Climate Change and Non-Residential Electricity Consumption in Colombia

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Abstract

More than two thirds of electricity consumption in the world is for commercial and industrial use. In this paper I estimate the relationship between non-residential electricity consumption and short-term weather fluctuations. I use a panel of daily mean temperatures and electricity consumption by large non-residential users in Colombia. I show that electricity usage is most sensitive to temperature for service sector users in warmer regions. I then use these results to describe the potential effect of climate change on non-residential electricity consumption in Colombia.

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1 Introduction

Approximately 70 percent of electricity consumption in the world is for commercial and industrial consumers. Electricity consumption in the non-residential sector is growing rapidly, especially in developing countries. Shopping malls, hotels, office buildings, and data centers are all major electricity users.

Commercial and industrial electricity consumption for air conditioning and refrigeration is greater at higher temperatures. This has two important implications for future growth in energy demand. First, economic growth in tropical regions will, all else being equal, cause larger increases in non-residential electricity consumption than the same growth in temperate regions. Second, more extreme heat days as a result of climate change will lead to further increases in electricity consumption.

The relationship between non-residential electricity consumption and temperature in developing countries is particularly important. Penetration of air conditioning in the commercial sector occurs faster than in the residential sector. Commercial air conditioning at shopping malls or movie theaters may act as a substitute for residential air conditioning. In most cases, the customers and workers who benefit from air conditioning in the commercial sector are not responsible for paying for it. With a zero marginal price, consumption may be higher than in the residential sector where most households are responsible for their electricity bills.

Several authors (including Mansur, Mendelsohn and Morrison (2008), Auffhammer and Aroonruengsawat (2011) and Chong (2012)) have studied the relationship between temperature, air conditioning demand, and electricity consumption for residential users. However, there has been very little analysis of this relationship for non-residential electricity consumption. Auffhammer and Mansur (2014) suggest that such studies are "urgently needed for the industrial and commercial sectors" (p. 522).

In this paper I use daily data from Colombia to estimate the response of non-residential electricity consumption to temperature. I show that the overall response is greatest in regions with a warm climate (where air conditioning penetration is highest) and for smaller users (generally commercial buildings instead of industrial plants). In the warmest region, shifting from the bottom quintile to the top quintile of the daily temperature distribution will increase the non-residential electricity consumption in the mean municipality by about 8 percent. I then combine these estimates of the usage-temperature gradient with data from global climate change simulation models. These provide the simulated distribution of future temperatures at a relatively fine geographical scale. I use these distributions to derive an overall effect for electricity consumption in the non-regulated sector in Colombia, accounting only for the change in the temperature distribution. The result implies an overall 1.1 percent increase in non-residential electricity usage due to temperature changes alone, holding everything else constant. This is likely to be a lower bound on the total effect.

Section 2 below describes the data that I use in the analysis. Section 3 sets out the empirical framework and Section 4 the empirical results. Section 5 then incorporates the climate change simulations. Section 6 concludes.

2 Data

The data set used for the analysis combines daily data on the electricity consumption of commercial and industrial firms in Colombia with daily weather data. The daily electricity consumption data is from XM, the system operator for the Colombian wholesale electricity market. All customers who wish to participate in the deregulated market are required to have a real-time meter. The publicly available daily consumption data from these real-time meters is aggregated by retailer, municipality, and distribution voltage level. For example, one observation is the consumption of Electricaribe customers in Cartagena with an 11kV connection on January 15, 2012.

This data is combined with quarterly reports with the identity of all customers who purchase electricity in the deregulated market. These reports list the name, municipality, industrial classification, and distribution voltage of all customers. For smaller municipalities, where there is only one firm with a particular voltage level in the municipality, the combination of these two datasets allows the daily electricity consumption of individual firms to be identified. For larger municipalities, although individual firm data is not available, the industrial composition of electricity users of a particular voltage level can be calculated.

Each municipality is matched with long-run average climate data at 464 weather stations from IDEAM, the government meteorological service in Colombia. These data are adjusted for differences in altitude between the weather station and the town centre using the relationship between temperature and altitude, estimated from the same data.

The primary source of daily weather data is the Global Surface Summary of the Day provided by the National Oceanic and Atmospheric Administration (NOAA). This has daily summaries of minimum, maximum, and mean temperatures, among other variables, for 26 locations in Colombia. In order to obtain a more complete geographical coverage, this data is supplemented by daily mean temperature data from IDEAM for several additional weather stations. Municipalities are matched to data from the nearest weather station within the same climate zone.

