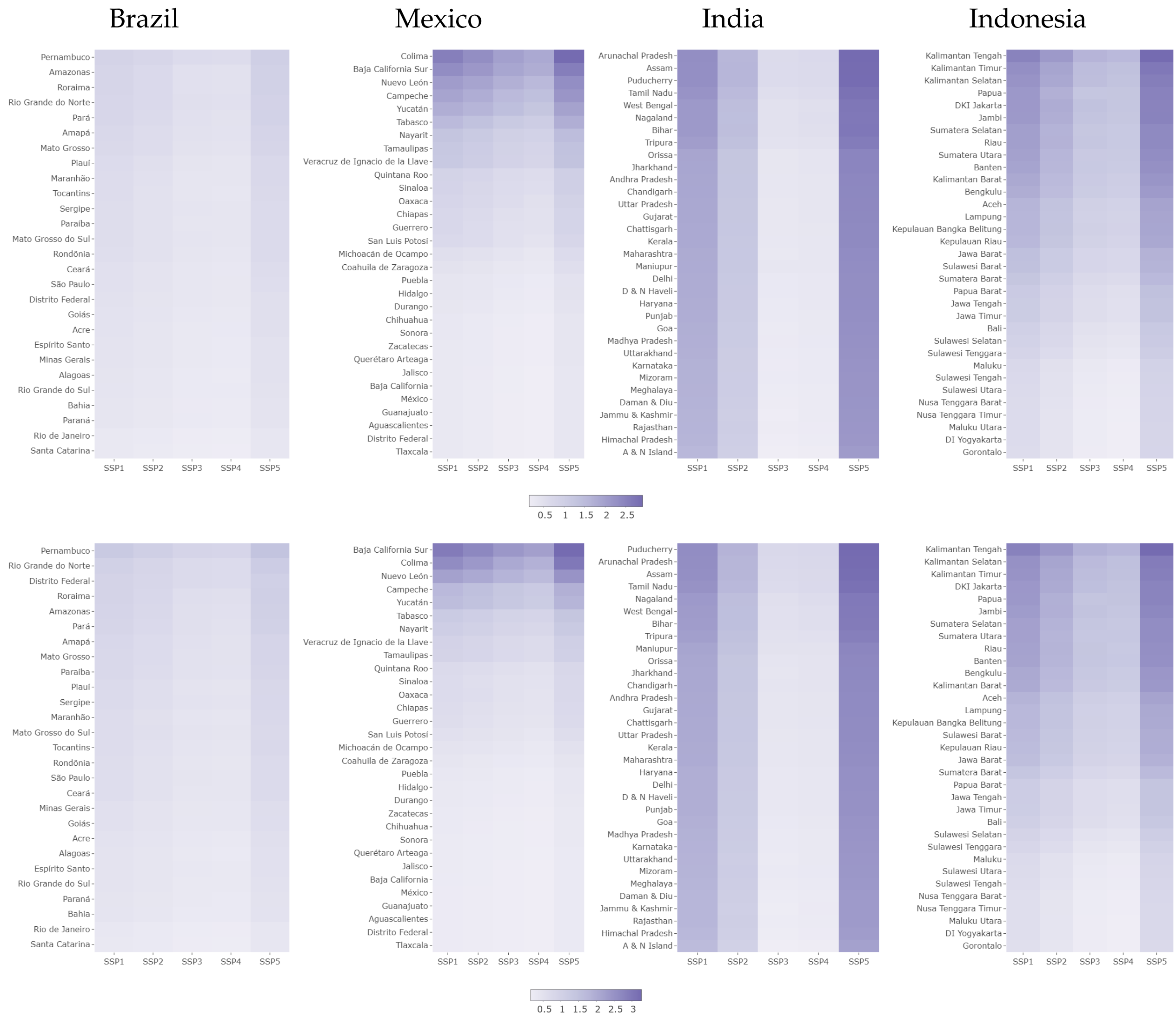
Supplementary Figure 4: Historical and future state-level adoption rates of air conditioners in the year 2040 under RCP4.5



Supplementary Figure 5: Ownership of air conditioners in relation to historical per capita expenditure (2011 US constant dollars at PPP). Adoption scenarios across SSPs



Supplementary Figure 6: Spatial distribution of historical (latest wave) and future (2040, SSP5 RCP 8.5) ownership of AC. Maps are generated using the sp, rgdal, and raster R packages.



Supplementary Figure 7: Electricity change compared to historical levels - growth factors in the year 2040 under RCP4.5 and RCP8.5

Supplementary Table 14: Growth rate in electricity use: Brazil. Summary statistics computed on state-level averages.

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
RCP85 - SSP1	27	0.686	0.233	0.317	1.298	0.486	0.672	0.819
RCP85 - SSP2	27	0.588	0.202	0.27	1.135	0.417	0.563	0.701
RCP85 - SSP3	27	0.465	0.167	0.209	0.935	0.329	0.441	0.555
RCP85 - SSP4	27	0.437	0.159	0.194	0.894	0.31	0.41	0.522
RCP85 - SSP5	27	0.791	0.267	0.367	1.47	0.566	0.777	0.945
RCP45 - SSP1	27	0.562	0.165	0.292	0.882	0.431	0.57	0.706
RCP45 - SSP2	27	0.48	0.141	0.248	0.77	0.369	0.482	0.603
RCP45 - SSP3	27	0.375	0.112	0.189	0.63	0.289	0.371	0.475
RCP45 - SSP4	27	0.352	0.106	0.176	0.601	0.272	0.345	0.446
RCP45 - SSP5	27	0.65	0.192	0.339	0.999	0.496	0.664	0.815

Note on interpretation. The value of 0.686 represents a 68.6% increase in 2040 compared to the latest wave.

Supplementary Table 15: Growth rate in electricity use: Mexico. Summary statistics computed on state-level averages.

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
RCP85 - SSP1	31	0.775	0.736	0.235	2.934	0.254	0.462	0.989
RCP85 - SSP2	31	0.705	0.679	0.207	2.704	0.229	0.43	0.897
RCP85 - SSP3	31	0.61	0.603	0.169	2.406	0.188	0.368	0.777
RCP85 - SSP4	31	0.557	0.56	0.149	2.245	0.163	0.316	0.713
RCP85 - SSP5	31	0.875	0.821	0.273	3.249	0.293	0.53	1.116
RCP45 - SSP1	31	0.588	0.432	0.235	1.685	0.248	0.395	0.82
RCP45 - SSP2	31	0.534	0.4	0.207	1.531	0.219	0.364	0.745
RCP45 - SSP3	31	0.459	0.357	0.169	1.327	0.18	0.31	0.644
RCP45 - SSP4	31	0.417	0.332	0.149	1.228	0.158	0.267	0.589
RCP45 - SSP5	31	0.666	0.48	0.273	1.904	0.287	0.454	0.926

Note on interpretation. The value of 0.775 represents a 77.5% increase in 2040 compared to the latest wave.

We exclude Morelos from the computation as it is an outlier after the simulation.

Supplementary Table 16: Growth rate in electricity use: India. Summary statistics computed on state-level averages.

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
RCP85 - SSP1	34	2.236	0.133	1.92	2.511	2.146	2.226	2.285
RCP85 - SSP2	34	1.904	0.114	1.631	2.146	1.825	1.896	1.964
RCP85 - SSP3	34	1.427	0.09	1.211	1.618	1.369	1.42	1.489
RCP85 - SSP4	34	1.446	0.091	1.226	1.637	1.385	1.44	1.485
RCP85 - SSP5	34	2.52	0.149	2.169	2.827	2.419	2.508	2.573
RCP45 - SSP1	34	2.172	0.114	1.92	2.41	2.088	2.148	2.201
RCP45 - SSP2	34	1.848	0.097	1.631	2.048	1.779	1.836	1.873
RCP45 - SSP3	34	1.381	0.076	1.211	1.541	1.33	1.372	1.399
RCP45 - SSP4	34	1.4	0.078	1.226	1.566	1.345	1.387	1.418
RCP45 - SSP5	34	2.449	0.127	2.169	2.713	2.354	2.421	2.483

Note on interpretation. The value of 2.236 represents a 223.6% increase in 2040 compared to the latest wave.

Supplementary Table 17: Growth rate in electricity use: Indonesia. Summary statistics computed on state-level averages.

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
RCP85 - SSP1	33	1.966	0.537	1.232	2.931	1.431	2.051	2.459
RCP85 - SSP2	33	1.75	0.476	1.098	2.619	1.277	1.832	2.183
RCP85 - SSP3	33	1.488	0.405	0.931	2.238	1.086	1.562	1.844
RCP85 - SSP4	33	1.438	0.398	0.89	2.148	1.042	1.498	1.796
RCP85 - SSP5	33	2.189	0.599	1.372	3.266	1.592	2.285	2.745
RCP45 - SSP1	33	1.817	0.442	1.228	2.607	1.393	1.808	2.23
RCP45 - SSP2	33	1.617	0.391	1.095	2.329	1.242	1.608	1.961
RCP45 - SSP3	33	1.373	0.332	0.928	1.987	1.055	1.368	1.654
RCP45 - SSP4	33	1.325	0.326	0.887	1.906	1.013	1.321	1.63
RCP45 - SSP5	33	2.024	0.493	1.369	2.906	1.55	2.013	2.486

Note on interpretation. The value of 1.966 represents a 196.6% increase in 2040 compared to the latest wave.

Supplementary Table 18: Air-conditioning adoption: Brazil. Summary statistics computed on state-level averages.

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
RCP85 - SSP1	27	0.825	0.17	0.405	0.996	0.766	0.857	0.96
RCP85 - SSP2	27	0.799	0.182	0.363	0.995	0.721	0.844	0.948
RCP85 - SSP3	27	0.759	0.197	0.311	0.992	0.659	0.799	0.912
RCP85 - SSP4	27	0.75	0.199	0.297	0.992	0.646	0.791	0.9
RCP85 - SSP5	27	0.85	0.16	0.444	0.998	0.792	0.891	0.977
RCP45 - SSP1	27	0.743	0.197	0.33	0.993	0.622	0.769	0.915
RCP45 - SSP2	27	0.711	0.207	0.297	0.992	0.581	0.722	0.896
RCP45 - SSP3	27	0.663	0.218	0.253	0.989	0.515	0.664	0.859
RCP45 - SSP4	27	0.652	0.221	0.245	0.986	0.494	0.649	0.846
RCP45 - SSP5	27	0.774	0.187	0.362	0.995	0.67	0.816	0.944

Note on interpretation. The value of 0.825 represents a 82.5% residential air-conditioning market saturation.

Supplementary Table 19: Air-conditioning adoption: Mexico. Summary statistics computed on state-level averages.

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
RCP85 - SSP1	31	0.406	0.396	0	0.982	0.004	0.191	0.911
RCP85 - SSP2	31	0.396	0.391	0	0.977	0.008	0.177	0.894
RCP85 - SSP3	31	0.382	0.383	0	0.972	0.008	0.166	0.864
RCP85 - SSP4	31	0.374	0.379	0	0.97	0.003	0.146	0.843
RCP85 - SSP5	31	0.417	0.4	0	0.987	0.005	0.207	0.928
RCP45 - SSP1	31	0.386	0.389	0	0.978	0.001	0.149	0.859
RCP45 - SSP2	31	0.376	0.383	0	0.976	0.001	0.142	0.844
RCP45 - SSP3	31	0.361	0.375	0	0.97	0.001	0.129	0.812
RCP45 - SSP4	31	0.352	0.369	0	0.967	0.001	0.118	0.775
RCP45 - SSP5	31	0.399	0.396	0	0.984	0.001	0.167	0.889

Note on interpretation. The value of 0.406 represents a 40.6% residential air-conditioning market saturation.

We exclude Morelos from the computation as it is an outlier after the simulation.

Supplementary Table 20: Air-conditioning adoption: India. Summary statistics computed on state-level averages.

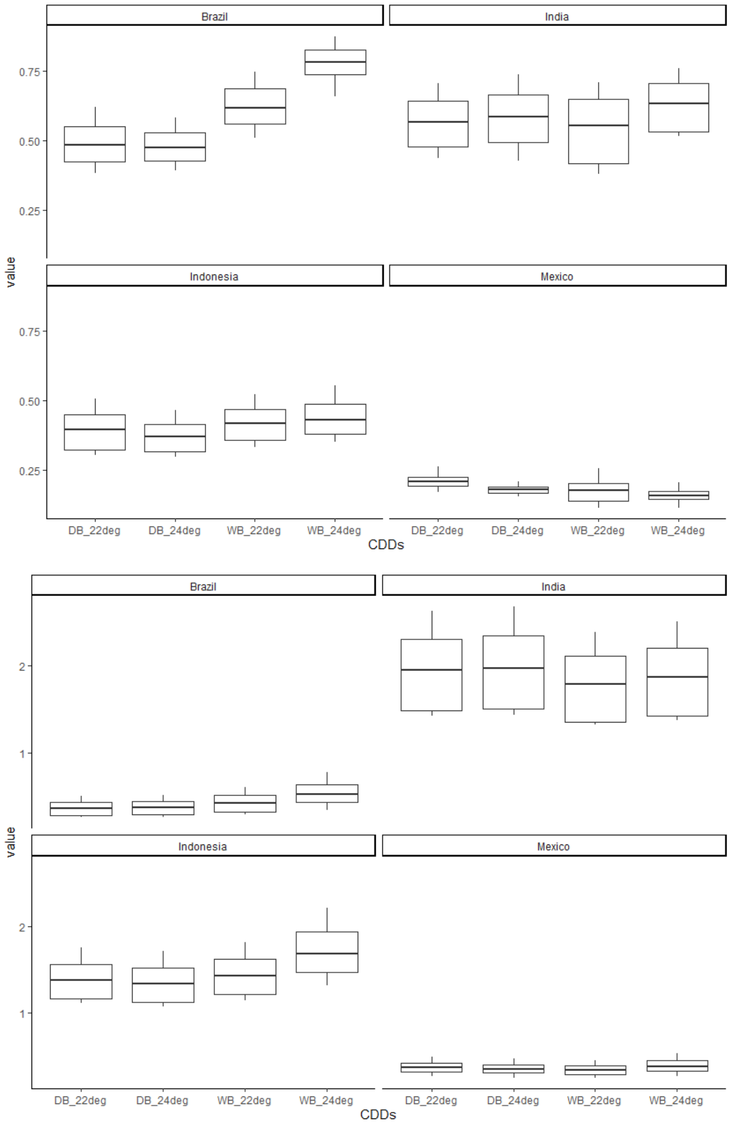
Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
RCP85 - SSP1	33	0.656	0.278	0.124	1	0.488	0.682	0.917
RCP85 - SSP2	33	0.605	0.289	0.089	1	0.429	0.596	0.887
RCP85 - SSP3	33	0.523	0.301	0.05	0.993	0.306	0.45	0.835
RCP85 - SSP4	33	0.528	0.3	0.053	0.993	0.316	0.459	0.836
RCP85 - SSP5	33	0.691	0.267	0.162	1	0.544	0.73	0.939
RCP45 - SSP1	33	0.623	0.292	0.095	1	0.451	0.632	0.905
RCP45 - SSP2	33	0.571	0.3	0.07	1	0.37	0.566	0.855
RCP45 - SSP3	33	0.488	0.305	0.042	0.993	0.263	0.397	0.79
RCP45 - SSP4	33	0.494	0.305	0.043	0.993	0.273	0.4	0.801
RCP45 - SSP5	33	0.663	0.28	0.132	1	0.477	0.678	0.919

Note on interpretation. The value of 0.656 represents a 65.6% residential air-conditioning market saturation.

Supplementary Table 21: Air-conditioning adoption: Indonesia. Summary statistics computed on state-level averages.

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
RCP85 - SSP1	33	0.568	0.23	0.106	0.994	0.382	0.535	0.725
RCP85 - SSP2	33	0.526	0.233	0.085	0.989	0.333	0.485	0.692
RCP85 - SSP3	33	0.47	0.231	0.066	0.981	0.278	0.435	0.629
RCP85 - SSP4	33	0.458	0.23	0.062	0.979	0.267	0.424	0.627
RCP85 - SSP5	33	0.607	0.225	0.127	0.997	0.429	0.581	0.775
RCP45 - SSP1	33	0.543	0.226	0.104	0.99	0.36	0.498	0.701
RCP45 - SSP2	33	0.499	0.227	0.084	0.984	0.319	0.458	0.658
RCP45 - SSP3	33	0.442	0.223	0.065	0.973	0.27	0.408	0.588
RCP45 - SSP4	33	0.429	0.222	0.062	0.969	0.256	0.399	0.569
RCP45 - SSP5	33	0.584	0.222	0.126	0.994	0.418	0.542	0.732

Note on interpretation. The value of 0.568 represents a 56.8% residential air-conditioning market saturation.



Supplementary Figure 8: Top panel: Predicted air-conditioning adoption rates in 2040 (between 0 and 1, full adoption). Bottom: Predicted growth rates of electricity demand. Sensitivity to temperature thresholds and to temperature measurement.

Adaptation to climate change: Air-conditioning and the role of remittances[*]

Teresa Randazzo[†] **Filippo Pavanello**[‡] Enrica De Cian[§]

Abstract

Do remittances improve the ability of households to adapt to global warming? We try to answer this question by studying the behaviours of households in Mexico, a country that experiences a large and stable flow of remittances. Using an instrumental variable approach, we find an important role of remittances in the climate adaptation process. Remittances are used for adopting air-conditioning, which is an important cooling device for responding to high temperatures and to maintain thermal comfort at home. We exploit climate and income heterogeneity by showing that large differences exist in the use of remittances for climate adaptation between coastal and inland regions, as well as among different income groups. We conclude by quantifying the overall increase in welfare that households attain by adopting air-conditioning.

