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Why Did Air Conditioning Adoption Accelerate Faster Than Predicted? Evidence from Mexico

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Abstract

A common theme in the vast literature on climate change is the estimation of models using historical data to make predictions many decades into the future. Although there is a large and growing number of these types of studies, researchers rarely return later to check the accuracy of their predictions. In this paper, we perform such an exercise. In Davis and Gertler (2015), we used household-level microdata from Mexico to predict future air conditioning adoption as a function of income and temperature. Revisiting these predictions with 12 years of additional data, we find that air conditioning in Mexico has accelerated, significantly exceeding our predictions. Neither errors in predicting income growth or rising temperatures, nor migration patterns, nor an overly restrictive model can explain the large prediction gap. Instead, our results point to the failure to account for falling electricity prices and technological changes in air conditioner efficiency as key drivers of the prediction gap.

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1 Introduction

A common theme in the vast literature on climate change is the estimation of models using historical data to make predictions many decades into the future. For example, Deschênes and Greenstone (2011) estimate the effect of temperature on mortality and then predict end-of-century mortality impacts from climate change, and Burke et al. (2015) estimate the effect of temperature on economic growth and then predict impacts up to 2100. Although there is a large and growing number of these types of studies, researchers rarely return later to check the accuracy of their predictions.[1]

In previous research, we used microdata from Mexican households to estimate a model of air conditioning (AC) adoption to predict adoption many decades into the future (Davis and Gertler, 2015). At the time we wrote that "*The use of air conditioning is poised to increase dramatically over the next several decades as global temperatures go up and incomes rise around the world.*" Now, with the benefit of 12 years of additional data, we revisit our predictions to ask how well we did.

We find that AC adoption in Mexico has not only accelerated rapidly, but significantly exceeded our predictions. Our previous analysis, using data from 2010, predicted that AC ownership would increase 3.3 percentage points (pp) by 2022. However, the actual increase was 5.8 pp, almost double our prediction. This is a prediction gap of 0.57, where the gap is defined as predicted/actual, implying that we under-predicted by 43%. The unexpected rapid acceleration is widespread throughout Mexico, but particularly pronounced in warm states, where AC ownership increased 11.0 pp, compared to our prediction of 6.2 pp.

[1]For examples of studies predicting future air conditioning adoption see Isaac and Van Vuuren (2009); Akpinar-Ferrand and Singh (2010); Pavanello et al. (2021); De Cian et al. (2025); Abajian et al. (2025). For studies predicting future energy consumption, see Rosenthal et al. (1995); Mansur et al. (2008); Franco and Sanstad (2008); Auffhammer and Aroonruengsawat (2011); Auffhammer et al. (2017); Wenz et al. (2017); Van Ruijven et al. (2019); Rode et al. (2021); Auffhammer (2022). Related studies have made predictions on agricultural productivity (Deschênes and Greenstone, 2007), crop yields (Schlenker and Roberts, 2009), conflict (Burke et al., 2009), and global mortality (Carleton et al., 2022).

Rapid acceleration in AC adoption has important implications for health and mortality, electricity demand, grid reliability, and the environment. AC provides relief on hot days and reduces heat-related mortality (Barreca et al., 2016), but is also much more energy-intensive than other climate adaptation technologies. Even a modest-sized room AC can use 1,000 watts, compared to only 50 to 80 watts for a ceiling fan. Recent forecasts from the International Energy Agency conclude that AC is the single largest driver of future global electricity demand, even greater than data centers, and our analysis provides empirical support for this conclusion.[2]

We next turn to possible mechanisms. Surprisingly, the prediction gap cannot be explained by inaccurate predictions of future income or temperature. In our earlier work, we modeled AC ownership as a function of income and temperature and we used estimates from the literature on income growth and temperature change in making our forecasts. Although our predictions for temperature change were reasonably accurate, household incomes increased substantially less than we expected, so incorporating updated information actually *widens* the prediction gap, rather than narrowing it.

The prediction gap is also not explained by migration from cold to warm municipalities. More households in warm municipalities would mean more adoption of AC, which could help explain the acceleration. However, there is relatively little migration during the 12-year study period, and the prediction gap is essentially identical with and without accounting for changes in the distribution of households between cold and warm municipalities.

The prediction gap also cannot be explained by the original model being too restrictive. Returning to the 2010 data, we ask whether a more flexible machine learning model (ML) that controls for overfitting and lets the data drive functional form could have done better.

[2] In the baseline scenario, IEA finds global electricity demand for space cooling increasing 3.7% per year to 2035. The increased demand for space cooling is also projected to lead to higher peaks in electricity demand, particularly in low- and middle-income countries where most of the increased adoption is expected to occur. See International Energy Agency (2024), p. 40 and p. 123.

The answer is no. Although the prediction gap narrows, there remains a substantial gap both for Mexico as a whole and for different categories of states.

Instead, we point to electricity prices and technological change as key drivers of AC adoption that were not incorporated into the predictions. Since our previous article was written, residential electricity prices have decreased 19% in real terms and energy efficiency of AC has increased 11% with almost no change in the cost of AC units. Putting both factors together implies that the price of cooling has decreased 30%. Estimates of the price elasticity of demand for AC from previous studies suggest that this reduction in the price of cooling is large enough to explain much of the observed increases in adoption. Moreover, the reduction in the price of cooling could explain most of the increase in AC adoption income elasticities from 2010 to 2022 based on Engel curves estimated with our data.

Our paper underscores the importance of prices and technological change. The climate change literature discussed above uses predictions about temperature and, in some cases, income in making forecasts many decades into the future. However, these studies typically do not incorporate predictions about prices or technological change, in part because of the difficulty of making such predictions. As difficult as it is, our paper illustrates the danger of such simplifications, even after a relatively short number of years.

In addition to contributing to the climate change forecasting literature, our paper contributes to a small literature on the causes and consequences of AC adoption (Hausman, 1979; Dubin et al., 1986; Mansur et al., 2008; Biddle, 2008; Rapson, 2014; Auffhammer, 2014; Carleton et al., 2022; McRae, 2023). AC has the potential to offer large benefits in terms of avoided mortality, human health, labor productivity, and educational attainment (Barreca et al., 2016; Park et al., 2020; Park, 2022), but it also uses a large amount of energy, so it is important to be able to accurately predict adoption.

Our paper also points to the importance of pricing energy efficiently, a long-standing theme in energy economics (Feldstein, 1972; Naughton, 1986; Kahn, 1988; Borenstein and Bushnell, 2022a,b). Mexico is one of dozens of countries that heavily subsidizes energy, and these subsidies have large implications for economic efficiency and the environment (see, e.g. Burgess et al., 2020; Parry et al., 2021). Removing subsidies is politically difficult, but our study points to a clear link between low prices and high consumption. Mexico is already facing blackouts and reduced grid reliability, and these challenges are directly related to this unwillingness to increase prices.

2 Davis and Gertler (2015)

Before continuing, we step back and summarize the data and methods used in Davis and Gertler (2015). The study focused on Mexico, which has several characteristics that make it an almost ideal setting for studying AC adoption: (i) *Widely varied climate*: The country is 3,200 kilometers long, with populated areas located from sea level up to 3,000+ meters of elevation, and with climate zones ranging from hot and humid tropical coastal areas, to subtropical steppes, to high-altitude temperate plateaus. (ii) *Widely-varied income*: Annual household income in 2022 averaged \$13,000 but ranged from below \$3,000 for the bottom decile to above \$40,000 in the top decile.[3] (iii) Unusually rich publicly-available microdata on AC adoption, income and climate.

2.1 Data

Although our previous paper was published in 2015, the underlying data date back to 2010. The core data came from Mexico's National Survey of Household Income and Expenditure (*Encuesta Nacional de Ingresos y Gastos de los Hogares, ENIGH*). ENIGH is a high-quality in-person household-level survey conducted every two years. The ENIGH uses a stratified

[3] ENIGH 2022, see `https://en.www.inegi.org.mx/temas/ingresoshog/`.

random sample that is representative at the state level.[4] The previous estimates were based on a single wave, ENIGH 2010, with a sample size of 27,655 households.

The key question in ENIGH is "Does this home have air conditioning?" (*¿Esta vivienda tiene aire acondicionado?*). The survey does not distinguish between different types of AC (e.g. window, minisplit, central) but, in practice, almost all residential ACs in Mexico are window or minisplit.[5] ENIGH also collects detailed information on income and expenditures. As is common in settings with a large amount of self-employment both agriculture and non-agriculture, we used expenditures rather than income in our main analysis, as expenditures tend to be measured more accurately.

Our previous research complemented these data with detailed temperature data. The primary measure of temperature was cooling degree days (CDDs), a widely used measure of cooling demand equal to the sum of daily mean temperatures above 65°F (18.3°C).[6] We measured average CDDs in 2010 using daily average temperatures 2009-2011 from 200+ monitoring stations.

2.2 Model and Estimation

We followed the literature in modeling income and temperature as the most important determinants of AC adoption. Our baseline model was a probit of the following form,

$$1(\textit{Air Conditioner})_i = \alpha_1 \textit{Expenditures}_i + \alpha_2 \textit{CDD}_m + \alpha_3 1(\textit{Warm Municipality})_m + \alpha_4 \textit{Expenditures}_i * 1(\textit{Warm Municipality})_m + \theta_s + \epsilon_i \quad (1)$$

[4] There are 32 states including the Federal District.

[5] A one-time-only survey conducted by Mexico's National Statistical Institute (INEGI) in 2018 found that the vast majority of residential ACs are either window or minisplit. See National Survey on Energy Consumption in Private Homes (ENCEVI) *Encuesta Nacional sobre Consumo de Energéticos en Viviendas Particulares (ENCEVI)*, `https://www.inegi.org.mx/programas/encevi/2018/`.

