Feeling the Heat:
How Households Manage High Electricity Bills

Abigail Ostriker*[1], Alexandra Lefevre[2], Daniel M. Sullivan[2], and Chris Wheat[2]

[1] *Corresponding author, ostriker@bu.edu; Questrom School of Business, Boston University*
[2] *JPMorganChase Institute*

May 16, 2025

Abstract

Climate change is increasing the threat of extreme heat. Air conditioning (AC) is an effective but costly way to combat heat, and lower-income households may struggle to pay energy bills. Using anonymized bank transaction data from three US cities, this paper studies how heat impacts household electricity expenditures, and how responses to temperature differ by income. We find one Celsius cooling degree-day costs households between \$1 - \$2, implying a single 85 °F day costs about \$5-\$10 more than a 77 °F day. In our sample locations of Chicago, Houston, and Los Angeles, we estimate climate change will increase annual electricity bills by \$100 - \$300. We also find that behavioral modifications can reduce the financial cost of extreme heat: low-income households spend about 25% less per hot day than high-income households, after controlling for house characteristics. While central AC does not change this phenomenon, elderly households are less likely to attenuate their electricity use, with potential implications for energy policy.

*The authors thank participants at the Harvard Energy Policy Seminar, MIT EEE Early-Stage Seminar, Lisbon Climate Adaptation Workshop, and UChicago Booth Internal Seminar for helpful comments. Ostriker thanks Peter Ganong and Pascal Noel for their guidance and assistance accessing the data. The opinions expressed in this paper are those of the authors alone and do not necessarily represent the views of JPMorganChase.

1 Introduction

By the end of the century, most of the United States is expected to see at least 50 days per year with a maximum temperature above 95 F (National Oceanographic and Atmospheric Administration, n.d.). Extreme heat causes severe negative impacts on health (Carleton et al., 2022; Deschênes & Greenstone, 2011); it is already estimated to cause about 1,300 premature deaths annually, and this is expected to grow to tens of thousands of premature deaths by the end of the century (Crimmins et al., 2016).

Temperature control is necessary to mitigate the negative health effects of climate change. However, this intervention is costly, and survey evidence indicates low-income households already struggle to pay energy bills: 20% of households earning less than $40,000 annually reported sometimes or always foregoing food or medicine to pay energy bills (United States Energy Information Administration, 2015). This paper investigates how extreme heat temperature impacts household energy bills and studies the extent to which low-income households manage extreme temperatures by using energy less intensively.

We combine administrative banking data from three metro areas – Chicago, Houston, and Los Angeles – with granular weather data to measure how energy bills change with monthly temperatures and household incomes. We find that households spend meaningful amounts on energy: a summer month that is 1 °C hotter on average leads to $25-$40 more electricity spending for low-income households. Back-of-envelope calculations suggest climate change will increase annual electricity bills by $100-$300 for the cities in our sample.

We also find that low-income households adapt less strongly to heat. Low-income energy expenditures are attenuated relative to high-income households: even controlling for house characteristics, low-income households consume 15-30% less electricity per marginal degree-day of heat than high-income households do. This attenuation is not reduced by more-efficient cooling technology: similar attenuation is seen in samples with and without central AC. We argue that these estimates reflect less-intensive temperature control, which can have particular negative impacts on health at hot temperatures (Gould et al., 2024). Back-of-the-envelope calculations suggest that the money saved by attenuated cooling may fall below the consequent mortality cost.

This paper contributes to a broad literature studying disparities in adaptation to climate change. A number of studies document that low-income households are more likely to be exposed to natural disasters.[1] As one example, Bakkensen and Ma (2020) find that low-income and minority households are more likely to move into high-risk flood zones. These studies focus on large, infrequent events which are expensive to protect against (e.g., by moving). By comparison, this paper studies high-frequency events which have relatively low barriers to accessing adaptation. Weaker protection from natural disasters in low-income households might be driven by lower financial literacy or liquidity. However, because purchasing and using air conditioning is relatively cheap and easy to understand, it might therefore be expected to exhibit no or small disparities. Despite this, we find that low-income

[1] See research summarized by United States Substance Abuse and Mental Health Services Administration (2017).

households consume substantially less electricity than high income households in response to the same heat changes, demonstrating income disparities in adaptation to climate change even for relatively cheap approaches.

This paper also builds on a literature studying the impacts of extreme temperatures on household expenditures (Auffhammer & Aroonruengsawat, 2011; Bhattacharya et al., 2003; Chirakijja et al., 2023; Cullen et al., 2004). Most closely related is the work of Doremus et al. (2022) and Kwon et al. (2023), who both study differences across income groups in the effects of temperature on energy expenditures. Like Doremus et al. (2022), we evaluate differences in the impacts of extreme heat on household expenditures. However, we build on this paper by using granular administrative data that enables us to reduce error in measuring temperature, which could otherwise attenuate estimates towards zero. This allows us to estimate the relative differences in consumption across income levels with high precision. Relative to this paper, which finds that low-income households spend 75% less on energy per hot day than high-income households do, our study finds discrepancies of only 15% - 30%. At the same time, we find that extreme heat is more expensive, with a 30 °C day causing an additional \$3-\$9 of electricity costs rather than \$0-\$1 as implied by their estimates. This research suggests that low-income households spend more on hot weather than was previously known, and climate change will consequently induce larger growth in cooling bills than implied by those estimates. The magnitude of our findings is closer to those of Kwon et al. (2023), who use billing data from an Arizona utility and find that low-income households consume about 11% less electricity than high-income households in response to heat – an estimate which is similar to our estimate for Houston. Relative to this paper, we are able to expand the analysis to cooler climates, which might be expected to exhibit smaller income disparities because of the comparatively smaller contribution of electricity bills to household budgets. Nevertheless, we find that the income disparity in electricity consumption with respect to heat is similar across climates. Relative to both papers, we are able to compare adaptation across elderly and non-elderly populations. While elderly populations are often targeted by energy assistance programs, perhaps because of their higher level of vulnerability to heat, we find that elderly populations exhibit smaller disparities in cooling behavior across income levels than the general population. Notably, we observe that these higher-risk households are more likely to protect themselves despite their likely-higher insurance coverage, suggesting that any moral hazard effects of insurance on self-protection in this setting are offset by costs of heat illness that are not covered by insurance, for example physical discomfort or death.[2]

This paper has implications for US energy assistance policies. Existing policy primarily focuses on cold weather. A major federal policy for energy assistance, the Low Income Home Energy Assistance Policy (LIHEAP), was established "to help people financially survive frigid winters and their heating costs" (Grandoni & Phillips, 2022), and allocations of LIHEAP funding are concentrated in the north of the country (Batlle et al., 2024). Although some states offer benefits to offset cooling expenditures

[2]We measure heat vulnerability as being over age 65. Most households above age 65 will have Medicare insurance, while households below that cutoff are less likely to be insured.