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1 Introduction

Air-conditioning is increasingly penetrating countries worldwide (IEA, 2018) and upward trends are especially observed in the emerging economies of the tropics and subtropics. A growing literature has highlighted the relative importance of income in relation to climatic conditions (Sailor & Pavlova, 2003; McNeil & Letschert, 2010; Auffhammer, 2014; De Cian et al., 2019; Randazzo et al., 2020), especially in the developing countries (Akpinar-Ferrand & Singh, 2010; Davis & Gertler, 2015; DePaula & Mendelsohn, 2010), and the fact that more households are about to reach an affluence level that makes air conditioners affordable. Prolonged exposure to extreme heat not only leads to thermal discomfort and reductions in working (Zander et al., 2015) and scholastic performance (Park et al., 2020), but can also cause dizziness, cramps, and cardiovascular and respiratory diseases (Basu & Samet, 2002; Barreca et al., 2016; Burgess et al., 2017). If heat stress affects the ability to accumulate human capital, in the long-term it can exacerbate existing inequalities. Access to air-conditioning is highly uneven, and current adoption rates are lower in the countries that need it most because more frequently exposed to high temperatures (Mastrucci et al., 2019). Within countries, adoption is highly concentrated among high-income deciles, leaving low-income households greatly exposed (Davis et al., 2021; Pavanello et al., 2021).

In the climate change literature, the process of adjustment to actual or expected changes in climate conditions is called *adaptation* (Smit & Wandel, 2006). Adaptive capacity refers to the ability to modify behaviours in order to better cope with existing or anticipated external stresses (Adger, 2006). Operating air-conditioning is a form of private or individual adaptation to climate change. Socio-economic conditions determine a household's adaptive capacity, which involves purchasing power and access to technology. The literature on adaptive capacity is highly fragmented (Siders, 2019), with heterogeneous contributions from diverse and disconnected disciplines. Still, scientific contributions from different fields of study agree on the importance of certain recurring determinants of adaptive capacity, namely education, technology, knowledge, and physical and financial resources. Financial assets have long been recognized as a crucial determinant of adaptive capacity (Smit & Wandel, 2006), and financial constraints are one of the barriers that can drive a wedge between desirable adaptation options and those that are actually implemented (Chambwera et al., 2015). Existing work on the drivers of adaptive capacity mainly focuses on the role of labour-related income and wealth (Yohe & Tol, 2002; Siders, 2019), while the potential contribution of non-labour-related income, such as remittances, remains inadequately studied.

Remittances are an important additional source of income that enables recipient households to invest also in riskier assets and activities. Officially recorded remittance flows to low- and middle-income countries reached \$540 billion in 2020 (World Bank, 2021). Even during the COVID-19 pandemic, remittances remained stable, registering in 2020 a very limited decline of just 1.6% below 2019 levels (World Bank, 2021). Remittances have received much less attention compared to the direct migration or displacement of people caused by climate change (Gray & Mueller, 2012; Belasen & Polachek, 2013; Mastrorillo et al., 2016; Baez et al., 2017; Bosetti et al., 2018; Cattaneo & Peri, 2016). Independently of why people migrate, remittances can serve as an economic safety net for recipient households that remain in the sending countries (Yang & Choi, 2007; Defiesta et al., 2014) and, especially in poor and emerging countries with stark inequalities, remittances are an important financial resource for improving the adaptive capacity of recipient households unable to relocate (Gemenne & Blocher, 2017; Giannelli & Canessa, 2021). Remittances are not only a source of income, but they also enable social transactions that create new social values (Rahman & Fee, 2012). Migrants sending remittances can also transfer back to the sending country of origin new skills, knowledge, ideas, and social practices acquired in the destination regions. Remitters might control how their transfers are spent by modifying intra-household bargaining power in expenditure allocation. Through these intangible mechanisms, remittances can contribute to re-orientating expenditure decisions (Anghel et al., 2015; Levitt, 1998).

Within the economic literature of migration, several studies show that remittance income has a positive effect on the acquisition of durable goods (Airola, 2007; Adams Jr & Cuecuecha, 2010a), but little attention has been given to what kind of durable goods are mostly affected. A few isolated contributions more closely related to our research have examined the relationship between remittances and energy consumption (Rahman & Fee, 2012; Akçay & Demirtaş, 2015), implicitly highlighting the role of more affordable energy-intensive appliances. Remittances are generally spent on consumption (Chami et al., 2005; Adams Jr & Cuecuecha, 2010b; Clément, 2011), but also on productive goods and activities with positive effects on economic development. Remittances contribute to children's education (Cox-Edwards & Ureta, 2003; Kifle, 2007; Yang, 2008; Adams Jr & Cuecuecha, 2010a; Mansour et al., 2011; Randazzo & Piracha, 2019), housing (Adams Jr & Cuecuecha, 2010a), health (Taylor & Mora, 2006) and/or investments (Taylor & Mora, 2006; Woodruff & Zenteno, 2007; Mendola, 2008; Veljanoska, 2021). Income constraints limit a household's consumer preferences, and receiving remittances relaxes that constraint by expanding the range of budgetary allocations. According to the permanent income hypothesis, remittances represent a transitory source of income that is used differently from the more stable labour income. The latter, such as expected income, is more likely to be saved, while less predictable income streams – such as remittances – encourage asset accumulation. Several studies support the stronger effect of remittance income than other income sources on asset accumulation by households (e.g. Adams Jr, 1998; Amuedo-Dorantes & Pozo, 2014).

Our paper builds upon the two streams of literature on climate adaptation and development economics, in order to investigate whether and how remittances on the acquisition of a specific type of durable good, namely air-conditioning, serves the purpose of adapting to rising temperatures. A recent paper by Veljanoska (2021), closely related to our work, looks at whether remittances promote fertilizer use among Uganda farmers as a means of coping with rainfall variability. The paper sees remittances as a source of financing new investments, and within the climate adaptation literature this is a way to improve adaptive capacity.

We focus our analysis on the impact of remittances on climate adaptation in Mexico, an emerging economy that is experiencing a rapid increase in the adoption of air-conditioning, in the context of a long tradition in remittance inflows. Because of its heterogeneous climate, Mexico is an ideal subject for an empirical study of air-conditioning. The country is 2,000+ miles long and its climate zones range from hot and humid tropics to arid deserts and high-altitude plateaus. Most of Mexico's remittances are sent by the millions of Mexicans living in the United States, where the household penetration rate of air-conditioning is above 85%.[1]

We use the Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH), a nationally representative household income and expenditure survey that the Mexican Statistical Institute has carried out biennially since 1984. We rely on household data from 2008 to 2018. Our empirical strategy is based on an instrumental variable approach for dealing with the potential endogeneity of remittance income. In line with previous studies, we find that climate and income are among the main drivers of the adoption of air-conditioning. Moreover, our variable of interest, remittance income, plays an additional role in the adaptation process. The probability of adopting air-conditioning increases by 8 percentage points when remittance income increases by 1000 pesos.[2] We exploit climate and income heterogeneity across Mexican households and states in order to show that remittances increase the ability of households to purchase air-conditioning (i)

[1] https://www.enerdata.net/publications/executive-briefing/the-future-air-conditioning-global-demand.html

[2] 1000 Mexican pesos correspond to 49 US$

mostly in the coastal areas and (ii) especially when they have a relatively low-income level. We then underscore the potential private benefits of this form of adaptation by computing the 2018 consumer surplus gain associated with the possession of air-conditioning. The possession of air-conditioning increases the consumer surplus by between \$231 and \$988 million (2012 PPP), depending on the estimation model and method employed.

The remaining part of the paper is structured as follows. Section 2 provides some background on remittances and air-conditioning penetration in Mexico. Section 3 presents the descriptive statistics, while Section 4 describes our theoretical and empirical approach. Results are discussed in Sections 5 and 6, and the concluding remarks in Section 7.

2 Study context

Mexico is the third country in the world and the first in Latin America and the Caribbean region for inflows of international remittances, which reached 43 billion USD in 2020 (World Bank, 2021). The vast majority of these remittances are generated in the US, where almost 11 million Mexican nationals live.[3] Since the 1980s, the total value of remittances has steadily increased (Figure 1), and in Mexico, more than in other emerging countries, remittances have significantly contributed to the country's economic development, accounting for 4% of its Gross Domestic Product (GDP) in 2020.

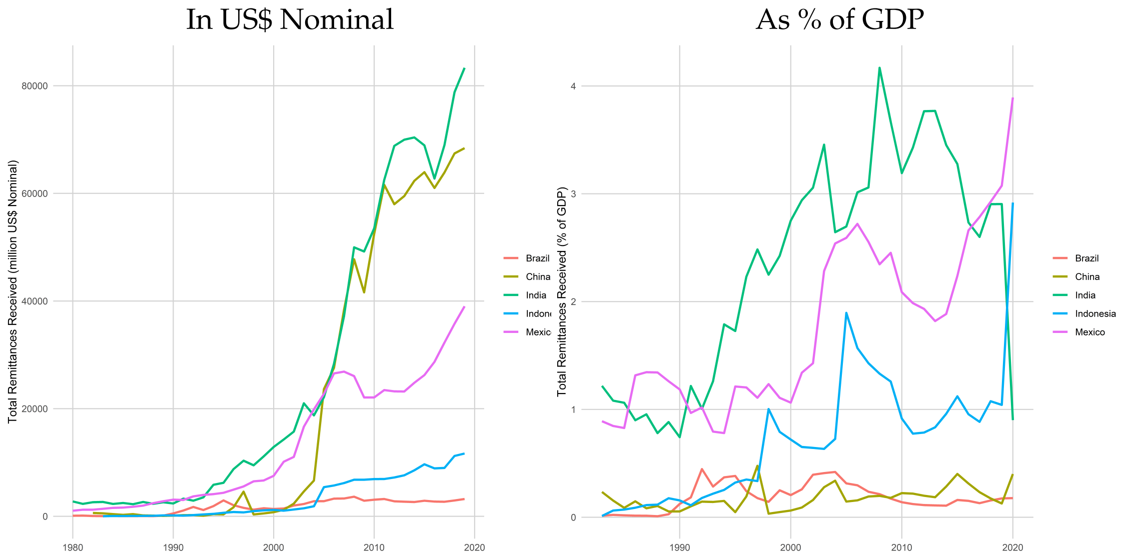

Figure 1: Remittance Inflows in Five Main Emerging Economies

Mexico's steady inflow of remittances has attracted the attention of researchers and policy makers, who have analysed its implications for Mexican households and economy. Several studies on how recipient households perceive and use remittances in Mexico have found that migration and remittances reshape expenditure in favour of investments (Taylor & Mora, 2006; Chiodi et al., 2012; Woodruff & Zenteno, 2007). In Mexico, remittances affect schooling (Alcaraz et al., 2012; McKenzie & Rapoport, 2011; Borraz, 2005; Hanson & Woodruff, 2003), health (Hildebrandt et al., 2005), poverty, and labour supply (Amuedo-Dorantes & Pozo, 2006) and Amuedo-Dorantes & Pozo (2011b) show that remittances can also help to contrast income volatility. The empirical work on remittances conducted in Mexico provides evidence of how remittances promote growth and development. The role of remittances in the adaptation process has been ne-

[3] https://www.migrationpolicy.org/article/mexican-immigrants-united-states-2019

glected and we attempt to fill this gap in the literature by showing how remittances in Mexico can promote climate adaptation through the adoption of air-conditioning.

Over the last ten years, air-conditioning penetration rates have doubled (Davis & Gertler, 2015), but not all households are equally able to afford this form of investment for adaptation and, in 2018, only around 18% of Mexican households had at least one air conditioner installed in their dwellings.[4] Mexico's highly heterogeneous climate determines an uneven distribution between inland and coastal areas (Figure 2). Temperatures are mild in the inland regions, where air-conditioning is relatively uncommon and adoption rates are close to zero. The coastal areas are exposed to much higher temperature levels, leading to higher penetration rates, reaching over 70% in some Pacific coastal states.

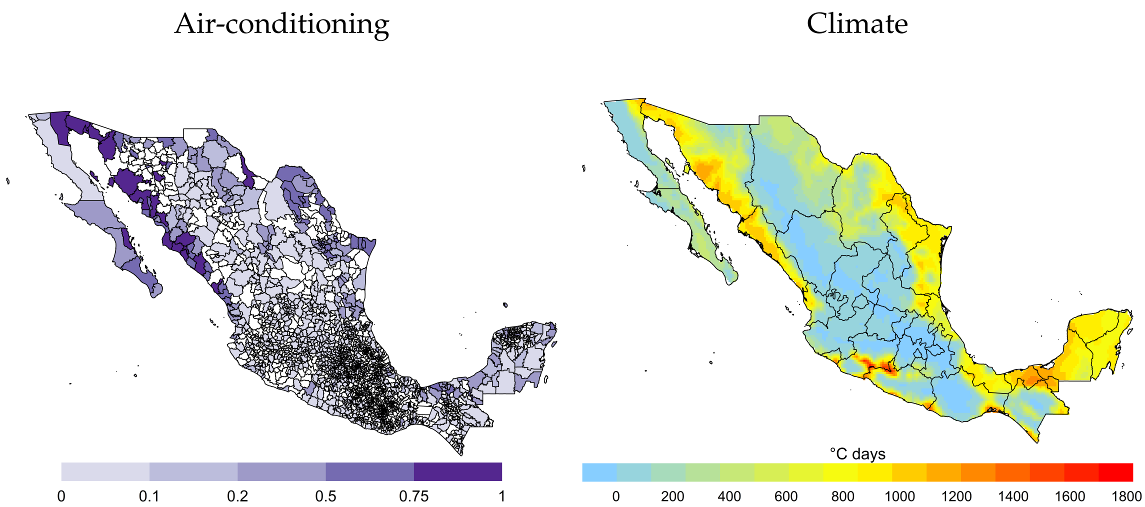

Figure 2: Left: Share of households with Air-conditioning in 2018 (ENIGH); Right: Mean (1970-2018) CDD dry-bulb (GLDAS)

3 Data

The *Encuesta Nacional de Ingresos y Gastos de los Hogares* (ENIGH) is a nationally representative repeated cross-section survey carried out biannually by the Mexican statistical institute, INEGI. We use the last six available waves,[5] covering the 2008-2018 period and consisting of 229,236 sample households. The survey provides information on the size, origin and distribution of the income and expenditures of Mexican households. We focus our attention on international remittances, defined as monetary transfers that households have received from abroad during the previous three months.[6] The survey also contains a comprehensive module on housing and household appliances, which makes it possible to determine whether households have air-conditioners installed in their homes. However, we cannot differentiate between the various kinds of air-conditioning units (e.g. window, split, central), hence our results aim at capturing

[4] Authors' calculation based on ENIGH 2018.

[5] Starting in 2008, INEGI has changed how it constructs income variables (*Nueva construcción*), making it difficult to consider previous waves

[6] In our analysis we focus only on international remittances. This is because for domestic remittances generated within Mexico, we do not have any information on where the remitter is located, and how internal migration is distributed inside Mexico. We follow Amuedo-Dorantes & Pozo (2006, 2011a,b), among others, who perform an empirical analysis based on international remittances only.

the impact of remittance income on the adoption of undifferentiated forms of air-conditioning.

We merge this data set with climate data taken from the reanalysis data set Global Land Data Assimilation System (GLDAS). Our climatic variable is the long-term annual average of dry-bulb Cooling Degree Days (CDDs), which measures typical intensity and duration of hot climate, and is widely used in the literature as determinants of space cooling (Davis & Gertler, 2015; De Cian et al., 2019; Pavanello et al., 2021). CDDs have been calculated by using daily temperature (°C) data computed from the 3-hourly global surface gridded temperature ($0.25° \times 0.25°$resolution) fields obtained from the GLDAS (Rodell et al., 2004), from 1970 up to the corresponding wave year. For each grid-cell the CDDs are calculated by using the American Society of Heating, Refrigerating and Air-Conditioning (ASHRAE) method (ASHRAE, 2009), and fixing 24 °C as temperature baseline. We use this threshold, rather than 18 °C, because Mexico is located between subtropical and tropical regions.

Table 1: Descriptive Statistics for the period 2000-2018

			Full Sample			
			Mean	SD		
Recipient (Yes = 1)			0.057	0.232		
Remittance Income (pesos) - if > 0			7,459.068	11,013.469		
Air-conditioning (Yes = 1)			0.166	0.372		
	Non Recipients		**Recipients**			
	Mean	SD	Mean	SD	Diff.	p-value
Air-conditioning (Yes = 1)	0.170	0.375	0.101	0.302	0.068	0.000
Long-term Mean CDD	383.879	419.002	298.275	392.776	85.604	0.000
Labour Income (pesos)	28,080.213	36,943.167	15,297.375	23,484.161	12,782.839	0.000
Total Income (pesos)	41,612.908	102,065.718	32,752.788	32,453.372	8,860.120	0.000
Urban (Yes = 1)	0.685	0.465	0.453	0.498	0.232	0.000
Female Head (Yes = 1)	0.252	0.434	0.425	0.494	-0.173	0.000
Head Age	48.830	15.775	53.710	17.269	-4.880	0.000
Head Education (None = 1)	0.257	0.437	0.447	0.497	-0.189	0.000
Head Education (Primary = 1)	0.212	0.409	0.222	0.416	-0.010	0.009
Head Education (Secondary = 1)	0.284	0.451	0.226	0.418	0.059	0.000
Head Education (Above = 1)	0.246	0.431	0.106	0.308	0.140	0.000
Child (< 15, Yes = 1)	0.549	0.498	0.549	0.498	-0.000	0.990
Elderly (> 65, Yes = 1)	0.213	0.409	0.343	0.475	-0.130	0.000
Home Ownership (Yes = 1)	0.717	0.450	0.747	0.435	-0.029	0.000
Head Employed (Yes = 1)	0.790	0.407	0.612	0.487	0.177	0.000
Household Size	3.733	1.885	3.730	2.069	0.003	0.819
Hist. Rem. 1992	0.176	0.100	0.228	0.114	-0.052	0.000
Avg. US Wage	25.409	2.118	25.587	2.115	-0.178	0.000
Hist. Rem. 1992 x Avg. US Wage	4.481	2.591	5.840	2.917	-1.359	0.000
Observations	216,158		13,078			

Descriptive statistics in Table 1[7] show that over the period 2008-2018 almost 6% of the households are remittance recipients, and they receive on average 7,459 pesos per quarter.[8] The air-conditioning adoption rate was around 17%, a figure that was significantly higher in non-recipient households (+6.8 percentage points). At the same time, households owning an air-conditioner received a significantly larger amount of international income remittance, showing that significant differences existed between households that owned an air-conditioner and those that did not (Table A2). On average, remittance recipients received 12,782 pesos less in tri-monthly labour income than non-recipients and tended to be less educated. These two results suggest that recipient households, in order to overcome income constraints, are liable to resort to the strategy of migration and remittance. Our argument is also supported by the household

[7] In the Appendix we define each variable used in the empirical analysis (Table A1).

