Supporting Information

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Data Description

Weather Data. The weather data are drawn from the US National Climatic Data Center (NCDC) Global Summary of the Day. Monitoring stations report daily minimum and maximum temperature. Following previous studies we focus on mean daily temperature, calculated as the simple average of these two measures (1, 2). In the NCDC data there are 127 monitoring stations in Mexico that report temperature data for at least 1 d during the period 2009–2011.

We include, in addition, 100+ stations from the United States, Guatemala, Belize, and Honduras that are close enough to help improve our weather measures. To focus the analysis on the highest-quality weather readings, we follow previous work and restrict the sample to stations for which data are available from at least 300 d per year (2). For the small fraction of observations for which data are missing in this restricted sample we impute observations using linear imputation.

Fig. S1 plots the geographic distribution of weather monitoring stations that meet the quality screening. There are 86 stations inside Mexico and 116 stations in the United States, Guatemala, Belize, and Honduras. Overall, the geographic coverage is very good. One exception is the northern half of the Baja Peninsula. The stations along the US–Mexico border provide accurate weather measures for population centers at Tijuana and Mexicali. Heading south from the border, however, there are no stations whatsoever. We exclude from the analysis one municipality, Ensenada, for which coverage is particularly poor. For Ensenada the nearest weather monitoring station is 288 km away from the municipality centroid. All other municipalities have at least one monitoring station within 250 km.

Finally, we imputed daily temperature for each municipality using an inverse-distance-weighted average over all stations within 320 km. Fig. S2 describes daily temperature from 2009 to 2011. Mean daily temperature across all stations ranges from a low in the winter of about 50 °F to a summer high near 80 °F. The figure also plots the minimum and maximum measures across all stations. That is, for each day we find the lowest and highest mean daily temperature across all stations. Each summer there is a monitoring station somewhere that has a mean daily temperature for an entire day above 100 °F, and each winter there is a station somewhere that has a mean daily temperature below 20 °F.

To calculate cooling degrees we take the difference between daily mean temperature and 65 °F, or zero, whichever is greater. For example, a day with average temperature of 60 °F has zero cooling degrees whereas a day with average temperature of 80 °F has 15 cooling degrees. The population-weighted average number of annual CDDs is 2,300 with an SD of 1,800. CDDs range widely across states from cool highland states with fewer than 600 CDDs per year to states on the Yucatan peninsula that have more than 5,500 CDDs per year. As a couple of points of comparison, Chicago has 800 CDDs per year, Washington, DC has 1,600, Las Vegas has 3,200, and Phoenix and Miami both have 4,400.*

Finally, we constructed daily measures of precipitation by municipality using the same approach. Although most stations report total precipitation during all 24 h in the day, a small fraction (5%) of stations report total rainfall only for a 6-h period during which rain fell. Thus, these data understate total rainfall in a small number of cases. Overall, geographic coverage for precipitation is very good, although there are somewhat fewer stations that meet the quality screening for precipitation (total 172) compared with temperature (total 202). In the empirical analyses that follow we use precipitation as a control variable. Estimates are extremely similar with and without controlling for precipitation, so we do not believe that our results are being unduly influenced by incomplete geographic coverage for precipitation.

Energy Consumption Data. In 2010, 99% of Mexican households reported having electricity in their homes (3). Annual electricity consumption per capita in Mexico was 2,000 kW·h in 2010. Countries with similar levels of per capita electricity consumption include Brazil (2,400), Costa Rica (1,900), Egypt (1,600), Panama (1,800), Romania (2,400), Syria (1,900), Tajikistan (2,000), and Thailand (2,200). As a point of comparison, per capita electricity consumption for the same year for the United States was 13,300 (4).

Our analysis of the intensive margin uses household-level electric billing records from the universe of Mexican residential customers. Most previous analyses of the effect of temperature on electricity consumption have used aggregate data (1, 5, 6). An important exception is work by Auffhammer and Aroonruengsawat (2), which uses household-level billing data from three electric utilities in California.

Residential customers are billed every two months using overlapping billing cycles. Using billing cycle codes we determined as accurately as possible the exact days corresponding to each bill. We exclude a small number of billing cycles (<2%) that are 3+ mo. These longer billing cycles arise, for example, because some households in rural areas have their meters read less than six times per year.

Microdata on Ownership of Air Conditioning. Our analysis of the extensive margin uses household-level microdata from the ENIGH, a nationally representative in-home household survey conducted every 2 y by the National Statistics Institute of Mexico. Nationwide 13% of households had air conditioning in 2010. Microdata from the 2012 ENIGH survey were recently made available but are from a much smaller sample so we prefer to focus on the 2010 data.

Fig. S3 plots air conditioning saturation by state. Air conditioning saturation ranges widely from near zero in in the central highlands to above 50% in some coastal states. In part, these differences reflect differences in climate. Two large mountain ranges run north to south with a highland central plateau in between with elevations ranging from 3,000 feet to 8,000 feet (Fig. S4). Mexico City, for example, is located at 7,300 feet and has a mild climate year-round. Temperatures are mild in this central plateau and air conditioning is relatively uncommon. The coastal areas tend to be much more extreme. Baja California gets hot in the summer and cold in the winter, as do the coastal areas along the Gulf of Mexico, Pacific Ocean, and Atlantic Ocean.

