IDB WORKING PAPER SERIES Nº IDB-WP-1477

# Residential Electricity Consumption and Adaptation to Climate Change by Colombian Households

Shaun McRae

Inter-American Development Bank
Department of Research and Chief Economist

July 2023

Inter-American Development Bank

# Residential Electricity Consumption and Adaptation to Climate Change by Colombian Households

Shaun McRae

Instituto Tecnológico Autónomo de México (ITAM)

July 2023

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

McRae, Shaun D.
Residential electricity consumption and adaptation to climate change by colombian households / Shaun McRae.
p. cm. — (IDB Working Paper Series ; 1477)
Includes bibliographical references.
1. Electric power consumption-Colombia. 2. Climatic changes-Colombia. 3. Electricity-Rates-Colombia. 4. Air conditioning-Climatic factors-Colombia. I. Inter-American Development Bank. Department of Research and Chief Economist. II. Title. III. Series.
IDB-WP-1477

http://www.iadb.org

## Abstract*

This paper provides the first empirical estimates of the relationship between temperatures and household electricity consumption in Colombia, using electricity billing and weather data from 2010 to 2019. I find that higher temperatures (or higher values of the heat index) increase electricity consumption, with the largest effects observed for high-income households in regions with hot climates. However, I show that there has been partial convergence between low- and high-income households, with the effect of temperature on electricity consumption in lower-income neighborhoods more than doubling between 2011 and 2019. These results align with survey evidence of increased air conditioning adoption. Nevertheless, further growth in air conditioning adoption and use is required to alleviate the health effects of more frequent and severe heatwaves due to climate change.



**JEL classifications:** L94, O13, Q41, Q54
**Keywords:** Electricity consumption, Climate change, Adaptation, Air conditioning



* This work was financed with the support of the Latin America and the Caribbean Research Network of the InterAmerican Development Bank as part of the project "Implications of Climate Change and Natural Disasters for Latin America and the Caribbean." The opinions expressed in this publication are those of the author and do not necessarily reflect the views of the Inter-American Development Bank, its Board of Directors, or the countries they represent. I thank the project organizers and other participants for many helpful comments and suggestions.


Author contact information: Centro de Investigación Económica and Department of Economics, ITAM, shaun.mcrae@itam.mx.

# 1. Introduction

Global surface temperatures between 2011 and 2020 were 1.09 degrees Celsius higher than in the pre-industrial period. This increase has led to more frequent and severe heatwaves, including in Northwestern South America, where significant increases in extreme hot temperatures have already been observed (Castellanos et al., 2022). By the end of the century, there is high confidence that most regions in Central and South America will undergo extreme heat stress conditions much more often than in the recent past (Ranasinghe et al., 2021).

Heatwaves have detrimental effects on human health and productivity, with informal housing and inadequate infrastructure exacerbating the vulnerability of the population in low- and middle-income countries. Using data for 40 countries, Carleton et al. (2022) show that the temperature-mortality gradient is steepest in low-income countries. For the specific case of Colombia, Helo Sarmiento (2023) finds that an additional day with temperatures above 27 degrees Celsius increases mortality rates by 0.72 percent, with children aged zero to nine at the highest risk. These heatwave-related risks in Colombia are expected to grow. Of the 20 countries studied by Guo (2018), Colombia has the highest expected increase in heatwave-related excess mortality for 2031–2080. In addition to their health effects, high temperatures have other economic consequences. For example, hot temperatures reduce worker productivity in factories (Adhvaryu et al., 2020; Somanathan et al., 2021), while excess heat in schools reduces student learning (Park et al., 2020) and reduces performance by students on high-stakes assessments (Park, 2022).

Given the predicted rise in extreme heat conditions and heat-related mortality, even for ambitious climate policy scenarios, adaptation to the changing climate is essential. One form of adaptation to more frequent heatwaves is adopting air conditioning to cope with extreme hot temperatures. Barreca et al. (2016) demonstrate that adopting residential air conditioning played a vital role in flattening the temperature-mortality gradient in the United States. Interestingly, the recent estimates of this gradient in Colombia resemble those in the United States prior to the widespread use of residential air conditioning (Helo Sarmiento, 2023).

In this paper, I use electricity consumption and weather data to infer the adoption and use of air conditioning in Colombia. Specifically, I combine a large sample of monthly residential electricity billing data with hourly gridded weather data from 2010 to 2019. I estimate the effect of the monthly mean heat index on logged monthly electricity consumption—that is, the percentage increase in electricity consumption for a one-degree Celsius increase in the mean heat index.[1] A larger effect of the heat index on electricity consumption would indicate greater use of air conditioning during warmer weather. Furthermore, by following the same households for nine years, I can measure the short-term effect of the heat index on electricity consumption and the long-term changes in this effect.

There are three main findings from my electricity consumption analysis. First, higher heat index values increase electricity consumption, especially in the hot climate regions of Colombia. Notably, there is no relationship between the heat index and electricity consumption in temperate regions. Second, the increase in electricity consumption for a one-degree increase in the heat index is largest for high-income households, where income is proxied by the socioeconomic stratum of the neighborhood used to assign electricity subsidies. The size of the estimated effect is economically meaningful: in hot regions, each one-degree increase in the mean heat index increases the electricity consumption of high-stratum households by about 6 percent. Finally, the effect of the heat index on electricity consumption is increasing for households in the lowest two strata, leading to partial convergence over time between low- and high-strata households.

These results from the electricity consumption regressions are consistent with the change in fan and air conditioning ownership between 2011 and 2019, calculated from the annual Living Standards surveys (DANE, 2020). The surveys provide information about income and expenditure, asset ownership, and other household characteristics for a regionally representative sample of households. The national share of households with air conditioners increased from 3.8 percent to 4.5 percent between 2011–15 and 2016–19, with the largest increase observed in the hot Caribbean region. Moreover, the ownership of fans and air conditioners is increasing in household income, and there was an upward shift in the adoption curves of both appliances in hot regions between 2011–15 and 2016–19.

The results in this paper provide the first evidence of a long-run change in the short-run relationship between residential electricity consumption and weather in a middle-income country. I show evidence, not just of the gap in air conditioning adoption and use between low- and high-income households, but of a narrowing in this difference over time. An advantage of my methodology compared to previous studies that rely on household survey data alone is that the

[1] The heat index is a composite measure that combines air temperature and relative humidity to measure the perceived temperature after accounting for the cooling effect from the evaporation of perspiration, the rate of which decreases when humidity is higher. I show my results using both the mean temperature and heat index. The magnitude of the results is similar for both measures, but the results for the heat index are more precisely estimated.

estimates from the electricity consumption regressions reveal the use of air conditioning, not just the presence of an appliance in the household.

Colombia is an ideal setting to study the adoption and use of air conditioning. It has vast disparities in adoption rates: in the Caribbean, more than 70 percent of households in the top five percent of income own air conditioners, compared to a share close to zero for the bottom five percent. This inequality in air conditioning ownership is a feature of all middle-income countries studied by Davis et al. (2021). Therefore, many of the findings may generalize to other middle-income countries such as Mexico, India, and China, especially given their similarities in climate. Moreover, given the expected growth in excess mortality from heatwaves in Colombia (Guo, 2018), understanding the role of air conditioning in climate change adaptation is essential.

This paper contributes to the literature on the relationship between higher temperatures, air conditioning adoption, and electricity consumption. Most of this research studies the extensive margin of adoption, that is, how higher incomes and temperatures will lead to greater adoption of air conditioning in low- and middle-income countries. Auffhammer (2014) estimates diffusion curves for air conditioning in China as a function of income and temperature, finding that hot weather leads to increased adoption of air conditioning in subsequent summers. Davis et al. (2021) use data for 16 countries to show how air conditioning adoption increases with income, especially for hot regions in middle-income countries, then use their estimates to predict future adoption. As shown by Biardeau et al. (2020), there will be rapid growth in air conditioning adoption, given the unmet cooling potential at a global scale. In a rare study using quasi-experimental variation in income, Randazzo et al. (2023) use pooled data from household surveys in Mexico to show that higher remittance income leads to greater air conditioning adoption, but only in the warm coastal states.

Fewer papers focus on the intensive margin relationship between higher temperatures and electricity consumption for cooling. Auffhammer (2022) most closely resembles the empirical strategy of this paper. He uses several years of billing data for residential electricity and natural gas to estimate the relationship between daily temperature observations and energy consumption in California. By comparing the temperature responsiveness of consumption across different climate regions in California, he recovers the extensive margin relationship between climate and air conditioning adoption. Another paper estimating temperature response functions from electricity consumption data is Li et al. (2019). They use daily electricity consumption for households from one part of Shanghai to estimate the nonlinear relationship between temperature and electricity consumption, finding that for warm days above 25 degrees Celsius, a one-degree increase in temperature increases electricity consumption by 14.5 percent.

Davis and Gertler (2015) is one of the few papers that studies both the intensive and extensive margins of air conditioning adoption and use. They use two years of household-level electricity billing data from Mexico to estimate a flexible relationship between local temperatures and electricity consumption. They show that each additional day above 32 degrees Celsius increases monthly electricity consumption by 3.2 percent. A separate analysis uses Mexican household survey data to estimate the relationship between air conditioning adoption, income, and climate. In warm regions only, they show that an additional $10,000 in household income increases air conditioning adoption by 27 percentage points. Finally, they combine these two estimates to predict electricity consumption and emissions under future climate change scenarios with higher incomes and temperatures.

This paper provides the first empirical estimates of the relationship between weather, air conditioning adoption, and electricity consumption in a South American country. Unlike the previous papers in the literature, this paper uses an extended sample period for each household to measure changes in the relationship between electricity consumption and weather. As a result, the methodology provides estimates of the intensive and extensive margin responses to warmer temperatures within a single empirical model.

The rest of the paper is organized as follows. Section 2 describes the three main datasets used for the analysis and provides summary statistics about the relationship between income, climate, and electricity consumption. Section 3 provides the empirical methodology used for the analysis. There are two sets of results: Section 4 provides the main results for the electricity consumption estimation, which are used to motivate the appliance adoption results in Section 5. Section 6 concludes.

## 2. Data

The three principal data sources for this paper are hourly gridded weather from climate reanalysis data, monthly household-level electricity consumption data, and household survey data on demographics, income, and appliance ownership.

### *2.1 Weather Data*

The weather data is from the ERA5-Land dataset (Muñoz Sabater et al., 2019), a global climate reanalysis dataset provided at an hourly frequency with an approximate nine-kilometer resolution. Climate reanalysis combines observational data with a physics model to interpolate data for regions and times where station-based observations are missing (Auffhammer et al., 2013). The advantage of this data is that it provides a consistent and complete panel of hourly temperatures at every location in Colombia. However, because the data is a model output rather than a physical measurement, it does not perfectly match station observations. In particular, Mistry et al. (2022) show that the discrepancies between the ERA5 and station-level data may be greater in tropical regions such as Colombia. Another limitation of the gridded data is that it smooths out local climate and weather variation, such as higher temperatures in urban areas due to the urban heat island effect.

I calculate a weighted average of the gridded reanalysis variables for each of the 1,122 municipalities in Colombia. The smallest municipalities are contained inside a single grid cell. However, for larger municipalities that cover multiple grid cells, I assign weights to each cell based on its population. Gridded population estimates at 100-meter resolution are from Data for Good (2020). These were constructed by combining census population data with high-resolution satellite photos to identify inhabited buildings (Tiecke et al., 2017).

The weighting procedure is illustrated for the municipality of Santa Marta on the Caribbean coast (Figure 1). Santa Marta is a large municipality with a remarkable variation in altitude: from sea level to a maximum altitude of 5,775 meters. The figure shows the gridded air temperature values at midday on September 15, 2015. These vary between 7 and 31 degrees Celsius. A simple average of the grid cells would understate the weather faced by the majority of the population who live along the coast. The black pixels on the figure are the inhabited locations from Data for Good (2020), each containing an estimate of the number of people at that location. These pixels are used to calculate a weighted mean of the temperature grid cells by municipality and hour.

Residential electricity consumption is influenced not just by the outside air temperature but also by the perceived temperature as measured by the heat index. In hot temperatures, the human body regulates its temperature through perspiration, with the evaporation of perspiration cooling the body. However, when the atmospheric moisture content is greater, the rate of evaporation decreases. As a result, the same air temperature is perceived as hotter when humidity is higher.

The heat index combines both air temperature and relative humidity to measure the perceived temperature, including this evaporative cooling effect (National Weather Service, 2023a). To calculate the heat index for each hour and municipality, I use two variables from the ERA5-land dataset—the two-meter air temperature and the two-meter dew point temperature (Anderson et al., 2013). The heat index has been used by economists as a measure of extreme heat exposure (Noy and Strobl, 2022).

As Colombia is a tropical country, there is limited variation during the year in the mean temperatures at any particular location. However, there is considerable variation in temperature across different locations, primarily determined by elevation (left panel of Figure 2). There are three major mountain ranges running from south to north, home to a significant share of the country's population and with cool temperatures throughout the year. Temperatures are much hotter in the inland valleys between the mountain ranges as well as on the two coasts and eastern lowlands. The highest temperatures are in the low-lying plains on the Caribbean coast.

I assign each municipality to one of the 23 climate zones from the Caldas Lang classification (IDEAM, 2023), based on the climate for the largest urban area in the municipality. I aggregate these detailed climate zones into three categories for the analysis: cold, temperate, and hot. While most of the land area of Colombia has a hot climate (Figure A2), many of these regions are sparsely populated, so the population is more evenly divided across the categories: approximately 40 percent for each of the cold and hot climates and 20 percent for the temperate climate.

### *2.2 Electricity Consumption Data*

The electricity consumption data come from a 10-percent random sample of household billing identifiers from the Colombian public utility regulator. Each observation in the data is at the household-month level. The dataset includes the metered electricity consumption for the month, the tariff type, the start and end dates of the billing cycle, the municipality code, and an anonymized identifier to follow a household over time. I divide the metered consumption by the number of days in each billing cycle to create a standardized measure (kilowatt-hours per day) that can be compared across billing cycles of different lengths. The dataset begins in August 2010 and ends in November 2019.

Colombia has nonlinear electricity tariffs based on the socioeconomic level (or stratum) of each neighborhood (McRae, 2015). Local authorities assign each dwelling to one of six strata based on observable characteristics of the neighborhood, such as the type of housing construction materials and the presence of paved streets. Each electricity distributor has a regulated base tariff that is updated each month. Households in Strata 1, 2, and 3 receive subsidies of approximately 55, 45, or 15 percent, respectively, for their initial monthly electricity consumption. The subsidized quantity depends on the municipality altitude, with lower altitudes receiving 173 kWh and higher altitudes receiving 130 kWh per month. The price for additional units consumed above the subsidized amount is the regulated base tariff. Notably, the Colombian tariffs are increasing block tariffs, meaning that the household keeps the subsidy on the inframarginal units if their consumption exceeds the threshold. Appendix A provides additional details and examples of the bill calculation.

Households in Strata 4 to 6 do not face a nonlinear tariff and instead pay the same price per kWh for their entire consumption. For households in Stratum 4 neighborhoods, this price is just the regulated base price. Households in Strata 5 and 6 contribute to subsidies by paying a 20 percent tax on the regulated base price for their consumption.

I use the stratum reported on the electricity bill as a proxy for the socioeconomic level of each household. Because households are sometimes reclassified to higher or lower strata, I assign each household to its lowest stratum during the sample period.

### *2.3 Household Survey Data*

I supplement the weather and billing datasets with the data from the annual Living Standards surveys (DANE, 2020) conducted by the Colombian statistical agency. The survey provides information on appliance adoption, electricity bill amounts (including the stratum used for the tariff), household income, and other household characteristics. Until 2016, the survey sample was representative at a regional level for nine regions. For 2018 and later, the sample size was increased to be representative at a department level. Unfortunately, the only geographical information provided in the public use data is the department, limiting the ability to connect the data to more detailed municipality-level climate variables. Although the households in the survey data cannot be linked to the households in the billing data, the richer detail in the survey data provide descriptive results that complement the main empirical estimates.