[8] This corresponds to around 770$ per quarter.

head's employment status. Household heads in recipient families are less likely to be employed (61%), compared to non-recipient households (79%). We do not find significant differences in household size and presence of children based on household remittance status, whereas recipients are substantially more likely to have an elderly family member in the household (34%). The household head, on average, is older by five years in recipient households. As expected, recipient households also have a higher proportion of female heads compared to non-recipient households. Finally, remittance-recipient households are less concentrated in urban areas (45%) compared to non-recipients (68%), and they also experience lower temperatures - on average a difference of 86 CDDs between remittance-recipient and non-recipient households.

4 Empirical Framework

4.1 Modelling Demand for Air-conditioning

We introduce a simple model for the demand for thermal comfort, following the framework used by Amuedo-Dorantes & Pozo (2011b) in the context of health care expenditure. We assume that each household i in a given location maximises a utility function that depends on consumption of market good (X) and the availability of for thermal comfort (T):

$$U_i = U(X_i, T_i) \tag{1}$$

Households may invest in thermal comfort (T) according to a production function that depends on the availability of air-conditioning (AC), the climatic conditions (C) in the given location d, and a set of households' characteristics ($\mathbf{H}$) such as demographics (e.g. age, household size), socio-economic conditions that include wealth and education, and unobservable factors (e.g. preferences).

$$T_i = f(AC_i, C_d, \mathbf{H}_i) \tag{2}$$

Assuming preferences do not change over time, each household maximises its utility by reaching the highest indifference curve possible subject to a budget constraint. The budget constraint is a function of both non-labour income, which we identify in remittances (R), and labour income (I). Income from any source is used to pay for market good X (with price P_X) and for air-conditioning appliances (priced at P_{AC}). That is:

$$\begin{aligned} \max_{X,T} \quad & U_i = U(X_i, T_i) \\ \text{s.t.} \quad & P_X X_i + P_{AC} AC_i \leq R_i + I_i \end{aligned} \tag{3}$$

The solution to this problem yields the optimal demand for air-conditioning:

$$AC_i = g(R_i, I_i, P_X, P_{AC}, C_d, \mathbf{H}_i) \tag{4}$$

An increase in remittances, all else being equal, produces an income effect that shifts a household's budget constraint to the right, enabling households to reach a higher indifference curve. Households with a higher disposable income can have access to a higher range of goods and consume more of the two normal goods, X and AC.

While both generic and remittance income are measured in monetary units, the literature provides ample evidence that a dollar (or peso) of remittance income is not the same as a dollar (peso) of wage income, because (i) remittance income is transitory as opposed to the permanent nature of wage income (Adams Jr & Cuecuecha, 2010a) and (ii) the remitter has a bargaining power in orientating transfer allocation (Amuedo-Dorantes & Pozo, 2011b). While expected wage income is more likely to be saved (permanent income hypothesis), less predictable income streams such as remittances encourage asset accumulation (precautionary savings). Air-conditioning can be seen as a risky asset that in the long-term benefits health and human capital (e.g. protecting health). Hence, we expect remittance income to have a positive impact on the adoption of air-conditioning.

4.2 Empirical Strategy

Starting from Equation 4, we pool the six waves of data available over time to obtain our empirical model describing a household's adoption of air-conditioning:

$$AC_{i(t)} = \beta_0 + \beta_1 R_{i(t)} + \beta_2 CDD_{d(t)} + \mathbf{F}_{i(t)}\beta_3 + \mu_s + \delta_{(t)} + \epsilon_{i(t)} \tag{5}$$

where $AC_{i(t)}$ is a dummy variable taking value 1 if household i has an air-conditioner installed in its dwelling in year t, 0 otherwise. $R_{i(t)}$ indicates the tri-monthly international remittance income from migrants living abroad (in thousand pesos). Hence, our coefficient of interest β_1 is to be interpreted as the effect of an additional 1000 pesos of remittance income every three months on the likelihood of having an air-conditioner. The variable $CDD_{d(t)}$ is the long-term average of dry-bulb Cooling Degree Days (CDD) experienced in district d across the 1970-t period. We also include a vector $\mathbf{F}_{i(t)}$ which groups income I_i and a household's characteristics $\mathbf{H}_i$ from equation 4.[9] We check for unobservable time-unvarying effects on the state level, as well for time-varying common trends by the means of state- and year-fixed effects, μ_s and $\delta_{(t)}$, respectively, and capture the remaining unobserved factors with an error term $\epsilon_{i(t)}$.

It is however problematic to estimate Equation 5 by using a Linear Probability Model (LPM). Remittance income is likely to be endogenous for adopting air-conditioning, and so the disturbance term $\epsilon_{i(t)}$ is to be correlated with $R_{i(t)}$. In our study, households are likely to turn to remittance according to their socio-economic status (observable selection bias). Negative selection may imply that poor households receive more remittances, but at the same time they are less likely to invest in air-conditioning. This would induce a downward bias in the LPM estimates which we limit by checking for labour income and family size that are determinants of poverty status. In addition, because we exploit repeated cross-sectional data, we cannot net out unobservable household determinants of receiving remittance income that may also be correlated with the adoption of air-conditioning. Because of omitted variable bias, we again expect the LPM estimates to be downward biased. For instance, more risk adverse households might be less likely to send a family member abroad because successful migration itself (e.g. settling down and finding a good job) is uncertain. At the same time, risk-adverse households with limited resources are less likely to invest in new appliances since negative income shocks may always occur.

To address the endogeneity of remittance income, we exploit a two-stage least squares (2SLS) approach and model the remittance equation as follows:

$$R_{i(t)} = \gamma_0 + \gamma_1 HR_{u(s)} \times W_{s(t)} + \gamma_2 CDD_{d(t)} + \mathbf{F}_{i(t)}\gamma_3 + \mu_s + \delta_{(t)} + v_{i(t)} \tag{6}$$

here $R_{i(t)}$ is the remittance income of household i at time t. The component $HR_{us} \times W_{s(t)}$ is our instrumental variable, which is given by the interaction between the historical share of remittances in stratum u of state s[10] and the weighted average of the US hourly wage assigned to state s at time t, $W_{s(t)}$.[11] The error component $v_{i(t)}$ is assumed to be independent of the set of control variables. In order to identify the model, we need to include in the first stage equation variables that are correlated with the remittance income but are not directly affecting the

[9]We include in $\mathbf{F}$: labour income, dummy for living in an urban area, household head's education, household head's employment status, household head's gender and age, household size, home ownership, and dummy variables for the presence of elderly persons and minors in the household. Given that income tends to be particularly skewed in developing countries, as a robustness we run our empirical model adding a quadratic term of labour income. Results are qualitatively the same, and therefore we present the regression with linear labour income only.

[10]For each state we can identify four strata: urban, suburban, small village and rural. This means that in total the historical share of recipient households in 1992 has 128 different values, 4 for each of the 32 states.

[11]All time variation in our instrument comes from the variation in US wages, which vary over time (t). Instead, the historical share of remittances in stratum u of state s is collected just for the year 1992 and therefore the variation is only between state and stratus and is fixed over time.

adoption of air-conditioning. As presented above, the instrumental variable chosen is an interaction between: (i) a historical share of households receiving remittances in 1992, varying by state and stratum level; (ii) the annual average in hourly wage in US destination states weighted by Mexican share of migrants by state of residence, varying by state and year level. Using this interaction, rather than the two components separately, allows to introduce more variability,[12] which we can exploit to identify the effect of remittance income.

For the first component, we follow the studies using historical migration rates and migration networks as instruments for remittances (Woodruff & Zenteno, 2007; McKenzie & Rapoport, 2011; Acosta, 2011; Salas, 2014; Veljanoska, 2021). They have proven to be a good proxy for local remittance norms, namely places that are used to receiving remittances. Specifically, we use the share of households receiving remittances taken from the 1992 ENIGH wave. The ratio is that Mexican locations where households are historically more likely to be recipients also have better infrastructure for receiving remittances, and so at present receive a higher amount of remittance income. Here the assumption is that, once we check for all the other exogenous covariates, the historical share of households receiving remittances in 1992 does not affect the present-day adoption of air-conditioning, apart from the impact through current remittance transfers.

For the second component, we follow the approach of Amuedo-Dorantes & Pozo (2011a,b). We first compute an annual average hourly wage for each wave-year and US state.[13] Then, we gather public data from the Instituto de los Mexicanos en el Exterior (IME) to determine the migrants' preferred US destination states from each Mexican state.[14] Finally, we assign to each Mexican state a weighted US country average hourly wage based on these stock of emigrants.[15] The idea is that the wage level in US destinations for Mexican emigrants are correlated with their remittance outflows. Here, we assume that US labour market conditions over the years do not affect AC adoption in Mexico other than via their remittance inflows.

One possible concern related to our instrumental variable is a correlation between the historical share of recipient households and the current level of development in the Mexican states. We resolve this issue by including the state's fixed effects, μ_s, and we also double-check for state-level per capita GDP as well as for state-time linear trends. In the next sections we provide several tests for conducting a thorough inspection of the econometric validity of our instrument.

We estimate Equation 6 by using an OLS estimator, even though we observe remittance income for only 6% of the sample. We do not exploit a Tobit model, since a non-linear first stage would lead to inconsistent results in the second stage (Angrist & Krueger, 2001). Moreover, assuming censoring of the dependent variable does not allow for the possibility of true zeros. For robustness, we combine both internal and international remittances to see whether our estimates remain unaffected. Finally, in both first- and second-stage regression standard errors are clustered at a district-year level to correlate observations within the same municipality included in the survey wave.

[12]To build this instrument we refer to the shift-share literature – see e.g., Borusyak et al. (2022)

[13]https://www.bls.gov/

[14]http://www.ime.gob.mx/

[15]Take as an example the Mexican states of Sonora. 38.7% and 30.6% of the Mexican migrants from Sonora go to Arizona and California, respectively. This means that we assign to Sonora the annual US average hourly wage in Arizona and California, weighted with the share of migrants, 0.387 and 0.306, respectively.

5 Results

5.1 Impact of Remittance Income on Air-conditioning Adoption

Table 2 presents the summary of our main estimates of the impact of remittance income on the adoption of air-conditioning, whose full results are included in the Appendix (Table A5). We first run an LPM as a baseline for the analysis (Columns (1)-(3), Table 2). When the endogeneity of remittances is not considered, we find that a thousand-peso increase in tri-monthly remittance income is associated with a rise in the probability of adopting air-conditioning by between -0.10 and 0.24 percentage points, depending on the specification. Yet, as discussed above, these estimates are likely to be downward biased.

Column (4) in Table 2 reports the second-stage estimates related to the impact of remittances on the adoption of air-conditioning when the potential endogeneity bias is addressed with a 2SLS IV model. Compared to the coefficient from the LPM estimates, we find a larger, significant effect. This is in line with the empirical literature on remittances showing that the remittance coefficient gets much larger when an IV-strategy is implemented.[16] In our case, a 1000-pesos rise in tri-monthly remittance income increases the probability of adopting air-conditioning by 8 percentage points.[17] This result suggests that remittances play a fundamental role in satisfying the cooling demand of Mexican households by relaxing credit constraints in accessing the technology. Our results also align with the existing evidence (Amuedo-Dorantes & Pozo, 2014) suggesting that the transitory nature of remittance income encourages asset accumulation. When that same specification is re-estimated by using fans (Table A8), which are a much cheaper alternative to air-conditioning, remittance income reduces the purchase of this good. That is, recipient households tend to invest more in a "riskier" asset such as air-conditioning than in a less-risky asset such as fans. When we divide our sample into recipient and non-recipient households and re-estimate our main specification to include total income as the only income covariate,[18] we find that households that receive remittances are more likely to buy an air-conditioner. This result suggests that the two sub-samples have a different propensity to invest in air-conditioning (Table A9).

The coefficients of the other covariates (Table A5) are in line with recent studies that have explored the determinants of air-conditioning adoption in Mexico (Davis & Gertler, 2015; Pavanello et al., 2021). Climate conditions are also an important driver of the demand for air conditioners. A hundred-unit increase in CDDs raises the likelihood of adopting air-conditioning by 3 percentage points. We also find a positive effect of labour income on the adoption. A 1000-pesos rise in labour income increases the likelihood of adopting the technology by 0.11 percentage points, a much smaller marginal effect compared to the remittance income discussed above.[19][20]

[16] See for example Alcaraz et al. (2012); Amuedo-Dorantes & Pozo (2006); Cuadros-Meñaca (2020); Cuadros-Meñaca & Gaduh (2020); Quisumbing & McNiven (2010); Veljanoska (2021).

[17] In other words, if we interpret our results in terms of elasticities, a 1% increase in remittance income leads to a 3.61 percentage points increase in air-conditioning adoption.

[18] Total income includes labour income, remittance income as well as other sources of income (such as capital income).

[19] We use labour income as opposed to total income because labour income excludes the income from physical and human capital assets, rents and interest. This distinction between labour income and capital income is important because capital income is generated by previous investment decisions in assets which remittances income may contribute to determine and this paper tries to explain (Adams Jr, 1998). In the Appendix, Table A5 allows for a direct comparison between linear remittance income and linear labour income showing a close to 73 fold difference between remittance and labour income effects. Our remittances-income ratio is in line with the literature (e.g. Veljanoska, 2021).

[20] The stronger effect of remittance income compared to labour income should be interpreted with caution. Alcaraz et al. (2012) state clearly that including income may cause some endogeneity problems. Additionally, from an econometric point of view, the effect of remittance income is a local average treatment effect (LATE) or complier average casual effect; the effect of income is an average treatment effect (ATE) which includes compliers and not compliers

By keeping labour income and climate constant, several demographics, economic and technological characteristics remain important factors in explaining adoption patterns. Urbanisation increases the likelihood of adopting the cooling durable (+9.3 percentage points) and so does home ownership. Education too substantially enhances the propensity to adopt the technology. Findings on gender suggest that the presence of a female family head decreases the propensity to adopt a cooling device (-4.7 percentage points).

Our first-stage results (Table A4) indicate that the recipient households are negative selected, confirming what the descriptive statistics already suggested. For instance, both a household head's education and his/her employment have a negative impact on remittance income. Home ownership, which represents a measure of wealth, is negatively associated with remittances. In line with previous studies, we find that female-headed households are more likely to receive international remittances (+595 pesos) and that the presence of children in the household is another important determinant of remittances (+116 pesos) (e.g Acosta, 2011; Amuedo-Dorantes & Pozo, 2011b). Our instrumental variable, given by the interaction between: (i) a historical share of households receiving remittances in 1992; (ii) the annual average in hourly wage in US destination states, is quite positively correlated with received remittances. This means that locations with greater remittance norms receive higher remittance income when there is an increase in the US hourly wage.

To verify the validity of our IV approach, we first implement Montiel Olea & Pflueger (2013)'s heteroscedasticity robust test, in which instruments are considered weak when the 2SLS bias is large relative to a benchmark. In our case, the effective F-statistic results are equal to 45.87, hence well above the Montiel-Pueger TSLS critical value at τ = 5%, with significance level set at 5%. We can therefore reject the null hypothesis of weak instrument and be confident that our estimates are unlikely to be biased by a weak instrument. To further inspect our instrument, we also report the 95% Anderson-Rubin confidence interval.[21] This confidence interval is robust to the presence of weak instruments and has the correct size under a variety of violations of the standard assumptions of the IV regression.

Table 2: Impact of Remittance Income on Air-conditioning Adoption

	LPM (1)	LPM (2)	LPM (3)	2SLS (4)
Remittance Income (in 1000s)	-0.0010**	0.0012***	0.0024***	0.0801**
	(0.0004)	(0.0002)	(0.0002)	(0.0337)
Mean CDD			0.0003***	0.0003***
			(3.97e-05)	(3.91e-05)
Covariates	No	No	Yes	Yes
State FE	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes
Effective F statistic				45.869
Montiel-Pflueger TSLS (τ = 5%)				37.418
Anderson-Rubin CI				[0.017, 0.153]
Observations	229,236	229,236	229,236	222,777

Notes: (1), (2), (3) and (4) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each equation includes as covariates: labour income, dummy for living in an urban area, household head's education, household head's employment status, household head's gender and age, household size, home ownership, and dummy variables for the presence of elderly persons and minors in the household. The table summarizes the estimation results presented in Table A5 available in the Appendix.

together.

[21] We conduct the Anderson-Rubin test, and we can reject the null hypothesis of no effect of remittance income on air-conditioning adoption at 0.01 significance level. Results of the test are available through the replication code.

5.2 Heterogeneity: Coast and Inland

Given Mexico's great climate heterogeneity, we explore whether remittances have a heterogeneous impact in warm and cold regions. We may indeed expect that only the recipient households living in high-temperature areas invest remittance income in air-conditioning purchase. We therefore divide our sample between households living in the warm coastal states and those living in the cold inland ones.[22] Table 3 shows the 2SLS estimates for these two subsamples. We find that remittance income is a significant driver of air-conditioning adoption in the coastal areas, whereas it has null effect in the inland areas. In terms of magnitude, in the coastal locations, remittances have an effect that is double in size compared to the estimates obtained when coastal and non-coastal locations are pooled together in the full sample specification. A 1000-pesos increase in tri-monthly remittance income increases the likelihood of adopting air-conditioning by 19 percentage points. As expected, recipient households tend to use the received remittances to increase their adaptive capacity, and adaptation opportunities only when they are exposed to high temperatures. Remittances are not only a source of income but can also have a social and cultural value that connect receiving to sending country communities and that can orientate expenditure decisions. Since most remittances are generated in the U.S., where air-conditioning is widely adopted, they might also have a contagious behavioural effect, especially in coastal areas where the temperatures are higher. In the inland regions, air-conditioning can be seen as a luxury good and not as a necessary need for a decent living, and therefore only the wealthy decide to adopt it, based on their income levels. In this case, remittances play no additional marginal role. However, the null effect of remittances for the inland households may not be precisely estimated. With a relatively weak instrument, the results for this subsample need to be interpreted with caution. Moreover, for the coastal sample we can reject the null hypothesis of a weak instrument only at 10% significance level, as we impose the Montiel-Pueger TSLS critical value at $\tau = 5\%$.[23] This suggests there might be some bias in these subsample estimates.[24]

[22]Table A3 presents descriptive statistics by area. Around 49% of the sample lives close to the coast (117,522 households) and 51% in inland areas (111,714 households). As expected, 24% of households living in the coastal areas possess air-conditioning while the percentage reduces to 8% in inland areas.