The pattern of air conditioning saturation also reflects economic factors. Average household incomes tend to be lower in the south and the very low levels of air conditioning saturation along the southern coast of the Pacific Ocean reflect that the states of Guerrero, Oaxaca, and Chiapas are among the poorest in Mexico. Air conditioning is also surprisingly low on the Yucatan Peninsula. This area is characterized by high temperatures but also low average household income.

*See www.ncdc.noaa.gov/oa/climate/online/ccd/nrmcdd.html.

One of the reasons why Mexico is a particularly conducive setting for an empirical study of air conditioning adoption is that household income varies widely. GDP per capita in Mexico was \$10,300 in 2013, but the variation is enormous, with the bottom 25% living on annual household income below \$3,000 (7).

End-of-Century Temperature Predictions. As we explain in the main text, to construct the end-of-century temperature predictions we started with the current temperature distribution by municipality and then added predicted temperature changes by month of year. To capture cross-sectional variation in temperature impacts, we used climate models with a high degree of geographic detail (0.5°). End-of-century temperature predictions were downloaded in August 2014 from Climate Wizard Custom, an online tool developed by the Nature Conservancy. Rather than rely on the output from any single model, we use average predicted changes from all 25 climate models for which data are available from Climate Wizard. We report results for both RCP 4.5 and RCP 8.5, the two emissions pathways for which Climate Wizard makes data available.

We matched gridded temperature change predictions to municipality centroids using inverse-distance weighting. Fig. S6 plots the distribution of changes in mean daily temperature under the RCP 8.5 scenario. Large increases in temperature are predicted by the end of the century. Days with an average temperature below 60 °F become relatively uncommon, the mode shifts to the 75–80° bin, and there is a dramatic increase in days above 85 °F. In the paper we report results from both the RCP 8.5 and RCP 4.5 scenarios. Under the RCP 8.5 scenario, the average temperature (population-weighted) increases by 4.2 °C (7.7 °F). Under the RCP 4.5 scenario, the average temperature (population-weighted) increases by 2.4 °C (4.3 °F).

Air Conditioning Potential. Table 2 was constructed using publicly available data. Population and annual GDP per capita come from the World Bank (8). These data are for 2013, the latest year for which data are available. The values reported for annual CDDs have been widely used (9–12) and came originally from the World Resources Institute. They are measured in degrees Celsius relative to 18 °C.

Additional Description of Results

Intensive Margin. Fig. S7 describes the relationship between temperature and residential electricity consumption for states with different levels of saturation of air conditioning. As with Fig. 3 constructed using all households, we plot the estimated coefficients and 95th percentile confidence intervals corresponding to all 10 temperature bins. The estimating equation is exactly the same for all three parts of the figure.

Fig. S7*A* plots the temperature–response function for households living in states with <10% saturation. The temperature–response function exhibits the same basic pattern observed in the figure constructed using all households, but the magnitudes are somewhat smaller. The fact that we are observing temperature response even in states with low saturation of air conditioning likely reflects the use of fans and other substitutes for air conditioning. Refrigerator electricity consumption has also been shown to increase with ambient temperature (13). Also, temperature increases may reduce outdoor activities, potentially leading households to watch more television and to engage in other indoor activities that use electricity.

Another potential substitute for aid conditioners is evaporative coolers (also known as "swamp coolers"), which cool the air through the evaporation of water. The 2010 ENIGH survey asks households about air conditioners, but not about evaporative coolers. Interestingly, the 2000 ENIGH survey asked a single question of whether a household had either type of cooling equipment and 9.6% of households reported in 2000 having one or the other. We are not aware of any more recent survey that reports saturation of evaporative coolers, but based on this evidence from 2000, along with anecdotal evidence, we believe that the saturation of evaporative coolers is low, but not zero.

Fig. S7 *B* and *C* plot temperature–response functions estimated using households living in states with medium (10–50%), and high (>50%) saturation of air conditioners. The functions continue to have the same basic pattern. Across samples, the response of electricity consumption is near zero for days below 70 °F, and then increases approximately linearly after 75 °F. These temperature–response functions are steeper, however. In states with >50% saturation an additional day in the >90° bin increases monthly consumption by 4.2%.

A useful point of comparison is work by Auffhammer and Aroonruengsawat (2), which estimates temperature–response functions using monthly billing data from California residential customers. Households in California's mild coastal regions (e.g., San Francisco) exhibit relatively flat temperature–response functions, with modest increases in consumption during both cold and hot days. These estimates are similar to our estimates for states with low saturation of air conditioning, except our estimates exhibit virtually no response on cold days. Households living in parts of California with more extreme weather (e.g., the Central Valley) exhibit temperature–response functions similar to what we are observing for households in states with high saturation of air conditioning.