as well, many do not, and in 2022 advocates reported that 85% of funds had been used to offset winter heating bills (ibid). In light of climate change, policymakers are being asked to consider whether to shift energy-assistance funding to hotter states and spend more on cooling assistance (Frank, 2023). Our work speaks to this debate by quantifying the expected impact of climate change on electricity expenditures for low-income households. However, the choice between funding heating and cooling also hinges on the factors motivating the energy-assistance policy. Relative to cash assistance, the LIHEAP program could be motivated by a form of paternalism: policymakers may be concerned that low-income households underestimate the benefits of medically-necessary heating and cooling, justifying transfer restrictions that increase consumption of temperature control. In this case, the relative propensity to underconsume heat versus cooling is a key input in determining how to allocate funding across temperature extremes. Our results suggest that households may underestimate the benefits of cooling, since the money they save by attenuating cooling likely falls below the implied mortality cost. However, more research is needed to determine whether these households are indeed efficiently foregoing cooling. Overall, our results underline the importance of considering and documenting motivations for energy assistance as policymakers adapt these programs to climate change.

2 Data

2.1 Bank Transactions

The primary data source used in this analysis describes account balances and debit card, credit card, and ACH transfer transactions of customers of JPMorganChase, a large retail bank in the United States. Transaction records include details about the date, amount, and counterparty of the transaction. Derived from administrative data, the dataset records these data for checking and savings accounts as well as Chase-branded credit cards.[3] Accounts that are associated with the same individual or multiple individuals with the same address are linked together, resulting in an identifier we interpret as being at the household level. For each household, we compute the total annual income in 2018 as well as age of the main account holder in December 2019. Within each metro area and age quartile, we compute quartiles of income and assign each household an income quartile bin. Constructing quartiles of income within age quartiles accounts for declines in income after retirement, causing the income quartile variable to better reflect lifetime socioeconomic status.

2.2 House Characteristics

To measure house characteristics at the block-group level, we use estimates from the 2014-2018 American Community Survey (ACS) of the median number of rooms in each house unit. We then match each household to the value in its block-group. (Block-groups contain at most about 3,000 people.) For a portion of households with mortgages, we observe characteristics of their homes gathered from

[3]We also observe payments to non-Chase branded credit cards, but cannot identify the category or date of transaction for this spending. We therefore do not include this spending in our main outcome.

CoreLogic Property and Tax Deed data. These characteristics include the year a house was built, total living square footage, and whether or not the unit has central AC. For the ACS sample, we define house characteristic bins as quartiles of number of rooms, within each metro area. For the CoreLogic sample, we likewise construct four house size bins according to within-city quartiles of house square footage. We further compute quartiles of house age, and then interact house age quartile and house size quartile to get 16 house characteristic bins.[4]

2.3 Temperature

We supplement the dataset on bank transactions and house characteristics with granular data on temperature from PRISM Climate Group (n.d.).[5] Specifically, we obtain data on daily maximum and minimum temperatures in a 4km by 4km grid from January 2018 to December 2019. We aggregate each measure of temperature to the census block level, taking the spatial- and population-weighted average of reported temperatures.[6] We then further aggregate to the weekly level.

To create a single-variable measure for heat, we compute cooling degree days per week. A cooling degree day (CDD) is a standard measure of the need for cooling. It is computed as the sum across days of the number of degrees by which each day's average temperature exceeded a particular benchmark, typically 65 °F, 20 °C (68 °F), or 25 °C (77 °F). Because of evidence suggesting that cognitive and health effects of excessive heat are concentrated above 25 °Celsius (Dell et al., 2014), we use that threshold as our benchmark.[7] In line with the use of CDDs as a measure of cooling need, we show that electricity bills exhibit an approximately linear relationship with CDDs in our sample. Therefore, we use this measure in our analysis of differential cooling across income groups, which benefits from a single measure of heat.

Customers may pay their bills immediately upon receipt, the day they are due, or anywhere in between. There may also be a delay between the time period covered by the bill and when a customer receives the bill. Therefore, the temperature that contributes to a given electricity bill may be from the 0-30 days preceding the bill payment; or it could be as many as 60-90 days ago. To establish the most relevant measure, for each customer we find the 30-day window that exhibits the highest correlation of bill payment with CDDs. For example, one customer's window might be 25-55 days prior to the bill. We then compute the number of CDDs over that 30-day window for every bill payment for that customer.

[4] We drop observations with missing house age and square footage.

[5] See here for more.

[6] The spatial weight is calculated as the percent of the census block group covered by a given PRISM grid cell, and the population weight is calculated as the percentage of the census block group's population found in a given block.

[7] Lee et al. (2016) similarly find that in the Southeastern United States, higher mortality from heat begins at a threshold of 28 °C. Braga et al. (2002) find a lower threshold of 20-25 °C for colder locations. Carleton et al. (2022) likewise find that for elderly individuals, in cold countries temperature-related mortality begins to increase at 25 °C, while in hotter countries the threshold is closer to 30 °C. A threshold of 25 °C therefore accommodates the range of climates in our study areas.

2.4 Sample Construction

We focus the analysis on three cities (specifically, Census Core-Based Statistical Areas) in which we can identify a large sample of utility bill payments: Chicago, Houston, and Los Angeles. While many locations in the US are serviced by utilities that provide both natural gas and electricity service, in these cities different providers are associated with each service, enabling us to cleanly identify electricity payments.[8]

We identify payments to these merchants via the channels of debit cards, credit cards, and ACH transfers between October 2017 and March 2020. In order to focus on a sample whose bills can be cleanly matched with relevant temperatures, we drop customers who over this time period ever pay two bills of a given type (e.g. two electricity bills) within 15 days of each other. We also drop customers who pay identical amounts on a given bill type for 3 consecutive months in a row because of the high probability that these customers are on payment plans.[9] To avoid customers whose bills may reflect more than one month of spending, for each bill type we require customers to make 24 payments between January 2018 and December 2019.To ensure we are measuring temperature accurately, we also restrict to customers whose maximum correlation between temperature and bill payments exceeds 0.4.[10]

To isolate customers who use Chase as their primary bank, we require customers to have at least 5 transactions per month for 29 of the 30 months in the period from October 2017 to March 2020. We also require customers to have an annualized income into their accounts of at least $12,000 over this time period to ensure the sample captures the majority of each household's financial activity.

We then combine observed bill payments with data on temperature. Each bill payment is paired with the number of CDDs in each customer's maximally-correlated 30-day window relative to the first day of the week in which the bill was paid (e.g. 25-55 days prior).