### *2.4 Construction of Weather Variables*

I combine the weather and electricity consumption data using the municipality of the household and the exact start and end date of each billing cycle. For each household, I calculate the mean temperature and the mean heat index (both in degrees Celsius) from the daily municipality means over the billing cycle. For example, suppose a household in Medellín receives an electricity bill for the period November 12, 2015, to December 14, 2015. The bill reports the total electricity consumption for this period, which I standardize to kilowatt-hours per day by dividing by the length of the billing cycle (33 days). I then calculate the mean heat index and the mean temperature for Medellín over those 33 days.

The limited temperature variation at any particular location motivates the choice of the mean temperature (or the mean heat index) as the primary regressor. Alternative measures used in the literature, such as heating degree days and cooling degree days, allow for nonlinear effects of temperature on energy consumption. For example, one additional degree Celsius might reduce energy consumption when the weather is cold but increase energy consumption when the weather is hot. The degree days measures are calculated by summing the degree days above or below a predefined threshold. For most locations in Colombia, the temperature is either always above or always below the threshold, implying that the number of heating or cooling degree days is just a multiple of the mean temperature. Only for regions where the temperature fluctuates above and below the threshold would there be a difference in the results using mean temperature and heating and cooling degree days.

Another common methodology to allow for a flexible nonlinear effect of temperature on outcomes uses the number of days in each month for which the mean temperature falls within a particular bin. For example, an additional day in the 28-to-30-degree Celsius bin may have a different effect on energy consumption than an additional day in the 25-to-27-degree bin. The limited temperature variation within a location in Colombia distorts the interpretation of this flexible functional form for temperature. At any particular location, almost all days will fall within one or two temperature bins, so it is not possible to estimate the full temperature response function. Combining data from different regions does allow the effect of all temperature bins to be estimated in a single regression, but this would conflate the effects of climate differences across regions and short-term temperature responses within a region (Mendelsohn, 2016).

As a robustness check, instead of a fully flexible temperature relationship, I estimate the effect of extreme temperature events by calculating the frequency of heatwaves in each billing cycle. I define a heatwave as two or more consecutive days with a maximum heat index exceeding 32 degrees Celsius, the threshold above which extreme caution is advised for people in high-risk groups. Figure 3 illustrates the geographical and temporal variation in heatwave events during my sample period. They are concentrated in the northern Caribbean region. Heatwaves occur most often in the years with an El Niño event. The El Niño-Southern Oscillation is a multiyear climate cycle of warm and cool surface sea temperatures in the central and eastern Pacific Ocean. El Niño events are the warm phase of the cycle, with the largest anomalies occurring most recently in 2009–2010, 2014–2016, and 2018–2019 (National Weather Service, 2023b). As well as heatwaves, El Niño events in Colombia are associated with a decline in precipitation and a reduction in hydroelectric generation potential (McRae and Wolak, 2016). The frequency of heatwaves in non-El Niño years appears to have increased throughout the decade, consistent with the increase in extreme hot weather events in Northwestern South America (Castellanos et al., 2022).

### *2.5 Descriptive Statistics*

Households in Colombia are unevenly distributed across the six strata (Table 1). Approximately 90 percent of households belong to Strata 1, 2, and 3 and receive a subsidized electricity block. In contrast, less than 5 percent of households are in Strata 5 and 6 and therefore contribute to the electricity cross-subsidies. The distribution across strata is similar in the billing and survey data, with the most significant difference in Stratum 1 (32.3 percent of households in survey data but only 24.6 percent in billing data). This discrepancy arises because the billing dataset excludes households without individual meters, and Stratum 1 households often lack meters or use community meters.

Although stratum assignment is determined using neighborhood rather than household characteristics, the mean household income is still strongly positively correlated with the stratum. For example, Stratum 1 households have a mean income of US$440 per month (in real 2018 dollars), while Stratum 6 households have a mean income of US$3,760 per month. The relative difference is even more pronounced per capita, as Stratum 1 households are larger by more than one additional member on average. Consequently, the mean income per capita in Stratum 6 is over 12 times larger than in Stratum 1.

Figure 4 compares the distribution of income per capita across the six strata. It is rare for Strata 1 and 2 households to have an income per capita exceeding US$500 per month, with only 5 percent of households in these strata above this threshold. Conversely, 77 percent of Strata 5 and 6 households have an income per capita above US$500 per month. Although truncated for the visualization, there is a long tail of high-income households: 19 percent of Stratum 5 and 39 percent of Stratum 6 households have a monthly income per capita above US$2,000. Moreover, Table 1 and Figure 4 may understate income differences across strata due to wealthier households' tendency to underreport income in surveys, particularly in Latin America (Lustig, 2020).

Like income, electricity consumption monotonically increases across strata (Table 1). Stratum 1 households have a mean consumption of 131 kWh per month, compared to 292 kWh per month for Stratum 6 households. Lower consumption in Stratum 1 reflects lower rates of appliance ownership: 87.5 percent of Stratum 1 households own a television, 70.3 percent own a refrigerator, and 37.5 percent own a washing machine. Nearly all Strata 5 and 6 households own these appliances. Of particular relevance for the present analysis are air conditioner and fan ownership. Only 2.1 percent of Stratum 1 households own an air conditioner, compared to 25.6 percent of Stratum 6 households. A higher proportion of Stratum 1 households own fans compared to households in other strata, reflecting the higher concentration of Stratum 1 households in hotter regions. The mean temperature for Stratum 1 households is 21 degrees Celsius, compared to a mean between 16 and 18 degrees Celsius for other strata.

Total electricity bill amounts also increase across strata. Based on the billing data, the average monthly bill for Stratum 1 is US$13, compared to US$57 for Stratum 6. Higher bills for higher strata households are caused by greater electricity consumption and steeper tariff schedules (Figure A1). The share of the electricity bill in household income is highest in Stratum 1 (approximately 4.5 percent of income), but the gradient remains relatively flat across strata. Electricity bills account for around 3 percent of income for households in Strata 4, 5, and 6.

Figures 2 and 5 offer additional insight into the geographic and temporal heterogeneity of electricity consumption in Colombia and its relation to climate. Mean residential electricity consumption is highest in the Caribbean coastal region (right panel of Figure 2), particularly in the northeastern departments of Magdalena, Cesar, and La Guajira. Electricity consumption is also higher in the eastern lowland regions, but not to the same extent as in the Caribbean. Despite their cold climate, high-altitude cities such as Bogotá, with many wealthy households, also have relatively high electricity consumption.

Figure 5 illustrates the relationship between electricity consumption, climate, and the household stratum. Each panel shows consumption trends for one of the three climate regions: cold, temperate, and hot. Within each panel, the six lines correspond to the mean electricity consumption for the six strata. As in Table 1, within every climate region, electricity consumption monotonically increases with the stratum (that is, the highest line represents the highest stratum). The figures display the trend in mean consumption between 2010 and 2019.[2]

The difference in consumption between the strata is relatively low in the cold region, with a mean consumption for Stratum 1 in 2019 of about 100 kWh per month, compared to about 230 kWh per month for Stratum 6. The difference between the strata has fallen over time in the cold regions. Mean consumption for the lowest strata is relatively constant, while consumption in the higher strata has declined substantially since 2010. This decline may be due to improvements in energy efficiency, such as the adoption of LED lighting.

The cross-strata variation is more prominent in the hot region, perhaps reflecting the greater use of air conditioning for households in higher strata. The mean consumption for Stratum 1 in 2010 was about 150 kWh per month, compared to about 450 kWh per month for Stratum 6. There has been a small degree of convergence between the strata over the decade from 2010 to 2019, as consumption for the highest strata has been relatively flat, while consumption in the lower two strata has increased.

## 3. Empirical Methodology

The empirical analysis estimates the effect of the mean heat index or the mean temperature on electricity consumption using the panel dataset of electricity consumption and weather described in Section 2. The base case regression specification is provided in equation (1).

$$\log(y_{isrt}) = \sum_{S=1}^{6} \beta_S I[s = S] Weather_{irt} + \gamma Z_{it} + \alpha_i + \omega_{st} + \varepsilon_{isrt} \tag{1}$$

[2] Unfortunately, the data for several electricity distributors are missing for seven months in 2018. For that reason, I exclude 2018 from the summary means in Figure 5, although I include all available data in the estimation.

In this equation, the dependent variable is the log of the electricity consumption for household $i$ assigned to stratum $s$ and living in municipality $r$ in month-of-sample $t$.[3] The main regressor of interest is $Weather_{irt}$, defined for household $i$ in municipality $r$ during the period $t$. In Section 4.1, I show results in which the weather variable is either the mean temperature or the mean heat index for the billing cycle. I use these results to justify using the mean heat index in the subsequent analysis. In Section 4.3, I show results using the proportion of days in a heatwave during the billing cycle. I also show the results for the mean, maximum, and minimum daily temperatures in Appendix B. In all cases, the weather variables differ across households in the same month and municipality due to differences in the billing cycle timing.

The effect of the weather variables on electricity consumption is allowed to vary by the stratum $s$. Differences in the $\beta_S$ reflect variation across the strata in the effect of weather on electricity consumption.

The base regression model includes household fixed effects $\alpha_i$ to absorb the determinants of household electricity consumption that do not change over time, such as location and housing characteristics. Month-of-sample fixed effects $\omega_{st}$ control for time-varying determinants of electricity consumption that are common to all households, including wholesale electricity prices and national economic shocks. These fixed effects vary by stratum $s$ to account for potential differences in the effect of these factors by stratum. The month-of-sample for a particular observation is determined by the first date of the billing cycle.

Household income is an important determinant of electricity consumption. The household fixed effect $\alpha_i$ controls for the mean level of each household's income during the sample period. However, there may be differences across households in the growth rate of income, and these may be correlated with the weather variables due to the correlation between weather and economic output in sectors such as agriculture and tourism. In the absence of time-varying income data at the household level, I include annual state-level Gross Domestic Product as a control variable $Z_{it}$. This variable controls for differential regional trends in economic activity.

The exact timing of the billing cycle may affect electricity consumption through the number of weekends and public holidays. For all regressions, I include a control variable in $Z_{it}$ for

[3] As discussed in Section 2, I divide the metered electricity consumption by the number of billed days to adjust for differences in the number of days in each monthly billing cycle.

the proportion of days that are Sundays or public holidays in each billing period. The historical dates of Colombian public holidays are from Festivos Colombia (2023).

In Section 4.2, I estimate the base specification in equation (1) for different subgroups in the data. First, I estimate the model separately by climate region. I expect that the base effect of weather $\beta_S$ will be larger for hot regions due to higher levels of air conditioning adoption. Second, I estimate the model separately by stratum, allowing the coefficients on the weather regressor to vary by year. This specification is used to examine changes over time in the effect of weather on electricity consumption.

The base specification assumes a linear relationship between the heat index (or temperature) and electricity consumption. As discussed in Section 2, most temperature variation in Colombia is across locations based on altitude, not within locations over time. Because no location experiences temperatures over the full range of the temperature distribution, estimating a flexible nonlinear regression may conflate the within-location and across-location variation in the temperature effects (Mendelsohn, 2016).

One variable that is omitted from Equation (1) is the electricity price. I assume that the tariff nonlinearities do not have a measurable effect on the relationship between weather and household electricity consumption. This assumption is only relevant for the households in Strata 1 to 3, as the households in Strata 4 to 6 face a uniform tariff with no nonlinearities. The households in Strata 1 to 3 pay a higher marginal price above the subsidy threshold, but there is no discontinuous change in their total bill amount at the cutoff.[4] The subsidy thresholds were calibrated to provide households with a "lifeline" quantity of electricity consumption, so most households using air conditioning will be above the threshold and pay the full regulated price for their marginal consumption. The tariff structure, the subsidized quantities, and the subsidy amount have not changed during the sample period—in particular, the tariffs do not change in response to short-term weather conditions. The assumption that the nonlinear tariff can be ignored for this analysis is consistent with the existing literature on electricity consumption and weather (Davis and Gertler, 2015; Auffhammer, 2022).

[4] The Colombian electricity tariffs are an example of an increasing block tariff. For this tariff type, the marginal price changes at the quantity thresholds, but households above each threshold keep the subsidy amount on their inframarginal units (Appendix A). An alternative tariff type is a quantity-differentiated tariff, for which households lose the subsidy on their inframarginal units if their consumption exceeds the quantity threshold (see, for example, Pellerano et al., 2017). Because of its "notch" in the total bill amount, a quantity-differentiated tariff would provide stronger incentives to keep electricity consumption below the threshold.

In all specifications, I cluster the standard errors by the municipality of the households. This allows for potential correlation in the error terms across households in the same municipality due to local economic shocks, electricity distribution outages, or disasters. Clustering by municipality also allows for correlation in the error term within a household over time.

## 4. Empirical Results

I first present the baseline results for the sensitivity of electricity consumption to the mean temperature and the mean heat index in each billing cycle. These results support the use of the heat index in the subsequent analyses. I show the heterogeneity in the sensitivity to the heat index by stratum and climate zone, then examine the changes in the heat index sensitivity over time. Finally, I provide additional results on the relationship between heatwaves and electricity consumption.

### *4.1 Baseline Results*

Table 2 shows the results for 18 separate regressions of equation (1) for the log of monthly electricity consumption on alternative weather variables. There are three regressions for each stratum, differing by the definition of the weather variable: the mean temperature during the billing cycle (Model 1), the mean heat index during the billing cycle (Model 2), and both regressors combined in a single estimation (Model 3). The estimation uses the full sample of households from all climate regions.

Higher temperatures during the month increase the electricity consumption of households in all six socioeconomic strata (Model 1). For Stratum 1 households, a one-degree Celsius increase in the temperature in the billing cycle increases electricity consumption by 2.4 percent. The magnitude of the temperature effect increases monotonically across the six strata. For the highest stratum, a one-degree temperature increase leads to a 6.0 percent increase in electricity consumption. All of the estimated effects are statistically significant at a 1 percent level.

Results for the mean heat index during the billing cycle are quantitatively similar to the mean temperature results (Model 2). However, the statistical precision of the heat index estimates is greater, with smaller standard errors than in Model 1. The greater precision is especially notable for the Strata 4 to 6 estimates, which rely on fewer observations from a smaller number of municipalities.

The final model is an encompassing model that embeds both regressors from Models 1 and 2 in a single equation. The estimated coefficients on the mean heat index increase in magnitude but remain positive and strongly statistically significant. However, the coefficients on the mean temperature change their sign and are statistically significant and negative. From the definition of the heat index, if the heat index is held constant, an increase in the air temperature must imply a reduction in the relative humidity. In other words, the negative sign on temperature implies that lower humidity reduces electricity consumption (or, conversely, higher humidity increases electricity consumption).

From a statistical perspective, the encompassing test strongly rejects both Model 1 and Model 2 in favor of the encompassing Model 3, implying that the temperature and heat index variables provide independent information about electricity consumption. However, the p-value for the encompassing test is lower for Model 1 than for Model 2. Similarly, goodness-of-fit measures like the $R^2$, and model selection criteria like the AIC and BIC, all support the use of Model 2 over Model 1. Based on this evidence supporting the use of the heat index, I show results only for the heat index (Model 2) in the next subsection.

### *4.2 Heterogeneity by Climate and Year*

In this subsection, I show the heterogeneity, by climate region and year, in the heat index results in Model 2 of Table 2. Each set of results is shown in both tabular and graphical form. First, for heterogeneity by climate region, Table 3 and Figure 6 show the results for separate estimations of Equation (1) by climate region. In the table, the uninteracted coefficient on the heat index variable shows the effect of a one-degree Celsius increase in the mean heat index on the logged electricity consumption of households in Stratum 1. The other coefficients show the interaction of the heat index with the stratum indicator variables. The overall heat index effect by stratum is the sum of the uninteracted heat index coefficient and the coefficient on its interaction with the stratum indicator. Figure 6 shows this combined effect, with its 95 percent confidence interval, for each climate region.