[6] For example, a day with an average temperature of 75°F has ten cooling degrees, whereas a day with 55°F has zero cooling degrees. CDDs have been widely used in previous studies of AC adoption (see e.g. Isaac and Van Vuuren, 2009; Akpinar-Ferrand and Singh, 2010; Pavanello et al., 2021).

where $1(\textit{Air Conditioner})_i$ is an indicator variable equal to one if household i has AC. The explanatory variables included household expenditures ($\textit{Expenditures}_i$), CDDs measured at the municipality level (CDD_m), and state fixed effects (θ_s). We hypothesized sharply different adoption behavior in cold versus warm municipalities. We captured this with an indicator variable $1(\textit{Warm Municipality})_m$ equal to one for households in municipalities with above average CDDs. Our baseline model included this indicator, as well as an interaction between the indicator and household expenditures.

2.3 Forecasts

We predicted future AC adoption using the estimated model. We assumed a conservative 2% annual real growth for household expenditures based on a US government forecast that predicted 3.7% annual real growth for Mexico's GDP for the period 2010-2040. We predicted future CDDs using temperature change predictions by municipality for a moderate emission scenario (RCP 4.5) from a suite of climate models from a now defunct tool called *Climate Wizard*. We adjusted the 2010 household data to reflect the 2022 estimated expenditures and CDDs, calculated household-level predictions using the model, and then aggregated up to the state and national levels using the 2010 ENIGH sampling weights. In the following section, we compare the predictions from the model for 2022 with actual levels of AC as observed in the 2022 ENIGH. See Appendix Table 1 for summary statistics.

3 How Accurate Were the Predictions?

Figure 1 evaluates our predictions. The top panel examines the growth in AC 2010-2022 in percentage points. Actual growth is in blue and predicted growth is in orange. For Mexico as a whole (all states), we predicted a 3.3 pp increase from a base of 12.7%. The actual increase was 5.8 pp. Thus, the prediction gap – the ratio of the predicted to actual value –

is 0.566 implying that we under-predicted by 43.4%.

We under-predicted AC growth not only for Mexico as a whole, but also for different groups of states. Here and throughout we refer to “warm” and “cold” states defined using median CDDs in 2010, as well as to “rich” and “poor” states defined using median household expenditures in 2010. See Appendix Table 2 for a list of states by category. Ownership growth was highest in warm states, increasing 11.0 pp compared to our prediction of 6.2 pp. Growth is slower in cold, rich, and poor states, but in all cases actual growth considerably exceeded our predictions.

The bottom panel examines AC ownership in 2022. That is, rather than looking at growth, this panel looks at the level of AC ownership at the end of our sample. Again, the actual adoption of AC considerably exceeds our predictions. In 2022, 18.5% of Mexican households have AC, while we predicted 15.9%. Actual levels of AC exceed our predictions in all four categories of states. As expected, AC ownership is highest in warm states, lowest in cold states, and somewhat higher in rich states than in cold states. See Appendix Figure 1 for state-by-state results. Thus, there is clear evidence of accelerated AC adoption in both growth and levels.

4 Mechanisms

What explains the under-prediction? We consider several possible mechanisms: (1) inaccurate predictions of future expenditures and temperature, (2) migration within Mexico to warmer municipalities, (3) flexibility of the estimated model, and (4) changes over time in prices and energy efficiency.

Table 1 compares the effect of various explanations in terms of the prediction gap. For example, with our baseline probit model in the top row, we predicted a 3.3 percentage point increase in AC nationwide, but the actual increase was 5.8, so the prediction gap is 0.566 = 3.3/5.8. A prediction gap of 1.0 would be that we perfectly predicted, whereas a prediction gap below 1.0 would be that we under-predicted. We begin in panel (A), looking at all states, before looking separately at warm and cold states in panels (B) and (C), and rich and poor states in panels (D) and (E).

Overall, the prediction gap remains well below 1.00 in all specifications. Below we discuss more clearly what we learn from the individual rows, but the broader takeaway from the table is that none of the first three hypotheses can explain the underprediction.

4.1 Expenditures and Temperatures

We modeled AC adoption as a function of expenditures and temperature, so it makes sense to start there. The top panel of Figure 2 compares actual household expenditures in 2022 with our predictions. For Mexico as a whole, household expenditures in 2022 averaged 154,000 Mexican pesos, whereas we predicted 196,000.[7] Actual expenditures are substantially below our predictions not only for Mexico as a whole, but also separately for warm, cold, rich, and poor states. At the time, we thought that assuming an annual real growth rate of 2% for expenditures was conservative. But, as it turns out, the period 2010-2022 was a period of surprisingly low economic growth for Mexico, well below expectations. The decrease in oil prices in 2014 was economically damaging and then Mexico was severely hit by COVID, with GDP per capita falling 15% in 2020, according to the World Bank.[8]

The bottom panel of Figure 2 evaluates our predictions for CDDs. These measures of annual CDDs (in 1000s, relative to 65°F) come from ERA5 Land, a public use dataset of global high-resolution gridded temperatures. We access these data through the Google Earth Engine,

[7] The exchange rate in 2022 was 20.1 pesos per dollar, so 154,000 is equivalent to approximately $7,700 dollars annually.

[8] `https://data.worldbank.org/`

uploading shapefiles for Mexican municipalities, downloading daily average temperatures, and then calculating CDDs. Because we are less interested in the variation from year to year, we used average annual CDDs from 2021-2023. To avoid comparing CDDs between sources, we use the exact same source to construct predicted CDDs. Specifically, we used as our measure for 2010, the average annual CDDs by municipality from 2009-2011. We then adjusted these CDDs to reflect climate change between 2010 and 2022 using the percentage change in CDDs by municipality assumed in our previous paper.

The actual CDDs are close to the predicted CDDs. Households experience on average 1,900 CDDs annually and this is close to what we predicted. CDDs are about twice the average in warm states and about half the average in cold states, but our predictions are approximately accurate both for Mexico and for different categories of states, so the acceleration in AC does not seem to be due to unanticipated changes in temperature. See Appendix Figures 2, 3, 4, and 5 for results by state, maps, and additional information about CDDs.

Neither errors in expenditure growth nor climate change predictions explain the prediction gap for AC. In each panel of Table 1, we report a prediction gap based on the actual state-level average growth in expenditures and CDDs 2010-2022. Household expenditures increased much less than we expected, so incorporating updated information substantially *widens* the prediction gap, rather than narrowing it.

4.2 Migration

Each panel of Table 1 also includes a prediction gap based on 2022 population weights. These rows test whether within-Mexico migration to warmer municipalities can explain the acceleration. Our baseline specification aggregates up to the state and national levels using the 2010 ENIGH sampling weights. This approach makes sense as this is the information that was available in 2010. Instead, with 2022 population weights we take into account the change in distribution of households in Mexico between 2010 and 2022. See Appendix Figure 6 for a scatterplot. This might have helped explain the acceleration if, for example, there had been widespread migration toward warmer areas. As it turns out, however, there was relatively little within-Mexico migration during this period and the weighting does not matter quantitatively, so that whether we use 2010 weights or 2022 weights, the prediction gap is essentially identical.

4.3 A More Flexible Model

Next, we explore the possibility that our original econometric model was overly restrictive. The probit described above is, by all accounts, a parsimonious parametric model and previous research has emphasized the importance of allowing for nonlinear patterns of durable good adoption (e.g. Wolfram et al., 2012; Gertler et al., 2016). At the time of the previous study, ML methods that efficiently facilitate the discovery of better predictive models had not yet become common in economics. So, it is natural to ask whether a more flexible ML model could have been better. We estimate this more flexible model using the original ENIGH 2010 dataset and then see whether it does better at predicting AC growth.

We consider, in particular, a LASSO model which selects variables from the same set of explanatory variables as in equation (1) plus a larger set of higher-order terms and interactions. Potential additional variables include household expenditures squared, household expenditures cubed, CDDs squared, CDDs cubed, and interactions between these variables and the other variables in our model. As usual, LASSO uses cross-validation to avoid overfitting. See Appendix Table 3 for a list of variables selected by the LASSO.

In each panel of Table 1, we report a prediction gap based on the LASSO. The LASSO model leads to higher predicted levels of AC, with the prediction gap nationwide increasing from 0.566 to 0.624. Nevertheless, we still substantially under-predict AC with the LASSO, both for Mexico as a whole and for the different categories of states. Across categories, the prediction gap with the LASSO ranges from 0.57 to 0.75, so none of the prediction gaps is close to 1.0.

4.4 Price of Cooling

Thus, neither expenditures, nor temperatures, nor migration, nor an overly restrictive model appear to be able to explain the accelerated AC adoption 2010-2022. To try to understand what might be happening, we considered two potentially important factors not considered in the original predictions; namely, prices and technological change. As economists have long pointed out, the demand for energy-using durable goods is a function of both the price of the durable good and the operating cost (Hausman, 1979; Dubin and McFadden, 1984). Although we did not model these factors explicitly in our previous work, we were aware of their potential importance. As we wrote at the time, *"The future pattern of air conditioning adoption and use will also reflect what happens to prices. Equipment prices are likely to continue to decrease, further accelerating adoption. What will happen to electricity prices is less clear. A substantial increase in electricity prices, for example, resulting from carbon legislation, would slow both adoption and use."*

Panel (A) of Figure 3 plots residential electricity prices in Mexico.[9] Not only was no carbon legislation introduced, but government subsidies increased during this period, pushing prices downward. Overall, electricity prices fell 19% between 2010 and 2025 in real terms. Mexico's electricity prices are now very low by international standards.[10]

[9]In Mexico over 99% of households have been connected to the grid since 2010, so it is prices not availability that matters for adoption.

[10]The exchange rate in 2025 is 19.5 pesos per dollar, so 1 peso per kWh is equivalent to 5.2 U.S. cents. For comparison, the average residential electricity price in the United States is 16 cents \https://www.eia.gov/electricity/monthly/), more than three times higher. And among all OECD countries, the average residential electricity price in 2023 was 19.7 cents, almost four times higher (https://www.iea.org/data-and-statistics/data-product/energy-prices).