The most striking feature of tropical climates is the lack of intra-annual variation in temperatures at a given location. Although there are large changes in temperature for different altitudes (even over short distances), at any altitude there is very little change in temperature over time. Figure 1 shows the historical distribution of temperatures for the four largest cities in Colombia, for the years in the sample data. As can be observed, the temperature distributions are very narrow and there is little overlap with temperatures in other climate zones. For example, during the sample, the maximum temperature observed for Bogota was less than the minimum temperature observed for Barranquilla.

3 Empirical methodology

An important feature to capture in the empirical analysis is the potential non-linear relationship between electricity consumption and temperature. At low temperatures, where electricity is being used for heating, an increase in temperature can reduce in electricity consumption. Conversely, at high temperatures, where electricity is being used for air conditioning, electricity consumption increases with temperature. In temperate conditions there might be no relationship between electricity consumption and temperature.

One widely used approach to this problem is to convert the temperature data into heating degree and cooling degree days. These measures are based on a base temperature (usually 18 degrees Celsius). Cooling degrees are calculated as the difference between the mean daily temperature and the base temperature, if this is positive, and zero otherwise. Heating degrees are calculated as the difference between the base temperature and mean daily temperature, if this is positive, and zero otherwise.[1] Heating degrees and cooling degrees can be summed over time to measure the total heating or cooling requirements over a given period. One disadvantage of these measures is that they impose an assumption about the base temperature. This might vary based on building characteristics and occupant preferences for indoor air temperature. Another problem is that they still impose a linearity assumption on temperature response at very low or very high temperatures.

Several recent studies of temperature response functions allow for a much more flexible relationship between the variable of interest and temperature. One approach is to divide the

[1] More complex versions of these formulae are used when the temperature fluctuates above and below the base temperature at different hours of the day.

data into temperature bins and count the number of days lying within each bin. This has the problem that there might be very few observations in some of the more extreme temperature bins. An alternative is to divide the data into equally-sized bins using percentiles of the temperature distribution.

There is a fundamental problem with applying these empirical methodologies to temperature data from a tropical country such as Colombia. As shown in the previous section, at a fixed location there is very little variation in temperature, even though there is considerable variation in temperature across locations based on altitude. In many locations in Colombia, the entire temperature distribution would lie within a single temperature bin used by Barreca et al. (2013). This limited variation means that it is not possible to estimate a single temperature response function over a wide range of temperatures, as in Auffhammer and Aroonruengsawat (2011).

Instead, I divide the country into three climate zones: cool, temperate, and warm. Cool regions have an average temperature of 20 degrees Celsius or less, temperate regions have an average temperature of between 20 and 26 degrees, and warm regions have an average temperature of more than 26 degrees.[2] I then estimate separate temperature response functions for each of these climate zones. For each municipality I calculate the quintiles of daily mean temperature and allow the electricity consumption effect to vary by quintile.

I exploit the panel structure of the data for my base regression specification:

$$\log q_{itm} = \sum_k \beta_k D_{kit} + \phi_m + \varepsilon_{it} \tag{1}$$

Here q_{itm} is the electricity consumption by unregulated users in municipality (and voltage level) i on day-of-sample t. The indicator variables D_{kit} correspond to the quintile of daily temperature on day-of-sample t in municipality i. The regression includes municipality and month-of-sample fixed effects ϕ_m. The inclusion of the ϕ_m mean that the temperature sensitivity parameters are identified from within-month variation in temperature for each municipality. I estimate this regression separately by climate region.

[2]The break points of 20 and 26 degrees were chosen based on natural breaks in the distribution of mean temperatures across weather stations in Colombia.

4 Results

Figure 2 plots the coefficients and confidence intervals from the estimation of Equation (1), separately for the three different climate zones. For each regression, the middle quintile of within-municipality daily temperature is the excluded group. Each coefficient can be interpreted as the log change in commercial electricity consumption in an average municipality from shifting the mean daily temperature from the middle quintile to a higher or lower quintile of daily temperatures. For example, in the warmest region, shifting the daily temperature from the lowest to the highest quintile would increase electricity consumption by approximately 8 percent.

The results show that the electricity consumption-temperature gradient is steepest in the warmest region where air conditioning penetration is highest. There is suggestive evidence (though not statistically significant) of a U-shaped relationship between temperature and electricity consumption in the cool region, possibly reflecting heating-related electricity use on the coldest days. For the temperate region, electricity consumption by the unregulated users has little relationship to temperatures. The point estimate for the change in consumption from shifting temperatures from the lowest to the highest quintile is less than two percent.