The lack of temperature response on the low end of the temperature distribution makes sense because in Mexico these colder days are relatively uncommon and most households do not have residential heating. In contrast, the distribution of average daily temperatures for the United States includes a substantial fraction of days below 50 °F and millions of households in the United States have electric heating.[†]

Extensive Margin. Table S1 reports the regression estimates corresponding to the air conditioning saturation plots in the paper. We report coefficient estimates and SEs from 10 separate least squares regressions and two probit models. In all regressions the dependent variable is an indicator variable for whether the household has air conditioning. Where indicated, the regressions include region and state fixed effects. In these specifications the relationship between climate and adoption is identified using within-region or within-state variation in CDDs.

The upper portion of Table S1 reports estimates from specifications that include annual household income and CDDs, but not the interaction between the two. Across specifications, both regressors are strongly statistically significant. In column 1, saturation increases by 12 percentage points per \$10,000 in annual household income. This is a large effect. The SD of household income in our sample is \$6,500 (mean \$7,600), so a one-SD increase implies an eight-percentage-point increase in saturation. Relative to the baseline level of 13% this is more than a 50% increase.

Effects are somewhat larger in columns 2–5 when annual household expenditure is used as a proxy for household income. These larger coefficients reflect that expenditure is measured with less error and because the SD for expenditure is smaller. Climate continues to be important, increasing saturation by four to seven percentage points per 1,000 CDDs. The SD of CDDs is 1,800 (mean 2,300), so a one-SD increase implies a 7- to 12-percentage-point increase in saturation. The estimates

[†]According to the U.S. Census Bureau, 41.8 million U.S. households (36%) use electricity as their primary home heating fuel. Only 1.0 million U.S. households (1%) have no home heating (14).

change little with the addition of state fixed effects or a quadratic in precipitation.

Column 6 reports estimates from a probit model. We report marginal effects and their SEs evaluated at the means of the explanatory variables. Coefficients are smaller than the least squares estimates, but with the same pattern. The advantage of the probit model is that it yields predictions that are bounded between zero and one, and, for this reason we rely on estimates from the probit model for our end-of-century forecasts.

The lower portion of Table S1 adds interaction terms between income and climate. In particular, we include a regressor that interacts income with an indicator variable for "warm" municipalities, defined as municipalities above the mean number of CDDs. After including the interaction term, the estimated coefficients on the uninteracted terms become considerably smaller and less statistically significant, whereas the interaction term is large and statistically significant.

As in the upper portion of Table S1, these estimates change very little across specifications. In column 5 with the full set of fixed effects the coefficient on the interaction is 0.31. That is, in warm municipalities, air conditioning saturation increases 31 percentage points per $10,000 in annual household income. Not coincidentally, this is about twice the effect observed in the upper portion of the table, which reflects the combined effect for both cool and warm municipalities. The probit model in column 6 yields estimates with the same general pattern, although again the point estimates tend to be considerably smaller than the least-squares estimates.

Forecasts. In the upper portion of Table 1 we calculate the change in electricity consumption by multiplying each element of the temperature–response function by the predicted change in the number of days in each temperature bin, and then taking the sum of these products.

The climate change predictions are changes in the number of days per year, whereas the temperature–response functions are percentage impacts in monthly electricity consumption. Accordingly, for these calculations we divided the climate change predictions by 12 to represent changes in the number of days per month before multiplying.

To calculate the total change in annual electricity expenditures we multiply the predicted percent change in consumption by total annual residential electricity consumption (52,771 GWh) and then by the average residential price of electricity in Mexico ($90.19 per megawatt hour).[‡] Then, to calculate the total change in carbon dioxide emissions we use the average carbon intensity of electricity generation, 0.68 tons of carbon dioxide per megawatt hour.[§]

The lower portion of Table 1 reports impacts allowing for changes in both the intensive and extensive margins. To predict the percentage of households with air conditioning in this panel we follow these steps. First, we estimate the fully saturated probit air conditioning adoption model using all households in the 2010 ENIGH survey. Second, we scale up these households' expenditure by 1.02^{75} (i.e., 2% growth for 75 y, roughly 2010–2085). Third, we replace each household's current CDDs with end-of-century values (corresponding to either RCP 4.5 or RCP 8.5) for the municipality where each household lives. Fourth, we use the fitted equation from the probit model to calculate an adoption probability for each household. This yields predicted air conditioning saturation of 71% (RCP 4.5) and 81% (RCP 8.5), as indicated in the table.

For the percent change in consumption in the second panel we incorporate both (*i*) the increase in electricity consumption from increased air conditioning adoption and (*ii*) the increase in electricity consumption from higher temperatures. Our predicted end-of-century saturation levels are quite similar to current saturation levels in Sinaloa and Sonora, the two states with the highest levels of saturation (68% and 74%, respectively). Accordingly, we use the estimated temperature–response function from these states to proxy for the end-of-century temperature–response function when making these calculations.

Finally, the predicted changes in total electricity expenditures and carbon dioxide emissions are calculated exactly as in the upper portion of Table 1. Incorporating the extensive margin implies much higher saturation of air conditioners, and thus much higher electricity expenditures and carbon dioxide emissions. In the RCP 4.5 scenario, the total change in carbon dioxide emissions is more than eight times as large as the predicted increase incorporating the intensive margin only. In the RCP 8.5 scenario the total change in carbon dioxide emissions is more than five times as large.

[‡]Both values come from the Mexican Energy Ministry (15). Total residential electricity consumption comes from table 3.2 and average residential prices come from page 33.