The mean heat index has a positive but relatively small effect on electricity consumption in cold regions. The coefficient on the mean heat index is 0.013, meaning that a one-degree increase in the mean heat index during the billing cycle is associated with a 1.3 percent increase in the electricity consumption of Stratum 1 households. With the exception of Stratum 5, there is no statistically significant difference in this effect across the other strata. For Stratum 5 households in cold regions, the effect of a temperature increase is larger: a one-degree increase in the mean heat index is associated with a 3.3 percent increase in electricity consumption.

A counterintuitive aspect of the cold region results is the absence of a negative coefficient on the heat index. We would expect that if households use electric heating in cold regions, an increase in the temperature or the heat index would reduce the heating requirement and thus decrease electricity usage. This effect was observed by Berkouwer (2020), who found a negative relationship between temperature and electricity consumption for households in South Africa, up to 23 degrees Celsius.[5] The small positive coefficient on the heat index suggests that electric heating is less common in Colombia than in South Africa and, instead, there is a more nuanced relationship between electricity consumption and weather in cold regions. One explanation consistent with the results is that households have multiple heating sources, other fuels are used for heating at low temperatures, and electricity is used when temperatures are relatively warm. Another possibility is that the usage of other appliances is correlated with the weather. For example, households in cold regions might use their clothes washers more when the weather is warmer.

For temperate regions, the effect of the heat index on electricity consumption is close to zero and, in all but Stratum 2, statistically indistinguishable from zero. Even for Stratum 2, the effect of 0.01 is smaller than the coefficients for any of the strata in cold regions. The point estimate for Stratum 6 is negative (-0.017), but its 95 percent confidence interval is wide and includes zero. These results suggest that there is little need to own and use heating and cooling appliances in temperate regions of Colombia.

Finally, there is a large, positive, and statistically significant relationship between the heat index and electricity consumption in hot regions. For Stratum 1 households in hot regions, a one-degree increase in the mean heat index increases electricity consumption by 2.5 percent (with a 95 percent confidence interval of 1.9 to 3.1 percent). Electricity consumption is more sensitive to the heat index for the higher strata. For Stratum 5 households, a one-degree increase in the heat index increases electricity consumption by 6.4 percent. The greater effect of the heat index on electricity

[5] Conversely, Davis and Gertler (2015) did not find any relationship between temperature and electricity consumption at low temperatures, which they attributed to the limited use of electric heating in Mexico.

consumption for the higher strata is consistent with the result in Table 1 that households in higher strata are more likely to own an air conditioner.

The second set of results reveals how the relationship between electricity consumption and the heat index changes over time for the different strata (Table 4 and Figure 7). For these results, I focus only on those households living in the hot climate region. Each column in Table 4 and each panel in Figure 7 shows the results for a separate regression for the households in a different stratum. The uninteracted coefficient on the heat index variable shows the effect of a one-degree increase in the mean heat index on the logged electricity consumption of households in the base period: the last five months of 2010 and all of 2011. The other coefficients in the table show the interaction of heat index with the year indicator variables. The overall heat index effect by year, shown in Figure 7, is the sum of the uninteracted heat index coefficient and the coefficient on its interaction with the year indicator.

The results show that the effect of the heat index on electricity consumption has increased over time for Strata 1 to 3 households, with the largest change for Stratum 1 households. In the 2010-11 base period, a one-degree increase in the heat index increased the electricity consumption of a Stratum 1 household in the hot region by 1.4 percent. This effect more than doubled to 3.3 percent by 2019. For Stratum 2 households, the effect of a one-degree change in the heat index increased from 2.4 percent in 2011 to 3.2 percent in 2019. The changes for both strata were statistically significant at the 1 percent level. Stratum 3 households had a slightly higher gradient between 2013 and 2017 relative to 2011, but the increase was no longer statistically significant by 2019.

As shown in Figure 6, the electricity consumption of Stratum 4 to 6 households in hot regions is especially sensitive to the heat index, with overall coefficient estimates between 0.057 and 0.064. For these strata, there is no statistically significant change in the effect between 2011 and 2019 (Table 4). Although there are small changes in the point estimates from year to year, the confidence intervals for the heat index coefficients are relatively wide because of the smaller number of municipalities containing households from the higher strata. Because of the imprecise estimates, I cannot reject that there was no change in the effect for these strata. Overall, the results in Figure 6 show substantial convergence across the strata in the effect of the heat index on electricity consumption.

The magnitude of the heat index effect for Colombian households in Strata 5 and 6 is comparable to previous results in the literature for Mexican households. Davis and Gertler (2015) find that moving one day in a month from 18-to-21 degrees Celsius to a temperature above 32 degrees Celsius will increase monthly electricity consumption by 3.2 percent. This change in the temperature distribution corresponds to an increase in the monthly mean temperature of approximately 0.45 degrees Celsius. Equivalently, the Davis and Gertler (2015) results can be interpreted as a 7.1 percent increase in electricity consumption for a one-degree Celsius increase in mean temperature.[6] This result is slightly higher than the Strata 5 and 6 point estimates for heat index in Figure 6, but is within the 95 percent confidence interval.[7] Conversely, the estimated effect for Strata 1 to 3 households is lower than the average for Mexican households in Davis and Gertler (2015).

Although the magnitude of the effect of the heat index on electricity consumption is smaller for Strata 1 to 3 households, the nonlinearity in the electricity tariff structure means that its effect on the electricity bill amount may be even larger than for the higher strata. For example, for Stratum 1 households in 2019, a one-degree Celsius increase in the mean heat index increases monthly electricity consumption by 3.3 percent. However, if the increase in consumption occurs at the unsubsidized price (for example, if monthly consumption exceeds 173 kWh in lowland regions), then the household electricity bill may increase by more than 7 percent. Moreover, as shown in Table 1, electricity bills are a larger share of income for households in Stratum 1 than for households in Stratum 6. As a result, this increase in the bill may be especially salient.

### *4.3 Alternative Weather Variables*

In this subsection, I provide additional robustness checks for the results in Section 4.2. I show that the qualitative results are not affected by the exact definition of the weather variables for the analysis.

Figure 8 shows the relationship between electricity consumption and the proportion of days with heatwave events (as defined in Section 2) for hot regions in Colombia. Heatwaves have a positive and statistically significant on electricity consumption for all six strata, with the estimates

[6] This calculation assumes a change from the midpoint of the lower bin (19.5 degrees) to a temperature of 33 degrees. Assume 30 days in the month: (33 − 19.5)/30 = 0.45. The result for a one-degree increase is 0.032/0.45 = 0.071.

[7] The results in Table 6 are not strictly comparable to Davis and Gertler (2015), because they measure the sensitivity to the heat index and not to temperature. However, the temperature results for Strata 5 and 6 in Figure A3 are very similar, just with larger confidence intervals.

increasing across the first five strata and the largest effect observed for households in Stratum 5. For Stratum 5 households, one additional day with a heatwave in a month increases electricity consumption for the month by 1.1 percent.[8]

I repeat the analysis in Section 4.2 using three alternative regressors instead of the heat index: the mean temperature, the mean of the daily maximum temperature, and the mean of the daily minimum temperature. Appendix B provides two figures for each of these regressors, equivalent to the results in Section 4.2.

The mean temperature results by climate region are very similar to the heat index results (Figure A3). There is a small positive relationship between mean temperature and electricity consumption in cold regions, no relationship in temperate regions, and a large positive relationship in hot regions that is increasing in the household stratum. Similarly, the annual results from 2011 to 2019 show a statistically significant increase in the effect of the mean temperature on electricity consumption for households in Strata 1 and 2 (Figure A4). The main difference between the heat index and the temperature results is in the precision of the estimates, as discussed in Section 4.1. Because the mean temperature coefficients are less precisely estimated, the confidence intervals for Strata 4 to 6 households are particularly wide in Figures A3 and A4.

In theory, the minimum and maximum daily temperatures might matter more for electricity consumption than the mean temperature. This would be the case if, for example, electric heaters or air conditioners are only turned on during the coldest or hottest hours of the day. In practice, there is much autocorrelation in within-day temperatures, so days in which the maximum temperature is higher will also tend to have higher mean and minimum temperatures too. This makes it difficult to separate the effect of the daily extreme temperatures from the mean temperature.

The overall results using the mean of the daily minimum and maximum temperatures are consistent with the results in Section 4.2. One notable exception is the result for cold regions in Figure A5. Although the coefficients on the mean maximum temperatures are all positive, they are much smaller in magnitude than the corresponding coefficients on the heat index or mean temperature. For Stratum 1, the coefficient is not statistically different from zero. Conversely, the effects of minimum temperature on electricity consumption in cold regions are large in magnitude

[8] The Stratum 5 estimate is 0.285, so the effect of one extra day of a heatwave on electricity consumption is $(1/30)\times(\exp(0.285)-1)$.

and statistically significant, except for an anomalous negative and insignificant coefficient for Stratum 6 (Figure A7). These results provide suggestive support for the positive effect of temperature on electricity consumption in cold regions being driven by household heating choices, for which the minimum daily temperature is more relevant than the maximum.

The final set of supplementary results uses the detailed hourly temperature data to estimate separate effects of temperature during hours when household members are more or less likely to be at home. For each billing cycle, I calculate the mean temperature and mean heat index for three different time periods: daytime hours (assumed to be from 8 a.m. to 6 p.m. on non-holiday weekdays and Saturdays), nighttime hours (6 p.m. to 8 a.m. on non-holiday weekdays and Saturdays), and any time on public holidays and Sundays. I then estimate a version of equation (1) including the three mean temperature or mean heat index variables in a single regression, restricting the sample to households living in the hot climate region.

Table A1 shows the results from splitting the overall mean temperature into the mean temperature for the three time periods. For every stratum, the coefficients on the mean daytime temperature are small in magnitude and statistically indistinguishable from zero. In contrast, the coefficients on the mean nighttime temperature are large, statistically significant at the 1 percent level, and increasing with the household stratum. The holiday temperature coefficients are smaller than the nighttime coefficients, though (except for Strata 4 and 5) still statistically significant. These results suggest that higher temperatures during hours when household members are more likely to be at home have the greatest effect on electricity consumption.

The results from splitting the mean heat index into the three time periods are more ambiguous (Table A2). For Strata 1 to 4 households, the coefficients on both the daytime and nighttime heat index variables are positive and statistically significant, with the nighttime coefficients typically smaller in magnitude. The Strata 5 and 6 coefficients are similar in magnitude but less precisely estimated. These results indicate that a higher heat index increases electricity consumption in hot regions, regardless of the time of day. The discrepancies in the results between Tables A1 and A2 may be caused by the high correlation between the three heat index or temperature variables. This collinearity makes it empirically challenging to separate their effect on a single outcome variable observed at a monthly frequency.

## 5. Survey Evidence on Fan and Air Conditioning Adoption

The results in the previous section show that the effect of the heat index or the temperature on electricity consumption is greater in hot regions and for households in the higher strata. However, the effects increased between 2011 and 2019 for the low-strata households, leading to partial convergence in the weather responses across the six strata.

Table 5 presents the share of households owning fans and air conditioners, categorized by the three climate regions and the two time periods 2011–15 and 2016–19. The hot region is further subdivided into the Caribbean and other low-lying parts of Colombia. As previously demonstrated in Table 1, fan ownership is more prevalent than air conditioning, with approximately ten times as many households owning fans as air conditioners. The differences in ownership of cooling appliances across climate regions are as expected. There are very few air conditioners in cold and temperate parts of Colombia, although fans are not uncommon in temperate regions.[9] Both appliances are more common in the Caribbean than in other hot parts of Colombia, with fans being nearly universal for Caribbean households.

Ownership of both fans and air conditioners increased in the second half of the decade (Table 5), both in aggregate and in all but one of the climate regions. The share of households with fans increased from 36.3 percent in 2011–15 to 38.5 percent in 2016–19, with this difference statistically significant at the 10 percent level.[10] The relative increase in the share of households with fans was greatest in cold and temperate regions. Conversely, the absolute and relative increase was lowest in the Caribbean because the baseline level of ownership in the earlier period was already so close to one. The share of households with air conditioners increased from 12.8 to 15.9 percentage points in the Caribbean, an increase of more than 20 percent that is significant at the 1 percent level. In other hot regions, the share of air conditioners increased from 2.9 to 4.1 percentage points, significant at the 5 percent level. The one exception to the increase in ownership occurred

[9] One limitation of the analysis is that the public use survey data only provides geographical identifiers at the department level. Because of this data limitation, I assigned each household to the climate region of the department capital. For the departments with considerable geographical variations in climate, such as Antioquia and Santander, this will introduce measurement errors in the climate assignment.

[10] Unfortunately, the public use survey data does not report the primary sampling unit to be able to account for spatial autocorrelation from the sampling methodology. As a substitute, when performing the test for equality of means between the two periods, I cluster the standard errors by a geographical identifier constructed from the department, location (urban/rural/village), and stratum.

for air conditioners in the temperate region, where the share fell by a statistically insignificant 0.5 percentage points.

Figure 9 illustrates the heterogeneity in fan and air conditioner ownership by income per capita, following the same split by climate region and time period as in Table 5. Each point in the figure represents the mean ownership for one of 20 equally-sized bins of income per capita. The lines show the results for a local linear regression through the binned mean values. The overall results in the figure indicate a positive relationship between household income per capita and the probability of owning a fan or an air conditioner. This finding is consistent with the results on appliance ownership by stratum in Table 1. The probability of air conditioning ownership is much higher in the Caribbean than in the rest of Colombia. Nonetheless, even in the Caribbean, households with the lowest income per capita (for example, monthly income less than $125 per capita) are unlikely to own air conditioners, with ownership rates below five percent. Conversely, as previously noted, fans are almost universal in the Caribbean, with ownership rates exceeding 90 percent across most income per capita bins.

Of particular relevance for interpreting the results from Section 4 is the change in the ownership rates between the two time periods. In the Caribbean region, air conditioner ownership increased across the whole income distribution, although this increase was greatest for households with monthly income above US$200 per capita. Despite the increase for low-income households, their ownership rates were still very low in the second period. For hot regions outside of the Caribbean, air conditioning ownership increased, but only for households with monthly earnings above US$500 per capita. However, the 4.1 percentage point increase in fan ownership in the non-Caribbean hot regions was remarkably uniform across the entire income distribution.

The results in Table 5 and Figure 9 showing an increase in air conditioning and fan ownership in hot regions, including for low-income households, are consistent with the findings in Section 4. As more households acquire and use these appliances, their electricity consumption will become more responsive to changes in the heat index. This prediction matches the result observed in Figure 6, showing an increase in the effect of the heat index on electricity consumption for Strata 1 and 2 households in hot regions. Moreover, the overall level of electricity consumption should increase, which we observe for Strata 1 and 2 households in Figure 5. Despite these increases in air conditioning and fan ownership, the results in Figure 9 demonstrate the significant inequalities that still exist in their adoption for households at different ends of the income distribution.

## 6. Conclusion

This paper provides the first empirical estimates of the relationship between weather, electricity consumption, and air conditioning adoption in a South American country. The results show that household electricity consumption increases when the temperature (or the heat index) is higher, with the greatest effect observed for higher-income households in regions with a hot climate. The results also show that the effect of temperature on electricity consumption for lower-income households more than doubled between 2011 and 2019. The increased effect of temperature on electricity consumption is consistent with household survey data showing a more than 20 percent increase in air conditioning ownership in hot regions.

An optimistic interpretation of these results is that they demonstrate enhanced resilience of households to extreme hot temperatures. Most high-income households in hot regions already had air conditioning, and the observed increase in the temperature responses for low-income households suggests some partial convergence in their capacity to cope with climate change. However, this convergence is still far from complete, and significant disparities remain in the ownership and usage of air conditioning between low and high-income households in hot regions of Colombia. Therefore, many households likely to be affected by extreme heat events remain unprotected.

A more pessimistic implication of the results is that overall electricity demand will continue to rise due to higher household incomes and higher temperatures. For low-income households in hot regions, the level of their electricity consumption and its responsiveness to temperature will increase as their incomes rise and they adopt air conditioning. This growth will strain the electricity system, especially during heatwaves.