[23]The effective F statistic is slightly lower than the Montiel-Pueger TSLS critical value at $\tau = 5\%$, with significance level set at 5% (Table 3 and Table A6). With $\tau = 10\%$, the same critical value is 25.8, and so it is smaller than our effective F statistic.

[24]The difference in instrument performance for the two sub-samples might be related to significant differences in the instrument mean and standard deviation across the two sub-samples (Table A3).

Table 3: Heterogeneous Impact of Remittance Income on Air-conditioning Adoption: Inland vs Coast

	Inland (1)	Coast (2)
Remittance Income (in 1000s)	-0.0309	0.191**
	(0.0318)	(0.0764)
Mean CDD	0.0004***	0.0003***
	(3.31e-05)	(5.19e-05)
Covariates	Yes	Yes
State FE	Yes	Yes
Time FE	Yes	Yes
Effective F statistic	11.881	25.833
Montiel-Pflueger TSLS (τ = 5%)	37.418	37.418
Anderson-Rubin CI	[-0.125, 0.031]	[0.061, 0.381]
Observations	108,564	114,213

Notes: (1) and (2) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each equation includes as covariates: labour income, dummy for living in an urban area, household head's education, household head's employment status, household head's gender and age, household size, home ownership, and dummy variables for the presence of elderly persons and minors in the household. The table summarizes the estimation results presented in Table A6 available in the Appendix.

5.3 Heterogeneity: Income Groups

Due to asymmetries in access to financial markets, remittances might be more important for lower-income households facing tighter budget constraints than for higher-income households. We therefore study whether poorer households are more likely than richer households to spend remittance income on their cooling needs. We divide the sample into three groups, based on income terciles, and we re-estimate our model for low-, medium- and high-income households. Table 4 presents the 2SLS estimates for the three subgroups. We find households are less responsive to increases in remittance income as household income increases. For low-income households a 1000-pesos increase in tri-monthly remittance income makes it more likely to adopt air-conditioning by 6.8 percentage points. The effect is smaller for medium-income households – 4.6 percentage points, whereas it becomes non-significantly different from zero to high-income households.[25] Interestingly, labour income is not significant in the low and middle-income sub-sample. This suggests that poorer households can adopt the technology only if they receive resources in addition to labour income. Indeed, for poor households, labour income is primarily geared towards primary goods. Remittances, as an additional income source, can be invested in assets such as air-conditioning only after basic needs are fulfilled. These results are in line with Gertler et al. (2016), demonstrating that households faced with credit constraints become much more likely to purchase energy-using assets with additional income once their income passes a threshold level. In their paper they study the role of an unconditional cash program, which, like remittance income, can be seen as transitory. In our context, remittance income may make it possible to surpass that threshold by increasing the adoption of air-conditioning. The situation is different for medium-income families, who can invest part of their labour income, together with remittances, in air-conditioning. Table 4 shows that the impact of remittances on air-conditioning is lower in comparison to poor households. Finally, high-income households do not need remittances to purchase air-conditioning, and we do not find any significant effect of remittances on its purchase. The impact of remittances on cooling needs has to be analysed by labour income levels. Our findings shed light on different perceptions that households in

[25] For the high-income sub-sample the first-stage regression F-test may suggest a weaker instrument. This might be due to the fact that richer households are less likely to receive remittances. For the high-income households labour income drives the adoption of air-conditioning (see Table A7).

different income groups might have of air-conditioning. It might represent a normal good for high-income households and a luxury good for low-income households. We conclude that remittance income contributes to equalising household adoption of air-conditioning by financing the purchase.

Table 4: Heterogeneous Impact of Remittance Income on Air-conditioning Adoption: Income Groups

	Low-Income	Med-Income	High-Income
	(1)	(2)	(3)
Remittance Income (in 1000s)	0.0681**	0.0467*	0.0569
	(0.0290)	(0.0271)	(0.0398)
Mean CDD	0.000136***	0.000343***	0.000516***
	(0.0000220)	(0.0000457)	(0.0000483)
Covariates	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Effective F statistic	67.22	60.68	12.40
Montiel-Pflueger TSLS (τ = 5%)	37.42	37.42	37.42
Anderson-Rubin CI	[0.014, 0.129]	[-0.004, 0.106]	[-0.020, 0.169]
Observations	74,625	74,090	74,062

Notes: (1), (2) and (3) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each equation includes as covariates: labour income, dummy for living in an urban area, household head's education, household head's employment status, household head's gender and age, household size, home ownership, and dummy variables for the presence of elderly persons and minors in the household. The table summarizes the estimation results presented in Table A7 available in the Appendix. Income groups are based on total income.

5.4 Robustness checks

We perform some robustness checks for our analysis. In Column (1), Table 5, we report our 2SLS estimates when we include the state-level per capita GDP. The estimates remain close to those obtained with the main specification, suggesting that state fixed effects are sufficient to check for the correlation between the historical share of recipient households and the current level of development in the Mexican states.

In Mexico City about 1% of households have air-conditioning, but here recipient households receive the highest amount of remittance income. We check whether excluding the capital may affect our estimates. In Column (2) we report the results, which remain robust.

In Column (3) we re-estimate our econometric model, including multiple instruments. Particularly, we use the interaction together with the two components alone. The objective is twofold: (i) to provide an over-identification test to examine the instruments' exogeneity; and (ii) to examine whether introducing a plurality of instruments may affect the magnitude of the effect of remittance income. We find a similar effect of remittance on the adoption of air-conditioning. Moreover, results for the Hansen J test allows us to reject the null exogeneity of our instruments. However, adding a plurality of instruments reduces the variability we can exploit to identify the effect of remittance income. Consequently, the first-stage regression F-test is much lower than before – but it remains above the commonly used threshold of 10.

One further concern for our analysis is that only 6% of our sample receives international remittances, and the large number of zeros might affect our estimates. For this reason, we create an alternative measure of remittance income, which combines remittances from both internal and international migrants. As a result, around 20% of households are now recipients. Column (4) reports the estimate by using the new definition of remittance. The results remain similar to our baseline estimate. Nevertheless, not unexpectedly, we note that our instrumental variables work better when applied only to international remittances.[26] Finally, in Column (5) we add state-time linear trends to check state-specific business cycles – also related to US employment conditions - that may influence both the penetration of air-conditioning and the amount of remittance income that Mexican households receive from abroad. The positive impact of remittance income is robust to this addition.

Table 5: Robustness Checks

	Per Capita GDP	No Mexico City	More Instruments	Total Remittances	Linear Trend
	(1)	(2)	(3)	(4)	(5)
Remittance Income (in 1000s)	0.0795**	0.0817**	0.0780***	0.0855**	0.0823**
	(0.0337)	(0.0339)	(0.0301)	(0.0336)	(0.0344)
Mean CDD	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Covariates	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Linear State-trend	No	No	No	No	Yes
Kleibergen-Papp rk Wald F statistic	45.872	45.371	17.970	28.833	45.198
Montiel-Pflueger TSLS (τ = 5%)	37.418	37.418	22.085	37.418	37.418
Anderson-Rubin CI	[0.0167, 0.153]	[0.019, 0.156]	[0.003, 0.177]	[0.020, 0.161]	[0.018, 0.157]
Lagrange multiplier K test			7.881		
Lagrange multiplier K test (p-value)			0.005		
K test CI			[0.024, 0.143]		
Hansen J			0.103		
Hansen J (p-value)			0.950		
Observations	222,777	213,466	222,777	222,777	222,777

Notes: (1), (2), (3), (4) and (5) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each equation includes as covariates: labour income, dummy for living in an urban area, household head's education, household head's employment status, household head's gender and age, household size, home ownership, and dummy variables for the presence of elderly persons and minors in the household.

6 Quantifying the Welfare Gain from Air-conditioning Adoption

We have shown that providing Mexican households with additional non-labour income can relax credit constraints, making air conditioners more affordable. Air-conditioning has been shown to bring benefits in terms of reduced heat-related mortality (Barreca et al., 2016), and increased productivity and learning (Zivin & Kahn, 2016; Park et al., 2020). To quantify these gains in welfare, we estimate the full consumer surplus of Mexican households that owned an air-conditioner in 2018. In doing so, we closely follow Barreca et al. (2016), who compute the same measurement that is applied to the US. We specify the following conditional electricity demand function:

$$Q_i = \beta_0 + \beta_1 AC_i + \beta_2 P_s + \beta_3 AC_i \times P_s + \beta_4 CDD_d + \mathbf{Z}_i \beta_5 + \mu_s + \epsilon_i \tag{7}$$

where Q_i is the annual electricity demand (in 1000s kWh) of household i living in state s. AC_i indicates whether the household i as an air-conditioning system installed in its dwelling. P_s is the unit price of electricity in state s. The interaction $AC_i \times P_s$ allows air-conditioning to affect the slope of the electricity demand. $\mathbf{Z}_i$ vector containing household characteristics, including total

[26] In some specifications, based on correlation and not on causation, we differentiate international remittance from internal remittance income. We find that both types of remittances have a positive and similar impact, in terms of magnitude, on the adoption of air-conditioning. However, without solving for internal remittance endogeneity, we cannot really compare the coefficients. Results available upon request.

income, and CDD indicates Cooling Degree Days.[27] Finally, μ_s represents state fixed-effects and ϵ_i is the error component. In this setting air-conditioning induces a shift in the electricity demand curve for adopters.[28] The surplus gain is then quantified by computing the area between the demand curves of adopters and non-adopters. Moreover, as opposed to Barreca et al. (2016), we also subtract the externality costs due to the CO2 emissions from air-conditioning use.[29] In doing so, we use three different median estimates[30] for the scenario RCP4.5-SSP2 of the Mexican Social Cost of Carbon (SCC) from Ricke et al. (2018). We estimate Equation 7 by means of Dubin & McFadden (1984)'s discrete-continuous approach.[31] This allows us to simultaneously estimate both the intensive margin, i.e. the change in electricity use for a given level of air-conditioning stock, and the extensive margin, i.e. the change in electricity use due to an increase in the air-conditioning stock.

[27] We include the same household characteristics used in the previous sections. However, for the sake of consistency with Barreca et al. (2016), in Table 6 we specify all household characteristics and Cooling Degree Days as dummies. Specifically, we create quintiles for CDD, total income and household size, and quartiles for household head age. We then conduct a robustness check by using both continuous and dichotomic covariates (Table A11).

[28] See the area "abcd" highlighted in Figure A1 for the case of perfectly elastic supply.

[29] See the area "bcfe" in red in Figure 1. We compute the externality cost by: (1) Multiplying the marginal effect of air-conditioning on electricity demand by the average carbon intensity in Mexico – 0.21 kgCO2/kWh in 2018 (https://ourworldindata.org/co2/country/mexico); (2) Transforming CO2 from Kg to tons; (3) Multiplying the emissions by the Mexican SCCs and the total number of households in Mexico. We thank the reviewers for suggesting this extension.

[30] These are, respectively, the minimum, the median and the maximum value across all Ricke et al. (2018)'s median estimates for the RCP4.5-SSP2 scenario.

[31] Dubin & McFadden (1984) propose three methods to estimate discrete-continuous models. As in Barreca et al. (2016) we exploit the third alternative, which consists of correcting for the selection of air-conditioning adopters by including a selection term. The latter is constructed by using predicted probabilities from a logit regression with air-conditioning as a dependent variable. Similar to Barreca et al. (2016), in the first stage we include interactions between the dummies for household size and electricity price. These interactions are then dropped in the electricity equation to have identification.

Table 6: Regression of Electricity Quantity on Air-conditioning Adoption - Surplus Gain Computation in 2018

	OLS	OLS	OLS	DMcF
	(1)	(2)	(3)	(4)
Panel A: Electricity Demand				
Air-conditioning	1.564***	5.028***	4.115***	3.048***
	(0.149)	(0.598)	(0.376)	(0.340)
Electricity Price	-0.860***	-0.523***	-0.893***	-1.067***
	(0.078)	(0.024)	(0.169)	(0.163)
Elec. Price $\times$ AC		-1.226***	-1.024***	-0.592***
		(0.200)	(0.119)	(0.127)
Covariates	No	No	Yes	Yes
State FE	No	No	Yes	Yes
Selection Corr.	No	No	No	Yes
Observations	65,832	65,832	65,832	65,832
Panel B: Consumer Surplus Gain (in Billions \$2012 PPP)				
No CO_2 Externality	0.928***	0.594***	0.334***	0.988***
	(0.102)	(0.062)	(0.058)	(0.241)
SCC = 6.85 \$/tCO_2	0.849***	0.542***	0.295***	0.932***
	(0.099)	(0.057)	(0.056)	(0.235)
SCC = 18.16 \$/tCO_2	0.719***	0.457***	0.231***	0.839***
	(0.097)	(0.050)	(0.052)	(0.226)
SCC = 69.11 \$/tCO_2	0.133	0.074	-0.059	0.422***
	(0.104)	(0.057)	(0.044)	(0.187)

Notes: (1), (2), (3) and (4) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Equation (3) and (4) include as covariates: quintiles for total income, CDDs, and household size, quartiles for household head's age, dummy for living in an urban area, household head's education, household head's employment status, household head's gender, home ownership, and dummy variables for the presence of elderly persons and minors in the household. SCC values for Mexico are taken from Ricke et al. (2018). The number of households in Mexico in 2018 is about 35 million. Consumer surplus gain SEs are computed using Delta Method.

Table 6 shows our estimates for residential electricity demand. We find that air-conditioning raises residential electricity demand by 773-1564 kWh per year. Moreover, Columns (2)-(4) suggest that air-conditioning causes an even more precipitous rise in residential electricity demand. That is, air-conditioning makes electricity costs more sensitive to the increase in electricity quantity, indicating that households with air-conditioning are more sensitive to price changes.

Assuming a perfectly elastic supply of electricity, we then estimate that the gain in consumer surplus associated with the adoption of air-conditioning ranges from about \$231 to \$988 million (2012 PPP) at the 2018 air-conditioning penetration rate of 18% (Table 6). This translates into an increase in consumer surplus per household in 2018 of \$7– \$28 (2012 PPP). The per household gains in welfare double once we focus only on the coastal sample (Table A10), where the increase is between 12\$ and 50\$ (2012 PPP) per household at the 2018 air-conditioning penetration rate (25%). Environmental costs reduce the welfare gains. In 2018, between 6% and 57% of the welfare gain from adopting air-conditioning is lost to due to the social costs of the additional CO2 emissions produced.

If we compare the case with no externality cost, the results are smaller than in Barreca et al. (2016), which find an increase by between $112 and $225 (2012 PPP) in consumer surplus per US household at the 1980 air-conditioning saturation rate (57%). This is likely due to country-specific characteristics. For instance, there might exist differences in the preferences for electricity consumption between Mexican and US households. Moreover, the large gap between the air-conditioning adoption rates likely influences the total surplus gain. While the computation provides an insightful approximate measurement of the expected private benefits associated with the adoption of air-conditioning in the specific context of Mexico, there are some important caveats. First, we have assumed a perfectly elastic supply, which is likely to be an oversimplification.[32] Second, we have no information on the capital cost of adopting the technology. Third, we do not take account of the possible endogeneity of electricity costs.[33]

The penetration of air-conditioning in Mexico is still low, and households owning this technology may be highly selective. The estimation of electricity demand may be sensitive to selection bias. Column (3) shows estimates with no selection correction, while Column (4) presents estimates based on the Dubin-McFadden approach, which through the selection term corrects the potential bias of electricity demand. This explains why the gain in welfare calculated on the basis of estimates in Column (3), which does not include the selection term, is much lower than the one calculated by using estimates provided by Column (4). The evidence we provide indicates that a certain bias exists.

7 Conclusion

Our paper contributes to understanding what role remittances can have in the climate adaptation process of households. By focusing on space cooling investments, we show that receiving remittance income strongly increases the likelihood of purchasing air-conditioning. This finding suggests that the availability of additional financial resources can indeed enhance the adaptive capacity of households, enabling them to adopt technologies that otherwise would not be affordable and that can contribute to reducing their vulnerability to climate change. For low-income households and for those exposed to a warm climate, remittance income can make a significant difference in their ability to adapt to climate change. For these households, remittances represent an additional financial resource that can be allocated for space cooling in the presence of income constraints. Moreover, we believe that remittances are not only a transitory source of income but that they also incorporate an additional social value. Mexican remittances originate prevalently from the United States, which is where the widespread use of air-conditioning was pioneered. From being a luxury system used originally in manufacturing to control indoor environmental quality, by 1980 it became a common feature in nearly all American households (Biddle, 2008). Migrant household members acquire new behaviours and social practices that can be transferred back to household members in their country of origin.

We use a revealed preference approach based on the change in electricity expenditure induced by the availability of air-conditioning to determine a household's gains in welfare related to the purchase of this space cooling technology. We show that air-conditioning is an important means of adapting to climate change. In 2018, ownership of air conditioners generated an increase in consumer surplus of from $231 to $988 million (2012 PPP). These estimates should be taken with care. At the household level, they are expected to provide a lower boundary because the adoption of air-conditioning in Mexico is on an exponential growth trajectory. From a perspective

[32] This would be a more plausible assumption if in Mexico electricity generation mainly came from renewables – which have zero marginal cost. However, according to the International Energy Agency, in 2019, fossil-fuel based power plants provided 73% of Mexico's electricity.