[§]According to the Mexican Energy Ministry, in 2012 a total of 143.49 million metric tons of carbon dioxide were emitted by electricity generation in Mexico (16) and total electricity consumption was 234,219 GWh (15). Dividing and using the fact that there are 1.102 tons per metric ton yields the average carbon intensity.

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16. Secretaría de Energía (2013) *Balance Nacional de Energía 2012* (Secretaría de Energía, Mexico City). Spanish.

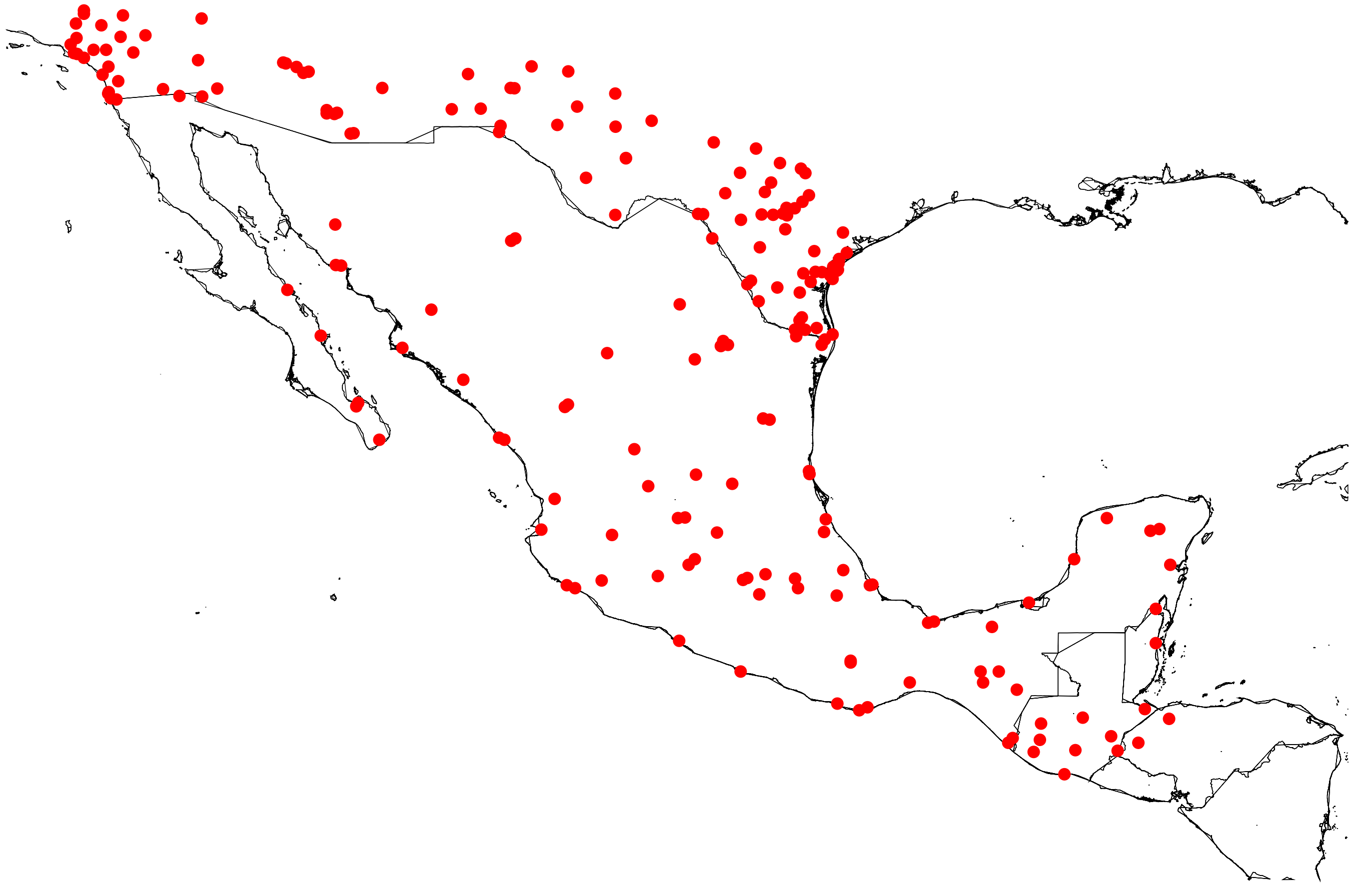

Fig. S1. Weather monitoring stations.