To better understand recent technological changes in AC, we compiled information from the US-based Consumer Reports (CR) magazine, 2010-2025. We would have preferred data from Mexico, but we are not aware of any comparable data source from Mexico. Moreover, most of the ACs in CR are manufactured in China and Southeast Asia by companies that export both to the United States and Mexico. During this period, there were a total of 21 CR articles discussing AC, including detailed information on 204 room AC models. For each model, we collected the retail price, energy efficiency (in BTU per watt), and capacity (in BTU).

Panels (B) and (C) plot AC prices and energy efficiency. Between 2010 and 2025, prices increased slightly (2.7%) in terms, while energy-efficiency increased sharply (11%). Thus by the end of the period, a typical AC produced 11% more cooling per unit of electricity with relatively little change in upfront cost.[11] The CR articles also discuss broader technological improvements in AC, with newer models described as "quiet", "sleek design", "easy to install" and "intuitive controls". In addition, while we focus here on room air conditioners, there have also been improvements in minisplits (i.e. ductless systems where an indoor unit is connected to an outdoor compressor) which are common in Mexico and can be installed even in cases where there is not a window well-suited for room AC.

Panel (D) combines the evidence on electricity prices with the evidence on energy efficiency. The price of cooling can be expressed as, $\frac{\$}{BTU} = \frac{\$}{watt} * \frac{watt}{BTU}$ where $\frac{\$}{watt}$ is the price of electricity and $\frac{watt}{BTU}$ is the inverse of the energy efficiency, that is, how many watts of electricity used per BTU of cooling. During this time period, the first term fell by 19% and the second term decreased by 11%, so the price of cooling decreased by 30%.

[11] Could these technological changes have been anticipated when we wrote the earlier paper? Perhaps. To shed light on this question, we went back and collected data from the earlier period 2000-2009. During that earlier period, room air conditioner prices decreased 50% in real terms, while energy efficiency improved 10%. Thus the earlier trend was a poor predictor of later price changes, but a good predictor of later efficiency improvements. See Appendix Figure 10 for details.

4.5 Does the Fall in the Price of Cooling Explain the Gap?

Is the decline in the price of cooling large enough to explain the prediction gap? We think so. From previous research, we know that low electricity prices increase AC adoption (Hausman, 1979; Mansur et al., 2008; Rapson, 2014). We are not aware of estimates of this price elasticity from Mexico, but using data from the United States, Biddle (2008) estimates a price elasticity of -0.59 for room ACs in 1960. Applying this elasticity to the 30% decline in the price of cooling yields an 18% increase in AC adoption, similar in magnitude to the difference between predicted and actual adoption.[12]

Another way to assess this question is in the context of the model in equation (1), which can be interpreted as an Engel curve. A simplified version of the Engel curve in (1) is, $x = \alpha + \beta Y$. The coefficient β is the share of income spent on good x and measures the responsiveness of demand to income Y. Engel curves are derived from demand functions, and if preferences are given by a Cobb-Douglas utility function $x^{\gamma} c^{\delta}$ where c is a composite good and the price of x is P_x, then demand is given by, $x = \frac{(\gamma Y)}{P_x}$. In this case, β in the Engel curve is:

$$\beta = \frac{\gamma}{P_x} \tag{2}$$

Hence, based on (2), the large decrease in the price of cooling should make households more income-responsive. We test this by re-estimating model (1) using data from the 2022 ENIGH. From the results reported in Table 2, income responsiveness increased from 0.050 in 2010 to 0.064 in 2022 or 28% in warm municipalities and 0.024 to 0.040 or 67% in cold municipalities.

How much of the increase in income responsiveness can be explained by the decrease in the price of cooling? If preferences are Cobb-Douglas and do not change over time, then

[12] In 2022, 18.5% of Mexican households have AC, while we predicted 15.9%. Increasing our prediction by 18% would have yielded 18.8% (15.9% * 1.18).

$\frac{P_t}{P_{t+1}} = \frac{\beta_{t+1}}{\beta_t}$. Then, the price would have had to have fallen by 28% in warm locations and by 67% in cold locations to fully explain the change in β between 2010 and 2022. We estimate that the price of cooling fell by 30% fully explaining the change in β in warm locations and explaining about half the change in cold locations. However, recall that almost all of the growth in AC ownership occurred in warm locations.

5 Conclusion

This paper provides a rare retrospective assessment of predictions in a literature that overwhelmingly focuses on prospective forecasting. We document that not only did AC adoption accelerate rapidly in Mexico between 2010 and 2022, but it accelerated substantially faster than predicted. Just 12 years after we made our original predictions, there are already nearly 1 million more ACs in Mexico than predicted. Accelerated adoption is particularly pronounced in warm states, where growth is almost twice what we predicted. If this accelerated pace of adoption continues, it will mean near-ubiquitous AC in Mexico more than a decade earlier than previously believed.

This acceleration has large economic and environmental implications for Mexico. AC is energy intensive, as mentioned above, so meeting the increased demand for electricity will require large investments in generation and transmission. Mexico already faces blackouts during heat waves so more AC can also threaten grid reliability.[13] In addition, most electricity in Mexico comes from fossil fuels, so more AC means increased carbon dioxide emissions.[14]

[13]"Rolling Blackouts Hit Several Cities as Heat Wave Scorches Mexico" *New York Times*, By Emiliano Rodríguez Mega and John Yoon, May 8, 2024.

[14]In 2023, electricity generation in Mexico was 61% natural gas, 7% coal, 7% oil, 3% nuclear, 21% renewables. This information comes from the International Energy Agency (IEA), `https://www.iea.org/countries/mexico/electricity`). As a point of comparison, electricity generation in the U.S. in that same year was 42% natural gas, 17% coal, 18% nuclear, 21% renewables. `https://www.iea.org/countries/united-states/electricity`.

Our paper also explores the mechanisms behind the prediction gap, with an emphasis on economic factors. As economists have long pointed out, the demand for energy is derived from the demand for energy services (Hausman, 1979; Dubin and McFadden, 1984). These services include transportation, lighting, heating, and yes, cooling. Households produce these services using durable goods, energy, and other inputs. Viewed through this lens, it makes sense to pay close attention to the price of energy services. When energy becomes cheaper or there are advances in energy efficiency, this reduces the price of energy services, leading households to consume more.

As with many existing climate change studies, our previous research emphasized income and temperature growth as explanatory factors. Although these factors explain a large share of AC adoption, they still leave a large gap between predicted and actual AC adoption. We argue that price reductions and technological change that improved energy efficiency likely explain much of the remaining prediction gap.

Our paper underscores the importance of prices and technological change. The climate change literature typically does not incorporate predictions about prices or technological change, in large part because of the difficulty of making such predictions. However, our paper illustrates the danger of such simplifications, even after a relatively short period of time.

In the end, the climate change literature must take a stand on how future prices and energy efficiency are likely to evolve to improve the credibility of future predictions of energy use and consequences. Looking back, this would not have been easy. We might have been able to predict improvements in energy efficiency based on recent trends, but not the decrease in electricity prices. At the time, we believed that electricity prices would rise, but did not anticipate the political costs of removing energy subsidies (Burgess et al., 2020).

Figure 1: Evidence of Accelerated Air Conditioning Adoption

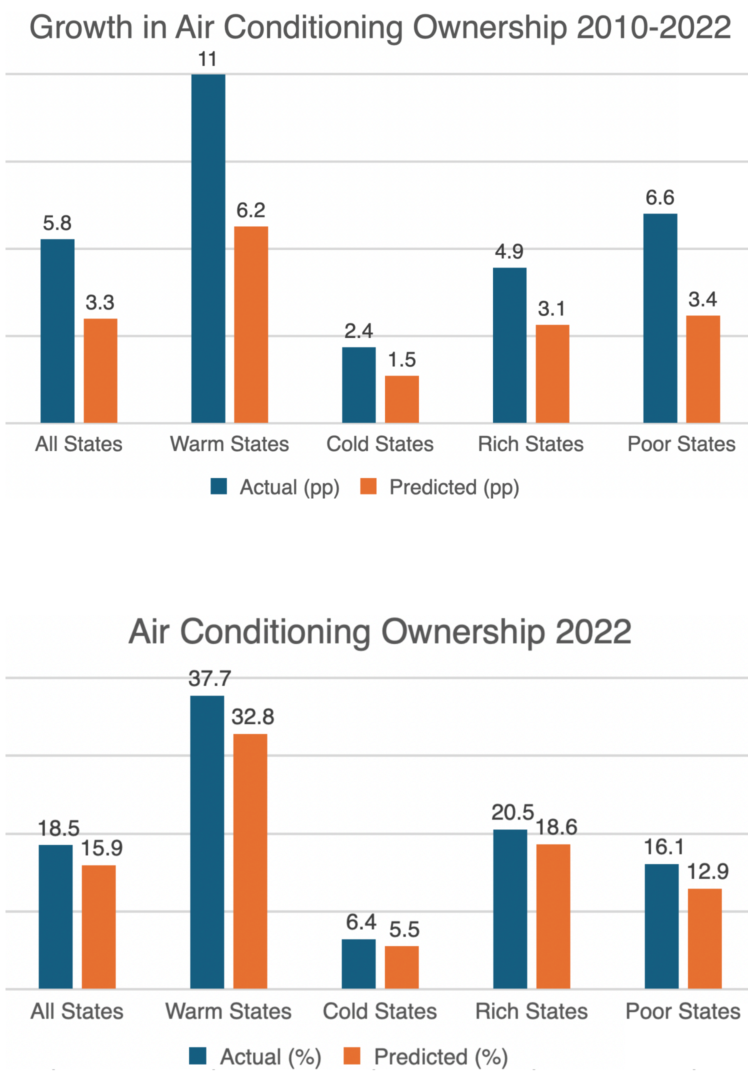


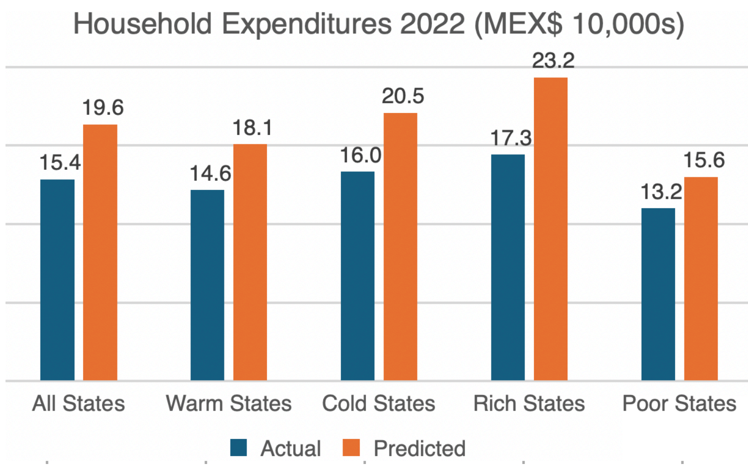
Table 1: Prediction Gap

(Prediction Gap = Predicted / Actual Growth in AC Ownership 2010-2022)