Table 1 describes summary statistics for the baseline (ACS) and CoreLogic analysis sample. Both samples are broadly similar, although the CoreLogic sample has higher incomes. The typical electricity bill in Chicago and Los Angeles is about $100, while Houston has higher bills, at about $150 per month. Houston is also substantially hotter than Chicago or Los Angeles, with on average 50 Cooling Degree Days (CDDs) per month, compared to 11 in Chicago and 20 in Los Angeles. In Houston and Chicago the maximally-correlated 30-day window starts about 50 days before the bill payment, and therefore ends about 20 days before the bill payment, though in Los Angeles the average window is closer to the bill payment: 40-10 days before.

[8] We focus on electricity-only utilities, ignoring water and power utilities or gas and electric utilities.

[9] Combined, these two restrictions drop 41% of the Chicago sample, 52% of the Houston sample, and 39% of the Los Angeles sample.

[10] This restriction drops 32% of the remaining Chicago sample, 23% of the Houston sample, and 43% of the Los Angeles sample.

3 Costs of Extreme Heat

To investigate how temperature affects electricity expenditures and how the effect varies by income, we begin by documenting these relationships in the raw data. We split all the bills we observe in each city into 40 heat bins containing an equal number of observations. We then compute the average bill payment and average number of cooling degree-days for the bills in each bin. We plot the bill payments against degree days, splitting by income quartile and estimating a line of best fit on observations with more than 10 degree days.[11]

Figure 1 reveals that electricity bill payments increase approximately linearly with CDDs. Under the reasonable assumption that the use of other electricity-consuming household appliances, like dishwashers and televisions, are not affected by temperature, we can interpret the slope of energy expenditures with respect to heat as air conditioning expenditures.[12]

Across cities and income groups, one Celsius CDD costs households between 80 cents to \$1.86. As a benchmark, this implies a single day with an average temperature of 85 °F costs about \$3-\$9 more than a 77 °F day. Technological changes can reduce this cost to a limited extent: comparing Chicago, a less heat-adapted city, to Houston, a more heat-adapted city with similar electricity prices, indicates that long-run adaptation to heat reduces the cost of a hot day by about 30%.[13] These reductions in cost are slightly larger than the 10-20% reductions documented for the Weatherization Assistance Program (Fowlie et al., 2021), but would likely be far more expensive to achieve.

Is climate change likely to cause financial distress through the channel of electricity bills? One way in which it could cause distress would be due to the volatility of temperature: a heat wave could rack up cooling expenses in one particular month, leading to an extremely high energy bill and potentially crowding out other consumption for liquidity-constrained households. Typical heat waves in the US last about 4 days and are about 2.5 °F – or 1.4 °C – above the 85th percentile of local summertime temperatures (United States Environmental Protection Agency, n.d.). A four-day excess temperature of 1.4 °C would, under our estimates, lead to \$4 - \$8 more in electricity expenditures for low-income households (4 days of 1.4 degrees times 0.79 - 1.36 dollars per CDD). At typical MPC estimates of about 0.10 (Fisher et al., 2020), this is not likely to distort other consumption significantly, even if heat waves become substantially more intense.

Instead, climate change is more likely to strain household finances through the channel of consistently high levels of heat. In our sample locations of Chicago, Houston, and Los Angeles, we estimate

[11] We implement this restriction to avoid bias from elevated electricity bills in the winter for households that heat with electricity.

[12] According to the 2020 Residential Energy Consumption Survey (United States Energy Information Administration, 2020b, 2020c), the end uses that consume the most electricity across the year are air conditioning (27%), space heating (17%), water heating (14%), and refrigeration (9%). Space heating does not contribute to the positive slope, as this use must consume less electricity as outside temperatures increase. Water heating may increase with temperature if higher temperatures lead to more frequent or longer showers or more loads of laundry, so a small portion of this positive slope could reflect water heating. Refrigeration likely does contribute to a positive slope, but refrigerators consume one-third as much electricity as air conditioning across the year, and thus they likely make up an even smaller share of marginal consumption in hot months. Furthermore, refrigerators would only consume more electricity at hotter temperatures across income levels if indoor temperatures were also different across incomes.

[13] In July 2018, the average residential electricity price in Texas was 11.25 cents/kWh; in Illinois the average price was 11.76 cents/kWh (United States Energy Information Administration, 2018). Prices are similar at other times.

climate change will increase annual electricity bills by \$100 - \$300. (Details of these estimates are described in Appendix A.1.) For Los Angeles, this estimate implies electricity bill growth of about 12%. This approximation is in line with estimates by Auffhammer and Aroonruengsawat (2011) that by the middle of the century, Californian electricity consumption will grow by 9-17%. Naturally, growth in cooling expenses will be offset by reductions in heating expenditures, but it is *ex ante* unclear whether this will be sufficient to reduce energy bills overall. Appendix A.3 replicates the analysis for cold weather and natural gas bills and finds that in Chicago, where almost all houses heat with natural gas, growth in summertime cooling expenses will outweigh declines in heating expenses during the winter if there is no change in home energy technology. In warmer areas, growth in summertime cooling expenses will also dominate.

3.1 Differential Electricity Use across Income Groups

Figure 1 reveals that in all three cities in our sample, low-income households consume electricity at a lower level and slope than high-income households. *Ceteris paribus*, the lower slope could be interpreted as evidence that low-income households cool less intensively than high-income households, yielding higher indoor temperatures. However, this relationship may be driven by differences in the types of houses owned by low-income and high-income households. Low-income households tend to have inferior insulation relative to high-income households; thus, the difference in slope is unlikely to be related to more-efficient cooling technologies operated by low-income households.[14] However, low-income households likely live in smaller houses that require less energy to cool indoor temperatures to a given level. To account for these differences, we estimate the differential slope of the relationship between bill payments and temperatures between income groups, controlling for house size.[15]

Specifically, we estimate the following model:

$$b_{it} = \sum_{j=1}^{J} \delta_j (1_{ij}^{inc}) + \sum_{l=2}^{L} \gamma_l (1_{il}^{X}) + \sum_{l=2}^{L} \alpha_l (1_{il}^{X} \times CDD_{it}) + \sum_{j=1}^{J} \beta_j (1_{ij}^{inc} \times CDD_i) + \varepsilon_i \tag{1}$$

where i denotes a household, t denotes a month, b_{it} is the bill payment of household i in month t, CDD_{it} is the number of cooling degree days in household i's maximally-correlated 30-day period prior to the bill payment in month t, 1_{ij}^{inc} indicates whether household i belongs to income bin j, and 1_{il}^{X} indicates whether household i falls into house characteristic bin l. Level differences in monthly energy use are projected onto the δ_j and γ_l terms, which allow the households of different income levels and houses of different characteristics to have different baseline electricity consumption. These variables capture the tendency of higher-income and larger households to have more televisions, dishwashers, hot tubs, and refrigerators. The component of monthly energy use that varies with temperature

[14] According to the EIA RECS Survey (United States Energy Information Administration, 2015), 22% of low-income households were poorly- or not insulated, compared to 15.5% of households with incomes above \$40,000 per year.