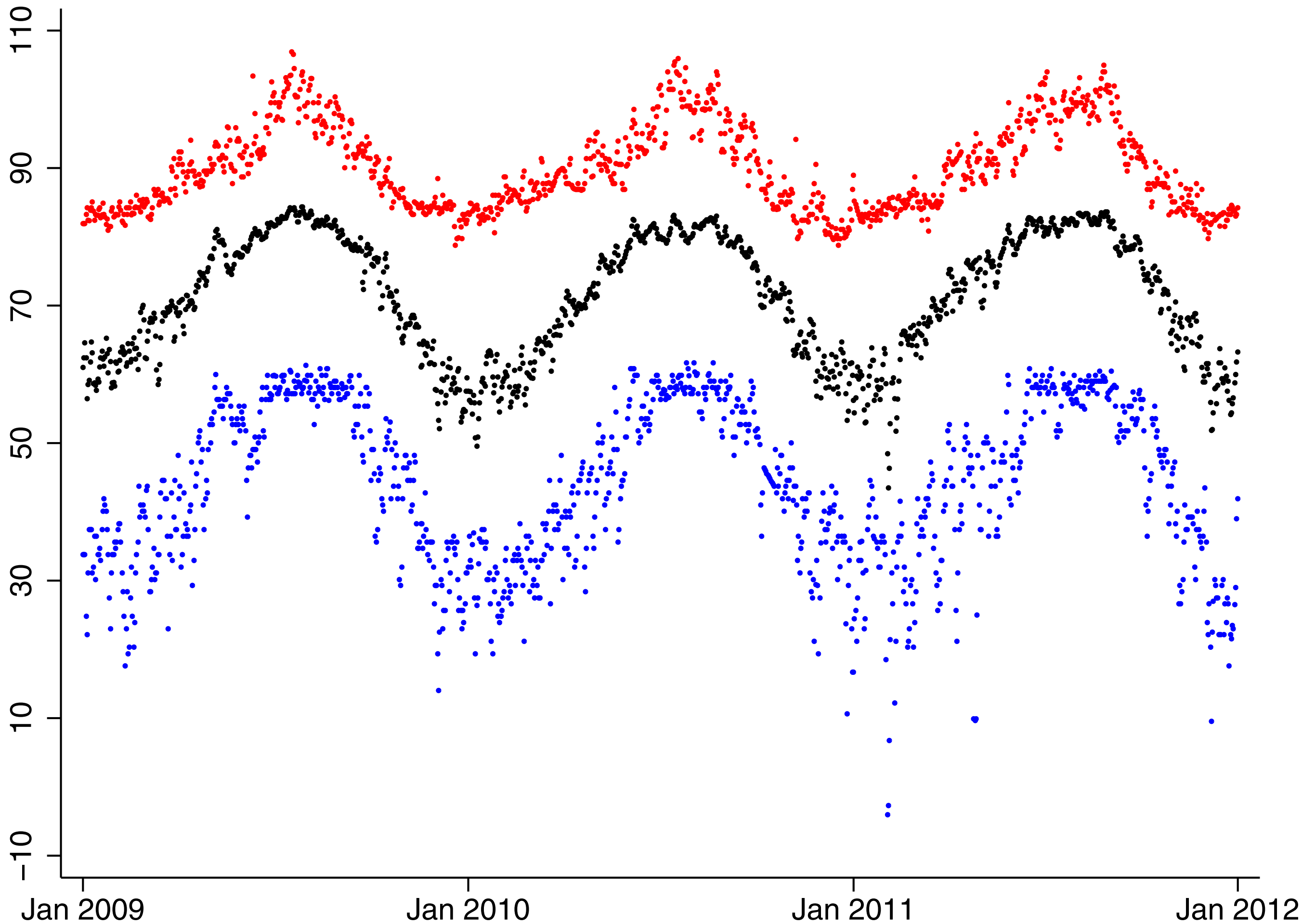

Fig. S2. Maximum, mean, and minimum temperature by day.

Fig. S3. Air conditioning saturation by state.