Model	Growth in Expenditures/CDDs	Population Weights	Prediction Gap
		A. All States	
Probit	Predicted	2010	0.566
Probit	Actual	2010	0.251
Probit	Predicted	2022	0.571
LASSO	Predicted	2010	0.629
		B. Warm States	
Probit	Predicted	2010	0.566
Probit	Actual	2010	0.253
Probit	Predicted	2022	0.570
LASSO	Predicted	2010	0.604
		C. Cold States	
Probit	Predicted	2010	0.613
Probit	Actual	2010	0.264
Probit	Predicted	2022	0.611
LASSO	Predicted	2010	0.753
		D. Rich States	
Probit	Predicted	2010	0.633
Probit	Actual	2010	0.123
Probit	Predicted	2022	0.657
LASSO	Predicted	2010	0.711
		E. Poor States	
Probit	Predicted	2010	0.517
Probit	Actual	2010	0.360
Probit	Predicted	2022	0.508
LASSO	Predicted	2010	0.569

Notes: This table describes model performance for our original probit model and a more flexible cross-validated LASSO. In each case we report the prediction gap, i.e. the ratio of the predicted change to the actual change. The rows with actual growth in expenditures and CDDs use the actual state-level average growth of household expenditures and CDDs 2010-2022; otherwise we use the predicted growth in expenditures and CDDs, for example, assuming 2% annual real expenditure growth. The rows with 2022 population weights adjust the predictions to weight more the states that grew between 2010 and 2022.

Figure 2: Are Income and Temperatures Higher Than Expected?



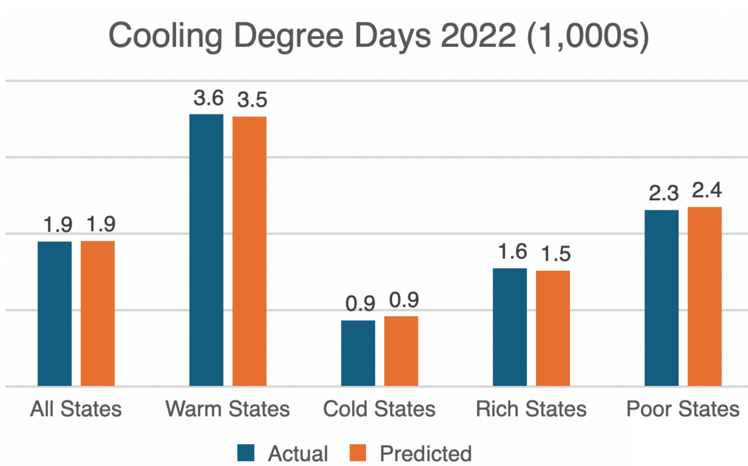
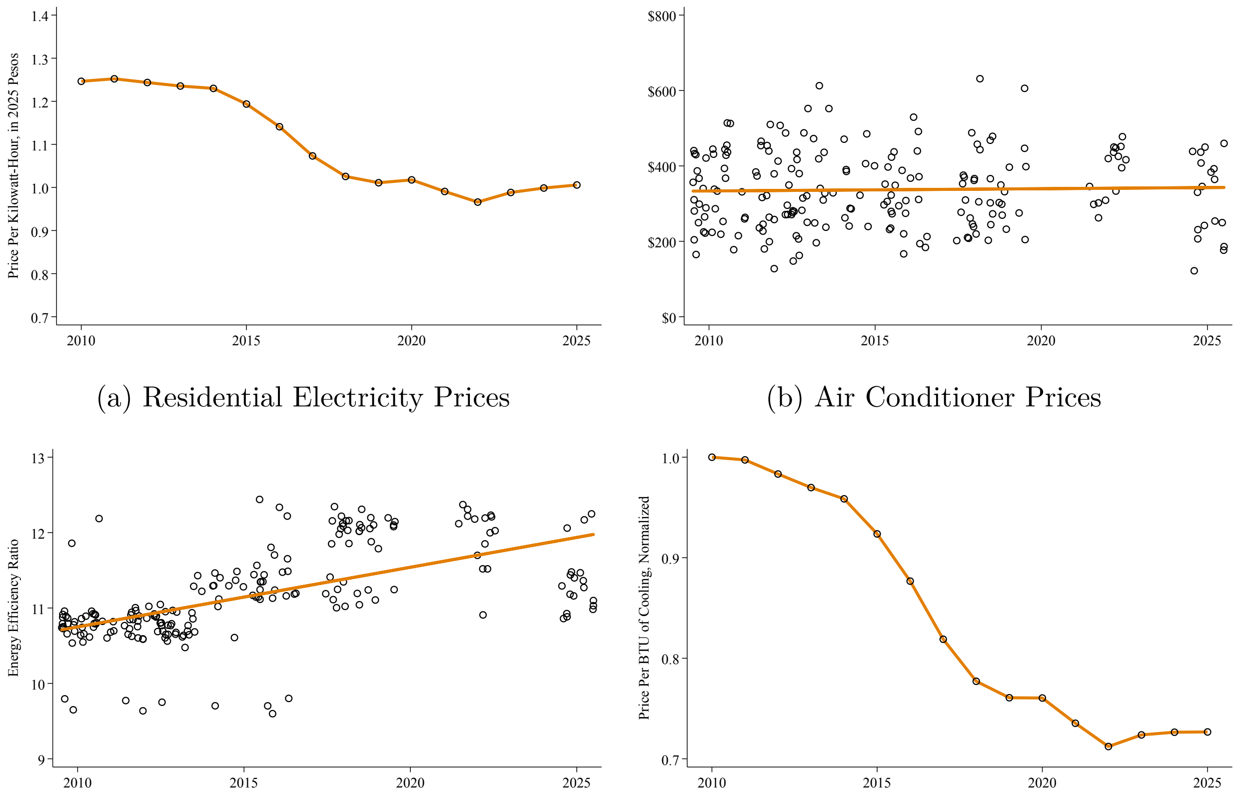


Figure 3: Additional Mechanisms



(a) Residential Electricity Prices

(b) Air Conditioner Prices

(c) Air Conditioner Energy Efficiency

(d) Price of Cooling

Notes: Panel A plots average electricity prices as of June in each year for one of the most common residential tariffs in Mexico (Tariff 1B). Prices have been normalized to reflect year 2025 pesos using the Mexican consumer price index from INEGI. As of 2025 the exchange rate is 19.5 pesos per dollar, so a price of 1.0 peso per kWh is 5.1 U.S. cents. For alternative tariffs, and additional information see Appendix Figures 7 and 8. Panel B plots retail prices in U.S. dollars for room ACs, normalized to reflect year 2025 dollars using the consumer price index from U.S. Bureau of Labor Statistics. Panel C plots room AC energy efficiency, measured as cooling output (BTU) per unit of electricity (watt), i.e. the energy-efficiency ratio. Each observation in panels B and C is a room AC profiled by U.S.-based Consumer Reports. These panels also includes a linear time trend, indicating a 2.7% increase in prices, and an 11.0% increase in energy-efficiency during the sample period. There are 204 total observations and a small amount of jitter has been added to each observation for visibility. For room AC average capacity and additional information see Appendix Figure 9. Panel D plots the implied price per unit of cooling, measured in pesos per BTU and normalized to 1.0 in 2010. This implied price is calculated by multiplying the price of electricity (in pesos per watt) by the average watts per BTU.

Table 2: Engel Curves

	Estimated Using Data from 2010 (1)	Estimated Using Data from 2022 (2)
Annual Household Expenditure	0.024**	0.040**
	(.003)	(.004)
Cooling Degree Days	0.062**	0.078**
	(.010)	(.008)
1(Warm Municipality)	-0.074**	-0.068**
	(.024)	(.023)
Annual Household Expenditure * 1(Warm Municipality)	0.026**	0.023**
	(.005)	(.004)
Partial Derivative in Warm Municipalities	0.050**	0.064**
$\frac{\partial 1(AirConditioning)}{\partial AnnualHouseholdExpenditure}$	(.003)	(.003)
State Fixed Effects	Yes	Yes
Observations	27,655	90,102
Psuedo R^2	.50	.50
Mean of Dependent Variable	.127	.185

Notes: This table reports coefficient estimates and standard errors from two separate Probit models. For column (1), the model is estimated using the 27,655 households in ENIGH 2010, and for column (2), the model is estimated using the 90,102 households in ENIGH 2022. The dependent variable in both models is an indicator variable for households with AC. Household expenditures (100,000s) have been normalized to reflect 2022 Mexican Pesos (2022 MXN) using the Mexican CPI, *Índice Nacional de Precios al Consumidor*, `https://en.www.inegi.org.mx/temas/inpc/`. Cooling Degree Days (1000s) are annual averages relative to 65°F. Both models are estimated using ENIGH sampling weights. Standard errors are clustered by municipality. *Significant at the 5% level. **Significant at the 1% level.