[15] Previous work has estimated the so-called "poverty gap" in energy expenditures by regressing energy bills against indicators for temperature bin-days interacted with income level indicators (Doremus et al., 2022). We chose to instead model temperature as a distance from a health-relevant cooling benchmark because this enabled us to also model house characteristics more intuitively: in our framework, different house types affect both the baseline energy consumption and the amount of energy required to cool to a certain level (baseline energy slope with outside temperature).

is projected onto the α_l and β_j terms. The α_l terms capture the contribution of house type to the energy consumption response to hot weather, e.g. the tendency of larger houses to consume more electricity when cooled to the same temperature on an 85 °F day. The remaining variation in electricity expenditures that is related to temperature is projected onto the β_j terms, which capture the differential effect of hot weather on electricity payments by income. This β_j is therefore the coefficient of interest that we will use to test whether cooling intensity differs across income bins.

As described in the Data section, we use two different methods to measure house characteristics. The first approach ("ACS data") uses a coarse measure of house size that is available for the entire sample, while the second ("CoreLogic data") uses a more fine-grained measure that is only available for the subset of the sample which has a mortgage. For the ACS dataset, we define the L house characteristic bins as the four quartiles of the median number of rooms in the house units in the household's census block group. For the CoreLogic dataset, we split house age and house size (square footage) into four quartiles each, dropping households if either variable is missing. We then interact the bins to create 16 granular house characteristic bins that reflect both insulation and size, both of which likely impact energy consumption for a given target cooling temperature.

Figure 2 presents the estimates of income-related marginal cooling intensity (β_j) by income, for both methods of measuring house characteristics. We see that across all cities, marginal cooling expenditure increases with income. When using the ACS measure, being in the lowest-income group tends to reduce the marginal cooling expenditure by about 25-30% relative to the highest-income group. When restricting to the CoreLogic sample, this gradient flattens slightly. This flattening could be due to unobservably higher wealth among the low-income group. It could also reflect better measurement of the relationship between income and marginal cooling intensity, attributable to more fine-grained measurement of house size in the CoreLogic sample. Nevertheless, even in this selected sample, all cities continue to exhibit an income gradient, and the difference between the lowest and highest income quartiles remains statistically-significant. Across all three cities, the ratio of estimated marginal energy consumption in the lowest-income group as a share of that of the highest-income group is below 0.85.

3.2 Ruling Out Alternative Explanations

Underpayment of electricity bills by low-income households does not explain this gap. Time-invariant differences in underpayment rates across income groups would be captured in income-group fixed effects. Any bias would need to be driven by differential underpayment that increases with heat. However, the scope for this potential divergence is small, since underpayment rates are low. Data about household bill underpayment are limited, but a recent Illinois regulation required utility companies to begin reporting arrearage data in October 2021. According to the earliest data available from the two largest electricity utilities in the state, between 6-9% of low-income households were more than 30 days overdue in September 2021, while 2-6% of high-income households were more than 30 days overdue.[16] Even at the maximum difference between these groups, 7 percentage points, and the maximum amount

[16] This data was recently used by Cicala (2021).

of underpayment that still enables inclusion in our sample, this difference would be far too small to explain the observed 15-30 percent gap.[17]

Means-tested electricity rates also do not explain this gap. While California's CARE program[18] provides low-income households with 30-35 percent discounts on their electricity bills, similar programs did not exist in Illinois and Texas over the time period of the study.[19]

Another potential explanation for these differences across income is that lower-income households predominantly cool with window units, which allow them to cool only the rooms they occupy, thus saving money without compromising on comfort or health. However, Table 2 shows that differences persist across income even for households with central AC, ruling out this explanation.

Finally, these differences are not explained by lower-income households cooling only when people are in the house. According to data from the 2015 RECS survey (United States Energy Information Administration, 2015), among households with central AC, households earning \$20,000-\$40,000 per year were approximately equally likely as households earning above \$40,000 per year to manually adjust the central AC temperature at night or when no one is home. Moreover, low-income households were 15 percentage points less likely to program their central AC to turn on and off at particular times, and they were 12 percentage points more likely to set the temperature to one level most of the time.[20]

Therefore, we interpret these estimated differences in expenditures across income as differences in cooling intensity caused by income. These results suggest that lower-income households, faced with similar outdoor temperatures, maintain their residences at higher indoor temperatures than higher-income households do. These differences in internal temperature could be further exacerbated by urban heat islands, poor insulation, and inefficient air conditioning technology, which are more likely to affect low-income families.

The differences we find in cooling intensities across income are both larger in levels and smaller in proportion than has been found in previous work. Doremus et al. (2022) estimate that relative to a 15-20 °C day, an additional day over 30 °C increases electricity expenditures by \$1.08 on average, but only 1.3 cents for households below 150% of the federal poverty line.[21] By contrast, our estimates imply that a 30 °C day would increase electricity expenditures by \$3-\$7 for a low-income household, and that after controlling for house characteristics low-income households consume at maximum one-third less electricity per hot day than high-income households (rather than almost 100% less). The difference in these results could be due to reduced measurement error of temperature in our sample, which would otherwise bias coefficient estimates of temperature towards zero. Importantly, our estimates reveal that the cost of cooling is substantially higher than previously estimated, though low-income households also appear willing to incur a large share of these costs to benefit from air conditioning.[22]

[17] Furthermore, the regulatory filings for Commonwealth Edison suggest that the difference in underpayment across income groups is actually lower in summer than it is in the fall, which would mean our analysis actually under-estimates the true gap in cooling intensity.

[18] California Public Utilities Commission, n.d.

[19] Illinois decided at the end of 2022 to offer discounted electric rates to low-income households (Dawson, 2022).

[20] Authors' calculations, among respondents with central air conditioning, weighting by EIA RECS sample weights.

[21] This definition of low-income approximately lines up with the lowest income quartile in our sample.

[22] By contrast, our estimate of the "poverty gap" is more similar to another recent estimate that extremely low-income households in Arizona consume 11% less electricity per unit of heat than high-income households (Kwon et al., 2023).

3.3 Health Implications

The preceding section demonstrates that lower-income households cool less intensively than high-income households. However, forgoing this form of adaptation increases health risks from extreme heat. We investigate the health costs of this behavior in a back-of-envelope calculation and compare the costs to the financial savings from "under-cooling." We also assess behaviors in the elderly population, which is a particular target of energy assistance policy.