[33] We reduce the impact of this issue by exploiting average electricity costs rather than marginal electricity costs, gathering cost data from an external source: https://www.inegi.org.mx/app/preciospromedio/?bs=18

of social well-being, we account for the negative externalities associated with air-conditioning. However, our estimates depend highly on the assigned social cost of carbon in Mexico, which is uncertain.

Warming temperatures will have harmful health impacts for exposed populations, particularly in emerging economies (Burgess et al., 2017), and air-conditioning has been shown to remarkably reduce mortality (Barreca et al., 2016). Yet, powering air-conditioning requires more electricity consumption, and this could contribute to creating new forms of vulnerability related to energy poverty. Socio-economic systems that depend on air-conditioning are more susceptible to collapsing under the impact of extreme weather events, such as heat waves, which will likely take place with ever-increasing frequency. Power outages that often occur during heat waves would then leave those households that depend on air-conditioning once again vulnerable.

Future research is needed for understanding whether there exist valid alternatives in a context such as Mexico, and what role remittances can play. Even when moving abroad, migrants remain in contact with their relatives living in their places of origin, and therefore they contribute to re-orientating expenditure and modifying the preferences of those remaining in the sending country by sharing new social norms or practices (Anghel et al., 2015). Whether the social value of remittances can support adaptive capacity through network effects and through changes in social preferences is difficult to quantify (Boccagni & Decimo, 2013), and this is left for future studies. A better understanding of the extent to which the social value of remittances can contribute to widespread adaptation practices can only be acquired by future research.

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Appendix

Additional Details on Data, Descriptives, and Analysis

Table A1: List of variables

	Type	Description
Recipient (Yes = 1)	Dummy	HH receives international remittances
Remittance Income (pesos)	Continuous	International remittance income
Air-conditioning (Yes = 1)	Dummy	HH has at least one AC
Mean CDD	Continuous	Long-term Average Cooling degree days
Labour Income (pesos)	Continuous	Labour income (wage)
Total Income (pesos)	Continuous	Total income
Urban (Yes = 1)	Dummy	HH lives in an urban area
Female Head (Yes = 1)	Dummy	HH head is female
Head Age	Continuous	HH head age
Head Education	Categorical	HH education level (4 categories)
Child (< 15, Yes = 1)	Dummy	HH has at least one member below 15 yrs
Elderly (> 65, Yes = 1)	Dummy	HH has at least one member above 65 yrs
Home Ownership (Yes = 1)	Dummy	HH owns its dwelling
Head Employed (Yes = 1)	Dummy	HH head is employed
Household Size	Ordinal	N°members
Hist. Rem. 1992 x Avg. US Wage	Continuous	Instrument

Table A2: T-tests: Air-conditioning group

	No AC	**AC**	**Difference**
Recipient (Yes = 1)	0.061	0.035	0.027***
Remittance Income (pesos)	7,094.243	10,700.584	-3,606.341***
Long-term Mean CDD	298.827	782.799	-483.972***
Labour Income (pesos)	24,512.561	41,647.830	-17,135.269***
Total Income (pesos)	36,113.754	66,260.482	-30,146.728***
Urban (Yes = 1)	0.639	0.834	-0.195***
Female Head (Yes = 1)	0.262	0.258	0.005*
Head Age	49.237	48.457	0.780***
Head Education (None = 1)	0.297	0.121	0.176***
Head Education (Primary = 1)	0.224	0.158	0.065***
Head Education (Secondary = 1)	0.279	0.292	-0.013***
Head Education (Above = 1)	0.200	0.429	-0.228***
Child (< 15, Yes = 1)	0.555	0.519	0.036***
Elderly (> 65, Yes = 1)	0.226	0.192	0.034***
Home Ownership (Yes = 1)	0.709	0.771	-0.062***
Head Employed (Yes = 1)	0.781	0.771	0.010***
Household Size	3.771	3.540	0.232***
Observations	191,264	37,972	

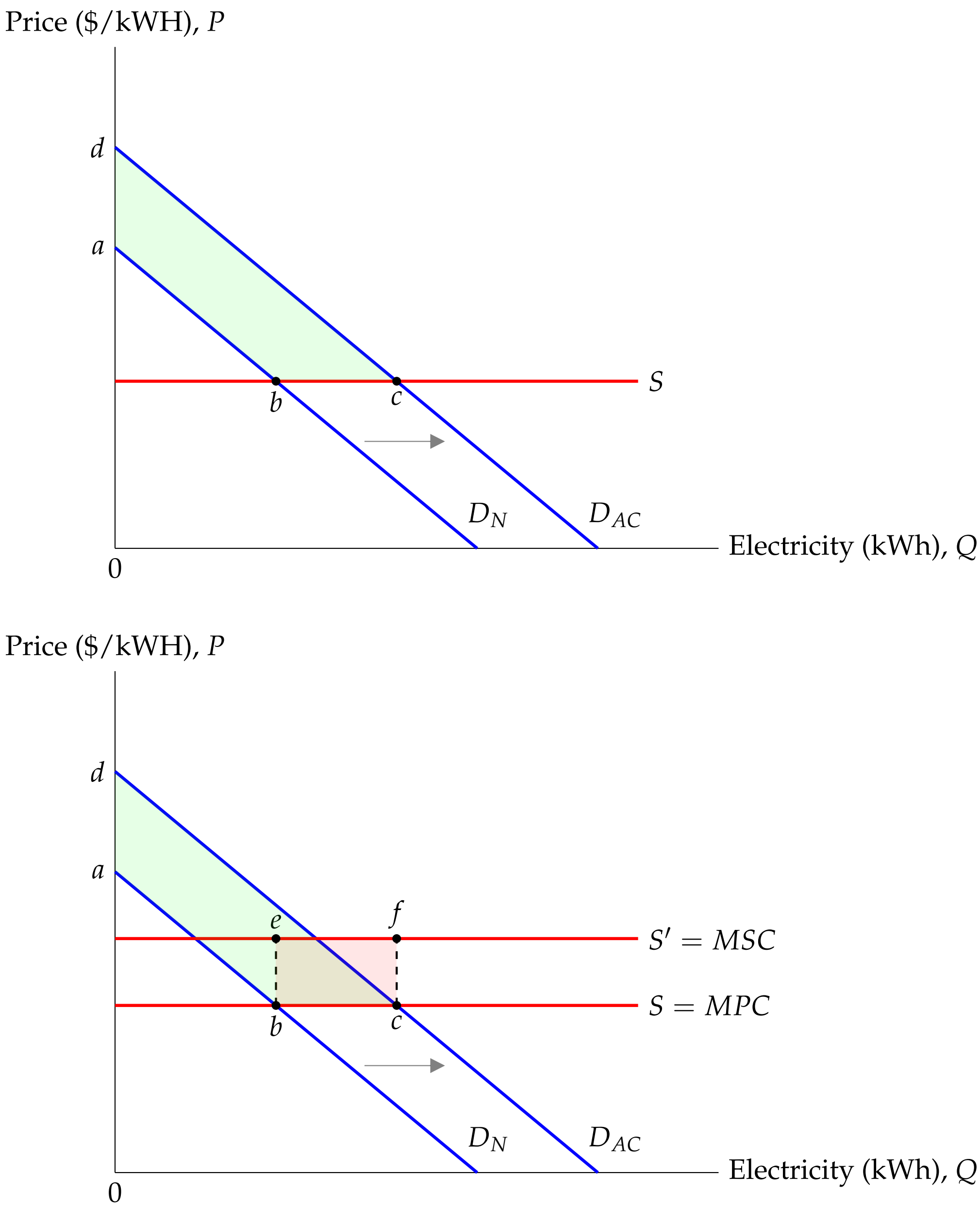

Figure A1: Above: Graphical representation of the Consumer Surplus Gain (abcd) with perfectly elastic supply S. D_N and D_{AC} are the demand of electricity from households without and with air-conditioning respectively. Below: Graphical representation of the Consumer Surplus Gain (abcd) with negative externalities (bcfe) from additional CO_2 emissions. MPC and MSC respectively represent the marginal private cost (supply S) and the marginal social cost (supply S')

Table A3: Descriptives: Coastal vs Inland Areas

	Inland		Coast		
	Mean	SD	Mean	SD	Difference
Recipient (Yes = 1)	0.062	0.242	0.051	0.220	0.009***
Remittance Income (pesos)	8029.213	10974.966	6825.022	11022.432	1204.190***
Air-conditioning (Yes = 1)	0.087	0.281	0.241	0.428	-0.154***
Mean CDD	150.612	264.583	618.670	416.692	-462.901***
Labour Income (pesos)	28,398.917	37,160.588	26,354.769	35,694.454	2,044.148***
Total Income (pesos)	42,411.103	130,782.922	39,868.195	54,992.844	2,542.908***
Urban (Yes = 1)	0.680	0.466	0.663	0.473	0.017***
Female Head (Yes = 1)	0.258	0.438	0.265	0.441	-0.006**
Head Age	49.396	15.869	48.834	15.934	0.562***
Head Education (None = 1)	0.242	0.428	0.293	0.455	-0.051***
Head Education (Primary = 1)	0.221	0.415	0.205	0.404	0.016***
Head Education (Secondary = 1)	0.305	0.460	0.258	0.438	0.046***
Head Education (Above = 1)	0.232	0.422	0.244	0.429	-0.012***
Child (< 15, Yes = 1)	0.552	0.497	0.545	0.498	0.007***
Elderly (> 65, Yes = 1)	0.224	0.417	0.217	0.410	0.006***
Home Ownership (Yes = 1)	0.711	0.453	0.727	0.446	-0.015*
Head Employed (Yes = 1)	0.771	0.420	0.663	0.473	-0.016***
Household Size	3.776	1.901	3.692	1.890	0.083***
Hist. Rem. 1992	0.179	0.109	0.184	0.093	-0.011***
Avg. US Wage	25.011	1.944	25.807	2.202	-0.796***
Hist. Rem. 1992 x Avg. US Wage	4.334	2.769	4.774	2.470	-0.441***
Observations	111,714		117,522		

Notes: Mean and SD for Remittance Income are only for recipients HHs.

Additional Results

Table A4: First Stage Estimation

	OLS
	(1)
Hist. Rem. 1992 x Avg Wage US	0.0496***
	(0.00732)
Mean CDD	2.39e-05
	(4.34e-05)
Labour Income (in 1000s)	-0.0019***
	(0.0003)
Urban (Yes = 1)	-0.327***
	(0.0242)
Female Head (Yes = 1)	0.595***
	(0.0284)
Head Age	-0.0058***
	(0.0008)
Head Edu. (Primary = 1)	-0.0481**
	(0.0200)
Head Edu. (Secondary = 1)	0.00857
	(0.0212)
Head Edu. (Above = 1)	0.0215
	(0.0248)
Child (< 15, Yes = 1)	0.116***
	(0.0206)
Elderly (> 65, Yes = 1)	-0.0898***
	(0.0234)
Home Ownership (Yes = 1)	0.0344*
	(0.0187)
Head Employed (Yes = 1)	-0.656***
	(0.0341)
Household Size	0.0174***
	(0.0058)
State FE	Yes
Time FE	Yes
Observations	222,777
R-sq	0.031
F-test	45.869

Notes: Clustered std. errors at district-year level in parentheses;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Impact of Remittance Income on Air-conditioning Adoption

	LPM (1)	LPM (2)	LPM (3)	2SLS (4)
Remittance Income (in 1000s)	-0.0010**	0.0012***	0.0024***	0.0801**
	(0.0004)	(0.0002)	(0.0002)	(0.0337)
Mean CDD			0.0003***	0.0003***
			(3.97e-05)	(3.91e-05)
Labour Income (in 1000s)			0.0010***	0.0011***
			(8.60e-05)	(0.0001)
Urban (Yes = 1)			0.0627***	0.0936***
			(0.0057)	(0.0146)
Female Head (Yes = 1)			-0.0010	-0.0470**
			(0.0016)	(0.0199)
Head Age			0.0008***	0.0013***
			(9.45e-05)	(0.0002)
Head Edu. (Primary = 1)			0.0375***	0.0406***
			(0.0024)	(0.0034)
Head Edu. (Secondary = 1)			0.0713***	0.0708***
			(0.0040)	(0.0043)
Head Edu. (Above = 1)			0.1630***	0.1610***
			(0.0080)	(0.0081)
Child ($<$ 15, Yes = 1)			0.0094***	0.0002
			(0.0020)	(0.0047)
Elderly ($>$ 65, Yes = 1)			-0.00297	0.00316
			(0.0024)	(0.0040)
Home Ownership (Yes = 1)			0.0421***	0.0397***
			(0.0028)	(0.0037)
Head Employed (Yes = 1)			-0.0142***	0.0371*
			(0.0024)	(0.0219)
Household Size			-0.0034***	-0.0048***
			(0.0007)	(0.0010)
State FE	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes
Effective F statistic				45.869
Montiel-Pflueger TSLS (τ = 5%)				37.418
Anderson-Rubin CI				[0.017, 0.153]
Observations	229,236	229,236	229,236	222,777

Notes: (1), (2), (3) and (4) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Heterogeneous Impact of Remittance Income on Air-conditioning Adoption: Inland vs Coast

	Inland (1)	Coast (2)
Remittance Income (in 1000s)	-0.0309	0.191**
	(0.0318)	(0.0764)
Mean CDD	0.000406***	0.000279***
	(0.0000331)	(0.0000519)
Labour Income (in 1000s)	0.000559***	0.00162***
	(0.0000909)	(0.000274)
Urban (Yes = 1)	0.0441***	0.111***
	(0.0166)	(0.0210)
Female Head (Yes = 1)	0.0250	-0.0817**
	(0.0247)	(0.0323)
Head Age	-0.0000454	0.00193***
	(0.000296)	(0.000379)
Head Edu. (Primary = 1)	0.0202***	0.0587***
	(0.00302)	(0.00791)
Head Edu. (Secondary = 1)	0.0414***	0.0979***
	(0.00418)	(0.00811)
Head Edu. (Above = 1)	0.0943***	0.215***
	(0.00891)	(0.0133)
Child ($<$ 15, Yes = 1)	0.00653	-0.00705
	(0.00495)	(0.0102)
Elderly ($>$ 65, Yes = 1)	-0.00516	0.0150
	(0.00385)	(0.0101)
Home Ownership (Yes = 1)	0.0286***	0.0456***
	(0.00367)	(0.00690)
Head Employed (Yes = 1)	-0.0319	0.0867*
	(0.0241)	(0.0443)
Household Size	-0.000990	-0.00536***
	(0.00124)	(0.00189)
State FE	Yes	Yes
Time FE	Yes	Yes
Effective F statistic	11.881	25.833
Montiel-Pflueger TSLS (τ = 5%)	37.418	37.418
Anderson-Rubin CI	[-0.125, 0.031]	[0.061, 0.381]
Observations	108,564	114,213

Notes: (1) and (2) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Heterogeneous Impact of Remittance Income on Air-conditioning Adoption: Income Groups

	Low-Income	Med-Income	High-Income
	(1)	(2)	(3)
Remittance Income (in 1000s)	0.0681**	0.0467*	0.0569
	(0.0290)	(0.0271)	(0.0398)
Mean CDD	0.000136***	0.000343***	0.000516***
	(0.0000220)	(0.0000457)	(0.0000483)
Labour Income (in 1000s)	0.00144	0.00223	0.000642***
	(0.00115)	(0.00177)	(0.000158)
Urban (Yes = 1)	0.0476***	0.0784***	0.116***
	(0.00715)	(0.0145)	(0.0383)
Female Head (Yes = 1)	-0.0124	-0.0264*	-0.0554
	(0.00795)	(0.0159)	(0.0338)
Head Age	0.000568***	0.00102***	0.00180***
	(0.000157)	(0.000387)	(0.000635)
Head Edu. (Primary = 1)	0.0195***	0.0400***	0.0694***
	(0.00251)	(0.00629)	(0.0173)
Head Edu. (Secondary = 1)	0.0324***	0.0657***	0.107***
	(0.00333)	(0.00794)	(0.0162)
Head Edu. (Above = 1)	0.0727***	0.121***	0.205***
	(0.00605)	(0.0106)	(0.0228)
Child ($<$ 15, Yes = 1)	-0.00642	0.00879*	0.00475
	(0.00404)	(0.00489)	(0.0108)
Elderly ($>$ 65, Yes = 1)	0.00684*	0.00695	0.00121
	(0.00391)	(0.00835)	(0.00644)
Home Ownership (Yes = 1)	0.0122***	0.0360***	0.0492***
	(0.00236)	(0.00353)	(0.00585)
Head Employed (Yes = 1)	0.0225***	0.0103	0.0182
	(0.00869)	(0.0117)	(0.0347)
Household Size	0.00224***	-0.00833***	-0.0120***
	(0.000657)	(0.000916)	(0.00163)
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Effective F statistic	67.224	60.685	12.401
Montiel-Pflueger TSLS (τ = 5%)	37.418	37.418	37.418
Anderson-Rubin CI	[0.014, 0.129]	[-0.004, 0.106]	[-0.020, 0.169]
Observations	74,625	74,090	74,062

Notes: (1), (2) and (3) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Income groups are based on total income.

Table A8: Impact of Remittance Income on Fan Adoption

	LPM (1)	2SLS (2)
Remittance Income (in 1000s)	0.00292***	-0.0577**
	(0.0004)	(0.0249)
Mean CDD	0.0004***	0.0004***
	(0.0000)	(0.0000)
Covariates	Yes	Yes
State FE	Yes	Yes
Time FE	Yes	Yes
Kleibergen-Papp rk Wald F statistic		45.866
Montiel-Pflueger TSLS (τ = 5%)		37.418
Anderson-Rubin CI		[-0.112,-0.011]
Observations	229,234	222,775

Notes: (1) and (2) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each equation includes as covariates: labour income, dummy for living in an urban area, household head's education, household head's employment status, household head's gender and age, household size, home ownership, and dummy variables for the presence of elderly persons and minors in the household.

Table A9: Impact of Total Income on Air-conditioning Adoption of Recipient and Non-recipient Households

	Recipients (1)	Non-recipients (2)
Total Income (in 1000s)	0.00103***	0.000208*
	(0.0001)	(0.0001)
State FE	Yes	Yes
Time FE	Yes	Yes
Observations	13,078	216,158

Notes: (1) and (2) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients are LPM estimations. Total income is the sum of labour income and remittance income. Each equation includes as covariates: dummy for living in an urban area, household head's education, household head's employment status, household head's gender and age, household size, home ownership, and dummy variables for the presence of elderly persons and minors in the household.