The results in Figure 2 are not weighted by the electricity consumption of the municipality. This means that they can be interpreted as the effect on an average municipality. However, for predicting the effect of climate change on aggregate electricity consumption for commercial users, it is necessary to place more weight on municipalities with higher electricity consumption.

Figures 3 to 6 show the results for estimation of Equation (1) with the data split based on the connection voltage of each customer. There are four categories of connection: less than 1 kV, between 1 kV and 30 kV, between 30 kV and 57.5 kV, and above 57.5 kV. Customers with lower voltage connection are typically service industry firms in commercial real estate. Higher voltage connections tend to be large industrial users instead of office buildings. The observations are weighted based on the monthly consumption of that category of consumers in each municipality.

Figures 3 and 4 show that, in aggregate, there is an upward-sloping relationship between electricity consumption and temperature for commercial users with connections below 30 kV. This relationship is steepest for firms in the warmest areas. Figures 5 and 6 show that there is almost no aggregate relationship between electricity consumption and temperature for users with connections above 30 kV. These results suggest that the electricity use of service industry firms (who typically have lower voltage connections) is more sensitive to fluctuations in temperature than the electricity use of industrial firms. This result is highly intuitive: we would not expect the electricity consumption for most industrial processes to be affected by weather conditions, while weather would be expected to have a strong effect on electricity consumption for commercial buildings.

5 Future climate change and non-residential electricity consumption

The previous section provides estimates of the relationship between short-term weather fluctuations and non-residential electricity consumption. In this section I use these estimates, combined with projections of future climate in Colombia from global climate models, to predict the change in commercial and industrial electricity consumption due to climate change.

There are a large number of models of future climate change. Two broad categorizations of these predictions are by emissions scenario and by climate model. In 2000, the IPCC set out six groups of scenarios for future emissions growth in a business-as-usual case with no major policies to reduce carbon emissions. These scenarios differ in the degree of global integration and the amount of fossil fuel use. The different climate models, known as General Circulation Models (GCMs), are each identified with a particular institute or working group. All of the GCMs are based on a three-dimensional grid of the Earth's atmosphere.

I use downscaled data from the World Bank's Climate Change Knowledge Portal. This data has a daily resolution on a spatial grid of 0.5 by 0.5 degrees. The forecast data is available for two twenty-year periods: 2045 to 2064 and 2081 to 2100. The dataset also has historical data that has been constructed using the same grid resolution. I use the historical data from 1981 to 2000.

For each grid cell in Colombia, I extract the historical and future time series of minimum and maximum daily temperatures. I take the midpoint of these as the estimate of mean daily temperature.[3] Figure 7 shows the distribution of historical and future temperatures for the four largest cities in Colombia.[4]

[3] Mean temperature is not available in the downscaled data provided by the Climate Change Knowledge Portal.

[4] Comparing the distribution of historical temperatures from the downscaled climate models, to the distribution of weather station data for these cities, there is a close match between the two distributions for Barranquilla and Bogota. However, for Medellin and Cali, the mean historical temperatures from the climate models are everal degrees below the measured temperatures in these cities. This reflects the location of these

Using the twenty years of historical data, I calculate the quintiles of daily temperature for each grid cell. I then count the number of days in the future climate data for 2045 to 2064 that lie within each of the historical deciles. I use the distribution of historical and future temperatures across the five quintiles to calculate the weighted average of the temperature bin coefficients reported in the previous section. The ratio of the weighted average future coefficient to the weighted average historical coefficient provides an estimate of the change in commercial electricity consumption directly attributable to the temperature effects of climate change.

These estimates are reported in Table 1. The increase in consumption is greater than two percent for the two customer groups with the smallest connection size, in both the warm and cool climate zones. Unsurprisingly, based on the coefficient estimates reported in the previous section, there is only a small change for customers in the temperate region. The overall increase in electricity consumption is 1.1 percent. This is at the bottom end of the range of 1–6 percent, reported by Auffhammer and Aroonruengsawat (2011), for the potential increase in residential electricity consumption in California by 2100.

6 Conclusion

In this paper I estimated the relationship between commercial electricity consumption and daily temperatures for Colombia. The degree to which electricity consumption rises with temperature depends on the climate zone and the capacity of the electricity connection. Small and medium commercial customers in the warmest region show the steepest relationship between electricity consumption and temperature. Usage by large industrial customers is largely unaffected by temperature.