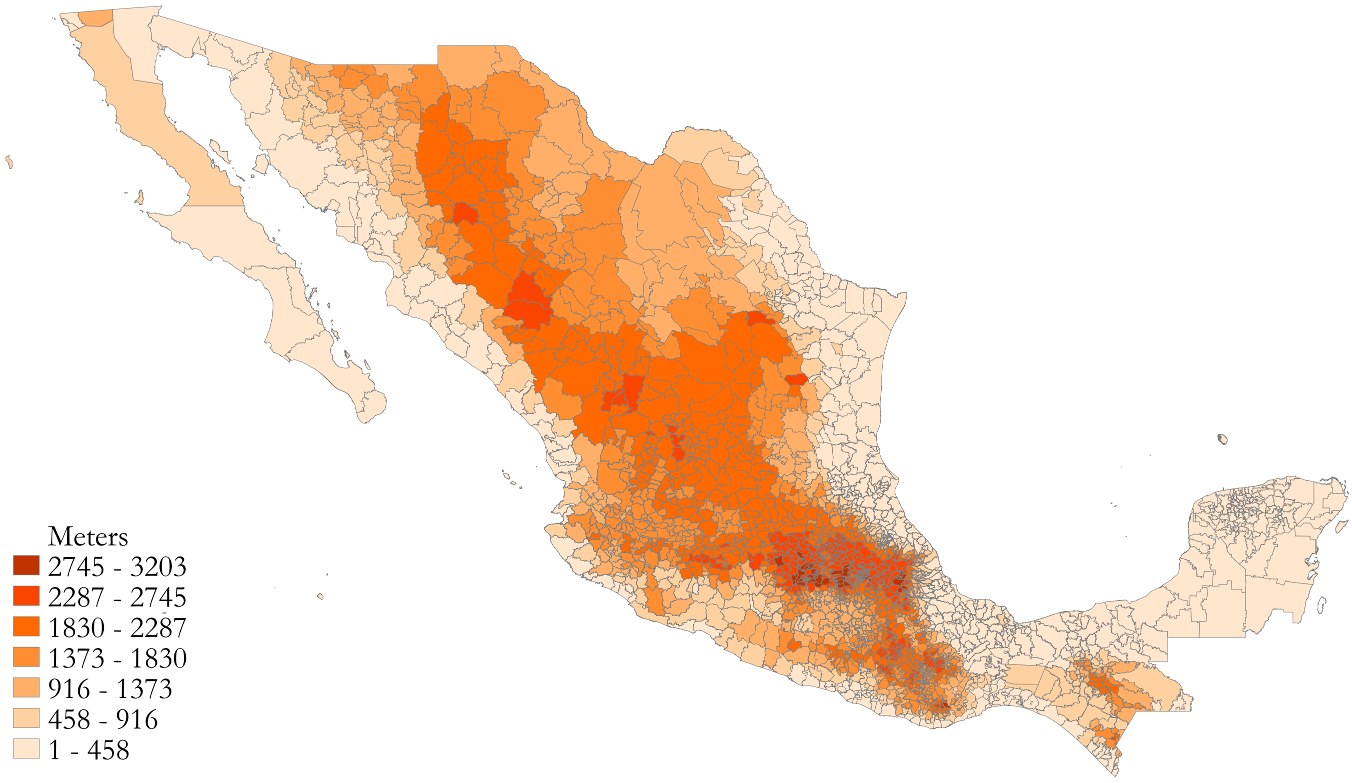

Fig. S4. Elevation by municipality.

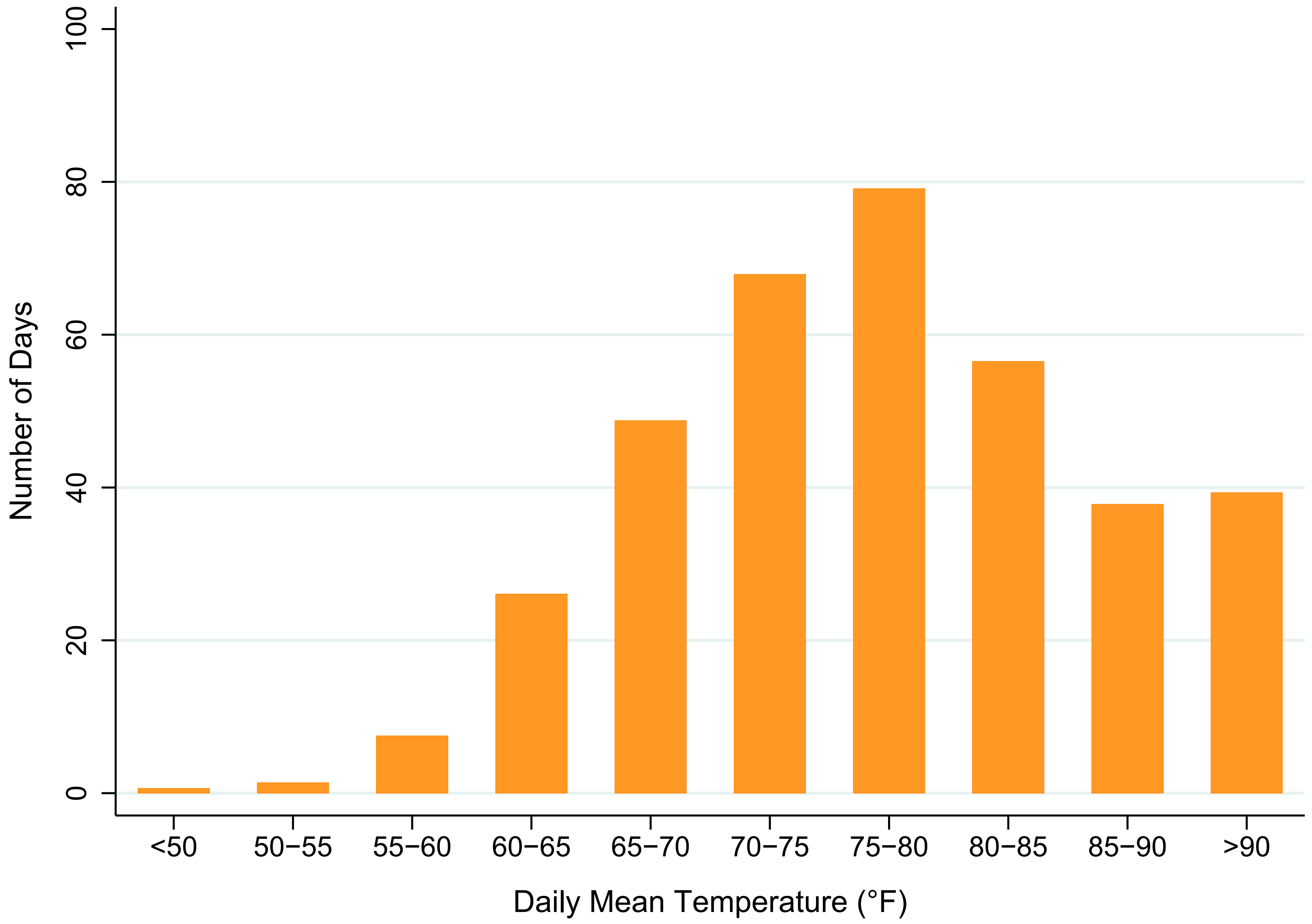

Fig. S5. Daily mean temperature 2070–2099, RCP 8.5 emissions scenario.