First, we perform a back-of-envelope calculation that estimates the mortality costs of observed reductions in cooling intensity in the general population. We focus on Chicago and Houston, the cities in which an income gradient in electricity expenditures can be safely interpreted as differences in cooling intensities because there is no low-income electricity subsidy program over the study time period. Under conservative assumptions, a 20% reduction in cooling intensity on a 95 °F day increases general-population mortality by 0.05-0.20 deaths per 100,000.[23] Based on the above estimates, the money saved by cooling less intensively amounts to \$2-\$6 per hot (35 °C / 95 °F) day. At the low end of mortality benefits of cooling, these two figures imply a value of statistical life (VSL) of \$8.6 million per 95 °F day, which falls just below the inflation-adjusted estimate of value of statistical life used by the EPA[24]. At the high end of mortality benefits, the cutback translates to a value of statistical life of only \$1.2 million, far below the standard VSL. Other effects of undercooling, like non-lethal health events (Gould et al., 2024) and decreased comfort, further increase the cost of attenuated cooling and reduce the implied VSL. This indicates that in the very best-case scenario, households could be efficiently trading off cooling costs with mortality benefits, but in other scenarios low-income households could be inefficiently under-cooling relative to a societal value of statistical life. While our calculations are back-of-the-envelope, they indicate that ascertaining more precisely whether households cool efficiently is an important area for future work.

Second, we compare behaviors in the general population to those of the elderly, who tend to be a particular target of energy assistance policies.[25] Deschênes and Greenstone (2011) estimate that the impact of a hot day on mortality is at least 3 times larger for the elderly (those older than 65) than the general population. In the United States, the elderly population is more likely to be insured, since Medicare eligibility starts at age 65. On the one hand, this greater penetration of insurance could reduce protective behaviors. On the other hand, higher uninsurable risk of heat (e.g. the emotional and psychological costs of hospital visits and greater risk of death) could motivate the elderly to engage in more self-protection. To determine whether the low-income elderly are more or less likely than the

[23]This calculation assumes that achieved indoor temperatures are linear in cooling intensity: if unrestricted AC operation on a 95 °F day cools to 77 °F, a 25% reduction in intensity is equivalent to cooling to 81.5 °F. We take heat-related mortality estimates fromDeschênes and Greenstone (2011) of 0.33 per 100,000 for an 81.5 °F day and 0.94 per 100,000 for a 95 °F day and assume linearity between these points. This is an extremely conservative estimate since the Deschênes and Greenstone (2011) estimates are for the effect of outside temperature on mortality, conditional on the presence of air conditioning. Barreca et al. (2016) estimate that air conditioning reduces heat-related mortality by about 4 times, so the true mortality impact of less-intensive cooling could be as much as 4 times higher as what we use. Thus, we report both low-end and high-end estimates of the effect of less-intensive cooling on mortality.

[24]https://www.epa.gov/environmental-economics/mortality-risk-valuation

[25]For example, in Illinois, elderly households and the disabled can submit applications for LIHEAP assistance one month earlier than other eligible households. Since LIHEAP programs are often oversubscribed, early application is a particular advantage.

general low-income population to cool less intensively than their higher-income peers, we replicate our main analysis for the elderly. In our focal cities, we see that for both the ACS and CoreLogic samples, restricting to the Over-65 population flattens the income gradient in electricity spent per hot day. This evidence suggests that elderly households are slightly less likely to cut back on AC use as a result of lower income than non-elderly households.[26] Combined with their higher mortality costs from extreme temperatures, this behavior potentially makes them a particular target for policymakers who aim to reduce high bills for low-income households. However, if energy assistance policy is motivated by concerns that households misperceive the health risks of heat and underconsume air conditioning, it is not clear that the elderly should be a particular target, since we do not find that the elderly are more likely to "under-cool" than the general population. Currently, many state energy assistance programs target elderly households with special enrollment advantages. When considering whether this focus on the elderly should persist if energy assistance for hot weather expands, the implications of this work depend on the exact motivations of policymakers. If they are motivated by concerns about misperception, further work would be needed to assess whether the elderly are more likely than the general population to misperceive the health benefits of cooling.

4 Conclusion

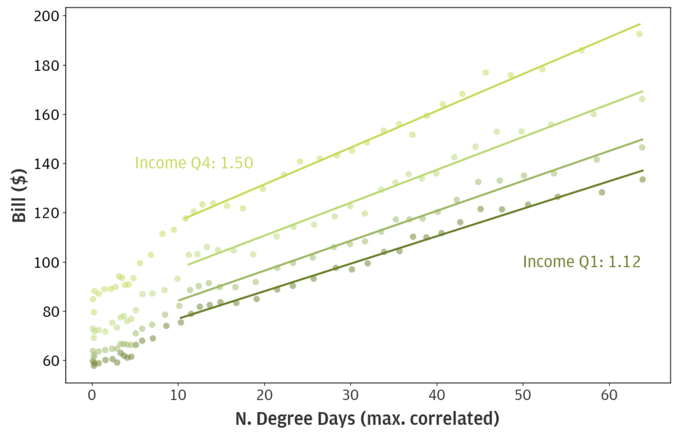
Because of climate change, extreme heat is a growing health threat. In the short run, households must use air conditioning to adapt to extreme heat, introducing additional costs. In this paper, we document the magnitude of these costs. Climate change will increase electricity bills by up to $300 annually in the hottest areas. Low-income households exhibit lower take-up of air conditioning: they consume about 25% less electricity per unit of outdoor heat than high-income households do, controlling for house characteristics. However, more heat-vulnerable households (the elderly) exhibit a weaker income gradient in cooling, reflecting higher benefits of cooling to this population.

These findings have implications for energy policy in the US. As summertime cooling bills grow and wintertime heating bills shrink, households may struggle more with the former. Currently, eligible low-income households receive seasonal grants from the federal Low-Income Home Energy Assistance Program; however, most LIHEAP funding goes to heating. More research is needed to determine whether households are more likely to inefficiently underconsume cooling than heating. However, if LIHEAP's aim is to provide in-kind transfers of a critical health good, summertime electricity bills will likely become an increasingly important channel for achieving this goal.

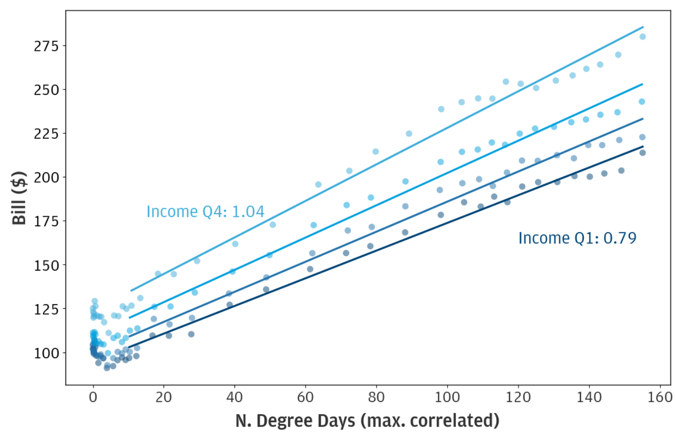
[26] Despite higher costs of mortality, the elderly may also have a lower value of statistical life. In parallel calculations to those of the general population, we find an implied VSL of the elderly cutbacks of $200,000- $2 million. Recent estimates of revealed VSL from elderly spending find a value of about $500,000 in 2018 dollars (Ketcham et al., 2023).