I then combined these estimates with output from climate simulation models to predict the change in electricity consumption for one particular scenario of future climate change. The results suggest an overall increase of slightly more than 1 percent in aggregate commercial and industrial consumption, purely as the result of the temperature effect on electricity consumption.

There are several reasons why this number may be an underestimate of the likely effect of climate change on commercial and industrial electricity consumption. Although the methodology allows for non-linearity in the temperature response, there is no additional effect from

cities in valleys with a large difference between the temperature in the cities and the temperature in nearby mountainous regions. Because the downscaling process averages the temperature over fairly large grid cells, the mean temperature in the grid cells containing these cities is lower than the temperature in the cities.

extreme heat days. These are considered to have the same effect as any other day in the top quintile of temperatures. Any additional electricity consumption increase from more extreme heat days will be additional to the previous calculations.

Second, a major reason why the aggregate effect is small is that a significant proportion of overall non-residential electricity use occurs for industrial processes that are unaffected by temperature. If the composition of non-residential electricity use changes over the next half-century, with an increase in the proportion of commercial relative to industrial usage, then the overall effect will be weighted more towards the commercial estimation results. These showed a stronger relationship between electricity consumption and temperature.

Third, the calculation assumes that the electricity usage gradient with respect to temperature remains constant for each customer category and climate zone. However, as shown in the analysis, the gradient is steeper for regions with warmer temperatures, most likely due to greater penetration of air conditioning. It is possible that future climate change will change the gradient of this relationship if it leads to more installations of air conditioners in areas that are currently temperate.

Finally, the overall impact of climate change on the electricity sector may be larger if high-temperature days are more common in low-water years. In that case, the increase in consumption estimated above could place considerable additional stress on the hydro-dominated generation sector in Colombia.

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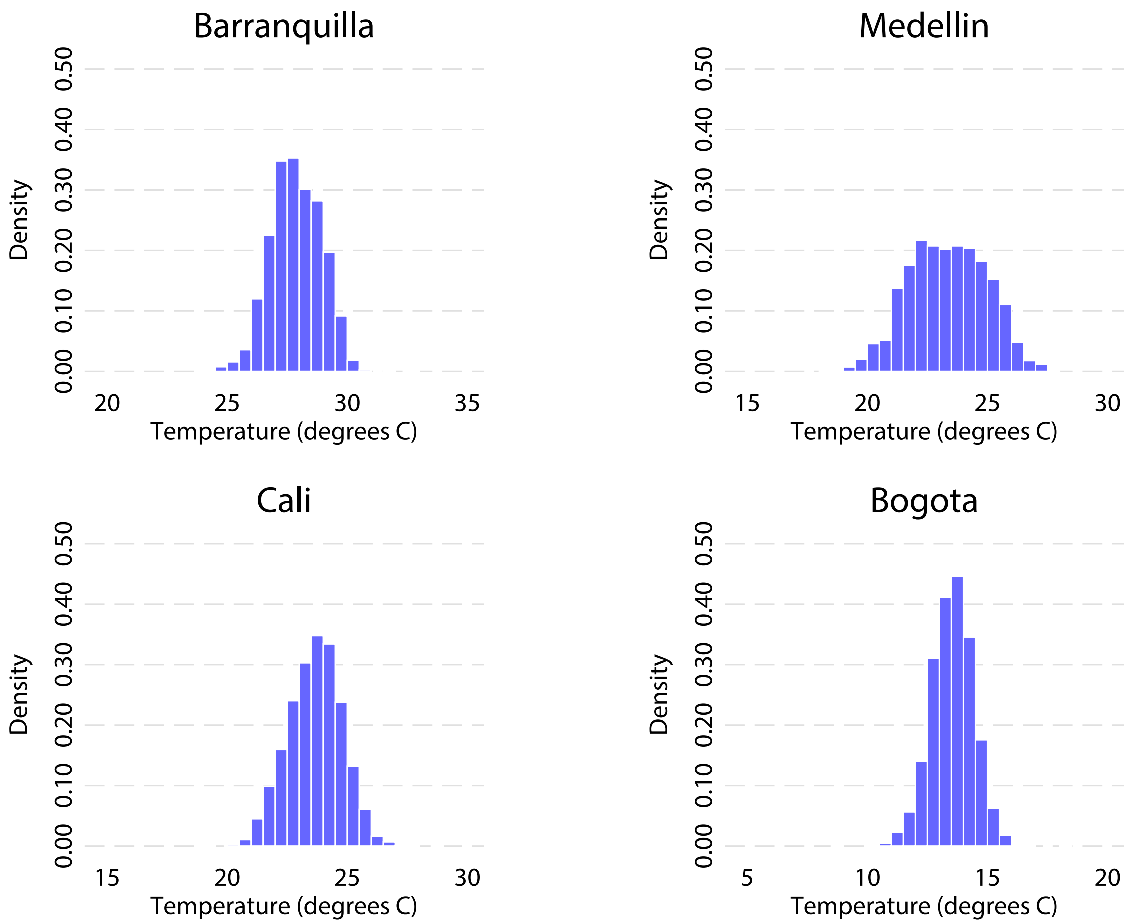
Table 1: Effect of climate change on non-residential electricity consumption