Table A10: Regression of Electricity Quantity on Air-conditioning Adoption - Surplus Gain Computation for Coastal Areas

	OLS (1)	OLS (2)	OLS (3)	DMcF (4)
Panel A: Electricity Demand				
Air-conditioning	1.894***	4.563***	4.159***	2.691***
	(0.159)	(0.624)	(0.411)	(0.364)
Electricity Price	-1.015***	-0.640***	-0.790***	-1.047***
	(0.109)	(0.039)	(0.159)	(0.154)
Elec. Price × AC		-0.980***	-1.002***	-0.399***
		(0.220)	(0.135)	(0.127)
Covariates	No	No	Yes	Yes
State FE	No	No	Yes	Yes
Selection Corr.	No	No	No	Yes
Observations	32,720	32,720	32,720	32,720
Panel B: Consumer Surplus Gain (in Billions $2012 PPP)				
No CO_2 Externality	0.757***	0.548***	0.350***	0.621***
	(0.094)	(0.070)	(0.123)	(0.087)
SCC = 6.85 $/t$CO_2$	0.716***	0.513***	0.325***	0.589***
	(0.093)	(0.068)	(0.123)	(0.085)
SCC = 18.16 $/t$CO_2$	0.648***	0.454***	0.283**	0.535***
	(0.091)	(0.065)	(0.122)	(0.083)
SCC = 69.11 $/t$CO_2$	0.344***	0.190***	0.0942	0.294***
	(0.088)	(0.058)	(0.117)	(0.075)

Notes: (1), (2), (3) and (4) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Equation (3) and (4) include as covariates: quintiles for total income, CDDs, and household size, quartiles for household head's age, dummy for living in an urban area, household head's education, household head's employment status, household head's gender, home ownership, and dummy variables for the presence of elderly persons and minors in the household. SCC values for Mexico are taken from Ricke et al. (2018). The number of households in the coastal states of Mexico in 2018 is about 15 million. Consumer surplus gain SEs are computed using Delta Method.

Table A11: Regression of Electricity Quantity on Air-conditioning Adoption - Surplus Gain Computation using Continuous Covariates

	OLS (1)	OLS (2)	OLS (3)	DMcF (4)
Panel A: Electricity Demand				
Air-conditioning	1.564***	5.028***	4.256***	2.902***
	(0.149)	(0.598)	(0.377)	(0.327)
Electricity Price	-0.860***	-0.523***	-0.845***	-1.071***
	(0.078)	(0.024)	(0.163)	(0.159)
Elec. Price $\times$ AC		-1.226***	-1.099***	-0.553***
		(0.200)	(0.119)	(0.116)
Covariates	No	No	Yes	Yes
State FE	No	No	Yes	Yes
Selection Corr.	No	No	No	Yes
Observations	65,832	65,832	65,832	65,832
Panel B: Consumer Surplus Gain (in Billions \$2012 PPP)				
No CO_2 Externality	0.928***	0.594***	0.309*	1.121***
	(0.102)	(0.062)	(0.181)	(0.173)
SCC = 6.85 $/tCO_2$	0.850***	0.543***	0.275	1.066***
	(0.099)	(0.057)	(0.180)	(0.168)
SCC = 18.16 $/tCO_2$	0.720***	0.458***	0.220	0.975***
	(0.097)	(0.050)	(0.178)	(0.161)
SCC = 69.11 $/tCO_2$	0.134	0.074	-0.029	0.565***
	(0.104)	(0.058)	(0.173)	(0.133)

Notes: (1), (2), (3) and (4) clustered std. errors at district-year level in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Equation (3) and (4) include as covariates: total income, CDDs, dummy for living in an urban area, household head's education, household head's employment status, household head's gender and age, household size, home ownership, and dummy variables for the presence of elderly persons and minors in the household. The Social Cost of Carbon (SCC) values for Mexico are taken from Ricke et al. (2018). The number of households in Mexico in 2018 is about 35 million. Consumer surplus gain SEs are computed using Delta Method.

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

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Abstract

As global temperatures rise, the unequal access to residential cooling technologies, especially air-conditioning, poses a critical challenge for heat adaptation in developing countries. To mitigate this disparity, affordable alternatives like evaporative coolers have been proposed. However, the extent to which they provide protection against extreme heat is uncertain. This paper investigates the inequality in heat adaptation, examining the effectiveness of alternative cooling technologies in mitigating mortality impacts from extreme heat 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 and use cheaper evaporative coolers, which we estimate offer reduced protection against heat stress. Our analysis then reveals that heat adaptation technologies have collectively reduced heat-related deaths by 21%, generating an annual gross welfare gain of $32 billion. Notably, the wide prevalence of evaporative coolers contributes to two-thirds of these benefits. Yet, our counterfactual scenario demonstrates that air conditioners, if as widespread as evaporative coolers, 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-off between 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 the choice of the cooling technology 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. Our quasi-experimental identification relies on the exogenous nature of short-term weather variations within the same unit of observation. Once we control for all time-invariant differences between units and all common differences between time periods, these variations are akin to random draws from the climate distribution, making them unexpected (Hsiang, 2016). We so 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

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

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

in monthly electricity consumption of 0.53%. However, this response is highly heterogeneous across income and installed technology. Households in the bottom decile of the income distribution exhibit smaller responses (0.42%), while the responses of high-income households are twice as large, and even greater if they live in urban areas. Similarly, households equipped with an air-conditioning are almost three times more responsive to very hot days compared to those relying on evaporative cooler. This is also because air conditioners are more energy intensive of evaporative coolers. This marked difference persists even when focusing solely on high-income families adopting different technologies. These findings remain robust across various specification checks.

Our intensive margin results reinforce the patterns observed in technology adoption at the extensive margin. Specifically, we find that households more inclined to own an air conditioner also exhibit greater responsiveness to elevated temperatures. Moreover, even when they have access to the the same technology, only richer households are really able to respond to extreme heat. Notably, these results unveil the crucial role of the synergy of income with technological choice for heat adaptation in emerging economies like India.

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 rates is not available for our analysis, several robustness checks corroborate our results. Indeed, we do not find any impact of the cooling appliances interacted with 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, such as the inclusion of interactions between temperature and income.

In the fourth part, we present estimates of lives saved through the adoption of these different cooling technologies. Utilising a conservative estimate of the Value of Statistical Life (VSL) at 180 thousand dollars, we then asses the associated monetary benefits. Furthermore, we conduct a cost-benefit analysis by comparing the benefits stemming from saved lives with the costs involved in a policy intervention aimed at subsidising air conditioners to achieve penetration rates comparable to evaporative coolers. Over our sample period, we find that 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). Notably, the widespread adoption of evaporative coolers contribute to two-third of these benefits, due to their presence in more than five times as many households compared to air-conditioning systems. However, our counterfactual analysis reveals that had the penetration rate of air conditioners equalled that of evaporative coolers, air conditioners alone could have prevented a substantial 47%, corresponding to a gross economic benefit of 73 billion dollars (4.9% of the annual GDP). Critically, these benefits substantially outweigh the costs associated with subsidising air conditioners. This result holds even when considering additional household electricity expenses and the social cost of new CO_2 emissions. These findings underscore the cost-effectiveness of subsidising air-conditioning as a policy measure to mitigate heat-related mortality in the Indian context.

Related Literature.— 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. 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 existing trade-offs in the choice of the technology; 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,

[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.

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 discusses the welfare and policy implications of our findings. Last section concludes our work.

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.

[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.

[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.

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 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^*:

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

[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).

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 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

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

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 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 ECMWF's ERA5 historical climate reanalysis data set with a resolution of 0.25 arc-degrees (Hersbach et al., 2020). Relying on information from weather stations, satellites, and sondes, this reanalysis data is less prone to station weather bias but might be biased via the 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]

[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/`

[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.

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%.

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 house-

[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.

holds (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 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 5.20 per 1,000 population, and this rate reaches 5.74 in 2019. The highest mortality rates are registered in urban areas, and in the Central, Southern and Western regions.

[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.

[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.

Extreme warm days ($\geq$ 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.

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 responds 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 found in more insulated houses.

Table 3: The 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)
$\overline{\text{CDD}} \times$ 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
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State $\times$ Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
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 in 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: The Impact of Temperature and Income 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)
$\overline{\text{CDD}}$ × 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 State × Year Trend	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 prevalence we propose alternative fixed-effects specifications (Table B7-B9). For both prevalence and adoption regressions we test clustering standard errors at state level (Table B10-Table B11); modelling $\overline{\text{CDD}}$ non-linearly up to degree 3 polynomials (Table B12-B17); and calculating CDD at a threshold of 18 °C rather than 24 °C (Table B18-B19). Finally, for prevalence we also employ different estimation methodologies, particularly logit (Table B20) and multinomial logit regressions (Table B21).[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:

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

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.

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

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, $T^j_{d(i)my}$. 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.

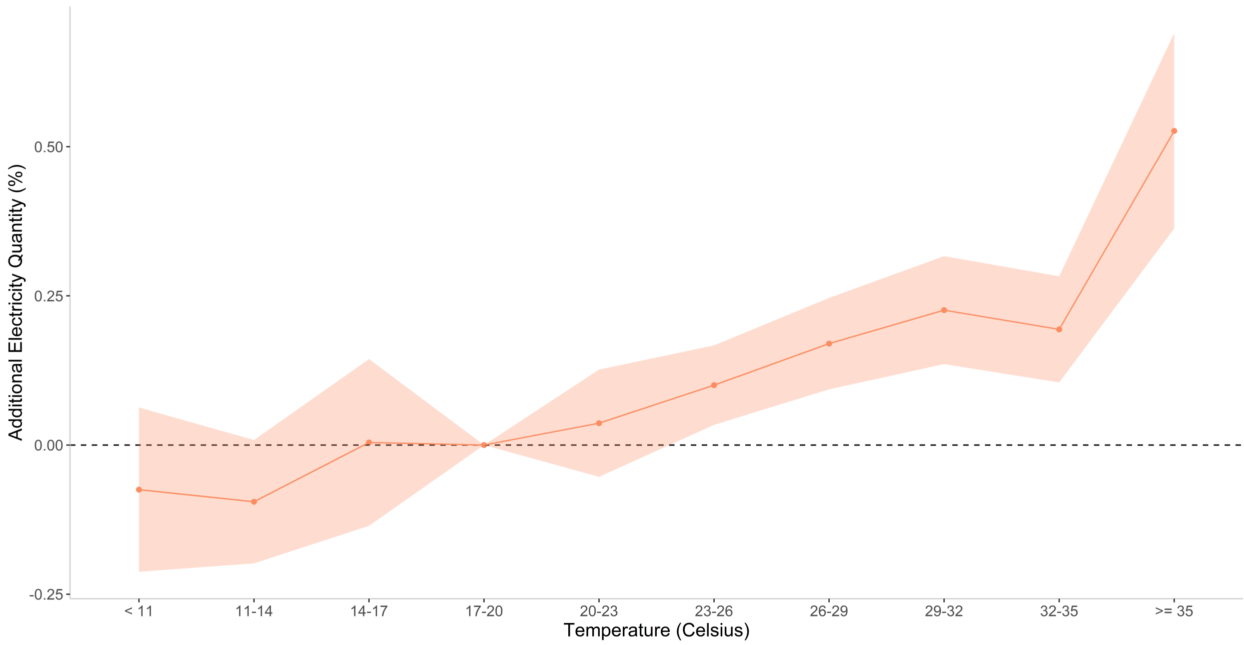
6.2 Results

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 0.19%, while an additional day at or above 35 °C increases annual electricity consumption by 0.53%. 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 more than 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 0.82%, while by 0.38 for a rural household.

Second, dividing again households in three income categories, we find that temperature-semi-elasticity is increasing in 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. Moreover, when we interpret the results in levels the differences across income groups become even more striking. For instance, on average for an additional day at or above 35 °C electricity consumption increases by 0.87 and 2.03 kWh for urban 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 patterns even after restricting these sub-samples only to high income households (Table C6). Critically, Table C6 also suggests that poor and middle-income households having an air-conditioner are not much responsive to the warmest temperature, while those with evaporative cooler respond only to the warmest bin. This can be attributed to either (1) the low statistical power due to a much smaller sample or (2) credit constraints in the utilisation of air-conditioning when it is very warm.

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 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 states.[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:

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

[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.

[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.

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 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 not significant for the colder bins — that is, when the appliances are expected not to be used. Additionally, we provide specifications where we include the natural logarithm of income per capita[33] and its interactions with the bins of temperature. In this way, we control that the interaction with air-conditioning ownership does not simply capture places that are richer, and so less subject to heat-related deaths because they have access to more private and public adaptation strategies.

7.2 Results

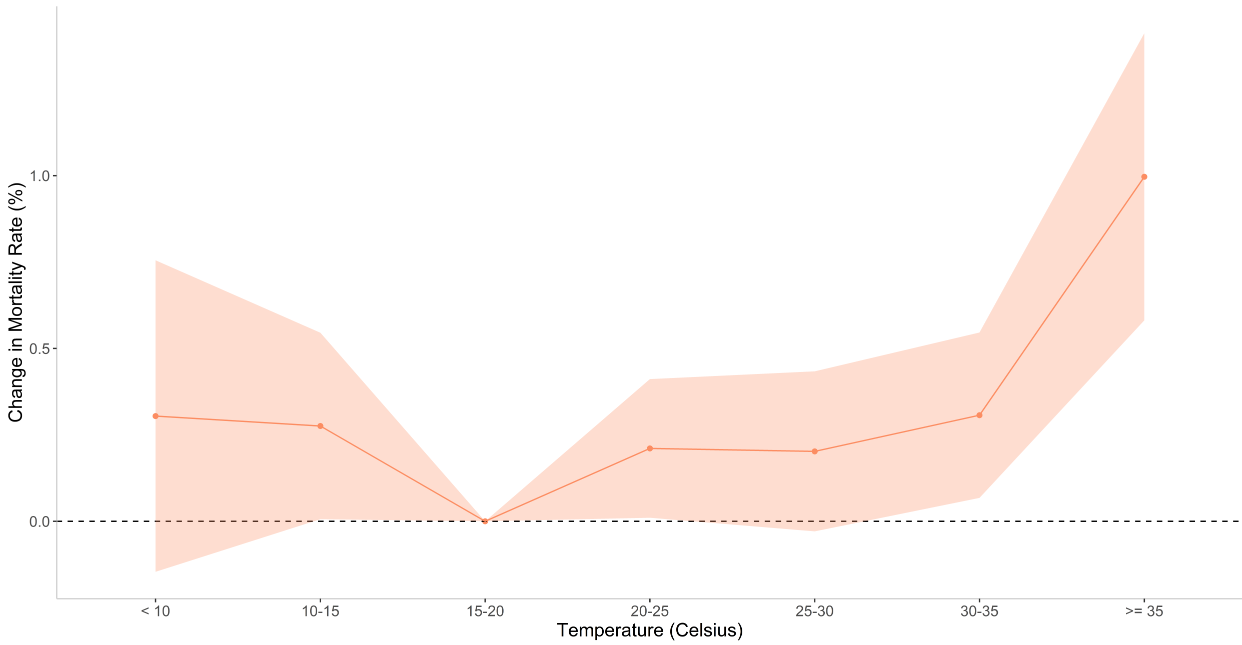
Main results.— Figure 2 presents the effects of an additional day in each temperature bin relative to the base range of 15-20°C. Our findings indicate that extreme warm temperatures have significant clinical implications and may lead to potentially fatal outcomes. It is however worthy to mention that, 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 0.31% 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.[34]

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 also obtained from the CHPS data using survey weights.
[34] This is obtained multiplying $0.00997 \times \overline{\mathrm{T}(\geq 35)} \times 100,000$

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 ≥ 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 (≥ 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.

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. Even after accounting for the interaction between extreme heat and humidity, all the results remain robust.

Heat Adaptation.— Table 5 presents the interaction coefficients from 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 25 percentage points between 2014 and 2019, the mortality effect of days at or above 35 °C was reduced by a further 32%.[35]

[35]This is computed as follows: $(0.25 \times -0.021)/0.016$

Table 5: Protective Effect of Heat Adaptation

	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)	-0.0270***		-0.0206**						
	(0.009)		(0.009)						
Cooler × T (≥ 35)		-0.00769*	-0.00629						
		(0.004)	(0.005)						
AC × H (≥ 18)				-0.000662		-0.000685			
				(0.002)		(0.002)			
Cooler × H (≥ 18)					0.000507	0.000538			
					(0.001)	(0.001)			
AC × T (≥ 35) × H (≥ 18)							-0.000422***		-0.000384***
							(0.000)		(0.000)
Cooler × T (≥ 35) × H (≥ 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 × 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. Results from the full regression are in Table D12.

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 D13). The results remain consistent. Second, in Table D14 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 D15). 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).[36] 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).[37]

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

[37] 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 yearly 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 yearly 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.[38] 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 outweighed by the benefits from saved lives. 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.[39] 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 ≥ 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

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

[39] To obtain this estimate we use the equation from Hausman (1979): $(\frac{d}{1+d}) \times (\frac{\rho}{1-(1+d)^{-q}})$. In the equation d is the discount rate and is set equal to 0.05; q is the durability and is assumed equal to ten years; and ρ is the capital cost of an air conditioner and is set equal to 25000 rupees.