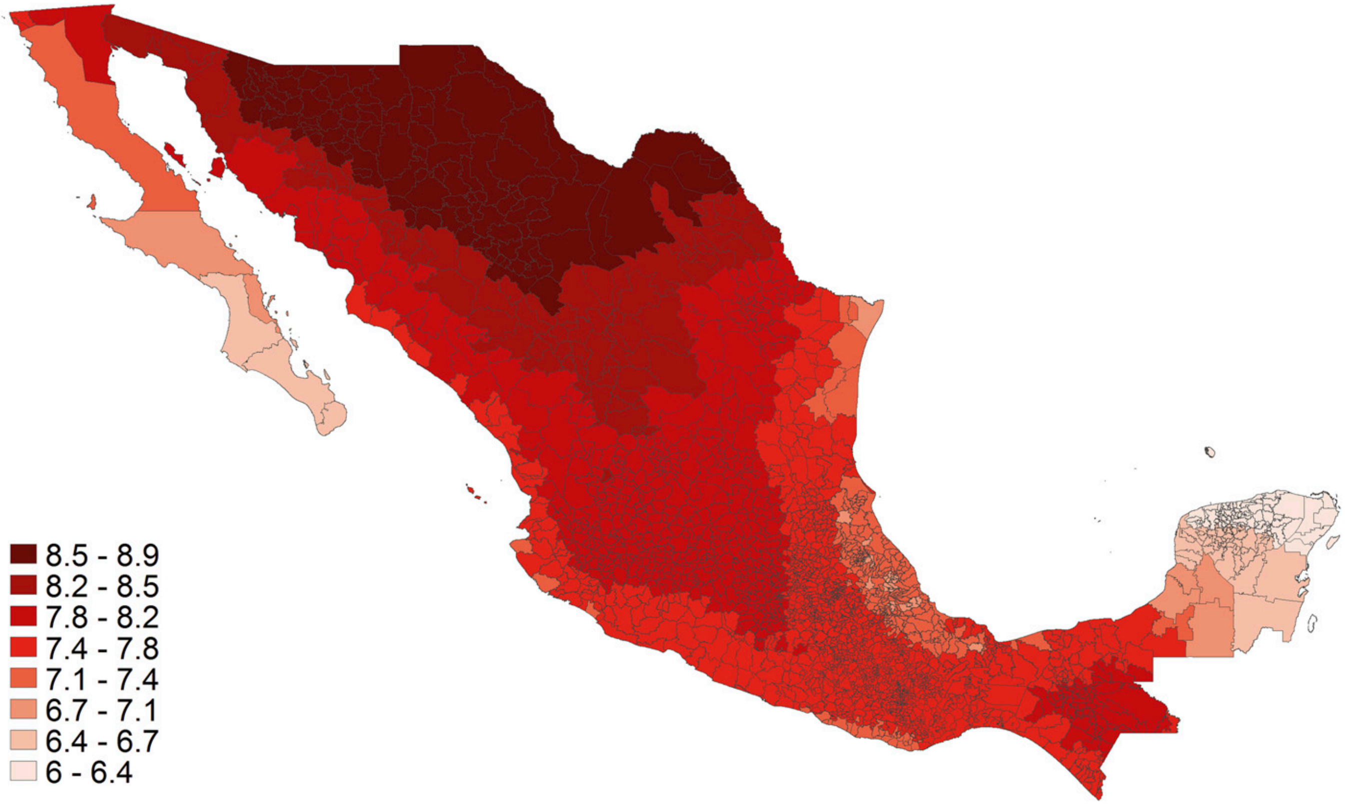

Fig. S6. Change in daily mean temperature (°F), RCP 8.5 emissions scenario.