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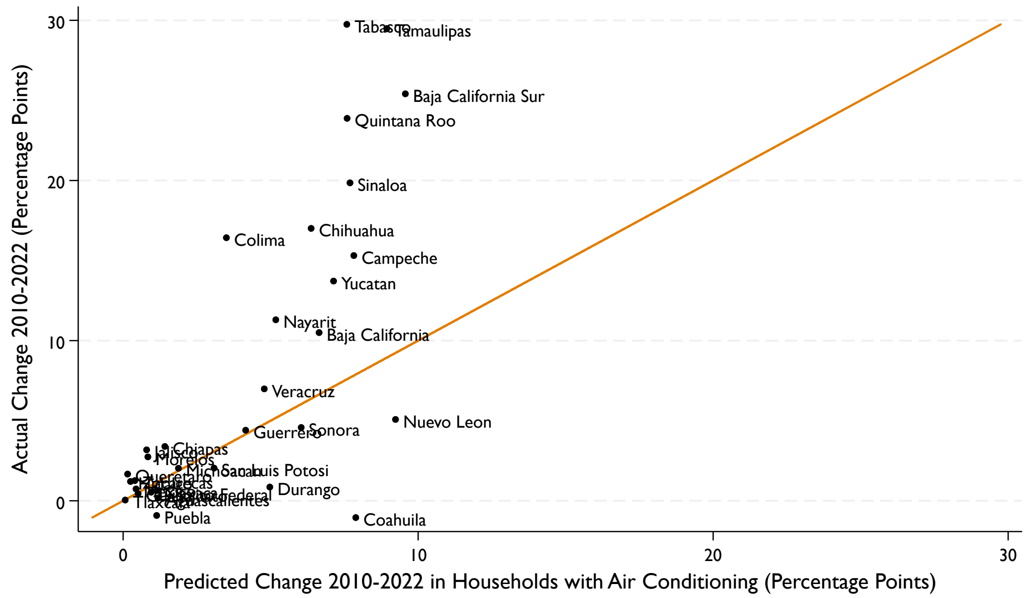
Online Appendix

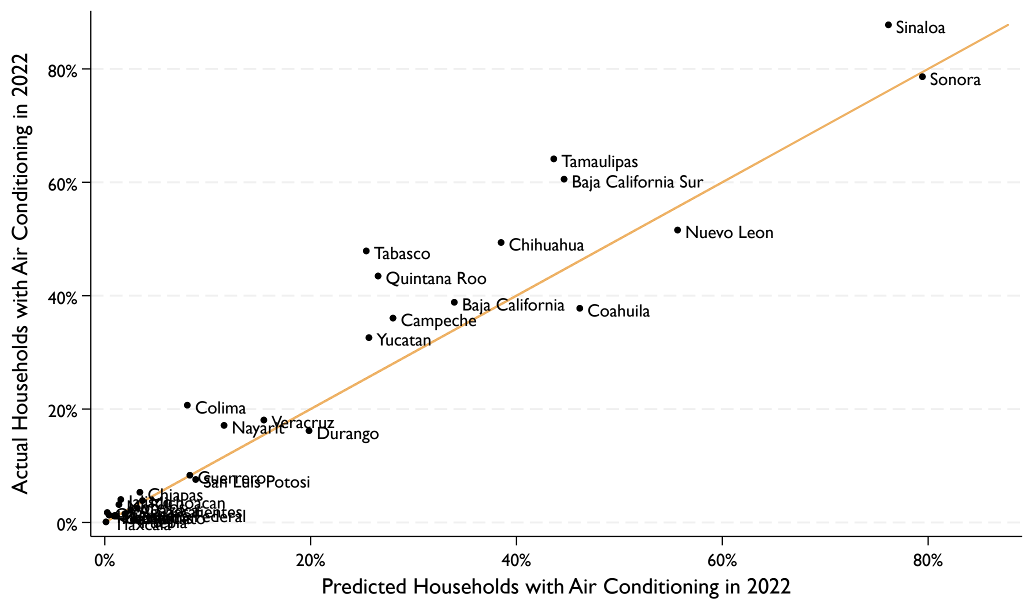
Why Did Air Conditioning Adoption Accelerate Faster Than Predicted? Evidence from in Mexico

Lucas W. Davis
Paul Gertler

Appendix Figure 1: Scatterplot By State



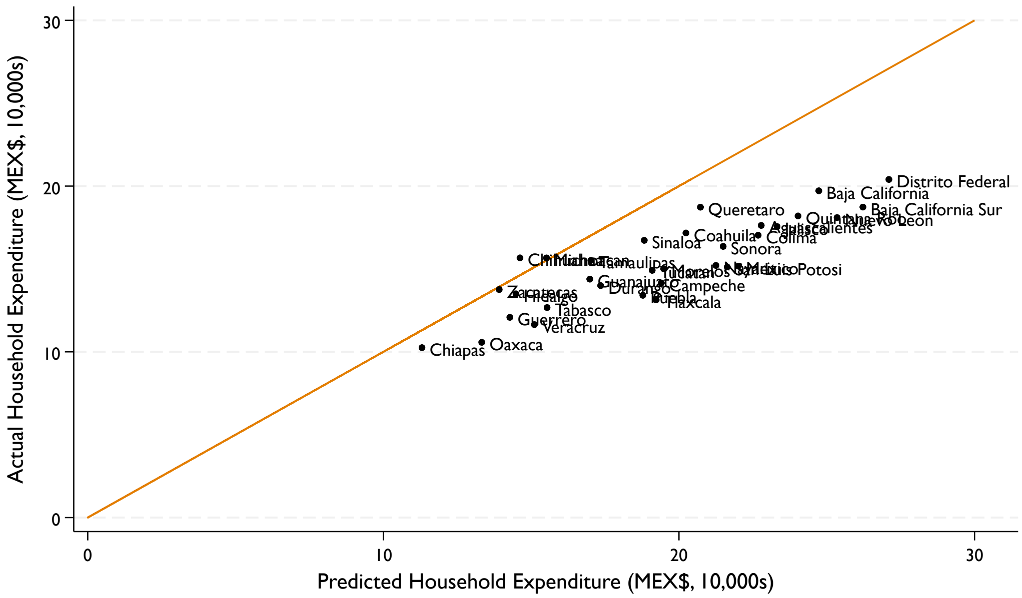
(a) Growth in Air Conditioning Ownership



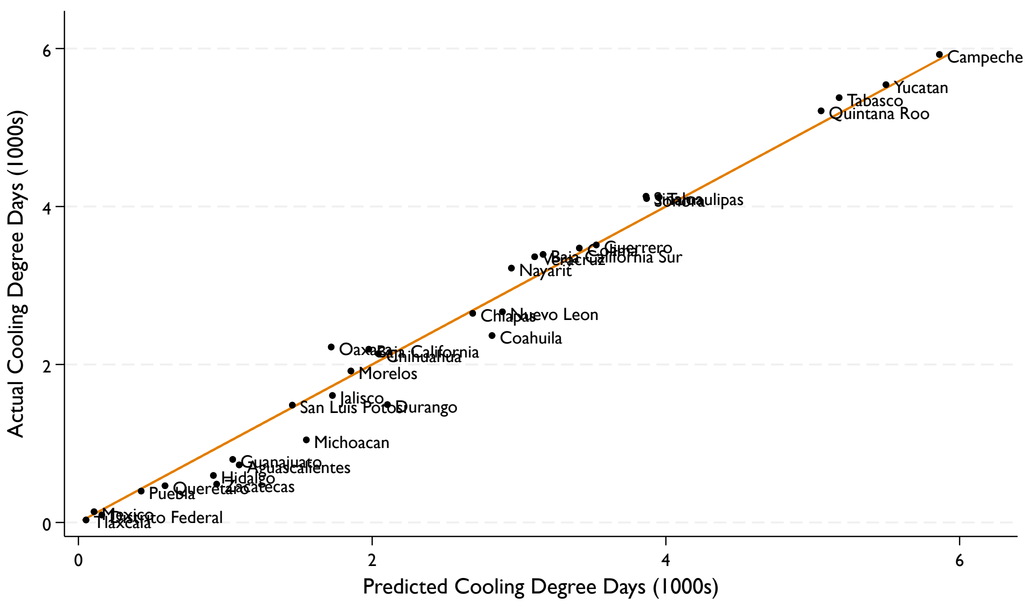
(b) Percent of Households with Air Conditioning

Notes: This figure compares the actual growth in AC 2010-2022 with what we predicted using 2010 data (Davis and Gertler, 2015). If our predictions were perfect, then all observations would be along the 45 degree line. Panel A plots changes in AC (in percentage points) between 2010 and 2022 and Panel B plots the percent of households with AC 2022. The underlying data and analyses are based on household-level microdata but have been aggregated for the purposes of this figure to include 32 observations: one for each of Mexico's 31 states and one for the federal district of Mexico City.