An especially pertinent issue for Colombia is the correlation between the timing of future heatwaves and the availability of generation from renewable sources such as hydroelectricity, wind, and solar power. Heatwaves are more likely during El Niño periods when rainfall is lower and hydro inflows fall. As a result, higher temperatures and broader adoption of air conditioning will leave the system increasingly vulnerable to supply shortfalls, especially during El Niño events. Avoiding these shortfalls might require design changes in the wholesale electricity market to provide incentives for maintaining non-renewable generation facilities or installing utility-scale electricity storage.

One limitation of the methodology in this paper is the inability to separately identify the utilization and efficiency of air conditioners using electricity consumption data alone. For example, households that greatly increase their electricity use when temperatures rise might place a high value on the cooling benefits from air conditioning—or they might have an old and inefficient appliance. The efficiency of room air conditioners increased by 30 percent between 1980 and 2010 (Davis et al., 2014) and is likely to keep improving due to technological advancements, dampening the expected increase in electricity consumption from greater cooling demand. However, it will be necessary to identify the barriers to adopting more efficient appliances and determine whether policy interventions such as mandates or subsidies are justified.

Adaptation to climate change presents challenging tradeoffs for society. Air conditioning is essential for reducing the excess mortality from extreme heat events, but its usage contributes to future climate change because most electricity is generated by burning fossil fuels. This tradeoff may be partially alleviated by renewable technologies such as wind and solar that reduce the carbon intensity of electricity generation. Complementary investments such as planting trees in urban areas could reduce air conditioning requirements. However, it seems inevitable that greater adoption and use of residential air conditioning is required to protect vulnerable members of society during more frequent and intense heatwaves.

## References


Adhvaryu, A., N. Kala, and A. Nyshadham. 2020. "The Light and the Heat: Productivity Co-Benefits of Energy-Saving Technology." *Review of Economics and Statistics* 102(4): 779–792.

Anderson, G.B., M.L. Bell, and R.D. Peng. 2013. "Methods to Calculate the Heat Index as an Exposure Metric in Environmental Health Research." *Environmental Health Perspectives* 121(10): 1111–1119.

Auffhammer, M. 2014. "Cooling China: The Weather Dependence of Air Conditioner Adoption." *Frontiers of Economics in China* 9(1): 70–84.

----. 2022. "Climate Adaptive Response Estimation: Short and Long Run Impacts of Climate Change on Residential Electricity and Natural Gas Consumption." *Journal of Environmental Economics and Management* 114:102669.

Auffhammer, M. et al. 2013. "Using Weather Data and Climate Model Output in Economic Analyses of Climate Change." *Review of Environmental Economics and Policy* 7(2): 181–198.

Barreca, A. et al. 2016. "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century." *Journal of Political Economy* 124(1): 105–159.

Berkouwer, S.B. 2020. "Electric Heating and the Effects of Temperature on Household Electricity Consumption in South Africa." *Energy Journal* 41(4): 209-230.

Biardeau, L.T. et al. 2020. "Heat Exposure and Global Air Conditioning." *Nature Sustainability* 3(1): 25–28.

Carleton, T. et al. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *Quarterly Journal of Economics* 137(4): 2037–2105.

Castellanos, E. et al. 2022. "Central and South America." In: H.O. Pörtner et al., editors. *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, United States: Cambridge University Press.

Data for Good. 2020. "High Resolution Population Density Maps." https://dataforgood.facebook.com/dfg/tools/high-resolution-population-density-maps#accessdata.

Davis, L., A. Fuchs, and P. Gertler. 2014. "Cash for Coolers: Evaluating a Large Scale Appliance Replacement Program in Mexico." *American Economic Journal: Economic Policy* 6(4): 207–38.

Davis, L. et al. 2021. "Air Conditioning and Global Inequality." *Global Environmental Change* 69: 102299.

Davis, L.W., and P.J. Gertler. 2015. "Contribution of Air Conditioning Adoption to Future Energy Use under Global Warming." *Proceedings of the National Academy of Sciences* 112(19): 5962–5967.

Departamento Administrativo Nacional de Estadística (DANE). 2020. "Encuesta nacional de calidad de vida (ECV)." https://www.dane.gov.co/index.php/estadisticas-por-tema/pobreza-y-condiciones-de-vida/calidad-de-vida-ecv.

Festivos Colombia. 2023. "Histórico de días festivos en Colombia." https://www.festivos.com.co/historico.

Guo, Y. et al. 2018. "Quantifying Excess Deaths Related to Heatwaves under Climate Change Scenarios: A Multicountry Time Series Modelling Study." *PLOS Medicine* 15(7): 1–17.

Helo Sarmiento, J. 2023. "Into the Tropics: Temperature, Mortality, and Access to Health Care in Colombia." *Journal of Environmental Economics and Management* 119: 102796.

Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM). 2023. "Clasificación Climática Caldas Lang 2012." http://bart.ideam.gov.co/cneideam/Capasgeo/Clasificacion_ Climatica_Caldas_Lang_2012.zip.

Li, Y., W.A. Pizer, and L. Wu. 2019. "Climate Change and Residential Electricity Consumption in the Yangtze River Delta, China." *Proceedings of the National Academy of Sciences* 116(2): 472–477.

Lustig, N. 2020. "The 'Missing Rich' in Household Surveys: Causes and Correction Approaches." Stone Center on Socio-Economic Inequality Working Paper 08. New York, United States: City University of New York. Available at: https://osf.io/preprints/socarxiv/j23pn/

McRae, S. 2015. "Infrastructure Quality and the Subsidy Trap." *American Economic Review* 105(1): 35–66.

McRae, S.D, and Frank A Wolak. 2016." Diagnosing the Causes of the Recent El Niño Event and Recommendations for Reform." Available at: https://web.stanford.edu/group/fwolak/cgi-bin/sites/default/files/diagnosing-el-nino_mcrae_wolak.pdf

Mendelsohn, R. 2016. “Measuring Weather Impacts Using Panel Data.” New Haven, United States: Yale University. Manuscript.

Mistry, M.N. et al. 2022. “Comparison of Weather Station and Climate Reanalysis Data for Modelling Temperature-related Mortality.” *Scientific Reports* 12(1): 1–14.

Muñoz Sabater, J. et al. 2019. “ERA5-Land Hourly Data from 1981 to Present.” Copernicus Climate Change Service (C3S) Climate Data Store (CDS) 10.

National Weather Service. 2023a. “Cold & Warm Episodes by Season.” https://www.weather.gov/ama/heatindex.

---- 2023b. “What Is the Heat Index?” https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php.

Noy, Ilan, and Eric Strobl. 2022. “Heat Waves and Innovation in Air Conditioning in the United States.” *Weather, Climate, and Society* 14(1): 143–154.

Park, R. Jisung. 2022. “Hot Temperature and High-Stakes Performance.” *Journal of Human Resources* 57(2): 400–434.

Park, R.J. et al. 2020. “Heat and Learning.” *American Economic Journal: Economic Policy* 12(2): 306–39.

Pellerano, J.A. et al. 2017. “Do Extrinsic Incentives Undermine Social Norms? Evidence from a Field Experiment in Energy Conservation.” *Environmental and Resource Economics* 67:413–428.

Ranasinghe, R. et al. 2021. “Climate Change Information for Regional Impact and for Risk Assessment.” In: V. Masson-Delmotte et al., editors. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, United States: Cambridge University Press.

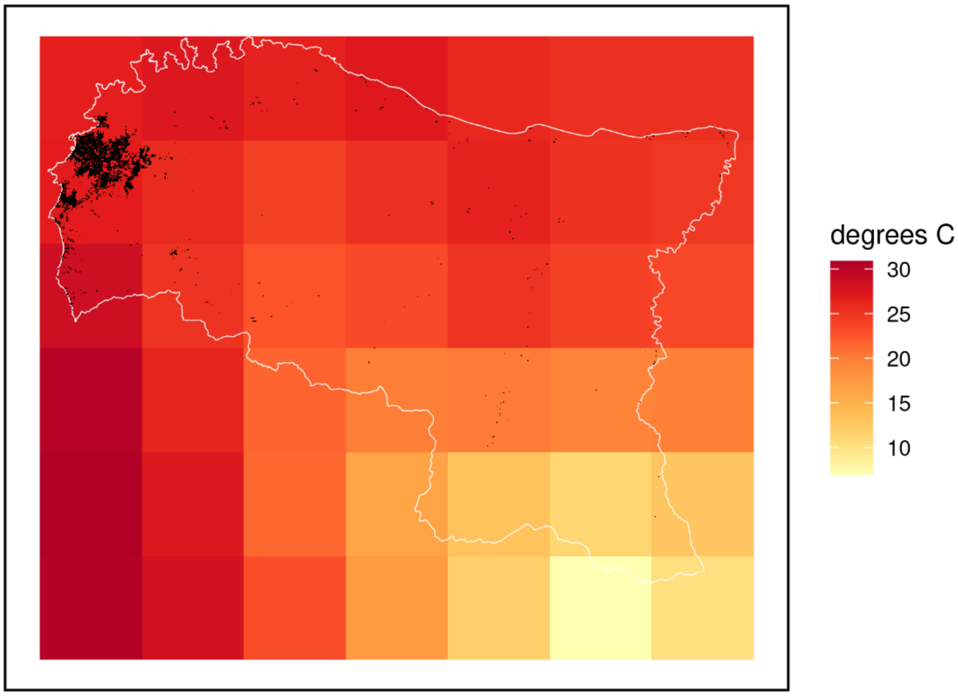
Randazzo, T., F. Pavanello, and E. De Cian. 2023. “Adaptation to Climate Change: Air-conditioning and the Role of Remittances.” *Journal of Environmental Economics and Management*; 102818.

Somanathan, E. et al. 2021. “The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing.” *Journal of Political Economy* 129(6): 1797–1827.

Tiecke, T.G. et al. 2017. “Mapping the World Population One Building at a Time.” Available at: https://arxiv.org/pdf/1712.05839.pdf

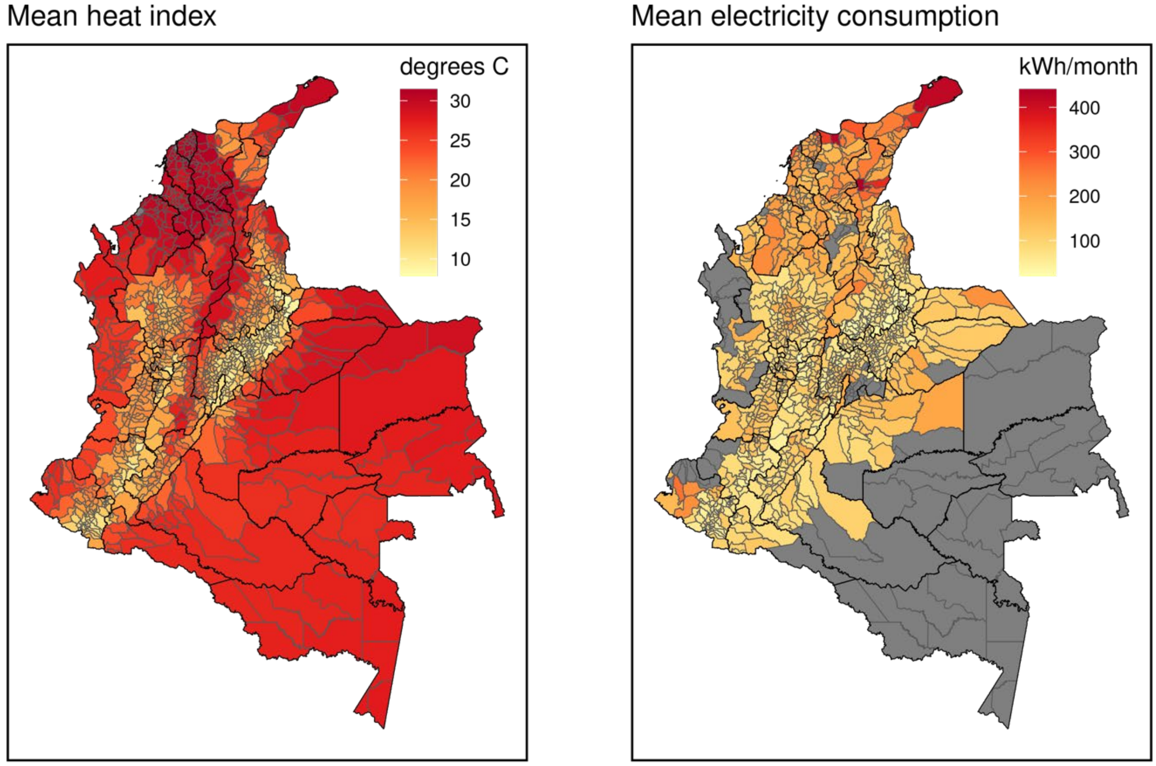
## Tables and Figures

**Figure 1. Calculation of Hourly Municipality Weather Variables from Gridded Population and Weather Data**



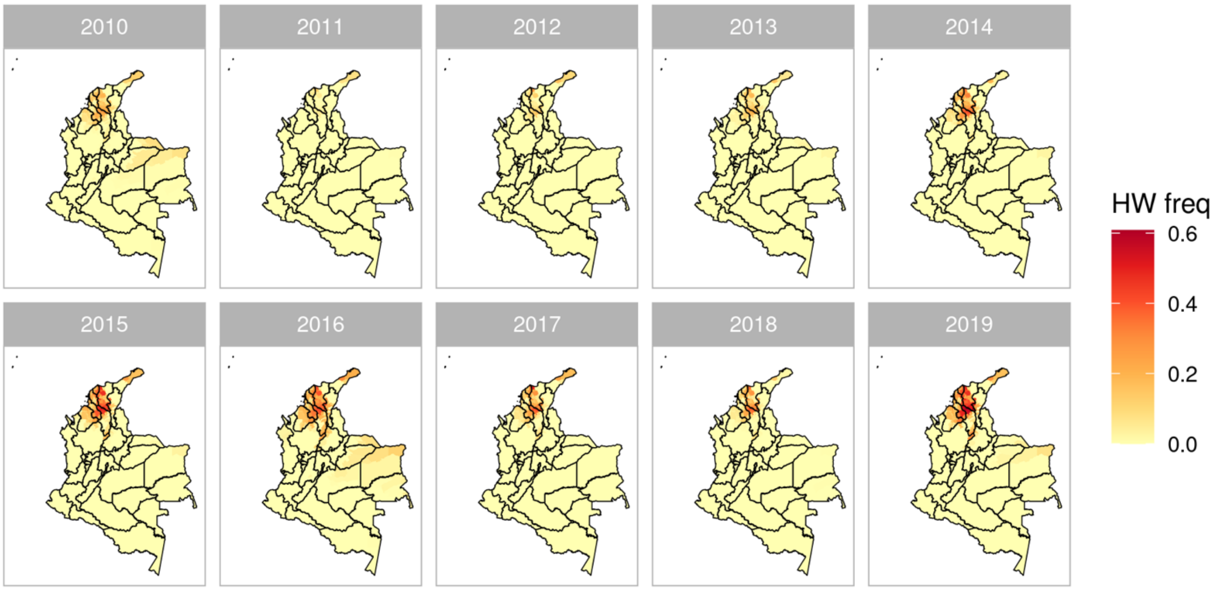

*Notes:* Each square represents an approximately 9x9 km grid cell from the ERA5-Land dataset, with colors indicating air temperature at midday on September 15, 2015. The white outline shows the Santa Marta municipality in northern Colombia, and black pixels represent inhabited locations (Data for Good, 2020). The population-weighted average temperature for Santa Marta during this hour is 23.4 degrees Celsius.