Climate zone	Connection type	Percent increase	Consumption 2014 (GWh)
Above 26 degrees	Below 1 kV	3.1%	36.1
	1 kV - 30 kV	2.1%	1965.0
	30 kV - 57.5 kV	1.0%	996.2
	Above 57.5 kV	0.1%	2401.3
20–26 degrees	Below 1 kV	1.1%	104.2
	1 kV - 30 kV	1.5%	1334.0
	30 kV - 57.5 kV	0.03%	2226.0
	Above 57.5 kV	0.01%	569.6
Below 20 degrees	Below 1 kV	2.6%	67.8
	1 kV - 30 kV	2.2%	1882.1
	30 kV - 57.5 kV	1.8%	1867.7
	Above 57.5 kV	1.4%	507.2
TOTAL		1.1%	13957.4

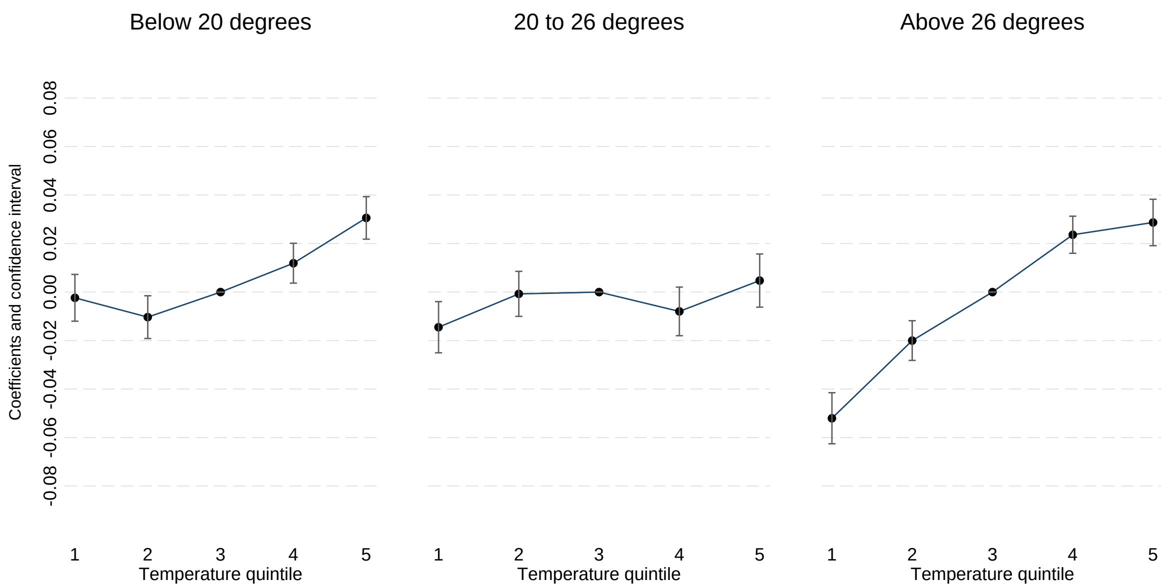
Note: The consumption effects in each climate zone and connection type are based on a reweighting of the temperature quintile coefficients using the new distribution of temperatures for 2046–2065. Aggregate consumption excludes 3385 GWh not assigned to a climate zone.