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 carbon 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 quite 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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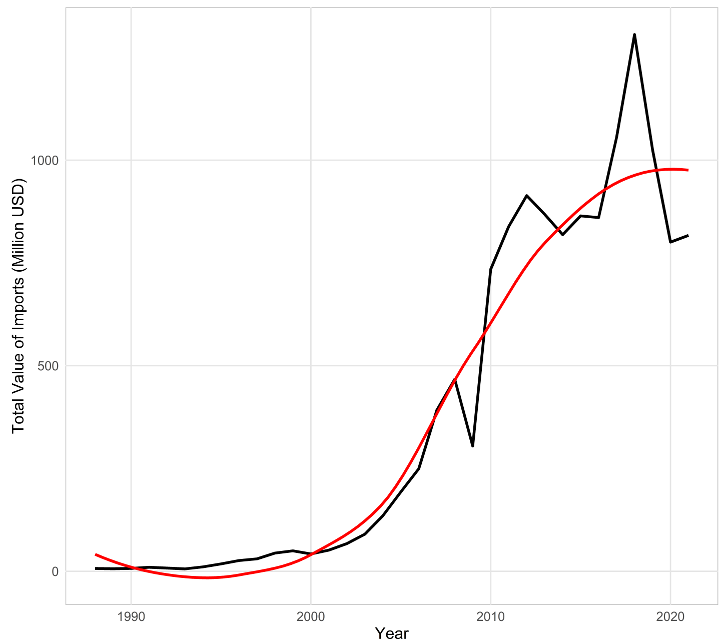
Appendix

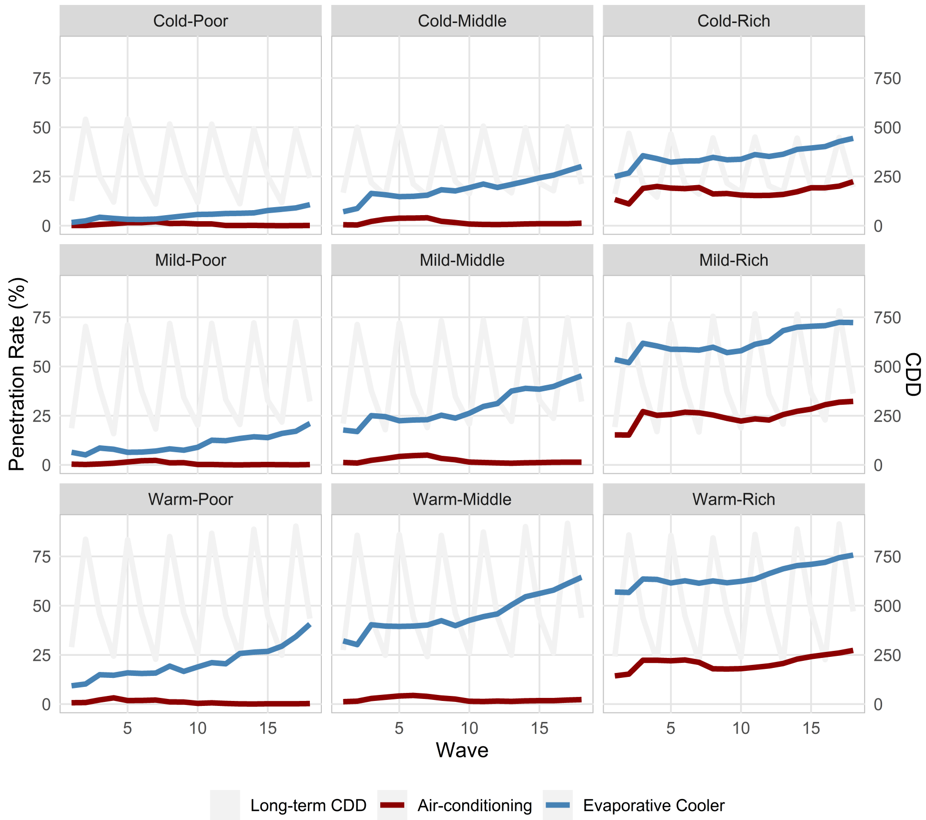
A. Data: Additional Statistics

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



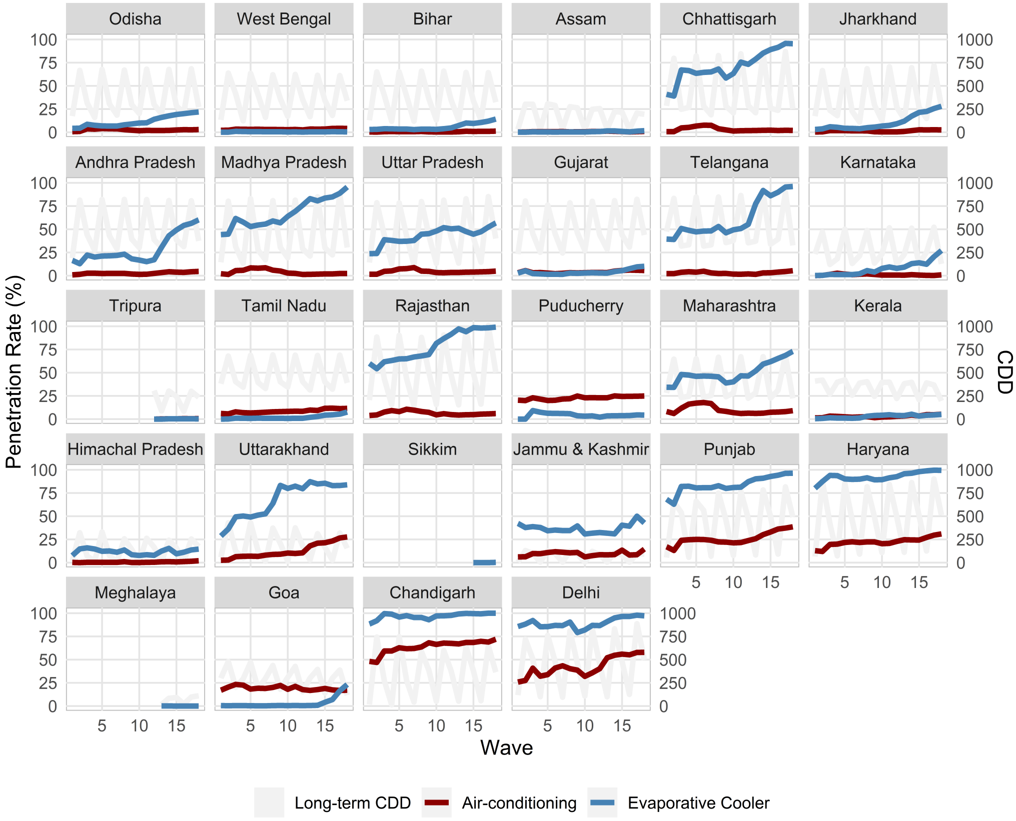
Notes: The black line represents the observed total value of air-conditioning imports in India. The red line is a locally weighted regression to capture the trend.

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: 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: 10-year moving average of quarterly CDD in the previous decade. Indian states are sorted by increasing household income.

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
ERA5	Panel	Grid	Daily	1981-2019	Cooling Degree Days, Precipitation
CRU	Panel	Grid	Daily	1981-2019	Temperature, Precipitation
			Intensive Margin		
CHPS	Panel	Household	Monthly	2014-2019	Electricity Consumption, Household Income
NSS	Cross-sectional	Household	Yearly	2011	Electricity Price
ERA5	Panel	Grid	Daily	1981-2019	Temperature, Precipitation
			Mortality		
CRS	Panel	District	Annual	2014-2019	Mortality Rates
CHPS	Panel	Household	(Four-)Monthly	2014-2019	Household Income, Air-conditioning, Evaporative Cooler
ERA5	Panel	Grid	Daily	1981-2019	Temperature, Precipitation, Humidity

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

	Rural						Urban					
	Total	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	Total	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
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)
$\overline{\text{CDD}}$ × 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)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
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 State $\times$ Year Trend	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 State $\times$ Year Trend	Yes	Yes	Yes	Yes
R^2	0.01	0.03	0.07	0.06
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 State $\times$ Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.01	0.03	0.10	0.07	0.02
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)
$\overline{\text{CDD}}$ × 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 State × Year Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.01	0.04	0.01	0.02	0.05	0.10	0.07	0.04	0.09	0.08	0.03
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 State × Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.02	0.03	0.01	0.08	0.08	0.05
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: The Impact of Temperature and Income 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	0.0154***	0.0146***	0.0146***
	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Log(Income)	0.0928***	0.101***	0.0858***	0.0868***	0.0863***
	(0.008)	(0.004)	(0.007)	(0.007)	(0.007)
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	0.50	0.51	0.51
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: The Impact of Temperature and Income on the Prevalence of Air-conditioning — Alternative Fixed-effects Specification

	FE (1)	FE (2)	FE (3)	FE (4)	FE (5)
$\overline{\text{CDD}}$ (100s)	-0.000631**	-0.000546***	-0.000194	0.0000269	0.0000375
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Log(Income)	0.0541***	0.0520***	0.0593***	0.0591***	0.0592***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
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	0.21	0.21	0.21
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: The Impact of Temperature and Income on the Prevalence of Cooler — Alternative Fixed-effects Specification

	FE (1)	FE (2)	FE (3)	FE (4)	FE (5)
$\overline{\text{CDD}}$ (100s)	0.00681***	-0.00000913	0.0156***	0.0145***	0.0145***
	(0.001)	(0.000)	(0.003)	(0.003)	(0.003)
Log(Income)	0.0711***	0.0840***	0.0611***	0.0617***	0.0611***
	(0.010)	(0.005)	(0.010)	(0.010)	(0.010)
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	0.49	0.51	0.51
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: The Impact of Temperature and Income on the Prevalence of Cooling Appliances — Alternative Standard Errors Specifications

	Both Appliances	Air-conditioning	Evaporative Cooler
	(1)	(2)	(3)
$\overline{\text{CDD}}$ (100s)	0.0146**	0.0000375	0.0145**
	(0.006)	(0.001)	(0.007)
Log(Income)	0.0863***	0.0592***	0.0611**
	(0.015)	(0.008)	(0.022)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes
R^2	0.51	0.21	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 state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Table B11: The Impact of Temperature and Income on the Adoption of Cooling Appliances — Alternative Standard Errors Specifications

	Both Appliances	Air-conditioning	Air Cooler
	(1)	(2)	(3)
$\overline{\text{CDD}}$ (100s)	-0.000669	0.000215	-0.000767*
	(0.000)	(0.000)	(0.000)
Log(Income)	0.0413***	0.0134***	0.0348***
	(0.005)	(0.002)	(0.006)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes
R^2	0.05	0.02	0.06
Observations	2432366	2432366	2432366

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 B12: The Impact of Temperature and Income on the Prevalence of Cooling Appliances — Nonlinear Specification

	FE (1)	FE (2)	FE (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
State FE	Yes	Yes	Yes
Wave 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 B13: The Impact of Temperature and Income 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
State FE	Yes	Yes	Yes
Wave 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 B14: The Impact of Temperature and Income 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
State FE	Yes	Yes	Yes
Wave 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 B15: The Impact of Temperature and Income on the Adoption of Cooling Appliances — Nonlinear Specification

	FE (1)	FE (2)	FE (3)
$\overline{\text{CDD}}$ (100s)	-0.000669	-0.00154	0.000413
	(0.000)	(0.001)	(0.003)
$\overline{\text{CDD}}^2$		0.0000890	-0.000394
		(0.000)	(0.001)
$\overline{\text{CDD}}^3$			0.0000307
			(0.000)
Log(Income)	0.0413***	0.0413***	0.0413***
	(0.003)	(0.003)	(0.003)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes
R^2	0.05	0.05	0.05
Observations	2432366	2432366	2432366

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 B16: The Impact of Temperature and Income on the Adoption of Air-conditioning — Nonlinear Specification

	FE	FE	FE
	(1)	(2)	(3)
$\overline{\text{CDD}}$ (100s)	0.000215	0.000398	0.000593
	(0.000)	(0.000)	(0.001)
$\overline{\text{CDD}}^2$		-0.0000187	-0.0000668
		(0.000)	(0.000)
$\overline{\text{CDD}}^3$			0.00000306
			(0.000)
Log(Income)	0.0134***	0.0134***	0.0134***
	(0.001)	(0.001)	(0.001)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes
R^2	0.02	0.02	0.02
Observations	2432366	2432366	2432366

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 B17: The Impact of Temperature and Income on the Adoption of Coolers — Nonlinear Specification

	FE (1)	FE (2)	FE (3)
$\overline{\text{CDD}}$ (100s)	-0.000767*	-0.00144	-0.000377
	(0.000)	(0.001)	(0.003)
$\overline{\text{CDD}}^2$		0.0000685	-0.000194
		(0.000)	(0.001)
$\overline{\text{CDD}}^3$			0.0000167
			(0.000)
Log(Income)	0.0348***	0.0348***	0.0348***
	(0.003)	(0.003)	(0.003)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Quadratic State × Year Trend	Yes	Yes	Yes
R^2	0.06	0.06	0.06
Observations	2432366	2432366	2432366

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 B18: The Impact of Temperature and Income on the Prevalence of Cooling Appliances — CDD18

	Both Appliances		Air Conditioner		Evaporative Cooler	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{CDD18}}$ (100s)	0.00805***	-0.0136**	0.000358	-0.00645	0.00784***	-0.00608
	(0.001)	(0.006)	(0.000)	(0.004)	(0.002)	(0.006)
Log(Income)	0.0861***	0.0624***	0.0592***	0.0517***	0.0609***	0.0456***
	(0.007)	(0.011)	(0.006)	(0.007)	(0.010)	(0.014)
$\overline{\text{CDD18}}$ × Log(Income)		0.00229***		0.000718		0.00147**
		(0.001)		(0.000)		(0.001)
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.

Table B19: The Impact of Temperature and Income on the Adoption of Cooling Appliances — CDD18

	Both Appliances		Air Conditioner		Evaporative Cooler	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{CDD18}}$ (100s)	-0.000642**	-0.00286	0.000141	-0.000597	-0.000646**	-0.00325
	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.002)
Log(Income)	0.0413***	0.0388***	0.0134***	0.0126***	0.0348***	0.0320***
	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
$\overline{\text{CDD18}} \times$ Log(Income)		0.000234		0.0000778		0.000274
		(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 State $\times$ Year Trend	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 B20: The Impact of Temperature and Income 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
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State $\times$ Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
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 B21: The Impact of Temperature and Income on the Prevalence of Cooling Appliances — Multinomial Logit

	Multinomial Logit (1)	Multinomial Logit (2)
$\overline{\text{CDD}}$ (100s) ×		
Evaporative Cooler	0.0168***	-0.0483***
	(0.002)	(0.012)
Air Conditioner	0.00105**	-0.00887**
	(0.000)	(0.003)
Log(Income) ×		
Evaporative Cooler	0.0388***	0.0100
	(0.008)	(0.013)
Air Conditioner	0.0484***	0.0442***
	(0.002)	(0.002)
($\overline{\text{CDD}}$ × Log(Income)) ×		
Evaporative Cooler		0.00696***
		(0.001)
Air Conditioner		0.00103***
		(0.000)
Precipitations Controls	Yes	Yes
Household Controls	Yes	Yes
State FE	Yes	Yes
Wave FE	Yes	Yes
Quadratic State × 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: The Impact of Temperature on Electricity Quantity using Temperature Bins

	FE (1)	FE (2)	FE (3)
< 11	-0.000434	-0.000842	-0.000748
	(0.001)	(0.001)	(0.001)
$11-14$	-0.000783	-0.000966*	-0.000950*
	(0.001)	(0.001)	(0.001)
$14-17$	0.000180	0.0000694	0.0000429
	(0.001)	(0.001)	(0.001)
$20-23$	0.000454	0.000395	0.000365
	(0.000)	(0.000)	(0.000)
$23-26$	0.00111***	0.00105***	0.00100***
	(0.000)	(0.000)	(0.000)
$26-29$	0.00183***	0.00176***	0.00170***
	(0.000)	(0.000)	(0.000)
$29-32$	0.00212***	0.00228***	0.00226***
	(0.000)	(0.000)	(0.000)
$32-35$	0.00180***	0.00200***	0.00194***
	(0.000)	(0.000)	(0.000)
≥ 35	0.00495***	0.00527***	0.00527***
	(0.001)	(0.001)	(0.001)
Log(Income)			0.0797***
			(0.006)
Precipitations Controls	No	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.00	0.00	0.02
Observations	8317298	8317298	8317298

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

	Rural	Urban
	(1)	(2)
< 11	-0.000738	-0.000119
	(0.001)	(0.001)
$11 - 14$	-0.000817	-0.00123*
	(0.001)	(0.001)
$14 - 17$	0.000346	-0.000243
	(0.001)	(0.001)
$20 - 23$	0.000303	0.000822
	(0.000)	(0.001)
$23 - 26$	0.000805**	0.00163***
	(0.000)	(0.001)
$26 - 29$	0.00139***	0.00274***
	(0.000)	(0.001)
$29 - 32$	0.00168***	0.00364***
	(0.001)	(0.001)
$32 - 35$	0.00151***	0.00329***
	(0.001)	(0.001)
≥ 35	0.00375***	0.00820***
	(0.001)	(0.001)
Log(Income)	0.0523***	0.221***
	(0.004)	(0.013)
Precipitations Controls	Yes	Yes
Household FE	Yes	Yes
Month-Year FE	Yes	Yes
R^2	0.01	0.06
Observations	2601924	5715374

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

	Poor	Middle	Rich
	(1)	(2)	(3)
< 11	0.00197*	-0.000227	-0.00201**
	(0.001)	(0.001)	(0.001)
$11 - 14$	0.00199**	-0.00164***	-0.000513
	(0.001)	(0.001)	(0.001)
$14 - 17$	0.000164	0.000495	-0.00128
	(0.001)	(0.001)	(0.001)
$20 - 23$	0.000611	0.000506	-0.000400
	(0.001)	(0.000)	(0.001)
$23 - 26$	0.000999**	0.000968**	0.000949*
	(0.000)	(0.000)	(0.001)
$26 - 29$	0.00181***	0.00165***	0.00185***
	(0.001)	(0.000)	(0.001)
$29 - 32$	0.00187***	0.00213***	0.00294***
	(0.001)	(0.001)	(0.001)
$32 - 35$	0.00150**	0.00168***	0.00319***
	(0.001)	(0.001)	(0.001)
≥ 35	0.00422***	0.00449***	0.00814***
	(0.001)	(0.001)	(0.001)
Log(Income)	0.108***	0.0610***	0.117***
	(0.010)	(0.004)	(0.013)
Precipitations Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.02	0.01	0.04
Observations	1062253	4879764	2375281

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: The 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	0.00189*	-0.000497	-0.00168*	0.00242	0.000880	-0.00175
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
$11-14$	0.00235**	-0.00153**	-0.000875	-0.000291	-0.00188**	-0.00103
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$14-17$	0.000224	0.000156	0.000230	0.000353	0.00165*	-0.00282
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$20-23$	0.000556	0.000149	-0.000177	0.00135*	0.00166**	-0.000534
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$23-26$	0.000997**	0.000620	0.000675	0.00147**	0.00209***	0.000922
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$26-29$	0.00156**	0.00111**	0.00180***	0.00361***	0.00326***	0.00186**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$29-32$	0.00163***	0.00143**	0.00219***	0.00353***	0.00402***	0.00323***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$32-35$	0.00128*	0.00117**	0.00259***	0.00316***	0.00334***	0.00343***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
≥ 35	0.00387***	0.00329***	0.00530***	0.00607***	0.00749***	0.00973***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Log(Income)	0.0989***	0.0441***	0.0485***	0.205***	0.184***	0.266***
	(0.010)	(0.004)	(0.005)	(0.015)	(0.012)	(0.016)
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	0.02	0.01	0.01	0.05	0.04	0.09
Observations	550374	1636916	414634	511879	3242848	1960647

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: The Heterogeneous Impact of Temperature on Electricity Quantity using Temperature Bins — Technology

	Air Conditioner	Evaporative Cooler
	(1)	(2)
< 11	-0.00257*	-0.00316**
	(0.001)	(0.002)
$11 - 14$	0.000296	-0.00301***
	(0.001)	(0.001)
$14 - 17$	-0.00191	-0.00158
	(0.002)	(0.001)
$20 - 23$	0.0000987	-0.00124
	(0.001)	(0.001)
$23 - 26$	0.00169***	-0.000260
	(0.001)	(0.001)
$26 - 29$	0.00228***	0.000805
	(0.001)	(0.001)
$29 - 32$	0.00441***	0.00167**
	(0.001)	(0.001)
$32 - 35$	0.00469***	0.00176**
	(0.001)	(0.001)
≥ 35	0.0112***	0.00469***
	(0.002)	(0.001)
Log(Income)	0.169***	0.0493***
	(0.021)	(0.004)
Precipitations Controls	Yes	Yes
Household FE	Yes	Yes
Month-Year FE	Yes	Yes
R^2	0.05	0.01
Observations	785745	3707868

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.