**Figure 2. Average Heat Index and Electricity Consumption by Municipality, 2010–19**



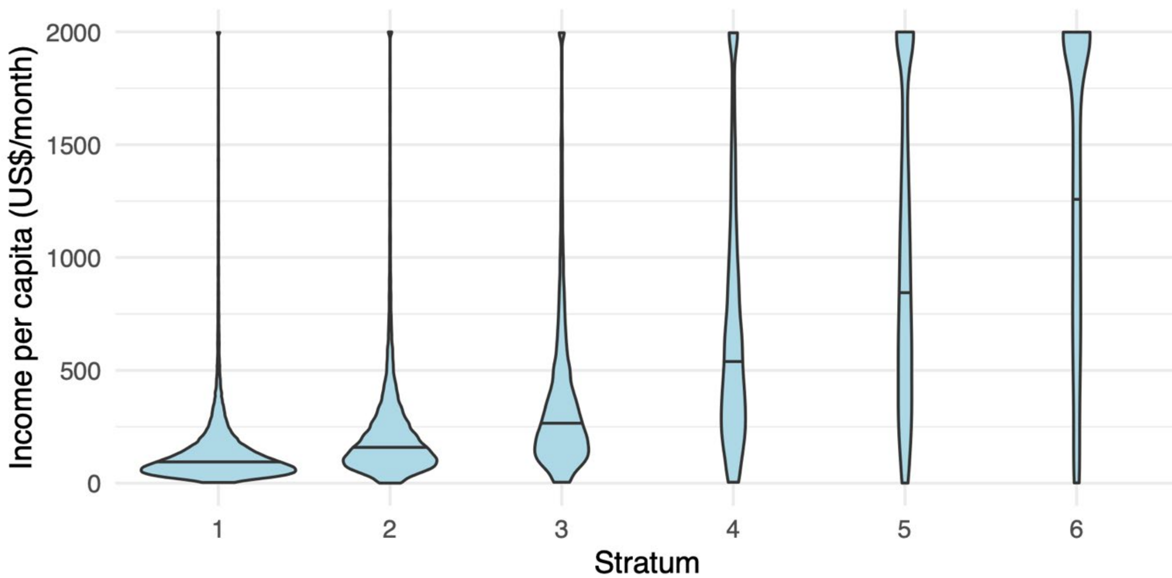

*Notes:* The left panel shows the mean hourly heat index for each municipality from 2010 to 2019, calculated using ERA5-Land air temperature and dewpoint temperature data, aggregated as shown in Figure 1. The right panel shows the mean monthly residential electricity consumption for each municipality from August 2010 to November 2019, based on the estimation dataset. Black outlines represent Colombia's 32 departments, while light gray outlines represent municipalities. Gray municipalities in the right panel are not included in the estimation dataset, mostly because they are not connected to the national transmission network.

**Figure 3. Frequency and Location of Heatwaves, 2010–19**



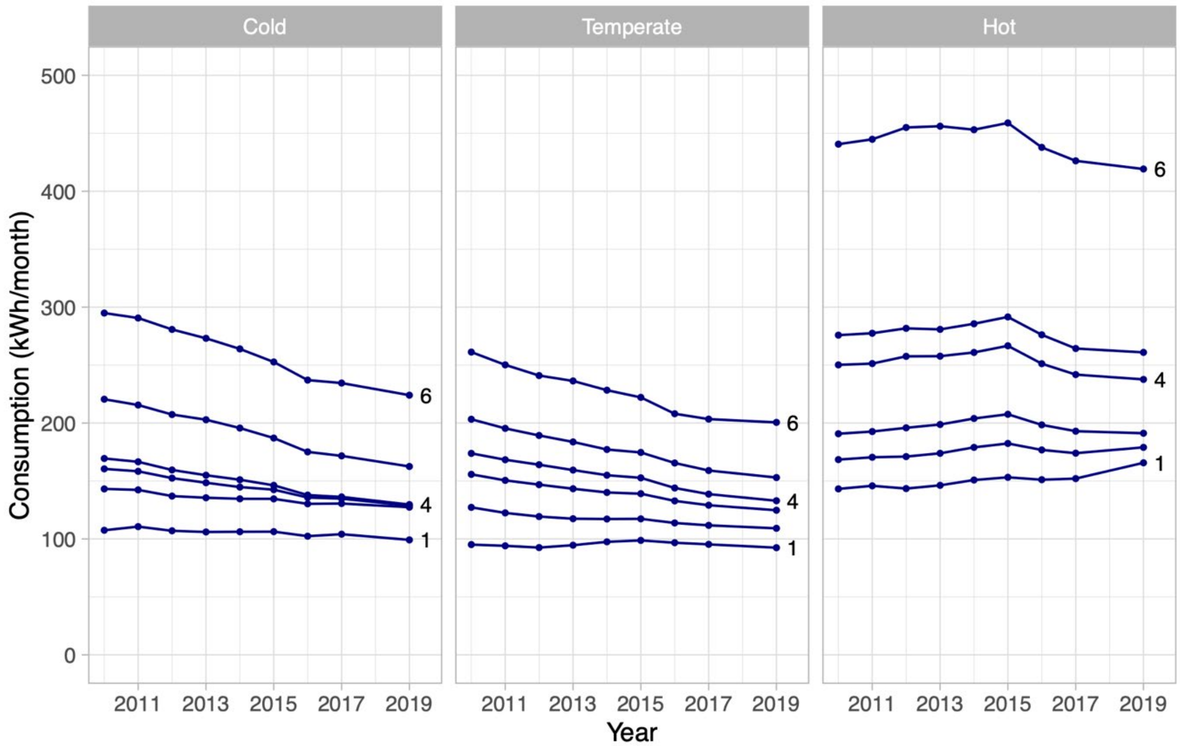

*Notes:* Each panel displays the annual proportion of heatwave days for each municipality. A heatwave is defined as two or more consecutive days with a maximum heat index above 32 degrees Celsius.

**Figure 4. Distribution of Household Income per Capita by Stratum**



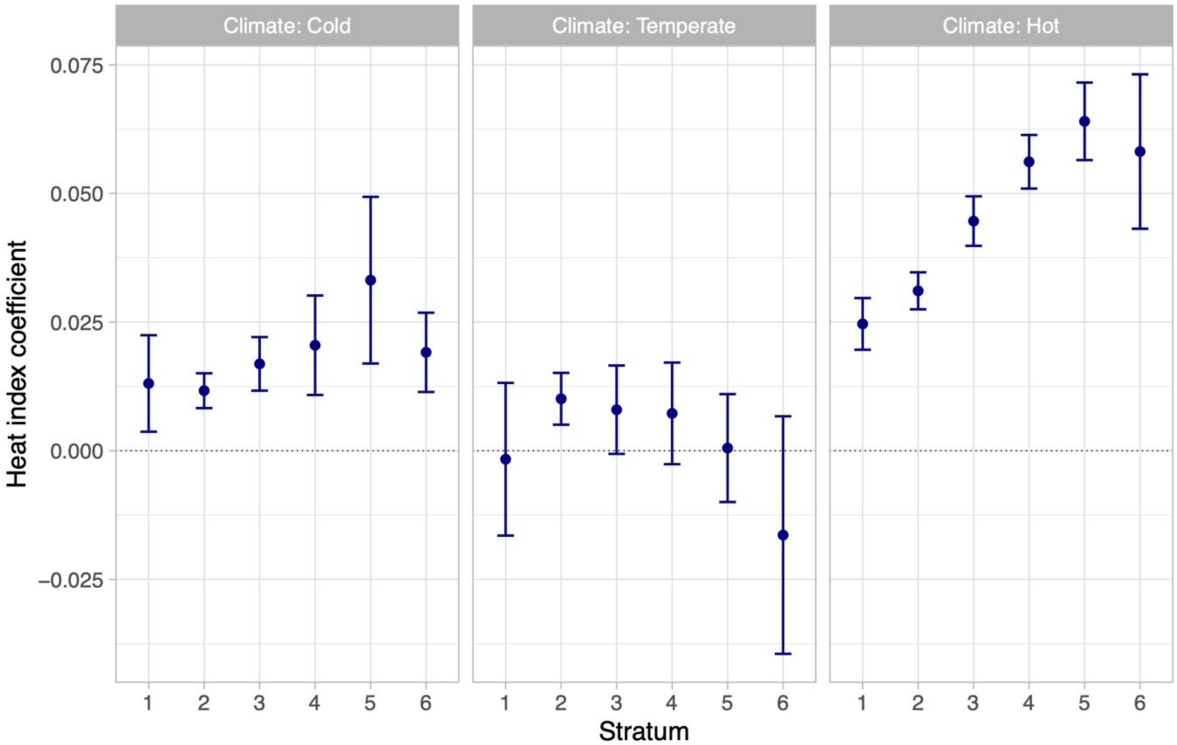

*Notes:* Income per capita data is from the Living Standards Surveys for 2011 to 2019 (excluding 2017). Nominal Colombian pesos were converted to real 2018 United States dollars using the Colombian Consumer Price Index deflator and the 2018 exchange rate. Values of income per capita exceeding $2,000 were set to $2,000 to maintain a reasonable vertical scale. The horizontal line shows the median income per capita for each stratum.

**Figure 5. Electricity Consumption by Climate Region and Stratum, 2010–19**



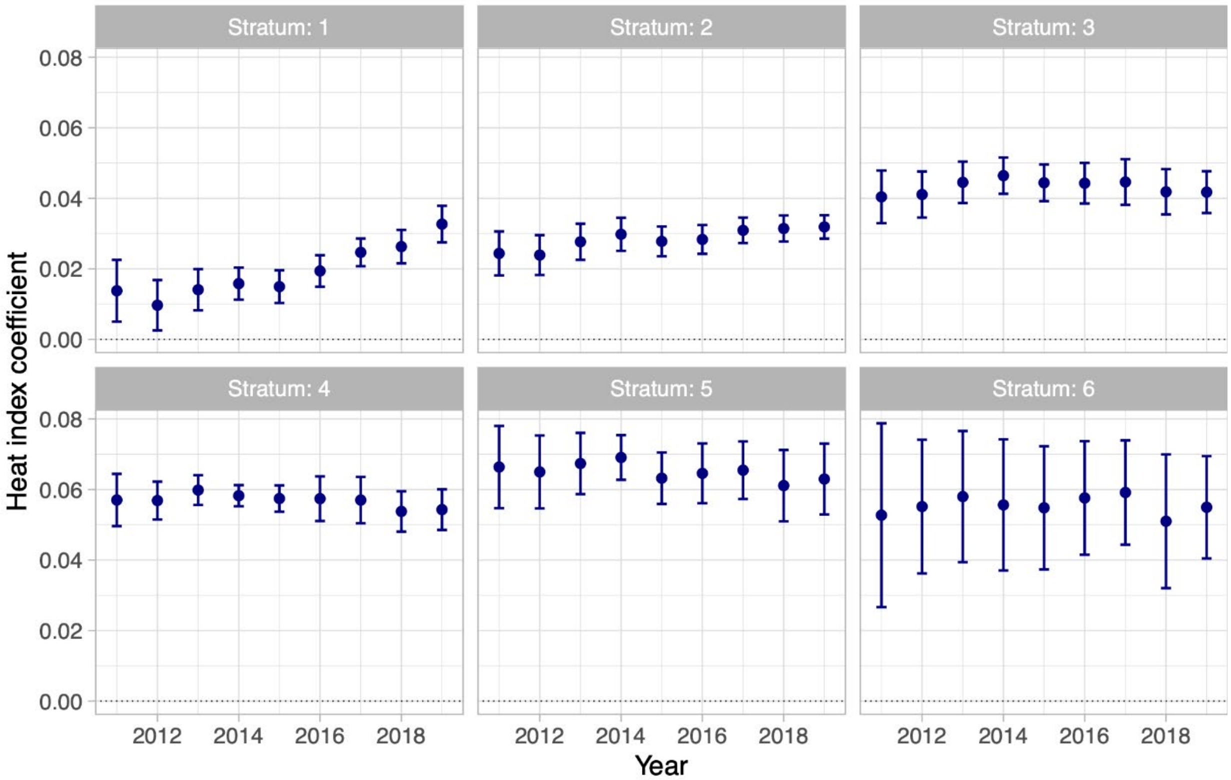

*Notes:* Each panel represents one of three climate regions, defined for each municipality based on the classification in IDEAM (2023). Within each panel, lines depict the mean monthly electricity consumption for households in different strata, with the lowest line for Stratum 1 and the highest line for Stratum 6. Annual means are based on observations in the estimation dataset. No results are shown for 2018 because of many missing observations.

**Figure 6. Effect of the Heat Index on Household Electricity Consumption by Climate Zone and Stratum**



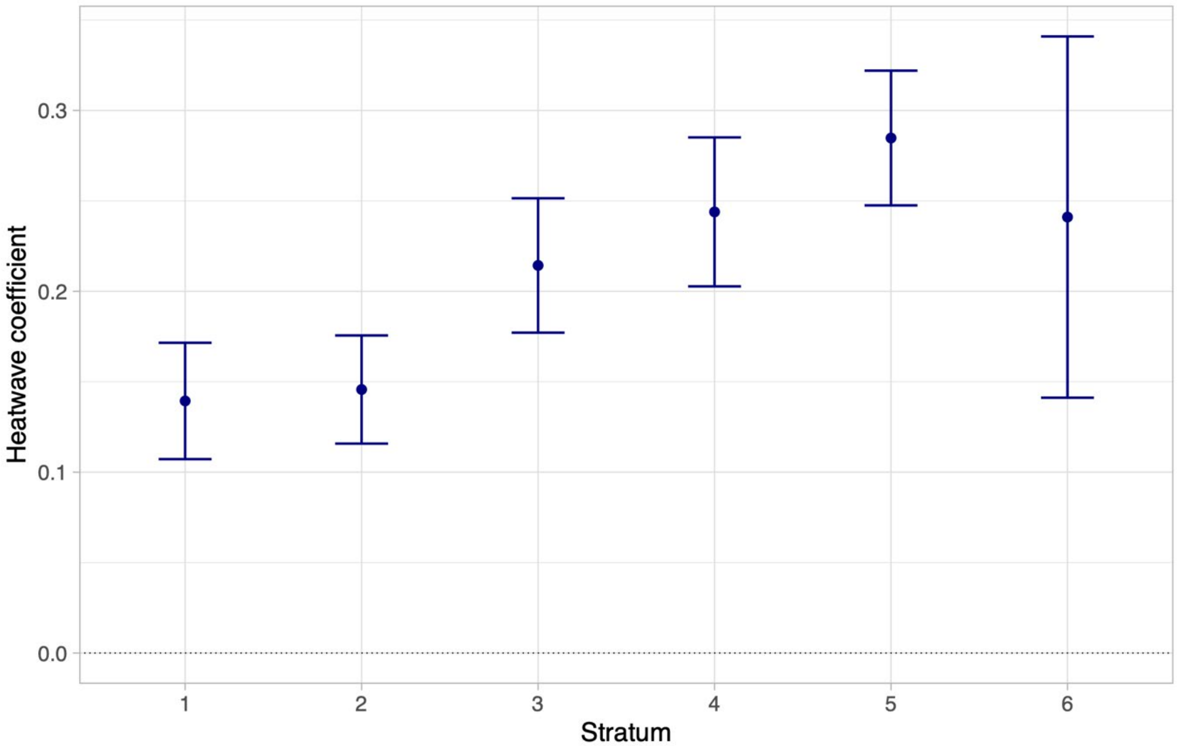

*Notes:* Each panel corresponds to one column in Table 3 and shows the coefficients for the interaction between stratum indicators and the heat index. The error bars show 95 percent confidence intervals, calculated using standard errors clustered by municipality. See also the notes to Table 3.