Figure 1: Distribution of daily mean temperatures for four cities in Colombia



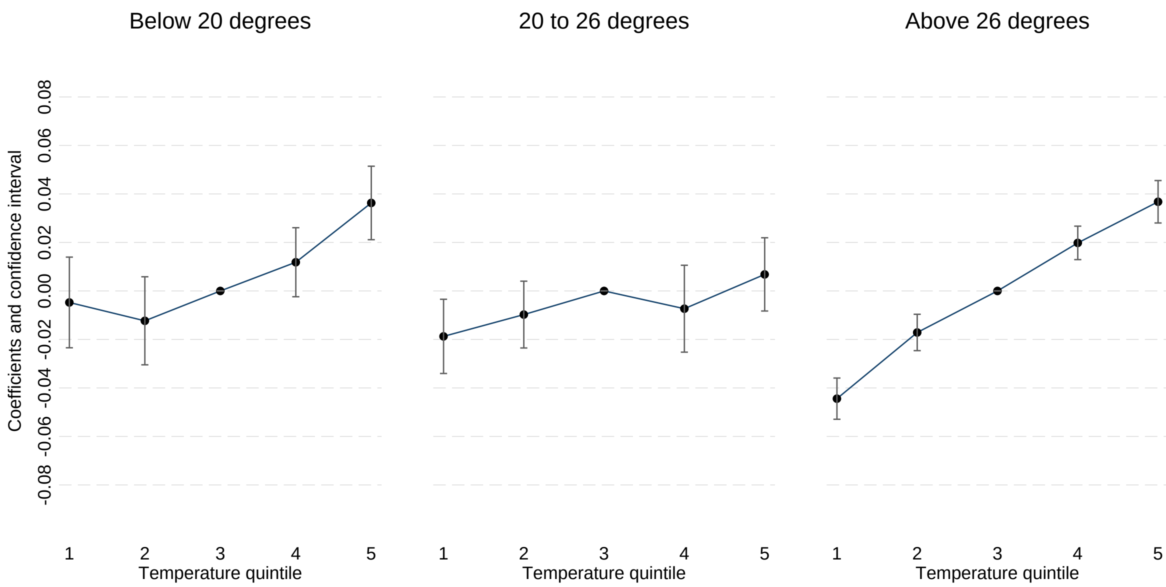
Notes: Data is from the Global Surface Summary of the Day for 2006–2014. Data for Medellin is missing before 2010.

Figure 2: Temperature response functions for unregulated electricity users, by climate region



Notes: Each graph shows the coefficients and standard errors for a regression of daily municipality-level electricity consumption for unregulated users on quintile bins of daily temperature.

Figure 3: Temperature response functions for unregulated electricity users, by climate region: connection less than 1 kV



Notes: Each graph shows the coefficients and standard errors for a regression of daily municipality-level electricity consumption on quintile bins of daily temperature, for unregulated users with connection voltage below 1 kV. Observations are weighted by the monthly total consumption by category in each municipality.

Figure 4: Temperature response functions for unregulated electricity users, by climate region: connection between 1 kV and 30 kV