Appendix Figure 2: Scatterplot By State, Incomes and Temperatures



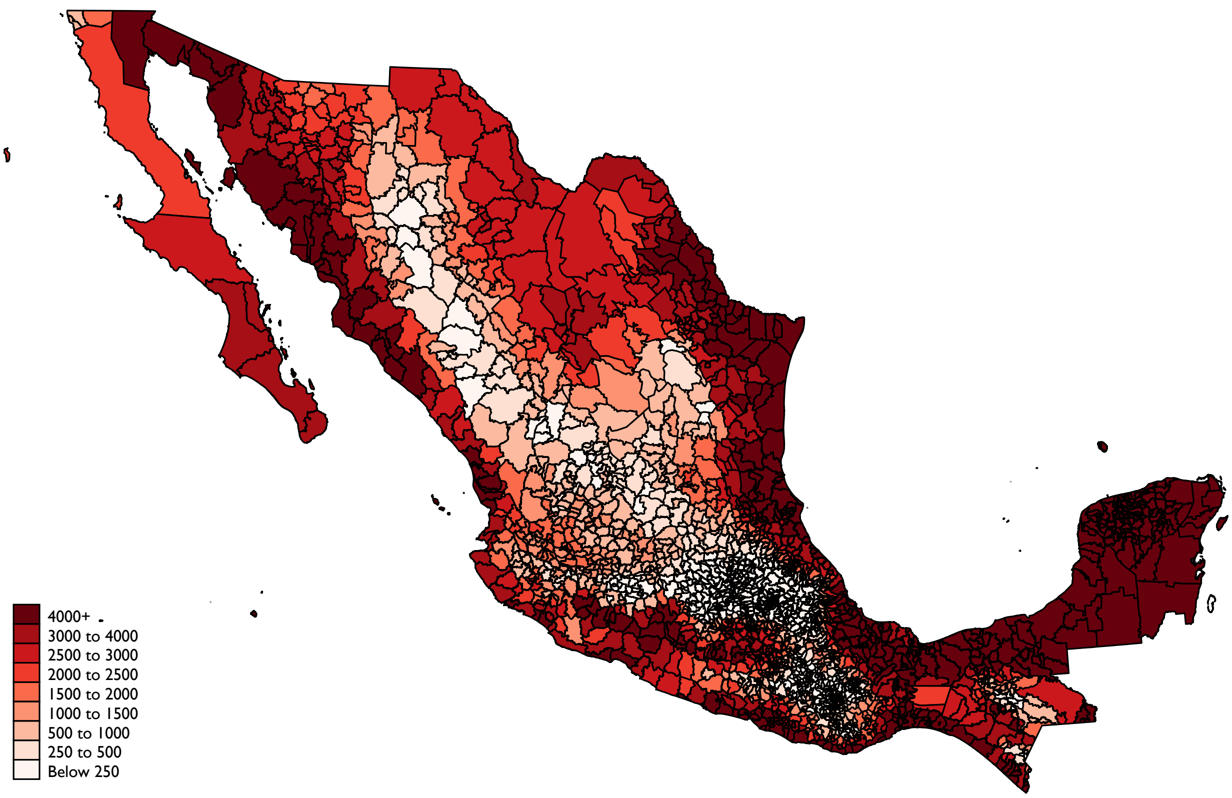
(a) Household Expenditure



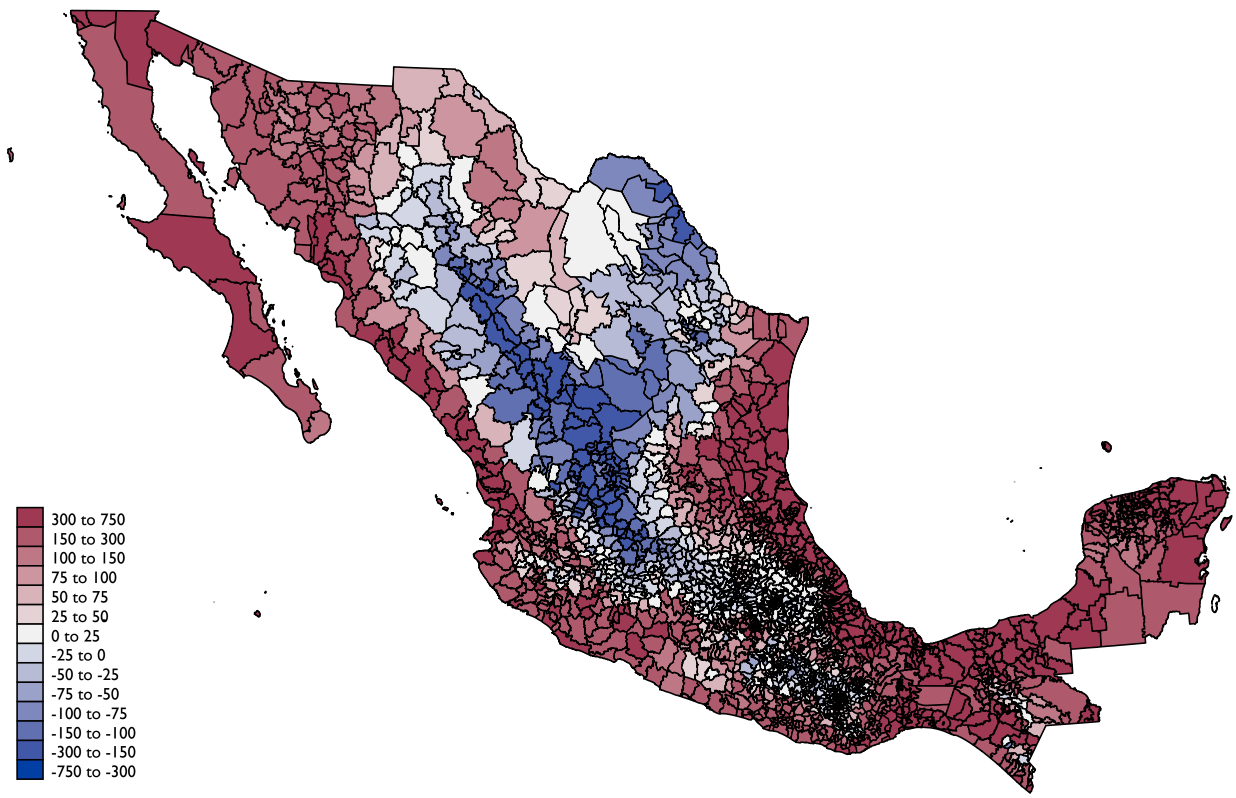
(b) Temperatures (Cooling Degree Days)

Notes: Panel A compares annual average household expenditures in 2022 (in Mexican Pesos, 10,000s) with what we predicted for 2022 using 2010 data and assumptions about future growth in expenditures (Davis and Gertler, 2015). Panel B compares cooling degree days in 2022 (in 1000s) with what we predicted using a suite of climate models (Davis and Gertler, 2015). In both panels the underlying data and analyses are based on household-level microdata but have been aggregated for the purposes of this figure to include 32 observations: one for each of Mexico's 31 states and one for the federal district of Mexico City.

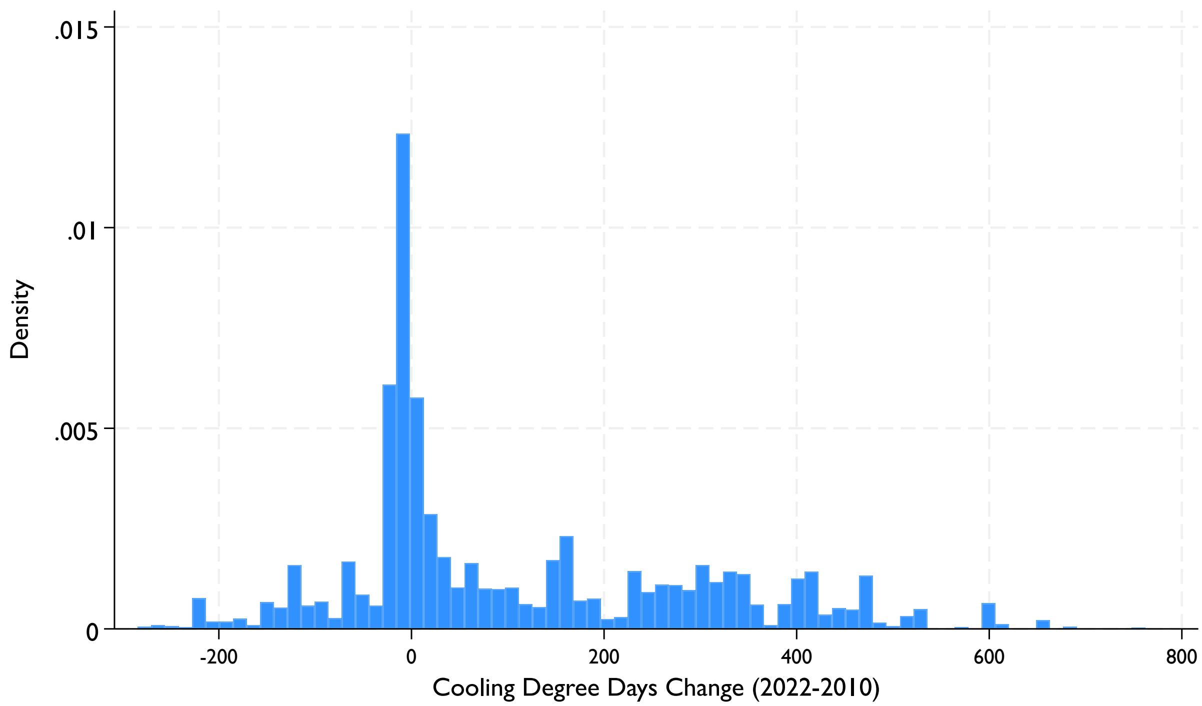
Appendix Figure 3: Cooling Degree Days as of 2022, by Municipality