**Figure 7. Effect of the Heat Index on Household Electricity Consumption in Hot Regions, by Year and Stratum**



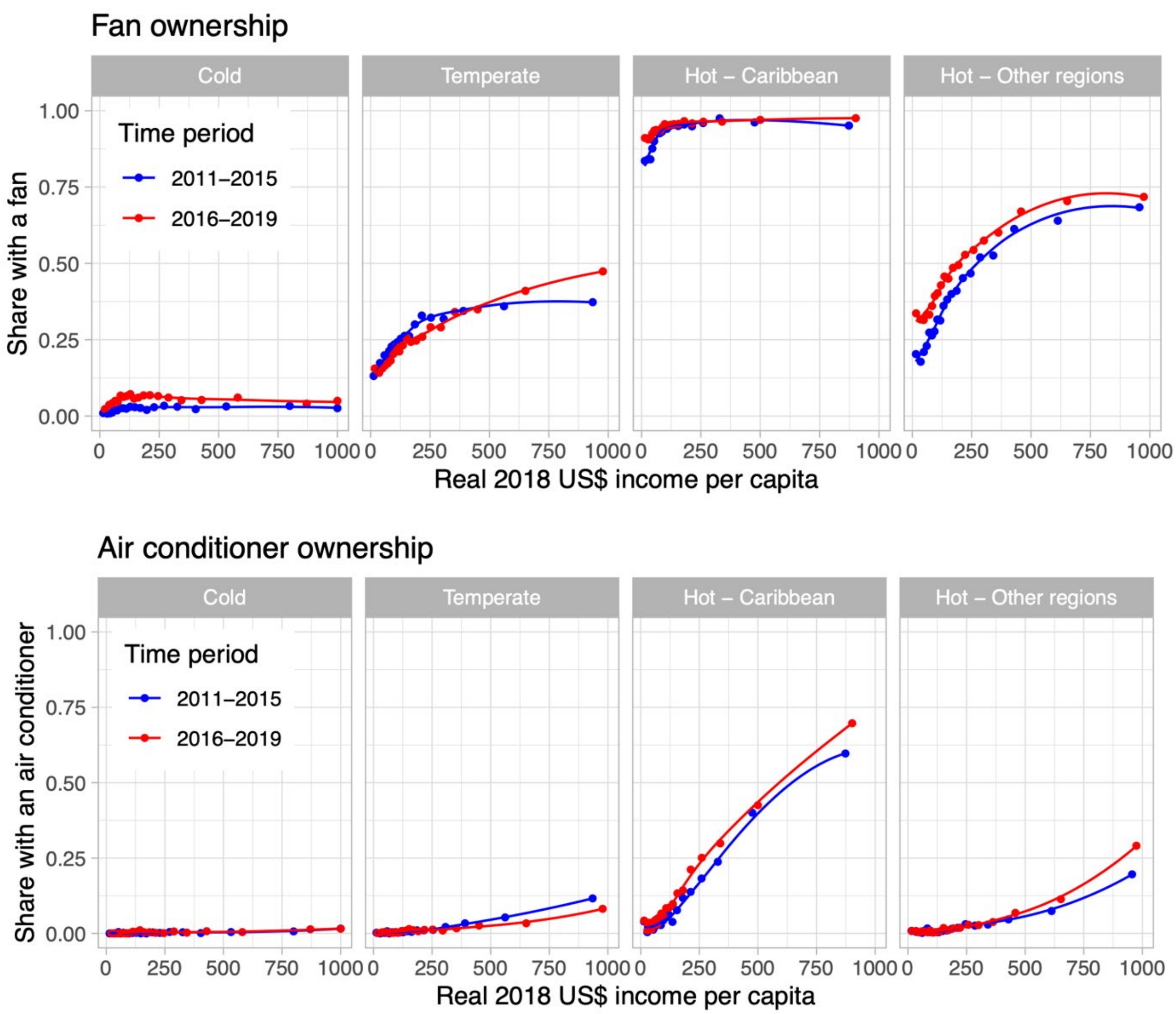

*Notes:* Each panel corresponds to one column in Table 4 and shows the coefficients for the interaction between year indicators and the heat index. The error bars show 95 percent confidence intervals, calculated using standard errors clustered by municipality. See also the notes to Table 4.

**Figure 8. Effect of Heatwaves on Household Electricity Consumption**




*Notes:* The figure shows results from a regression of log electricity consumption on an interaction between stratum indicators and the proportion of heatwave days in the month. Heatwaves are defined as two or more consecutive days with a maximum heat index exceeding 32 degrees Celsius. The sample consists only of households living in a hot climate region. The error bars show 95 percent confidence intervals, calculated using standard errors clustered by municipality.

**Figure 9. Share of Households with Cooling Appliances by Climate Region, Time Period, and Income per Capita**




*Notes:* Each panel shows the share of households owning a fan (top) and an air conditioner (bottom), split by the climate region. See the notes for Table 5 for the definition of the regions. For each period and region, households are divided into 20 equally sized bins of their income per capita. The dots on the graph show the mean share of households owning the appliance for the period, region, and income per capita bin, calculated using the household sampling weights. The lines show a local linear regression fitted through the binned points.

## Table 1. Mean Values of Principal Variables in Billing and Household Survey Data, by Stratum

| | Stratum | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| **Electricity billing data** | | | | | | |
| Consumption (kWh/month) | 130.6 | 144.2 | 156.4 | 174.7 | 207.4 | 292.4 |
| Bill total (US$/month) | 12.85 | 17.14 | 25.25 | 30.41 | 42.42 | 56.65 |
| Temperature (degrees Celsius) | 21.2 | 18.2 | 16.7 | 16.5 | 16.4 | 16.3 |
| Heat index (degrees Celsius) | 22.1 | 18.4 | 16.7 | 16.6 | 16.4 | 16.4 |
| Share of bills | 0.246 | 0.383 | 0.242 | 0.079 | 0.031 | 0.018 |
| **Household survey data** | | | | | | |
| Income (US$/month) | 439.7 | 649.3 | 1020.6 | 1772.1 | 2750.9 | 3763.0 |
| Income per capita (US$/month) | 142.7 | 227.9 | 388.2 | 737.5 | 1195.6 | 1727.5 |
| Number of household members | 3.7 | 3.4 | 3.1 | 2.7 | 2.7 | 2.6 |
| Electricity bill (US$/month) | 11.41 | 16.31 | 27.18 | 34.14 | 46.28 | 87.97 |
| Electricity bill (share of income) | 0.045 | 0.042 | 0.043 | 0.030 | 0.027 | 0.034 |
| Television (0/1) | 0.875 | 0.944 | 0.965 | 0.966 | 0.983 | 0.994 |
| Refrigerator (0/1) | 0.703 | 0.840 | 0.903 | 0.948 | 0.986 | 0.995 |
| Washing machine (0/1) | 0.375 | 0.570 | 0.763 | 0.882 | 0.959 | 0.976 |
| Air conditioner (0/1) | 0.021 | 0.030 | 0.040 | 0.131 | 0.170 | 0.256 |
| Fan (0/1) | 0.483 | 0.321 | 0.279 | 0.404 | 0.378 | 0.391 |
| Share of households | 0.323 | 0.387 | 0.202 | 0.056 | 0.019 | 0.013 |

*Notes:* The table reports the means of selected variables from the billing and household survey data, split by the stratum assigned to each household. Income and bill totals in nominal Colombian pesos were converted to real 2018 United States dollars using the Colombian Consumer Price Index deflator and the 2018 exchange rate. Electricity consumption, bill totals, and income data were trimmed by excluding the top and bottom 0.1 percent of observations. The means of household survey variables are weighted by the survey sampling weights.

**Table 2. Baseline Results for the Effect of the Temperature and Heat Index on Household Electricity Consumption**

| | Stratum | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** |
| **MODEL 1** | | | | | | |
| Temperature | $0.024^{***}$ | $0.028^{***}$ | $0.034^{***}$ | $0.049^{***}$ | $0.055^{***}$ | $0.060^{***}$ |
| | (0.003) | (0.002) | (0.005) | (0.009) | (0.014) | (0.016) |
| **MODEL 2** | | | | | | |
| Heat index | $0.025^{***}$ | $0.032^{***}$ | $0.040^{***}$ | $0.051^{***}$ | $0.060^{***}$ | $0.066^{***}$ |
| | (0.003) | (0.001) | (0.004) | (0.004) | (0.005) | (0.007) |
| **MODEL 3** | | | | | | |
| Temperature | $-0.014^{***}$ | $-0.021^{***}$ | $-0.034^{***}$ | $-0.039^{***}$ | $-0.052^{***}$ | $-0.070^{***}$ |
| | (0.004) | (0.004) | (0.006) | (0.008) | (0.015) | (0.018) |
| Heat index | $0.035^{***}$ | $0.048^{***}$ | $0.064^{***}$ | $0.077^{***}$ | $0.093^{***}$ | $0.103^{***}$ |
| | (0.004) | (0.004) | (0.003) | (0.003) | (0.007) | (0.012) |
| *Fixed effects* | | | | | | |
| Month of sample (112) | Y | Y | Y | Y | Y | Y |
| Household | Y | Y | Y | Y | Y | Y |
| # Household | 224,917 | 356,751 | 221,158 | 69,524 | 28,170 | 16,806 |
| Observations | 22,092,965 | 36,019,770 | 22,591,037 | 7,101,201 | 2,880,283 | 1,722,953 |

*Notes:* The dependent variable in all regressions is the log of monthly electricity consumption for one household. Each column presents the results for one of the six strata. Within each column, the models vary by their regressors: Model 1 includes the mean temperature (in degrees Celsius) during the billing cycle, Model 2 includes the mean heat index (in degrees Celsius) during the billing cycle, and Model 3 includes both. All models include the proportion of Sundays and public holidays, annual state-level GDP, month-of-sample fixed effects, and household fixed effects. Standard errors in parentheses are clustered by municipality. Signif. codes: ***=0.01, **=0.05, *=0.10.

**Table 3. Effect of the Heat Index on Household Electricity Consumption by Climate Zone and Stratum**

| | Climate classification | | |
|---|---|---|---|
| | **Cold** | **Temperate** | **Hot** |
| Heat index | 0.013*** | -0.002 | 0.025*** |
| | (0.005) | (0.008) | (0.003) |
| × Stratum 2 | -0.001 | 0.012 | 0.006*** |
| | (0.005) | (0.007) | (0.002) |
| × Stratum 3 | 0.004 | 0.010 | 0.020*** |
| | (0.004) | (0.009) | (0.003) |
| × Stratum 4 | 0.007 | 0.009 | 0.032*** |
| | (0.006) | (0.009) | (0.003) |
| × Stratum 5 | 0.020** | 0.002 | 0.039*** |
| | (0.010) | (0.010) | (0.004) |
| × Stratum 6 | 0.006 | -0.015 | 0.033*** |
| | (0.006) | (0.013) | (0.007) |
| Prop. holidays | -0.112** | -0.030 | -0.059*** |
| | (0.048) | (0.023) | (0.011) |
| Log(state GDP) | -0.094** | 0.418*** | 0.075** |
| | (0.041) | (0.150) | (0.034) |
| *Fixed effects* | | | |
| Household | Y | Y | Y |
| Month × stratum (672) | Y | Y | Y |
| # Household | 297,870 | 257,406 | 364,248 |
| Observations | 30,629,813 | 25,956,421 | 35,821,975 |

*Notes:* The dependent variable in all regressions is the log of monthly electricity consumption for a household. Each column represents one of the three climate regions, aggregated from the 23 climate zones in the Caldas Lang classification (IDEAM, 2023). The main regressor is the mean heat index (in degrees Celsius) for the billing cycle, interacted with indicators for households in Strata 2 to 6. All models account for the proportion of Sundays and public holidays, annual state-level GDP, month-of-sample-by-stratum fixed effects, and household fixed effects. Standard errors in parentheses are clustered by municipality. Signif. codes: ***=0.01, **=0.05, *=0.10.

**Table 4. Effect of the Heat Index on Household Electricity Consumption in Hot Regions, by Year and Stratum**

| | Stratum | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** |
| Heat index | 0.014*** | 0.024*** | 0.040*** | 0.057*** | 0.066*** | 0.053*** |
| | (0.004) | (0.003) | (0.004) | (0.004) | (0.006) | (0.013) |
| × 2012 | -0.004** | 0.000 | 0.001 | 0.000 | -0.001 | 0.002 |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.005) |
| × 2013 | 0.000 | 0.003** | 0.004*** | 0.003 | 0.001 | (0.005) |
| | (0.003) | (0.001) | (0.001) | (0.002) | (0.002) | (0.005) |
| × 2014 | 0.002 | 0.005** | 0.006** | 0.001 | 0.003 | 0.003 |
| | (0.004) | (0.002) | (0.003) | (0.003) | (0.004) | (0.006) |
| × 2015 | 0.001 | 0.003 | 0.004* | 0.000 | -0.003 | 0.002 |
| | (0.005) | (0.002) | (0.002) | (0.002) | (0.003) | (0.007) |
| × 2016 | 0.006 | 0.004* | 0.004** | 0.000 | -0.002 | 0.005 |
| | (0.004) | (0.002) | (0.002) | (0.001) | (0.003) | (0.007) |
| × 2017 | 0.011*** | 0.007*** | 0.004*** | 0.000 | -0.001 | 0.006 |
| | (0.004) | (0.002) | (0.002) | (0.001) | (0.002) | (0.007) |
| × 2018 | 0.013*** | 0.007*** | 0.001 | -0.003* | -0.005 | -0.002 |
| | (0.004) | (0.002) | (0.002) | (0.002) | (0.003) | (0.009) |
| × 2019 | 0.019*** | 0.008*** | 0.001 | -0.003 | -0.003* | 0.002 |
| | (0.004) | (0.003) | (0.002) | (0.002) | (0.002) | (0.009) |
| Prop. holidays | -0.098*** | -0.047*** | -0.061*** | 0.006 | -0.007 | 0.180 |
| | (0.013) | (0.010) | (0.021) | (0.058) | (0.106) | (0.228) |
| Log(state GDP) | 0.135*** | 0.055 | 0.021 | -0.008 | 0.046 | -0.114 |
| | (0.041) | (0.036) | (0.034) | (0.034) | (0.061) | (0.163) |
| *Fixed effects* | | | | | | |
| Month of sample (112) | Y | Y | Y | Y | Y | Y |
| Household | Y | Y | Y | Y | Y | Y |
| # Household | 134,660 | 135,658 | 63,555 | 18,385 | 7,997 | 3,993 |
| Observations | 13,069,647 | 13,438,138 | 6,315,522 | 1,820,100 | 789,540 | 389,028 |

*Notes:* The dependent variable in all regressions is the log of monthly electricity consumption for a household. Each column represents one of the six strata. The main regressor is the mean heat index (in degrees Celsius) for the billing cycle interacted with indicators for each year from 2012 to 2019. The base period is the last five months of 2010 and all of 2011. All models account for the proportion of Sundays and public holidays, annual state-level GDP, month-of-sample fixed effects, and household fixed effects. The sample is restricted to households in hot regions. Standard errors in parentheses are clustered by municipality. Signif. codes: ***=0.01, **=0.05, *=0.10.