5 Figures and Tables

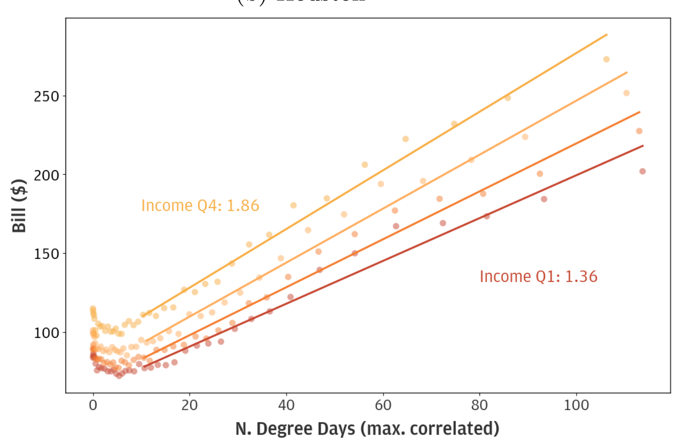
5.1 Figures



(a) Chicago

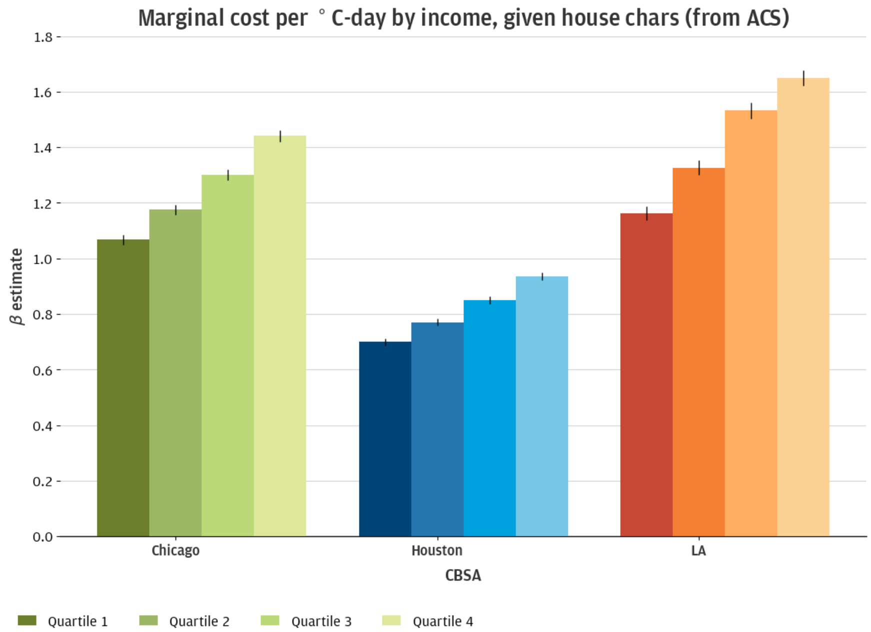


(b) Houston

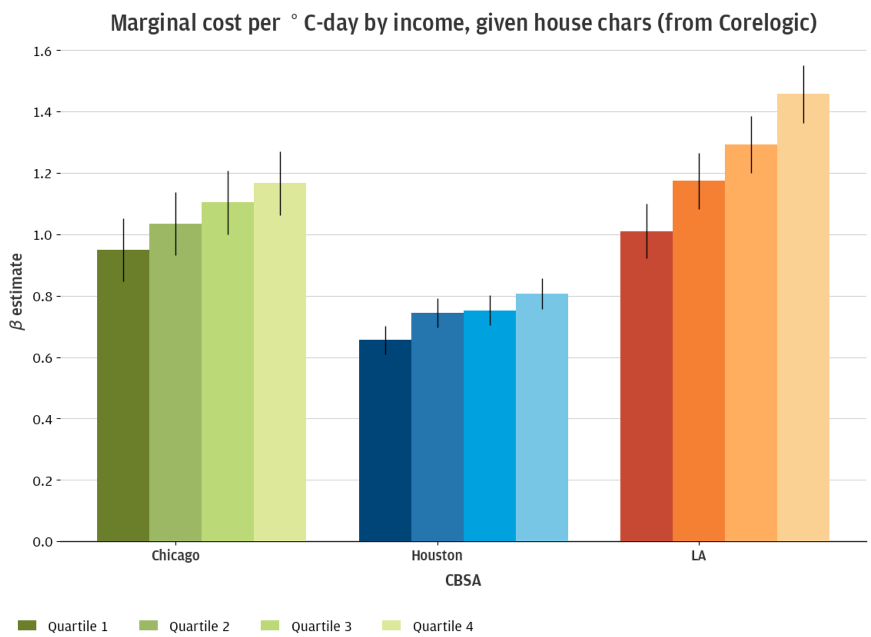


(c) Los Angeles

Figure 1: Electricity Payments vs Heat, Split by Income Quartile



(a) ACS



(b) Corelogic

Figure 2: Marginal cost per Cooling °C-day by income quartile, given house characteristics

5.2 Tables

Variables	Chicago	Houston	Los Angeles
Baseline			
Electricity bill monthly payment	\$93.3	\$153.6	\$112.2
	(\$47.6)	(\$84.6)	(\$72.2)
Monthly cooling degree days	11.3	52.4	19.5
	(17.1)	(55.3)	(26.6)
Median rooms in Census block-group	6.07	6.18	5.51
	(1.63)	(1.45)	(1.24)
Annual income in 2018 (thousands)	\$109.8	\$86.7	\$113.0
	(\$153.8)	(\$107.2)	(\$187.4)
Account owner age	50.9	54.2	51.6
	(15.3)	(16.0)	(15.0)
Beginning of max corr 30-day temp window	-52.4	-51.7	-42.2
	(8.4)	(14.1)	(9.1)
Corr of bills with CDDs in max corr window	0.75	0.83	0.70
	(0.14)	(0.17)	(0.15)
N customer-bills	395,586	216,606	208,533
N customers	16,465	8,995	8,669
CoreLogic Subsample			
Electricity bill monthly payment	\$100.8	\$154.8	\$113.8
	(\$46.0)	(\$86.2)	(\$71.9)
Monthly cooling degree days	11.5	52.3	20.4
	(17.3)	(55.2)	(27.9)
Square feet of living space	1,879	2,288	1,723
	(796)	(808)	(607)
Year built (if recorded)	1967	1995	1971
	(30)	(19)	(21)
Central AC	0.65	0.97	0.51
	(0.48)	(0.18)	(0.50)
Annual income in 2018 (thousands)	\$126.9	\$103.6	\$117.9
	(\$132.0)	(\$97.0)	(\$91.6)
Account owner age	49.0	50.9	51.0
	(12.3)	(13.5)	(12.6)
Beginning of max corr 30-day temp window	-52.2	-52.0	-42.1
	(7.9)	(14.2)	(8.5)
Corr of bills with CDDs in max corr window	0.74	0.84	0.71
	(0.14)	(0.16)	(0.15)
N customer-bills	123,356	64,779	66,362
N customers	5,134	2,690	2,759