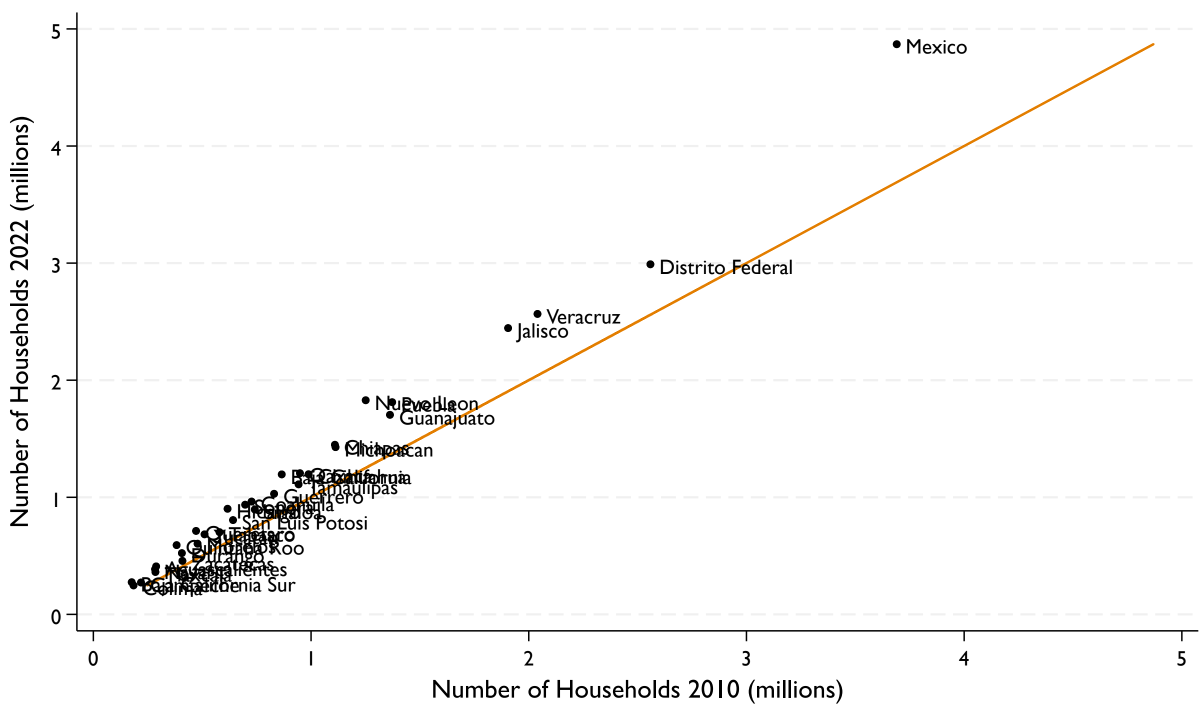
Appendix Figure 4: Cooling Degree Day Change 2010-2022, by Municipality



Appendix Figure 5: Cooling Degree Day Change, Weighted by Population

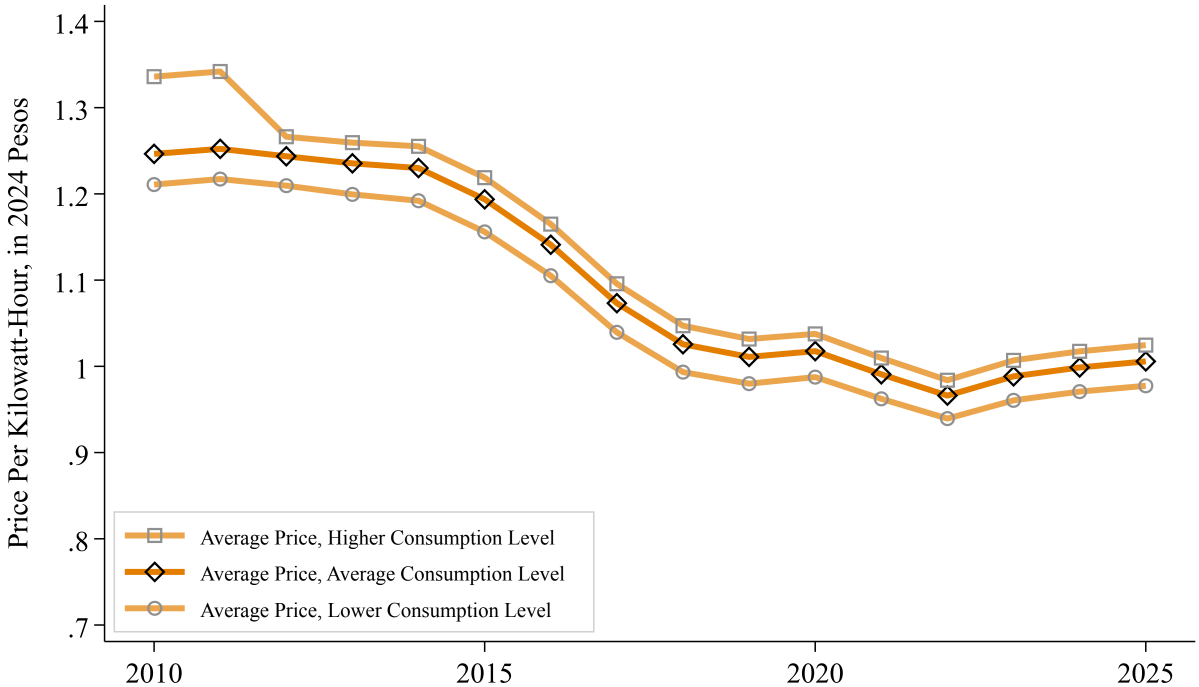


Appendix Figure 6: Number of Households By State



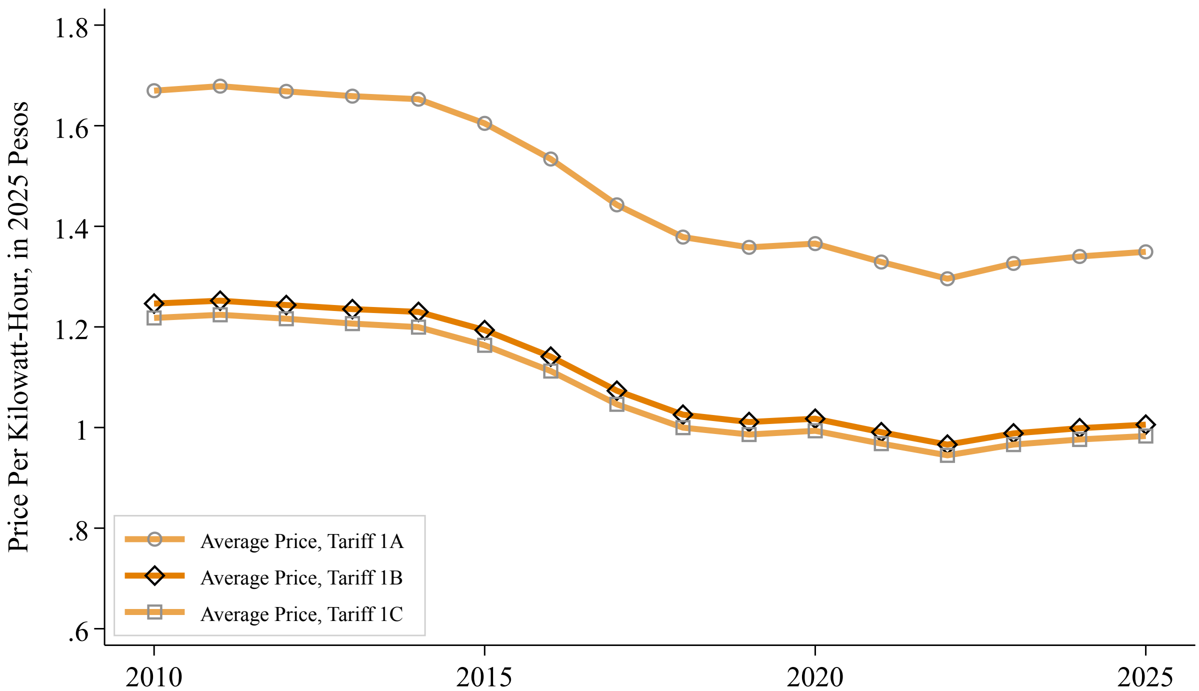
Notes: This figure plots the number of households by state based on ENIGH 2010 and ENIGH 2022. The figure includes 32 observations: one for each of Mexico's 31 states and one for the federal district of Mexico City.

Appendix Figure 7: Residential Electricity Prices in Mexico, Alternative Consumption Levels



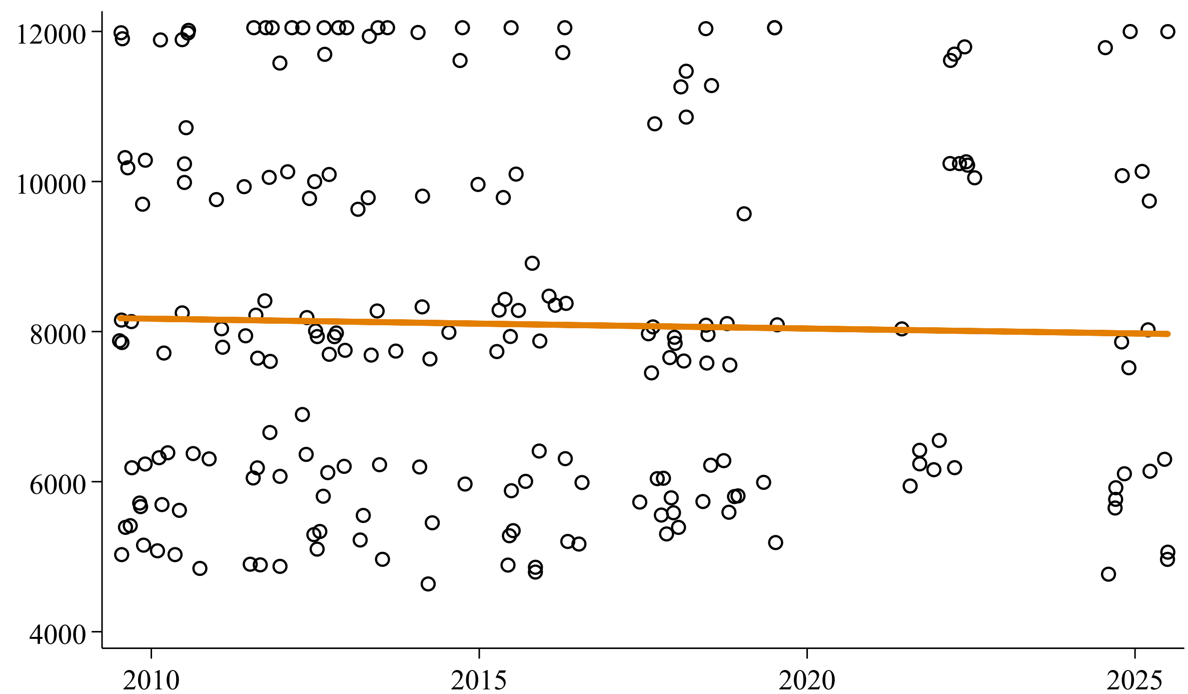
Notes: Mexico has increasing block rates for electricity so households that consume more pay somewhat higher average prices while households that consume less pay somewhat lower average prices. The purpose of this figure is to show how much this matters in practice. We collected the prices and length for each block for 2010-2014 from Hancevic and Lopez-Aguilar (2019) and for 2014-2025 from the Federal Electricity Commission (*Comisión Federal de Electricidad*, `https://www.cfe.mx/`). The darkest data series in the middle is the average price for a household consuming 170 kilowatt hours per month, the national average (Hancevic and Lopez-Aguilar, 2019). This darkest data series is exactly the same as what is plotted in the paper. The figure also plots average prices for a household consuming 20% more, and for a household consuming 20% less. The second block was lengthened in 2012 which explains why average prices at the higher consumption level were somewhat higher in 2010 and 2011. Higher consumption households experienced a 23% decline in prices over this period, compared to a 19% decline in the other two categories.