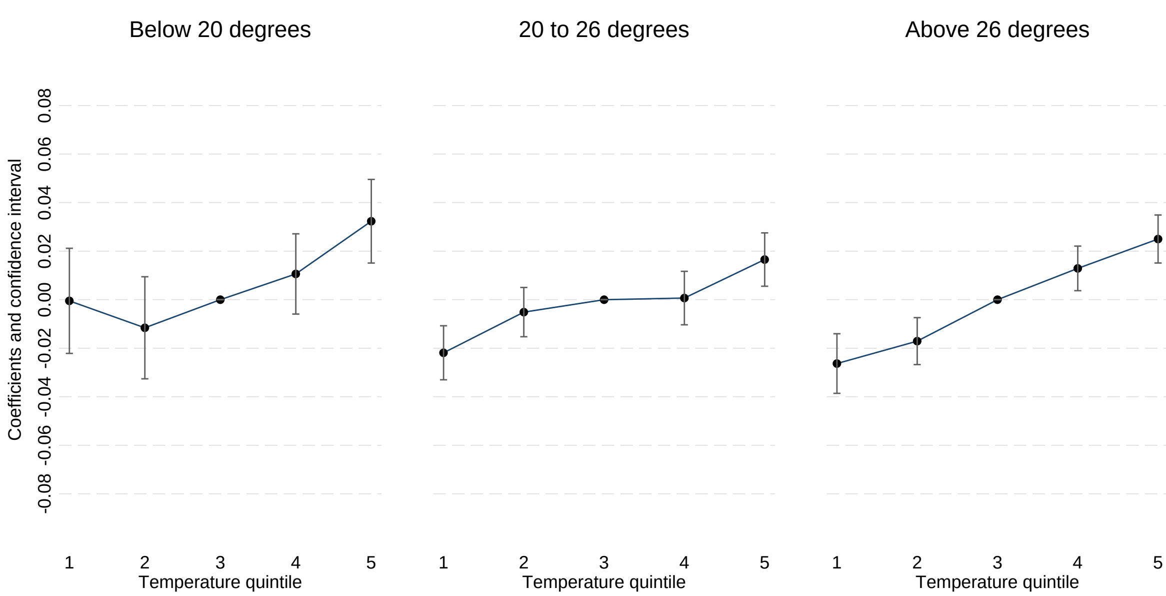


Figure 5: Temperature response functions for unregulated electricity users, by climate region: connection between 30 kV and 57.5 kV

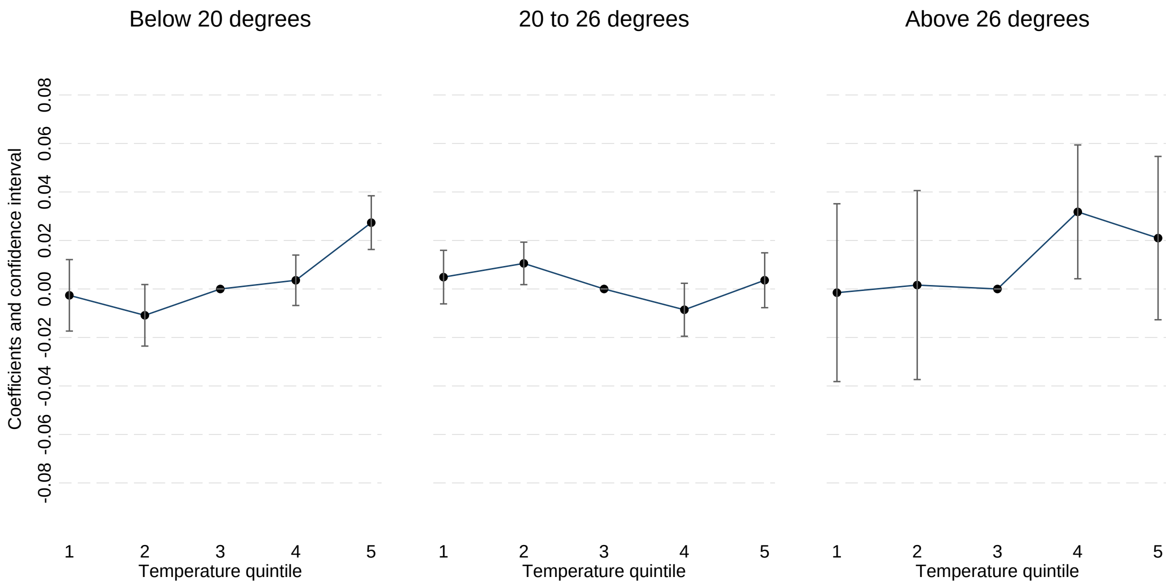


Figure 6: Temperature response functions for unregulated electricity users, by climate region: connection above 57.5 kV