**Table 5. Share of Households with Cooling Appliances by Climate Region and Time Period**

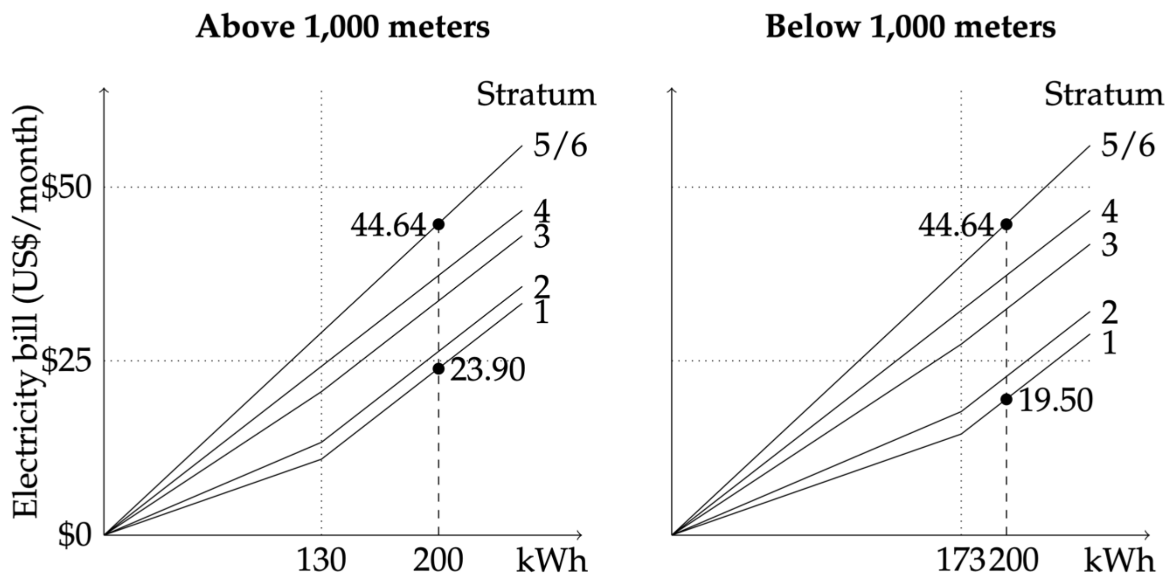
| Climate region | Period | | Difference | t-value |
|---|---|---|---|---|
| | 2011-2015 | 2016-2019 | | |
| **Fan ownership** | | | | |
| Cold | 0.014 | 0.025 | 0.012 | 2.00 |
| Temperate | 0.290 | 0.330 | 0.040 | 1.94 |
| Hot — Caribbean | 0.946 | 0.957 | 0.011 | 1.55 |
| Hot — Other regions | 0.391 | 0.433 | 0.041 | 1.75 |
| All regions | 0.363 | 0.385 | 0.022 | 1.76 |
| **Air conditioner ownership** | | | | |
| Cold | 0.003 | 0.006 | 0.002 | 1.71 |
| Temperate | 0.019 | 0.015 | -0.005 | -1.06 |
| Hot — Caribbean | 0.128 | 0.159 | 0.030 | 2.71 |
| Hot — Other regions | 0.029 | 0.041 | 0.012 | 2.26 |
| All regions | 0.038 | 0.045 | 0.007 | 2.49 |
| Number of observations | 111,848 | 185,908 | | |

*Notes:* The first two columns show the mean share of households owning a fan or air conditioner for the time periods 2011–15 and 2016–19, split by the climate region. The assignment of each household to a region is based on the climate of the capital city in the household's department. The hot region is divided into the Caribbean (defined as the Sucre, Cordoba, Bolivar, Atlantico, Magdalena, Cesar, and La Guajira departments) and other areas. The third column shows the change in ownership between the two periods, and the final column shows the test statistic for a test of equality of the means for the two periods (higher values are stronger evidence against equality). The test statistic is calculated using standard errors clustered by department, location (urban/rural/village), and stratum.

## Appendix A. Examples of Electricity Bill Calculation

Figure A1 illustrates the electricity bill calculation to supplement the description in Section 2.2. The calculations for the figure use the mean regulated base tariff in June 2018: 535 Colombia pesos per kWh, or 18.6 US cents per kWh.

**Figure A1. Calculation of Household Electricity Bills in Colombia**




*Notes:* This figure shows the electricity bill as a function of monthly electricity consumption, by stratum, for households in municipalities above or below 1,000 meters elevation. A regulated base tariff of 18.6 US cents per kWh, the 2018 mean, is assumed for the calculation.

The figure shows the total electricity bill as a function of the monthly consumption in kWh on the horizontal axis. The two panels show the bills for households living above or below 1,000 meters, where this altitude threshold determines the subsidized quantity for Strata 1 to 3 households. Within the panels, each line shows the bill for a different stratum. There are three features to note in the figure. First, at no quantity is there a discrete jump in the bills for Strata 1 to 3 households. The nonlinearity in the tariff only changes the slope of the total bill function at the threshold of 130 or 173 kWh. Second, the marginal price (the slope of the total bill function) is the same for Strata 1 to 3 households and is equal to the regulated base tariff. Finally, while Strata 4 to 6 households face uniform tariffs with constant slopes, the slope is 20 percent greater for Strata 5 and 6.

The figure includes the total bill amounts for three households with monthly consumption of 200 kWh. Consider a Stratum 1 household living at an altitude above 1,000 meters. It receives a 55 percent subsidy for its first 130 kWh of consumption, then pays 18.6 cents for each additional kWh. The total bill for monthly consumption of 200 kWh is US$23.90:

$$Bill_1 = 130 \times (1 - 0.55) \times 0.186 + (200 - 130) \times 0.186 = 23.90$$

A Stratum 1 household living at an altitude below 1,000 meters receives the 55 percent subsidy for its first 173 kWh of consumption. The total bill for monthly consumption of 200 kWh is US$19.50:

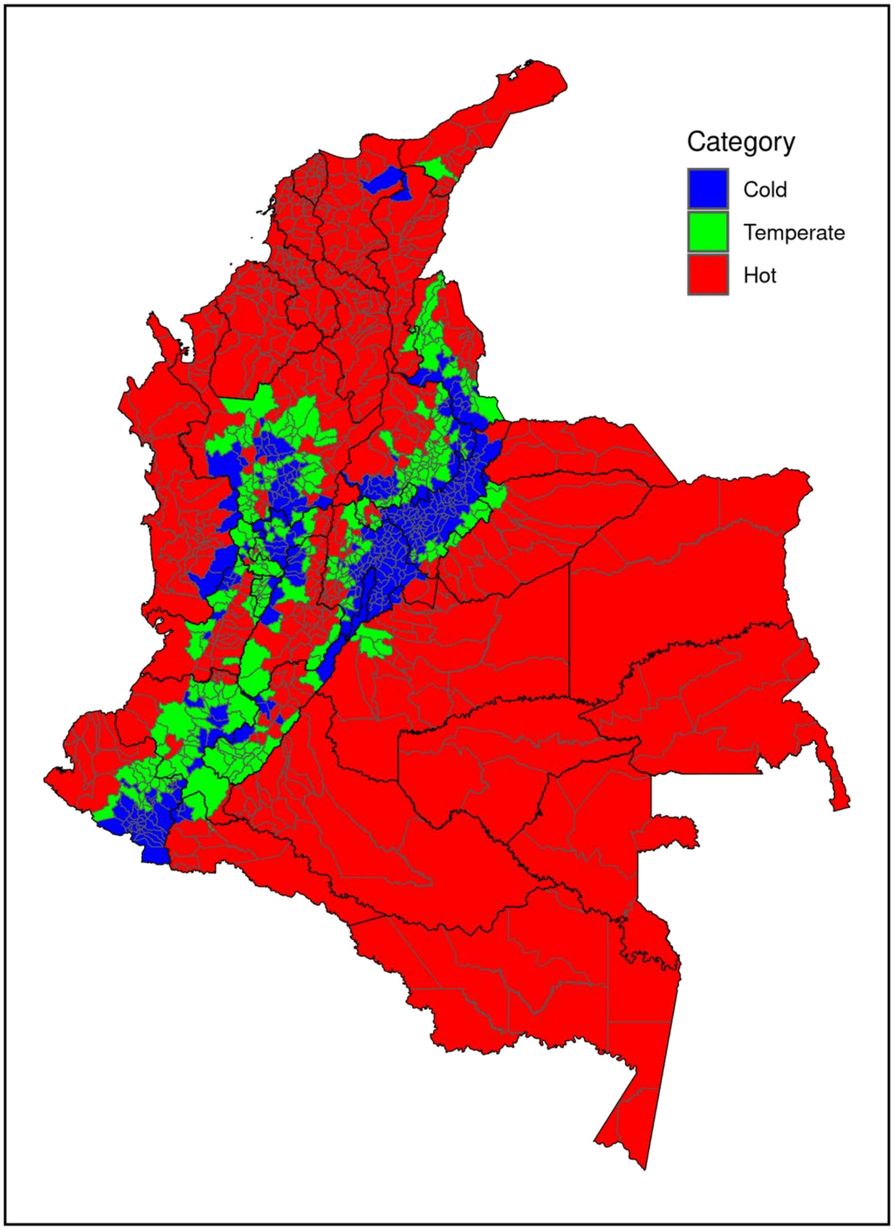
$$Bill_2 = 173 \times (1 - 0.55) \times 0.186 + (200 - 173) \times 0.186 = 19.50$$

For a Stratum 6 household, the price per kWh is the same for all units and includes a 20 percent contribution above the regulated base tariff. The total monthly bill for a consumption of 200 kWh is US$44.64:

$$Bill_3 = 200 \times (1 + 0.2) \times 0.186 = 44.64$$

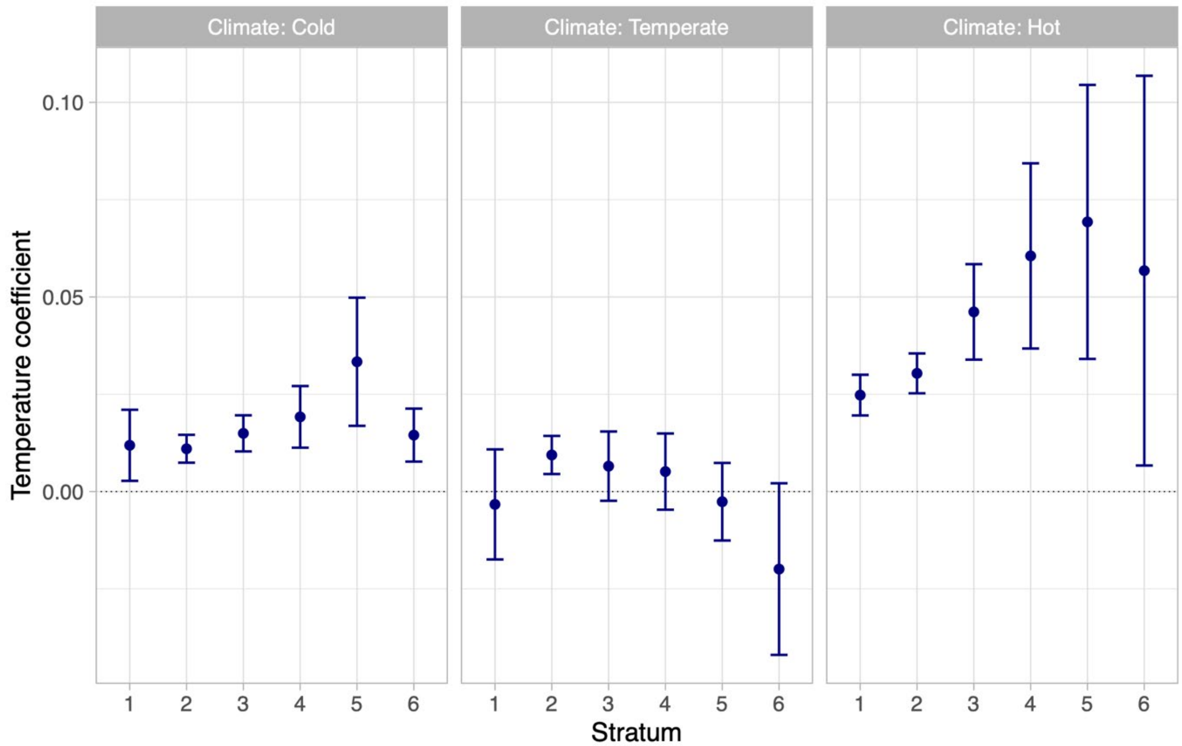
## Appendix B. Additional Tables and Figures

**Figure A2. Classification of Climate Regions**



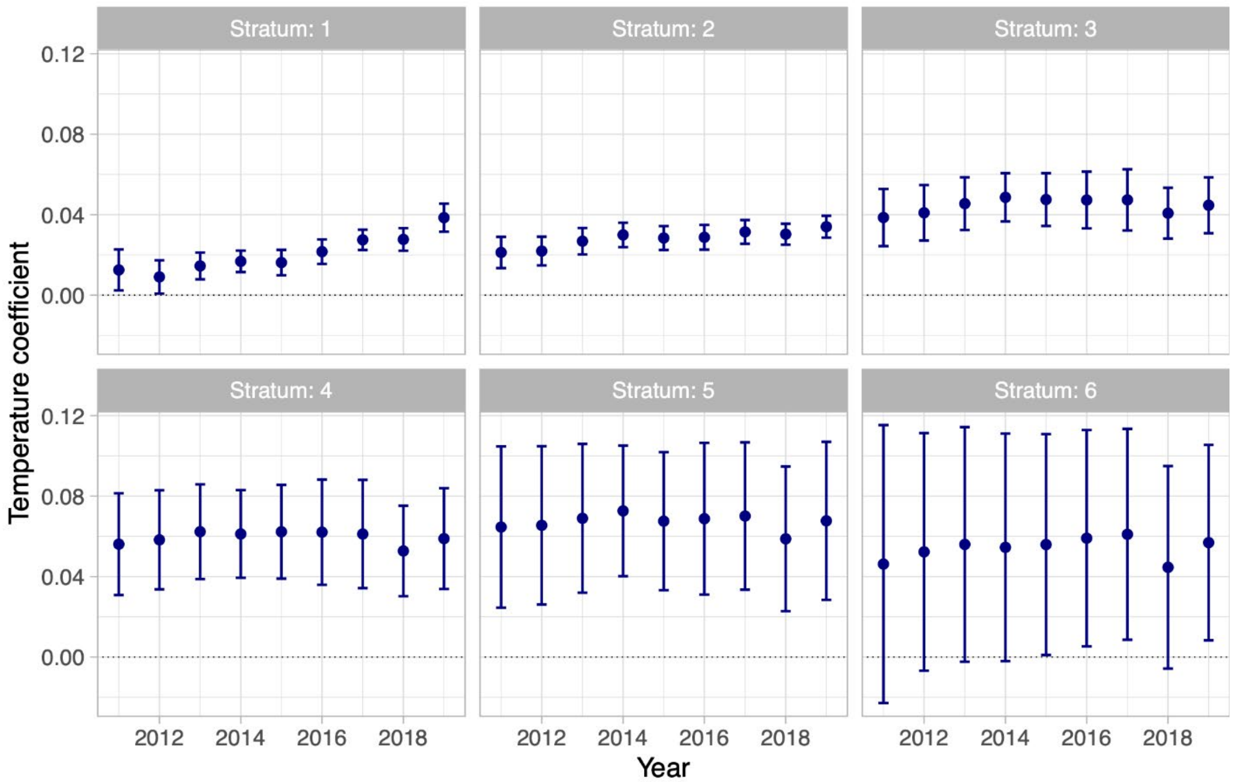

*Notes:* The climate classification is based on the 23 climate zones in IDEAM (2023), aggregated to the three temperature categories of cold, temperate, and hot. Each municipality is assigned to the climate of the largest urban center in the municipality.

**Figure A3. Effect of Mean Temperature on Household Electricity Consumption by Climate Zone and Stratum**



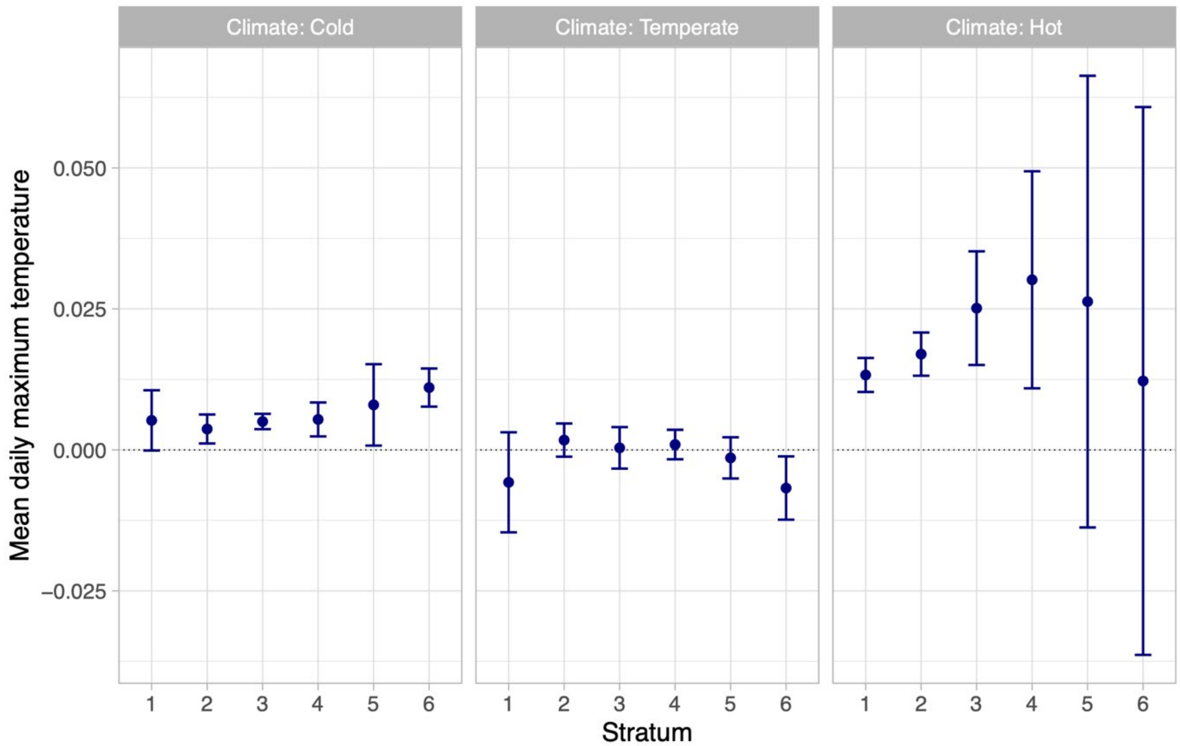

*Notes:* Each panel shows the coefficients for the interaction between stratum indicators and the mean temperature. The error bars show 95 percent confidence intervals, calculated using standard errors clustered by municipality. See also the notes to Table 3.