Appendix Figure 8: Residential Electricity Prices in Mexico, Alternative Tariffs



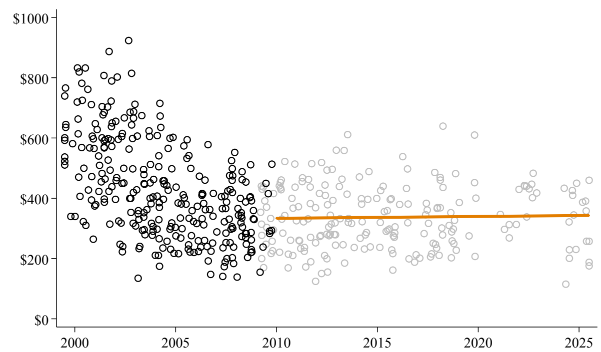
Notes: Residential electricity tariffs in Mexico differ by climate zone with warmer areas having longer blocks and thus lower average electricity prices. The purpose of this figure is to show how much this matters in practice. The darkest data series in the middle is the average price for Tariff 1B, exactly the same as what is plotted in the paper. Average prices are higher for Tariff 1A (cooler areas), and almost identical for Tariff 1C (warmer areas). According to Hancevic and Lopez-Aguilar (2019), 7% of Mexican households are on Tariff 1A, 12% on Tariff 1B, and 15% on Tariff 1C. In all three cases, average prices decreased by 19% between 2010 and 2025.

Appendix Figure 9: Air Conditioner Capacity

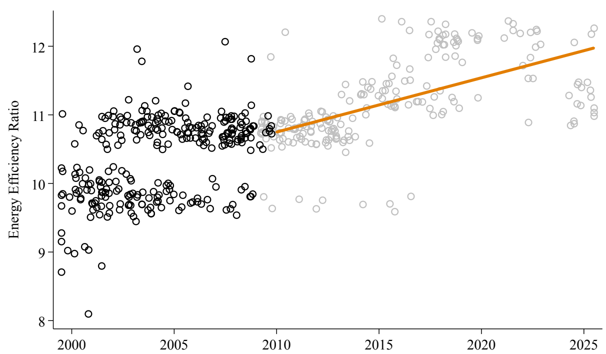


Notes: This figure plots room AC capacity, in BTU. A typical small AC is 6,000 BTU, compared to 8,000, 10,000, and 12,000 for medium, large, and extra large. Each observation is a room AC profiled by U.S.-based *Consumer Reports*. The figure also includes a linear time trend, indicating a 2.4% decrease in capacity during the sample period. There are 204 total observations and a small amount of jitter has been added to each observation for visibility. We exclude ACs from Friedrich, a high-end brand whose models typically sell for twice as much as other brands. We also exclude "inverter" units which were introduced late in our sample period and are more energy-efficient, more expensive, and not comparable to traditional units.

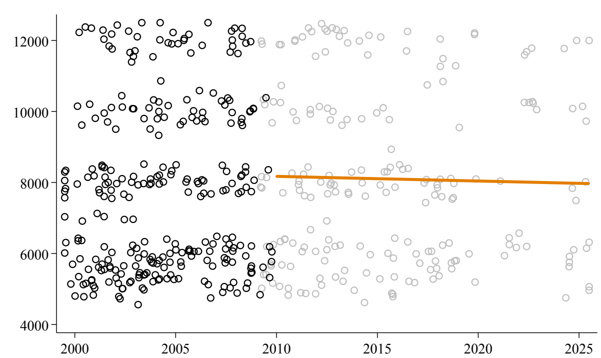
Appendix Figure 10: Air Conditioner Characteristics 2000-2025



(a) Air Conditioner Prices



(b) Air Conditioner Energy Efficiency



(c) Air Conditioner Capacity

Notes: It is reasonable to ask whether the technological change in air conditioners could have been anticipated. In order to shed light on this question, we went back and collected 10 years of additional data from *Consumer Reports* from 2000-2009. Darker observations are the 286 room air conditioners profiled by the magazine 2000-2009. Lighter observations are the 204 room air conditioners profiled from 2010-2025. A small amount of jitter has been added to each observation for visibility. During this earlier period 2000-2009, there was a 50.0% decrease in prices, an 8.8% increase in energy efficiency, and a 9.9% increase in capacity.

Appendix Table 1: Summary Statistics

	A. ENIGH 2010		B. ENIGH 2022	
	Mean	St Dev	Mean	St Dev
		A. All States		
Percent With Air Conditioning	12.7	33.3	18.5	38.8
Annual Household Income (10,000s)	22.7	21.3	24.6	19.7
Annual Household Expenditure (10,000s)	15.5	14.0	15.4	11.7
Cooling Degree Days (1000s)	1.78	1.70	1.90	1.84
		B. Warm States		
Percent With Air Conditioning	26.7	44.3	37.7	48.5
Annual Household Income (10,000s)	21.2	20.1	23.7	19.5
Annual Household Expenditure (10,000s)	14.3	13.0	14.6	11.3
Cooling Degree Days (1000s)	3.34	1.41	3.56	1.51
		C. Cold States		
Percent With Air Conditioning	4.1	19.8	6.4	24.6
Annual Household Income (10,000s)	23.6	21.9	25.1	19.8
Annual Household Expenditure (10,000s)	16.2	14.5	16.0	11.8
Cooling Degree Days (1000s)	0.82	1.03	0.87	1.15
		D. Rich States		
Percent With Air Conditioning	15.6	36.3	20.5	40.4
Annual Household Income (10,000s)	27.0	23.5	28.1	21.2
Annual Household Expenditure (10,000s)	18.3	15.6	17.3	12.5
Cooling Degree Days (1000s)	1.42	1.50	1.55	1.63
		E. Poor States		
Percent With Air Conditioning	9.5	29.3	16.1	36.8
Annual Household Income (10,000s)	17.8	17.3	20.5	17.0
Annual Household Expenditure (10,000s)	12.3	11.2	13.2	10.2
Cooling Degree Days (1000s)	2.20	1.82	2.31	1.99

Notes: This table reports summary statistics for the 27,655 households in 2010 ENIGH and 90,102 households in 2022 ENIGH. Microdata from ENIGH are publicly available online: `https://en.www.inegi.org.mx/programas/enigh/`. Income and expenditures from 2010 have been normalized to reflect 2022 Mexican Pesos (2022 MXN) using the Mexican CPI, *Índice Nacional de Precios al Consumidor*, `https://en.www.inegi.org.mx/temas/inpc/`. Cooling Degree Days are Annual Relative to 65°F (in 1000s). ENIGH sampling weights are used in all calculations.

Appendix Table 2: Categorizing States

	Rich	**Poor**
Cold	Aguascalientes, Baja California, Distrito Federal, Jalisco, Mexico, Morelos, Queretaro, San Luis Potosi	Chihuahua, Guanajuato, Hidalgo, Michoacan, Oaxaca, Puebla, Tlaxcala, Zacatecas
Warm	Baja California Sur, Coahuila, Colima, Nayarit, Nuevo Leon, Quintana Roo, Sinaloa, Sonora	Campeche, Chiapas, Durango, Guerrero, Tabasco, Tamaulipas, Veracruz, Yucatan

Note: Throughout the paper we refer to “warm” and “cold” states, as well as to “rich” and “poor” states. This table lists the states in each category. We determined these categories using CDDs and household expenditure as measured in the 2010 ENIGH. In each case we first calculated state-level averages for Mexico’s 31 states plus Mexico’s Federal District (“Distrito Federal”). With those 32 values we then calculated the median and assigned 16 states to above and below the median. At a state level the correlation between these two variables is -.04. This lack of correlation between the values explains why we ended up with 8 in each of the four categories without imposing that requirement explicitly. Had there been a perfect negative correlation, for example, we would have ended up with 16 states in Warm/Poor, and 16 states in Cold/Rich. The rich heterogeneity across both dimensions is one of the reasons Mexico is well-suited for studying AC adoption.

Appendix Table 3: Variables Selected By Lasso

Potential Variables	Selected
Household Expenditures (HHEX)	X
Cooling Degree Days (CDD)	X
Warm	X
HHEX * Warm	X
HHEX Squared	X
HHEX Cubed	X
CDD Squared	X
CDD Cubed	
HHEX Squared * Warm	X
HHEX Cubed * Warm	X
HHEX * CDD Squared	X
HHEX * CDD Cubed	X
S2	X
S3	X
S4	X
S5	X
S6	X
S7	X
S8	X
S9	X
S10	X
S11	X
S12	X
S13	X
S14	X
S15	X
S16	X
S17	X
S18	X
S19	X
S20	X
S21	X
S22	X
S23	X
S24	X
S25	X
S26	X
S27	X
S28	X
S29	X
S30	
S31	X
S32	X