Table 1: Summary statistics for sample of electricity bills

Table 2: Alternative Specifications of Equation (1)

City	Income group	ACS	CoreLogic	ACS Over 65	CoreLogic Over 65	CoreLogic Has AC	CoreLogic No AC	ACS Summer	CoreLogic Summer
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chicago	Income Q1 x CDD	1.07	0.95	0.91	0.72	0.97	0.88	1.16	1.08
		(0.01)	(0.05)	(0.02)	(0.10)	(0.06)	(0.10)	(0.01)	(0.07)
	Income Q2 x CDD	1.18	1.04	1.00	0.86	1.09	0.92	1.28	1.17
		(0.01)	(0.05)	(0.02)	(0.11)	(0.06)	(0.10)	(0.01)	(0.07)
	Income Q3 x CDD	1.30	1.10	1.05	0.83	1.15	1.00	1.43	1.25
		(0.01)	(0.05)	(0.02)	(0.11)	(0.06)	(0.10)	(0.01)	(0.08)
	Income Q4 x CDD	1.44	1.17	1.17	0.80	1.20	1.09	1.60	1.32
		(0.01)	(0.05)	(0.02)	(0.11)	(0.06)	(0.10)	(0.01)	(0.08)
	Ratio of Q1 to Q4	0.74	0.81	0.78	0.89	0.82	0.80	0.73	0.81
	N	395,586	123,356	79,808	14,461	79,968	43,388	166,354	51,822
Houston	Income Q1 x CDD	0.70	0.66	0.71	0.40	0.66	0.68	0.71	0.66
		(0.01)	(0.02)	(0.01)	(0.06)	(0.02)	(0.20)	(0.01)	(0.04)
	Income Q2 x CDD	0.77	0.74	0.75	0.54	0.75	0.62	0.76	0.73
		(0.01)	(0.02)	(0.01)	(0.06)	(0.02)	(0.20)	(0.01)	(0.04)
	Income Q3 x CDD	0.85	0.75	0.85	0.48	0.75	0.83	0.83	0.72
		(0.01)	(0.02)	(0.01)	(0.06)	(0.02)	(0.22)	(0.01)	(0.05)
	Income Q4 x CDD	0.94	0.81	0.88	0.47	0.81	0.88	0.91	0.77
		(0.01)	(0.03)	(0.01)	(0.06)	(0.03)	(0.22)	(0.01)	(0.05)
	Ratio of Q1 to Q4	0.75	0.81	0.81	0.85	0.82	0.77	0.78	0.86
	N	216,606	64,779	61,459	11,391	62,585	2,194	90,401	27,059
Los Angeles	Income Q1 x CDD	1.16	1.01	1.09	0.78	1.02	1.56	1.23	1.09
		(0.01)	(0.05)	(0.03)	(0.11)	(0.05)	(0.20)	(0.02)	(0.06)
	Income Q2 x CDD	1.33	1.17	1.30	1.00	1.18	1.70	1.40	1.26
		(0.01)	(0.05)	(0.03)	(0.12)	(0.05)	(0.20)	(0.02)	(0.06)
	Income Q3 x CDD	1.53	1.29	1.39	1.08	1.28	1.86	1.61	1.38
		(0.01)	(0.05)	(0.03)	(0.12)	(0.05)	(0.20)	(0.02)	(0.07)
	Income Q4 x CDD	1.65	1.46	1.47	1.24	1.43	2.03	1.74	1.55
		(0.01)	(0.05)	(0.03)	(0.12)	(0.05)	(0.20)	(0.02)	(0.07)
	Ratio of Q1 to Q4	0.70	0.69	0.74	0.62	0.72	0.77	0.70	0.70
	N	208,533	66,362	43,124	10,193	34,165	32,197	86,783	27,633

[a] Table shows estimates of Equation (1) for each city for hot weather, in addition to the ratio of the estimated slope for income quartile 1 to income quartile 4. "Has AC" means a household has a mortgage on a house with central air conditioning; "No AC" means a household has a mortgage on a house with no central air conditioning.

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A Appendix

A.1 Details of Calculations of Estimated Impact of Climate Change on Electricity Bills

We perform back-of-envelope calculations to combine estimates of the impact of climate change on cooling degree days with our estimates of the financial cost of cooling degree days to yield estimates of the impact of climate change on electricity bill payments. We consider the difference between recent historical average temperatures and the mid-century average. We focus on the RCP4.5 emissions pathway.

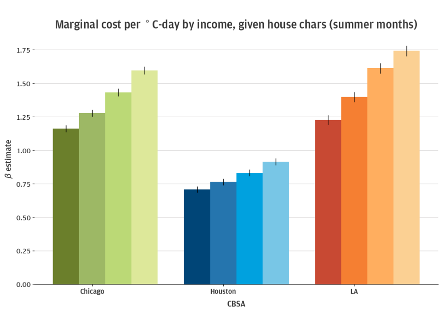
For the greater Chicago area, we use the estimate from Winkler et al. (2014) that in the Midwest, CDDs will increase by 66% by the middle of the century. Using the annual average of 136 CDDs per year from our sample, this implies an increase of about 90 CDDs by the middle of the century due to mid-scenario climate change. For Houston, we use the estimate from Stoner and Hayhoe (2020) that under RCP4.5, by the middle of the century total spring, summer, and fall Fahrenheit CDDs will grow from 3375 to 3900.[27] Converting to Celsius CDDs by multiplying by 5/9 yields an increase of 292 more CDDs per year. Finally, for Los Angeles we use the estimation tool on Cal-Adapt's website that aggregates downscaled CMIP5 climate projections across Los Angeles County (Geospatial Innovation Facility at the University of California, Berkeley, n.d.). We set a baseline of 77 °F to match our measure of CDDs, and convert from Fahrenheit CDDs to Celsius CDDs by multiplying by 5/9. Under the RCP4.5 pathway, LA County is expected to have 100 more Celsius CDDs per year by the middle of the century compared to the historical baseline. We multiply the estimates of growth in annual CDDs by the high-income and low-income estimates of the effect of temperature on electricity bill payments to yield Table A1.

	Chicago	Houston	Los Angeles
Low-Income	\$100	\$230	\$136
High-Income	\$134	\$303	\$186

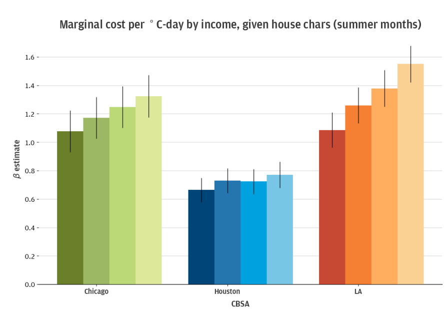
Table A1: Estimates of the effect of climate change on household electricity bills

A.2 Restricting to Summer Months

Figure A1 repeats the main analysis, restricting to summer months only. The results look similar, and Table 2 shows that the estimated ratio of first-quartile to fourth-quartile cost per marginal unit of heat are almost identical to the main specification.