**Figure A4. Effect of the Mean Temperature on Household Electricity Consumption in Hot Regions, by Year and Stratum**



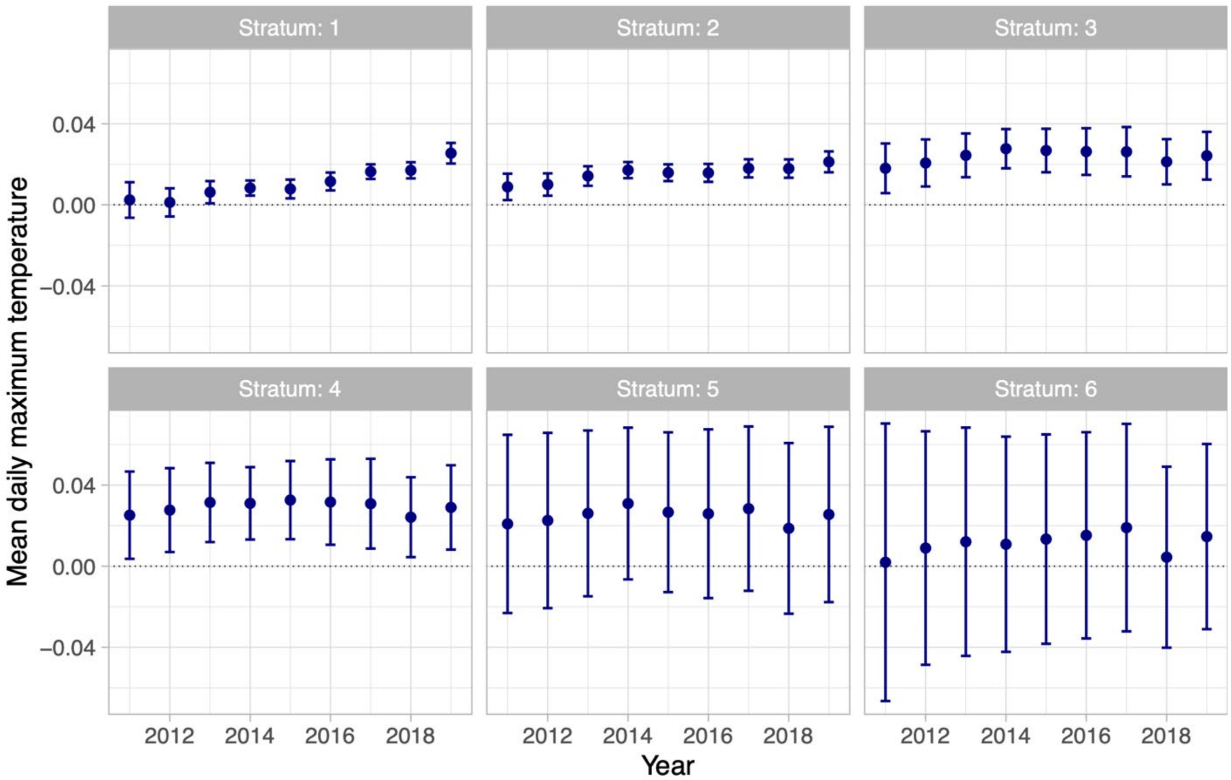

*Notes:* Each panel shows the coefficients for the interaction between year indicators and the mean temperature. The error bars show 95 percent confidence intervals, calculated using standard errors clustered by municipality. See also the notes to Table 4.

**Figure A5. Effect of the Daily Maximum Temperature on Household Electricity Consumption by Climate Zone and Stratum**



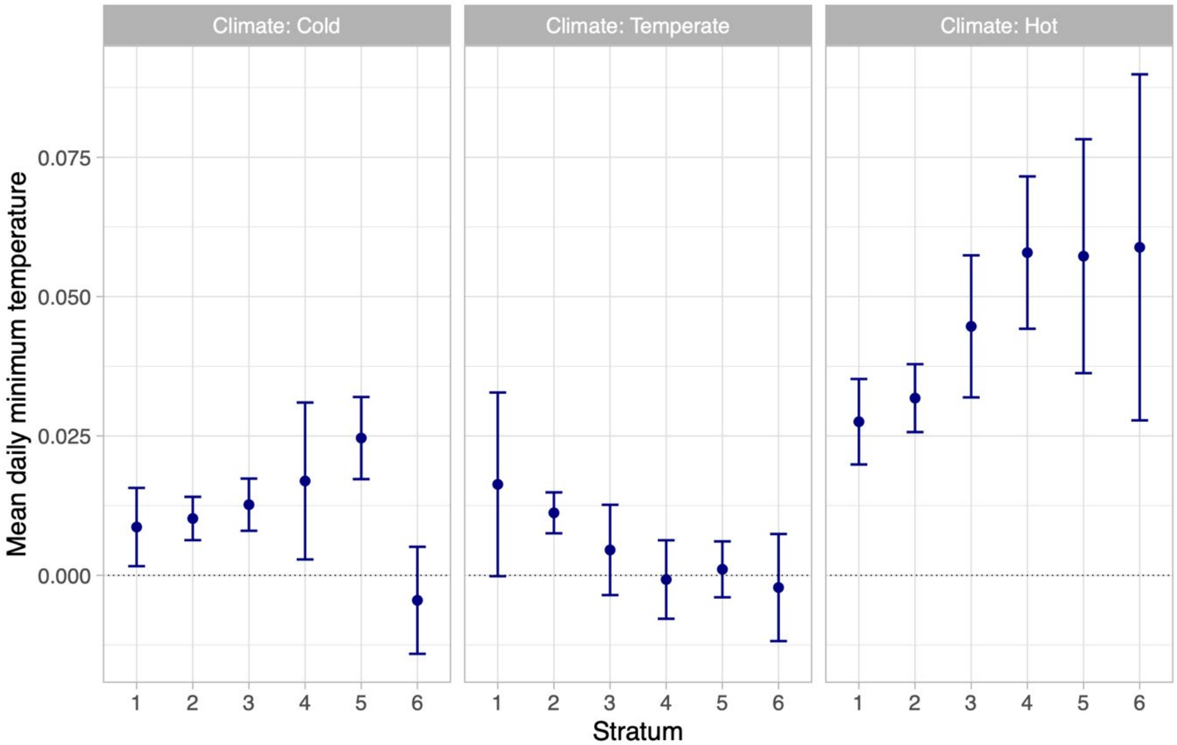

*Notes:* Each panel shows the coefficients for the interaction between stratum indicators and the mean of the daily maximum temperatures during the billing cycle. The error bars show 95 percent confidence intervals, calculated using standard errors clustered by municipality. See also the notes to Table 3.

**Figure A6. Effect of the Daily Maximum Temperature on Household Electricity Consumption in Hot Regions, by Year and Stratum**



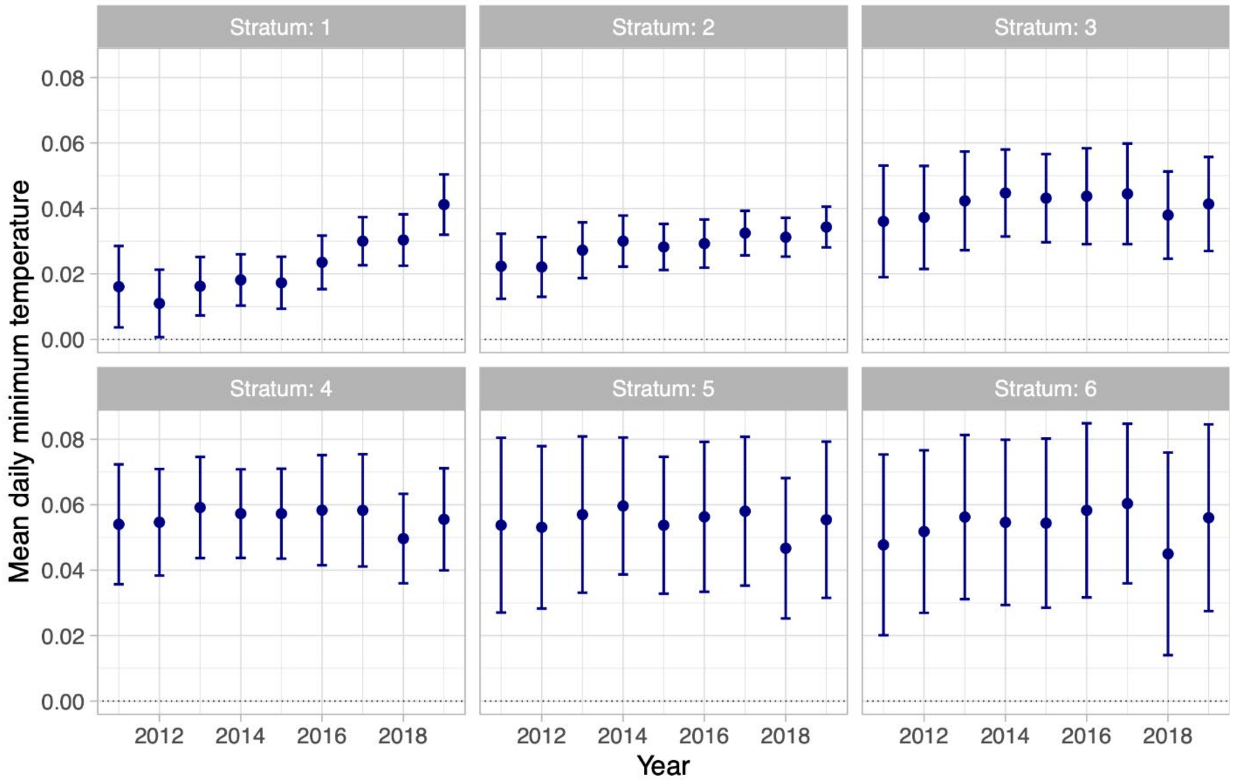

*Notes:* Each panel shows the coefficients for the interaction between year indicators and the mean of the daily maximum temperature. The error bars show 95 percent confidence intervals, calculated using standard errors clustered by municipality. See also the notes to Table 4.

**Figure A7. Effect of the Daily Minimum Temperature on Household Electricity Consumption by Climate Zone and Stratum**




*Notes:* Each panel shows the coefficients for the interaction between stratum indicators and the mean of the daily minimum temperatures during the billing cycle. The error bars show 95 percent confidence intervals, calculated using standard errors clustered by municipality. See also the notes to Table 3.

**Figure A8. Effect of the Daily Minimum Temperature on Household Electricity Consumption in Hot Regions, by Year and Stratum**




*Notes:* Each panel shows the coefficients for the interaction between year indicators and the mean of the daily minimum temperature. The error bars show 95 percent confidence intervals, calculated using standard errors clustered by municipality. See also the notes to Table 4.

**Table A1. Effect of the Mean Temperature on Household Electricity Consumption in Hot Regions, Split by Time-of-Day and Holiday Periods**

| | Stratum | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** |
| Daytime temperature | 0.000 | 0.002 | 0.002 | -0.002 | -0.005 | -0.024 |
| | (0.003) | (0.003) | (0.006) | (0.007) | (0.018) | (0.021) |
| Nighttime temperature | 0.016*** | 0.025*** | 0.045*** | 0.075*** | 0.084*** | 0.080*** |
| | (0.006) | (0.006) | (0.010) | (0.013) | (0.025) | (0.028) |
| Holiday temperature | 0.012*** | 0.008*** | 0.007** | 0.002 | 0.004 | 0.023* |
| | (0.003) | (0.002) | (0.003) | (0.004) | (0.007) | (0.012) |
| Prop. holidays | -0.093*** | -0.043*** | -0.055** | 0.004 | 0.001 | 0.181 |
| | (0.012) | (0.011) | (0.021) | (0.055) | (0.106) | (0.221) |
| Log(state GDP) | 0.151*** | 0.062* | 0.034 | 0.034 | 0.090* | -0.054 |
| | (0.045) | (0.037) | (0.038) | (0.038) | (0.046) | (0.122) |
| *Fixed effects* | | | | | | |
| Month of sample (112) | Y | Y | Y | Y | Y | Y |
| Household | Y | Y | Y | Y | Y | Y |
| # Household | 134,660 | 135,658 | 63,555 | 18,385 | 7,997 | 3,993 |
| Observations | 13,069,647 | 13,438,138 | 6,315,522 | 1,820,100 | 789,540 | 389,028 |

*Notes:* The dependent variable in all regressions is the log of monthly electricity consumption for one household. Each column presents the results for one of the six strata. The three main regressors of interest are: the mean temperature during daytime hours (8 a.m. to 6 p.m.) for non-holiday weekdays and Saturdays, the mean temperature during nighttime hours (6 p.m. to 8 a.m.) for non-holiday weekdays and Saturdays, and the mean temperature on Sundays and public holidays. All models include the proportion of Sundays and public holidays, annual state-level GDP, month-of-sample fixed effects, and household fixed effects. Standard errors in parentheses are clustered by municipality.

**Table A2. Effect of the Mean Heat Index on Household Electricity Consumption in Hot Regions, Split by Time-of-Day and Holiday Periods**

| | Stratum | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** |
| Daytime heat index | 0.007*** | 0.016*** | 0.021*** | 0.031*** | 0.032 | 0.025 |
| | (0.003) | (0.002) | (0.003) | (0.009) | (0.019) | (0.029) |
| Nighttime heat index | 0.008** | 0.007* | 0.019*** | 0.023** | 0.027 | 0.021 |
| | (0.004) | (0.004) | (0.005) | (0.009) | (0.021) | (0.031) |
| Holiday heat index | 0.010*** | 0.007*** | 0.004 | 0.002 | 0.005 | 0.014* |
| | (0.002) | (0.002) | (0.003) | (0.003) | (0.006) | (0.007) |
| Prop. holidays | -0.094*** | -0.042*** | -0.059*** | 0.008 | -0.002 | 0.201 |
| | (0.012) | (0.011) | (0.021) | (0.056) | (0.106) | (0.229) |
| Log(state GDP) | 0.140*** | 0.049 | 0.019 | 0.006 | 0.067 | -0.090 |
| | (0.045) | (0.037) | (0.036) | (0.036) | (0.056) | (0.130) |
| *Fixed effects* | | | | | | |
| Month of sample (112) | Y | Y | Y | Y | Y | Y |
| Household | Y | Y | Y | Y | Y | Y |
| # Household | 134,660 | 135,658 | 63,555 | 18,385 | 7,997 | 3,993 |
| Observations | 13,069,647 | 13,438,138 | 6,315,522 | 1,820,100 | 789,540 | 389,028 |

*Notes:* See the notes to Table A1. The only difference is that the regressors in this table are based on the mean heat index during daytime, nighttime, and holidays, not the mean temperature.