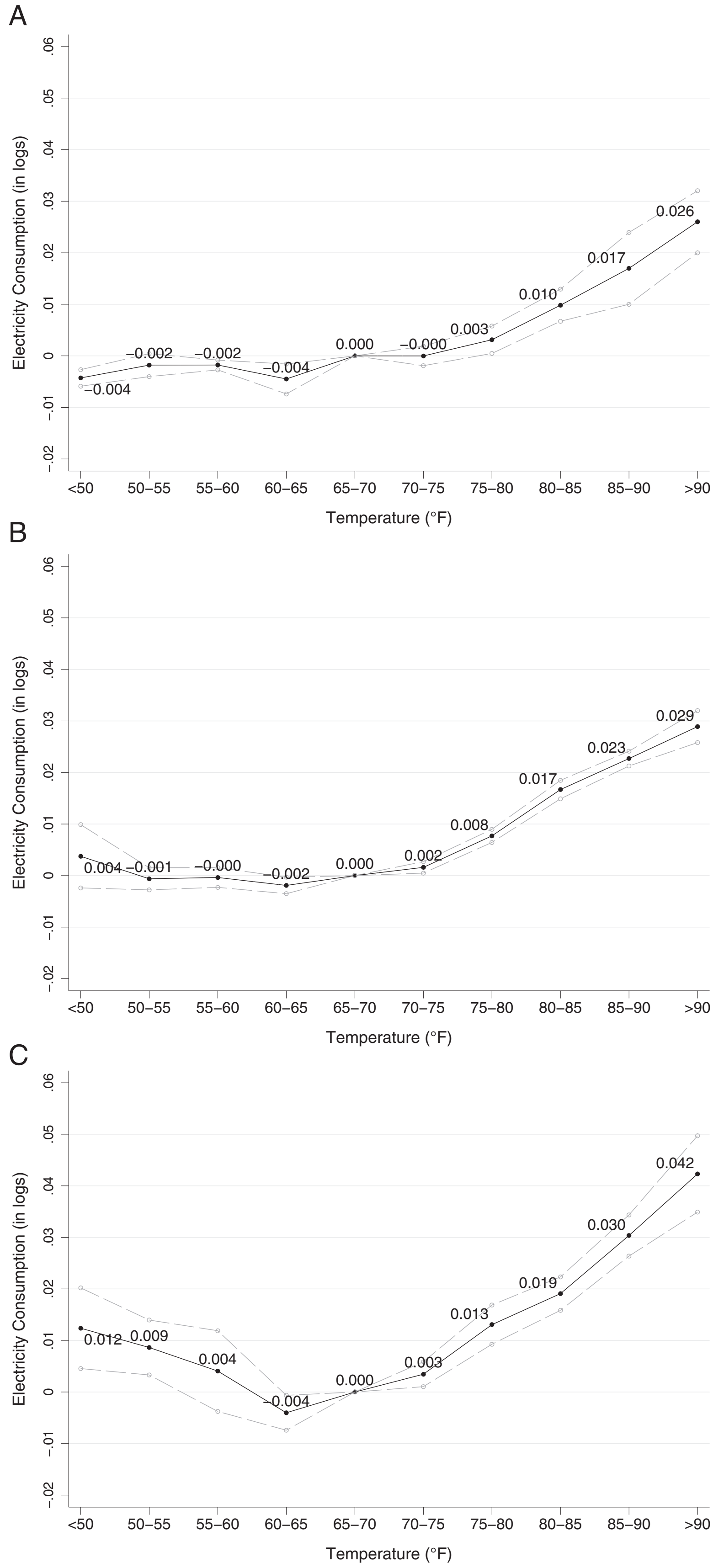

Fig. S7. The effect of temperature on residential electricity demand: (*A*) <10%, (*B*) 10–50%, and (*C*) >50% saturation of air conditioning.

Table S1. Predicting air conditioning adoption

Variable	1	2	3	4	5	6
	Income and climate					
Annual household income (in US 2010 dollars, 10,000s)	0.12** (0.01)	0.17** (0.02)	0.15** (0.02)	0.15** (0.02)	0.15** (0.02)	0.06** (0.01)
Annual CDDs (Based on 65 °F, 1,000s)	0.07** (0.01)	0.07** (0.01)	0.05** (0.01)	0.04** (0.01)	0.04** (0.01)	0.02** (0.01)
R^2	0.18	0.17	0.32	0.37	0.37	0.46
	Income, climate, and the interaction					
	7	8	9	10	11	12
Annual household income (in US 2010 dollars, 10,000s)	0.03* (0.01)	0.03** (0.01)	0.03* (0.01)	0.03* (0.01)	0.03* (0.01)	0.04** (0.01)
Annual CDDs (Based of 65 °F, 1,000s)	0.02 (0.02)	0.01 (0.02)	0.04* (0.02)	0.04* (0.02)	0.04 (0.02)	0.02** (0.01)
1(warm municipality)	0.03 (0.06)	0.02 (0.06)	−0.12** (0.04)	−0.14** (0.04)	−0.14** (0.04)	−0.02 (0.02)
Annual household income* 1(warm municipality)	0.24** (0.02)	0.36** (0.03)	0.32** (0.03)	0.31** (0.03)	0.31** (0.03)	0.05** (0.01)
R^2	0.25	0.24	0.36	0.41	0.41	0.46
Proxy for income using expenditure	No	Yes	Yes	Yes	Yes	Yes
Region fixed effects	No	No	Yes	Yes	Yes	Yes
State fixed effects	No	No	No	Yes	Yes	Yes
Quadratic in precipitation	No	No	No	No	Yes	Yes
Probit model	No	No	No	No	No	Yes

Table S1 reports coefficient estimates and SEs from 12 separate regressions. Columns 1–5 report estimates from linear probability models and column 6 reports estimates from probit models. In all regressions the dependent variable is an indicator variable equal to 1 for households who have air conditioning at home. The indicator variable 1(warm municipality) is equal to 1 for municipalities with more than the mean number of annual CDDs. The sample for all regressions includes all 27,395 households in the 2010 ENIGH survey and all regressions are estimated using ENIGH sampling weights. SEs are clustered at the municipality level. Single and double asterisks denote statistical significance at the 5% and 1% levels, respectively.