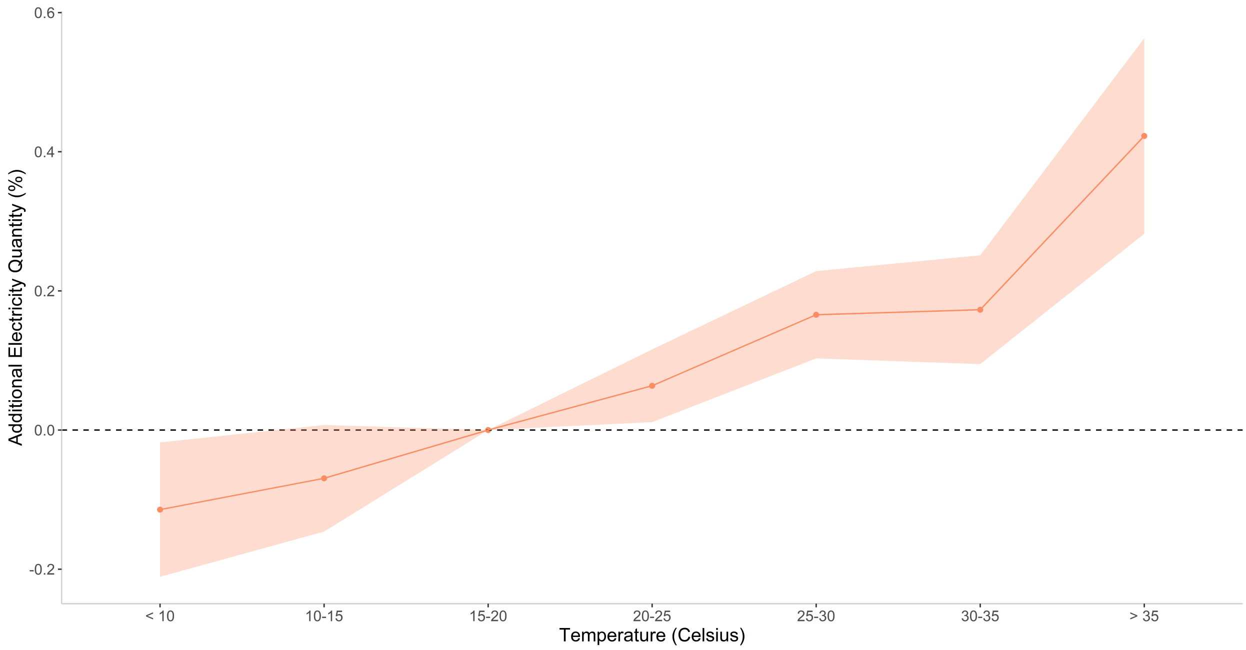
Table C6: The Heterogeneous Impact of Temperature on Electricity Quantity using Temperature Bins — Technology and Income Level

	Poor-Middle		Rich	
	Air Conditioner	Evaporative Cooler	Air Conditioner	Evaporative Cooler
	(1)	(2)	(3)	(4)
< 11	-0.000258	-0.00272	-0.00345**	-0.00378*
	(0.002)	(0.002)	(0.002)	(0.002)
$11-14$	0.0000337	-0.00396***	0.000386	-0.000606
	(0.001)	(0.001)	(0.001)	(0.001)
$14-17$	0.000766	-0.000738	-0.00257	-0.00274
	(0.001)	(0.001)	(0.003)	(0.002)
$20-23$	-0.000252	-0.00144*	0.00200**	0.000356
	(0.001)	(0.001)	(0.001)	(0.001)
$23-26$	0.000460	-0.000478	0.00200**	0.000356
	(0.001)	(0.001)	(0.001)	(0.001)
$26-29$	0.00107	0.000535	0.00265**	0.00130
	(0.001)	(0.001)	(0.001)	(0.001)
$29-32$	0.00118	0.000956	0.00576***	0.00366***
	(0.001)	(0.001)	(0.001)	(0.001)
$32-35$	0.00205**	0.00102	0.00572***	0.00383***
	(0.001)	(0.001)	(0.001)	(0.001)
≥ 35	0.00123	0.00350***	0.0147***	0.00909***
	(0.002)	(0.001)	(0.003)	(0.002)
Log(Income)	0.0699***	0.0378***	0.198***	0.0875***
	(0.013)	(0.003)	(0.027)	(0.011)
Precipitations Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
R^2	0.01	0.01	0.06	0.02
Observations	161766	2264280	538787	1018452

Notes: The dependent variable is log of monthly electricity quantity (in kWh). Reference bin category is 17-20. (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.

C.2 Intensive Margin: Additional Figures

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



C.3 Intensive Margin: Robustness Checks

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

	FE (1)	FE (2)	FE (3)	FE (4)
< 11	-0.00204***	-0.000748	-0.00231***	-0.00102
	(0.001)	(0.001)	(0.001)	(0.001)
$11 - 14$	-0.00209***	-0.000950*	-0.00180***	-0.000620
	(0.001)	(0.001)	(0.001)	(0.001)
$14 - 17$	0.000125	0.0000429	-0.0000898	-0.0000491
	(0.001)	(0.001)	(0.001)	(0.001)
$20 - 23$	0.000130	0.000365	0.0000187	0.000392
	(0.000)	(0.000)	(0.000)	(0.000)
$23 - 26$	0.00131***	0.00100***	0.00110***	0.000985***
	(0.000)	(0.000)	(0.000)	(0.000)
$26 - 29$	0.00208***	0.00170***	0.00209***	0.00173***
	(0.000)	(0.000)	(0.000)	(0.000)
$29 - 32$	0.00294***	0.00226***	0.00252***	0.00206***
	(0.000)	(0.000)	(0.000)	(0.000)
$32 - 35$	0.00268***	0.00194***	0.00246***	0.00207***
	(0.000)	(0.000)	(0.000)	(0.000)
≥ 35	0.00656***	0.00527***	0.00523***	0.00506***
	(0.001)	(0.001)	(0.001)	(0.001)
Log(Income)	0.0938***	0.0797***	0.0797***	0.0803***
	(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	0.03	0.02	0.02	0.02
Observations	8317298	8317298	8317298	8317298

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

	FE (1)	FE (2)	FE (3)
< 11	-0.000748	-0.000505	-0.00293*
	(0.001)	(0.001)	(0.002)
$11 - 14$	-0.000950*	-0.000911	0.00192*
	(0.001)	(0.001)	(0.001)
$14 - 17$	0.0000429	0.000380	-0.000481
	(0.001)	(0.001)	(0.001)
$20 - 23$	0.000365	0.000456	-0.0000230
	(0.000)	(0.000)	(0.001)
$23 - 26$	0.00100***	0.00113***	0.00202***
	(0.000)	(0.000)	(0.001)
$26 - 29$	0.00170***	0.00181***	0.00506***
	(0.000)	(0.000)	(0.001)
$29 - 32$	0.00226***	0.00246***	0.00751***
	(0.000)	(0.000)	(0.001)
$32 - 35$	0.00194***	0.00198***	0.00416***
	(0.000)	(0.000)	(0.001)
≥ 35	0.00527***	0.00559***	0.0108***
	(0.001)	(0.001)	(0.001)
Log(Income)	0.0797***	0.188***	0.232***
	(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	0.02	0.10	0.13
Observations	8317298	8319814	8319814

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: The Impact of Temperature on Electricity Quantity — Electricity in Level

	FE (1)	FE (2)	FE (3)
< 11	-0.440***	-0.508***	-0.493***
	(0.155)	(0.157)	(0.154)
$11 - 14$	-0.462***	-0.494***	-0.491***
	(0.111)	(0.113)	(0.114)
$14 - 17$	-0.0516	-0.0705	-0.0747
	(0.121)	(0.120)	(0.121)
$20 - 23$	-0.0589	-0.0703	-0.0750
	(0.070)	(0.070)	(0.070)
$23 - 26$	0.0503	0.0382	0.0307
	(0.050)	(0.050)	(0.049)
$26 - 29$	0.132**	0.120**	0.110*
	(0.058)	(0.059)	(0.059)
$29 - 32$	0.191***	0.219***	0.217***
	(0.072)	(0.071)	(0.071)
$32 - 35$	0.0976	0.130*	0.120
	(0.075)	(0.074)	(0.075)
≥ 35	0.735***	0.789***	0.789***
	(0.173)	(0.174)	(0.172)
Log(Income)			12.83***
			(1.175)
Precipitations Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.00	0.00	0.01
Observations	8317298	8317298	8317298

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: The Impact of Temperature on Electricity Quantity — CRU Weather Data

	FE	FE	FE
	(1)	(2)	(3)
T (°C)	0.00449***	0.00473***	0.00458***
	(0.001)	(0.001)	(0.001)
Log(Income)			0.0778***
			(0.006)
Precipitations Controls	No	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.00	0.00	0.02
Observations	8317298	8317298	8317298

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

	District	State
	(1)	(2)
< 11	-0.000748	-0.000748
	(0.001)	(0.001)
$11 - 14$	-0.000950*	-0.000950
	(0.001)	(0.001)
$14 - 17$	0.0000429	0.0000429
	(0.001)	(0.001)
$20 - 23$	0.000365	0.000365
	(0.000)	(0.001)
$23 - 26$	0.00100***	0.00100**
	(0.000)	(0.000)
$26 - 29$	0.00170***	0.00170***
	(0.000)	(0.000)
$29 - 32$	0.00226***	0.00226***
	(0.000)	(0.000)
$32 - 35$	0.00194***	0.00194***
	(0.000)	(0.001)
≥ 35	0.00527***	0.00527***
	(0.001)	(0.001)
Log(Income)	0.0797***	0.0797***
	(0.006)	(0.020)
Precipitations Controls	Yes	Yes
Household FE	Yes	Yes
Month-Year FE	Yes	Yes
R^2	0.02	0.02
Observations	8317298	8317298

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

	FE (1)	FE (2)	FE (3)
< 10	-0.000366	-0.000703	-0.000631
	(0.001)	(0.001)	(0.001)
$10 - 15$	-0.000497	-0.000643	-0.000650
	(0.000)	(0.000)	(0.000)
$20 - 25$	0.000644**	0.000621**	0.000587**
	(0.000)	(0.000)	(0.000)
$25 - 30$	0.00170***	0.00169***	0.00164***
	(0.000)	(0.000)	(0.000)
$30 - 35$	0.00172***	0.00190***	0.00188***
	(0.000)	(0.000)	(0.000)
≥ 35	0.00466***	0.00493***	0.00490***
	(0.001)	(0.001)	(0.001)
Log(Income)			0.0797***
			(0.006)
Precipitations Controls	No	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.00	0.00	0.02
Observations	8317298	8317298	8317298

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: The Impact of Temperature on Electricity Quantity — Non-linearities

	FE	FE	FE
	(1)	(2)	(3)
T (°C)	0.00479***	0.00170	0.00333***
	(0.001)	(0.001)	(0.001)
T^2		0.0000742***	-0.0000422
		(0.000)	(0.000)
T^3			0.00000221
			(0.000)
Log(Income)	0.0796***	0.0796***	0.0796***
	(0.006)	(0.006)	(0.006)
Precipitations Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
R^2	0.02	0.02	0.02
Observations	8293964	8293964	8293964

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: The Impact of Temperature on Electricity Quantity — Cooling Degree Days

	FE	FE	FE
	(1)	(2)	(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	0.00	0.00	0.02
Observations	8293964	8293964	8293964

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 ($\geq$ 35)	0.00996***	-0.0101	0.00994***	0.000320	0.000195
	(0.002)	(0.011)	(0.002)	(0.003)	(0.003)
Humidity $\times$ T ($<$ 10)		-0.000428			
		(0.001)			
Humidity $\times$ T ($10-15$)		0.0000728			
		(0.000)			
Humidity $\times$ T ($20-25$)		0.000585**			
		(0.000)			
Humidity $\times$ T ($25-30$)		0.000439**			
		(0.000)			
Humidity $\times$ T ($30-35$)		-0.000197			
		(0.000)			
Humidity $\times$ T ($\geq$ 35)		0.00162*			
		(0.001)			
T ($\geq$ 35) $\times$ H ($0-3$)			0.000500		0.00109
			(0.001)		(0.001)
T ($\geq$ 35) $\times$ H ($\geq$ 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 $\times$ 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 × 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 (≥ 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 (≥ 18)		-0.000666	0.000450	-0.000270
		(0.001)	(0.001)	(0.001)
T (≥ 35) × H (≥ 18)				0.000126**
				(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	0.03	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 ($\geq$ 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 ($\geq$ 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 ($\geq$ 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 ($\geq$ 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 $\times$ 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 (≥ 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 (≥ 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 × 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

	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)
T (< 10)	0.000184	-0.000632	0.0000770	-0.000653	-0.000838	-0.000721	0.000312	-0.000760	0.000235
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
T $(10-15)$	0.00335**	0.00270*	0.00300*	0.00300*	0.00310**	0.00308**	0.00316**	0.00274*	0.00305*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
T $(20-25)$	0.00229**	0.00199**	0.00209**	0.00221**	0.00218**	0.00220**	0.00226**	0.00200**	0.00218**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T $(25-30)$	0.00321***	0.00287***	0.00295***	0.00318***	0.00313***	0.00315***	0.00312***	0.00288***	0.00302***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T $(30-35)$	0.00502***	0.00462***	0.00473***	0.00495***	0.00496***	0.00498***	0.00500***	0.00469***	0.00489***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T (≥ 35)	0.0120***	0.0160***	0.0161***	0.0105***	0.0106***	0.0106***	0.00563**	0.00662**	0.00593**
	(0.002)	(0.004)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
T (≥ 35) × H (≥ 18)							0.0000866**	0.0000816	0.0000947*
							(0.000)	(0.000)	(0.000)
AC × T (≥ 35)	-0.0270***		-0.0206**						
	(0.009)		(0.009)						
Cooler × T (≥ 35)		-0.00769*	-0.00629						
		(0.004)	(0.005)						
AC × H (≥ 18)				-0.000662		-0.000685			
				(0.002)		(0.002)			
Cooler × H (≥ 18)					0.000507	0.000538			
					(0.001)	(0.001)			
AC × T (≥ 35) × H (≥ 18)							-0.000422***		-0.000384***
							(0.000)		(0.000)
Cooler × T (≥ 35) × H (≥ 18)								-0.0000512	-0.0000238
Precipitation Terciles	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Humidity Bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.05	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.

Table D13: 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)
Precipitation Terciles	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Humidity Bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 D14: Protective Effect of Heat Adaptation — Interactions with All Temperature Bins

	Air Conditioner	Evaporative Cooler	Both
	(1)	(2)	(3)
AC × T (≤ 10)	0.00109		-0.000206
	(0.009)		(0.009)
Cooler × T (≤ 10)		0.0000828	0.000279
		(0.003)	(0.003)
AC × T ($10-15$)	-0.0114*		-0.0102
	(0.006)		(0.007)
Cooler × T ($10-15$)		-0.00219	-0.000694
		(0.004)	(0.004)
AC × T ($20-25$)	-0.00499		-0.00523
	(0.004)		(0.004)
Cooler × T ($20-25$)		-0.00195	-0.00153
		(0.002)	(0.002)
AC × T ($25-30$)	-0.00293		-0.00278
	(0.005)		(0.005)
Cooler × T ($25-30$)		0.000724	0.00104
		(0.002)	(0.002)
AC × T ($30-35$)	-0.00903		-0.0101
	(0.006)		(0.006)
Cooler × T ($30-35$)		0.00309	0.00365*
		(0.002)	(0.002)
AC × T (≥ 35)	-0.0246**		-0.0155
	(0.010)		(0.011)
Cooler × T (≥ 35)		-0.00752	-0.00646
		(0.005)	(0.005)
Precipitation Terciles	Yes	Yes	Yes
Humidity Bins	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quadratic Trend × 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 D15: 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
Precipitation Terciles	Yes	Yes
Humidity Bins	Yes	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.