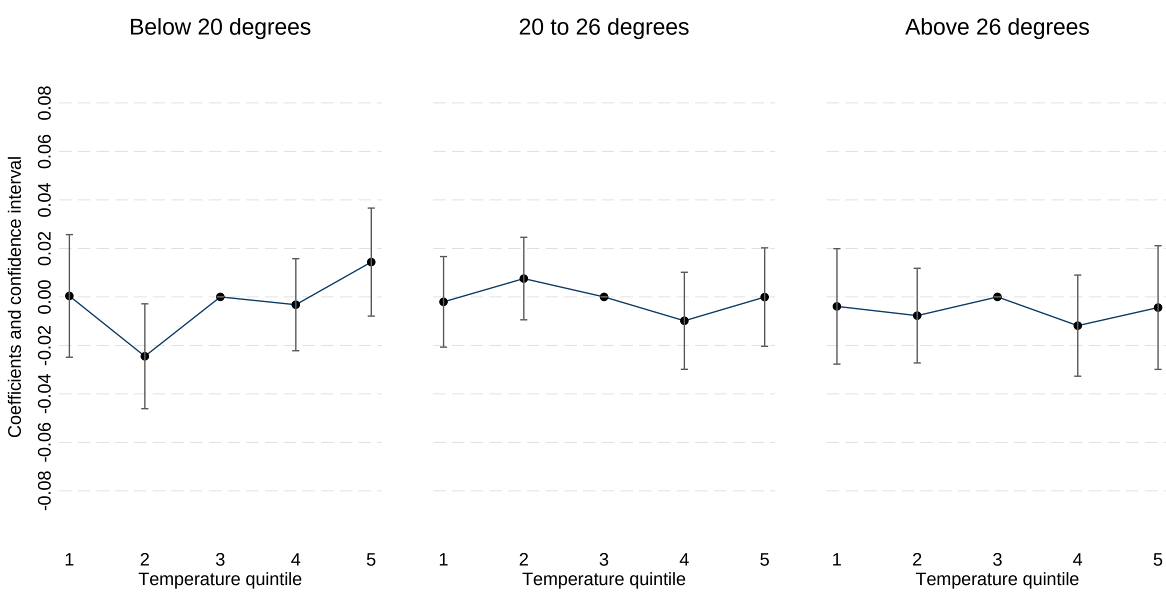
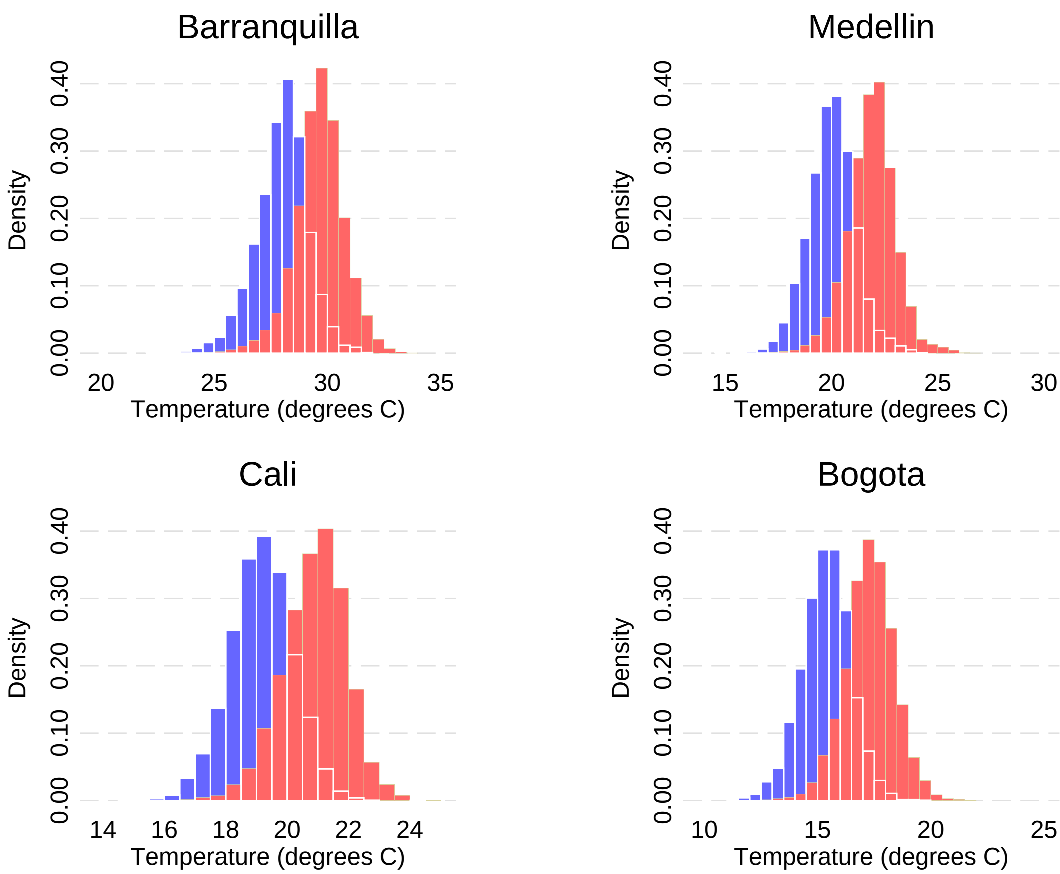


Figure 7: Distribution of daily temperatures for major cities, historical and simulated



Notes: Data are from the downscaled CGCM3.1 model. Historical data (blue bars) show the distribution of daily mean temperatures between 1981 and 2000. Future simulated data (red bars) are for the period 2046 to 2065 under the A1B scenario.