(a) ACS



(b) Corelogic

Figure A1: Marginal cost per Cooling °C-day by income, given house characteristics

[27]Note that since this omits wintertime CDDs, this estimate is a lower bound on the growth in CDDs.

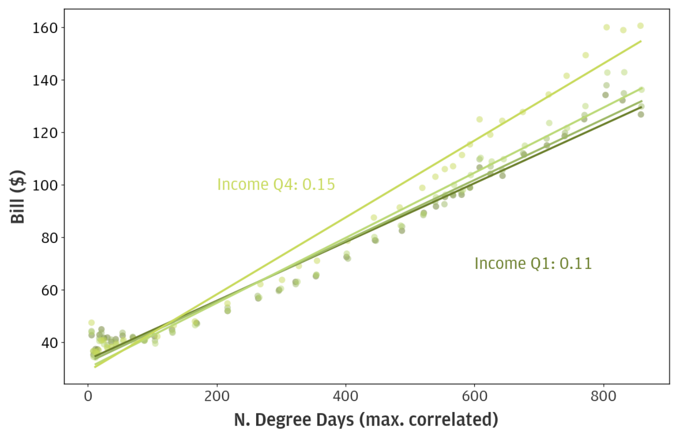
A.3 Natural Gas Analysis

We repeat the analysis for cold weather and natural gas bill payments by constructing a sample parallel to the electricity bills sample. In this analysis, we combine natural gas bill payments with measures of heating degree days (HDDs). We compute heating degree days relative to a benchmark of 20 °C, the low end of the range typically used in the literature. Appendix Table A2 describes summary statistics for the natural gas bill sample. The typical natural gas bill is between $40-$80 per month, substantially lower than electricity bills. Chicago is substantially colder than Houston or Los Angeles, with more than three times as many Heating Degree Days (HDDs) per month. As with the electricity bills, the maximally-correlated 30-day window starts about 40-60 days before the bill payment.

Variables	Chicago	Houston	Los Angeles
Baseline			
Natural gas bill monthly payment	$76.0	$42.1	$61.7
	($50.2)	($23.7)	($47.4)
Monthly heating degree days	356.4	93.7	116.4
	(286.2)	(104.0)	(87.1)
Median rooms in Census block-group	6.16	6.76	5.67
	(1.57)	(1.60)	(1.30)
Annual income in 2018 (thousands)	$114.4	$126.9	$127.6
	($190.4)	($163.4)	($203.3)
Account owner age	53.0	53.6	57.0
	(15.9)	(15.3)	(17.2)
Beginning of max corr 30-day temp window	-49.7	-55.5	-43.3
	(7.5)	(12.6)	(9.3)
Corr of bills with HDDs in max corr window	0.92	0.88	0.79
	(0.09)	(0.13)	(0.12)
N customer-bills	237,804	74,596	59,382
N customers	9,893	3,104	2,472
CoreLogic Subsample			
Natural gas bill monthly payment	$78.7	$42.2	$60.1
	($51.5)	($23.9)	($45.1)
Monthly heating degree days	356.2	94.6	120.1
	(286.3)	(104.6)	(89.8)
Square feet of living space	1,920	2,783	2,014
	(831)	(933)	(818)
Year built (if recorded)	1969	1998	1969
	(29)	(17)	(22)
Central AC	0.70	0.98	0.53
	(0.46)	(0.15)	(0.50)
Annual income in 2018 (thousands)	$128.8	$142.9	$144.1
	($131.4)	($131.1)	($135.7)
Account owner age	49.9	48.8	53.9
	(12.6)	(12.2)	(13.8)
Beginning of max corr 30-day temp window	-50.1	-54.4	-43.6
	(7.1)	(11.5)	(9.5)
Corr of bills with HDDs in max corr window	0.93	0.89	0.79
	(0.08)	(0.12)	(0.12)
N customer-bills	75,206	27,874	18,925
N customers	3,129	1,160	788

Table A2: Summary statistics for sample of natural gas bills

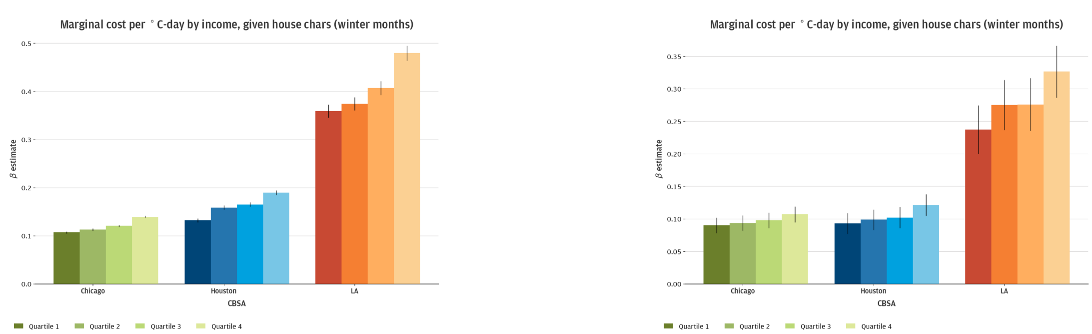
As in the electricity bill analysis, we plot natural gas bill payments against heating degree days. We focus on Chicago, since Los Angeles and Houston have a large share of households that heat with electricity. Figure A2 shows that in Chicago, natural gas bills also increase approximately linearly with heating degree days. About one-quarter of this usage likely reflects water heating, while the remainder likely reflects space heating (United States Energy Information Administration, 2020a). We therefore interpret natural gas use as heating.



(a) Chicago

Figure A2: Natural Gas Payments vs Cold, Split by Income Quartile

Figure A3 repeats the main analysis for the natural gas sample, controlling for house characteristics to isolate the income effects on heating slope with respect to cold weather. As in the main analysis, both figures show that low-income households consume energy at a lower level and slope with respect to heating needs than high-income households.



(a) ACS (b) Corelogic

Figure A3: Marginal cost per Heating °C-day by income, given house characteristics

To estimate how much will be saved from reduced heating costs because of climate change, we use the estimates of Winkler et al. (2014) that heating degree days in the Midwest will decline by 15%. At the average annual HDDs in our sample, this implies Chicago will see about 640 fewer HDDs per year. At current costs of heating, this implies savings of \$70-\$95 per year, which is about two-thirds the amount of the increase in bills due to higher cooling costs according to Chicago's current cost of cooling ($100-$133). Thus, even in areas as cold as Chicago, climate change will likely increase annual household energy expenditures overall.