Sweating the energy bill: Extreme weather, poor households, and the energy spending gap

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Abstract

We estimate the relationship between temperature and energy spending for both low and higher-income US households. We find both groups respond similarly (in percentage terms) to moderate temperatures, but low-income households' energy spending is half as responsive to extreme temperatures. Consistent with low-income households cutting back on necessities to afford their energy bills, we find similar disparities in the food spending response to extreme temperature. These results suggest adaptation to extreme weather, such as air conditioning use, is prohibitively costly for households experiencing poverty.

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1 Introduction

Many U.S. households report struggling to pay their energy bills. Eleven percent of households kept their home at an unhealthy or unsafe temperature for at least one month in 2015, and over 20 percent reduced or went without basic necessities to pay a home energy bill (Energy Information Administration, 2018). These households are disproportionately low income (Energy Information Administration, 2018), as are households that are *energy burdened*, spending more than 10 percent of household income on energy services (Jessel et al., 2019). These hardships exist despite energy assistance and other social programs.

Climate change makes understanding energy costs for households experiencing poverty urgent. Air conditioning dramatically reduces the effects of heat exposure on mortality (Barreca et al., 2016), but this form of adaptation to a warmer climate is only available if households can afford to run their air conditioners. Households that cannot afford cooling may be more susceptible to the effects of extreme heat, such as increased emergency room visits (White, 2017), poor mental health (Mullins and White, 2019b), diminished learning (Park et al., 2020), and death (Deschenes and Moretti, 2009). Climate policies also have distributional consequences, and may make energy less affordable. For example, both of Washington state's failed 2016 and 2018 carbon tax initiatives would have increased energy prices, but only one made redistributing revenues to low-income households a priority (Anderson et al., 2019).

We estimate the relationship between temperature and energy spending for both low and higher-income households. Our analysis relies on nationally representative, household-level data from the Consumer Expenditure Survey (CEX) for 2004–2018. We pair these data with mean daily temperatures aggregated to counts of days in temperature bins at the state-month level. We estimate the causal effect of additional hot or cold days on energy spending, allowing for heterogeneity by household poverty status. Because we include state-by-month fixed effects, temperature shocks (unseasonably hot or cold weather) provide identifying variation for our estimates.

We find low-income households' energy spending is much less responsive to extreme weather than that of other households. Events like the 2017 polar vortex or the 2011 heat wave can sharply increase exposure to extreme weather: for example, in August 2011, Oklahoma experienced 14 more days with a daily average temperature above 30C (86F) than is typical. We estimate replacing a temperate day (15–20C/59–68F) with a very cold day (< -5C/$<$ 23F) increases monthly energy spending by 1.2 percent for higher-income households but only 0.5 percent for low-income households. This difference of 0.7 percentage points, which we refer to as a "poverty gap," is statistically significant. For electricity spending, which better reflects air conditioning use than total energy spending, we also find a statistically significant poverty gap in response to extreme heat. Replacing a temperate day with a very hot day ($>$ 30C/$>$ 86F) increases electricity spending for higher-income households by 0.5 percent but does not increase electricity spending for low-income households. The implied magnitude of the difference in electricity use would power a typical air conditioner for four hours.

These differences are best explained by low-income households foregoing heating and cooling during extreme weather. We first show spending disparities reflect underlying differences in energy consumption, rather than differences in prices. We then find differences in consumption are not driven by lower energy needs for the dwellings of low-income households: our preferred specification yields estimates of proportional, not level, changes in energy spending, and estimates are robust within housing sizes and types. Instead, we propose differences in use during unseasonable weather reveal a pattern of low-income households opting for more extreme indoor temperatures. Surveys documenting systematic differences in energy efficiency—households experiencing poverty tend to live in homes that are leakier and more poorly insulated—suggest differences in energy consumption could even understate resulting differences in dwelling temperatures.

We find similar poverty gaps for food spending, consistent with low-income households cutting back on necessities to afford their energy bills. While food spending by higher-income households is unaffected by extreme weather, food spending by low-income households falls in response to additional days of extreme heat or cold. The resulting food spending poverty gaps are statistically significant and about twice as large as the energy poverty gaps. We focus on food because it is consistently Americans' third greatest expense category, after housing and transportation, and it is likely more flexible in the short run than the other two (Bureau of Labor Statistics, 2019). Liquidity constraints may explain why low-income households are unable to smooth these shocks.

Taken together, these results indicate energy assistance programs fail to adequately insulate low-income households from energy bill shocks. Our nationally-representative estimates corroborate surveys and qualitative studies that find energy insecurity is widespread among low-income households, and imply policies that raise energy prices will disproportionately impact low-income households. The symmetry of our findings—poverty gaps in energy spending that are of similar magnitudes for both hot and cold weather—suggests energy assistance programs focused primarily on winter heating costs may miss a substantial part of the burden of energy bills. While nearly all U.S. households use air conditioning in their home, the largest energy assistance program in the United States allocated over five times as much funding to heating assistance as it did to cooling assistance in 2014 (Perl, 2018). As the climate warms, social programs will also need to adapt.

We contribute to the literature by documenting a novel poverty gap in the energy spending response to hot weather. Previous work has found differential responses to extreme cold, and we also provide contemporary estimates of this cold weather gap. Using data from 1980–1998, Bhattacharya et al. (2003) finds low-income households spend less on energy and food in response to extreme cold, compared to other households.[1] More recently, Beatty et al. (2014) finds similar poverty gaps in response to unseasonable cold in the United King-

[1] The working paper version, Bhattacharya et al. (2004), tests for hot weather energy and food spending gaps by estimating the main specification on a subsample of Southern households in July and August. It finds that neither rich nor poor households spend more on energy in response to unseasonably hot summers (p.14).

dom.[2] Previous work also suggests the spending disparities we document lead to health disparities. Frank et al. (2006) links participation in energy assistance to improved nutrition among low-income children; Nord and Kantor (2006) finds an association between increased energy costs and food insecurity; and Chirakijja et al. (2019) finds higher home heating costs increase mortality, especially in low-income counties.

We also contribute to the literature describing how climate damages vary across populations and highlighting how socioeconomic inequality leaves low-income households distinctly vulnerable to extreme temperature. Mullins and White (2019a) finds access to health care mitigates the effect of heat on mortality, and Garg et al. (2020) shows income lessens the effect of heat on test scores. Globally, increases in both temperatures and incomes will drive air conditioner adoption (Davis and Gertler, 2015). Finally, Barreca et al. (2016) attribute dramatic reductions in heat-related mortality to air conditioner access. Our results contextualize this finding. In countries like the United States, where income inequality is high and adoption is approaching saturation, air conditioner operating costs may be just as important as access for the distribution of climate damages.

2 Energy insecurity and energy assistance

Household energy consumption is an adaptive response to extreme outdoor temperatures: adequate indoor heating in cold weather and cooling in hot weather can prevent not just discomfort but severe health consequences, including mortality.[3] On average, people increase energy use in response to extreme temperatures (Deschenes and Greenstone, 2011; Davis and Gertler, 2015; Hsiang et al., 2017).

However, this heating and cooling response to extreme temperature is costly, and these costs are not trivial for low-income households. The related concepts of *energy insecure* and

[2]Beatty et al. (2014) does not find a hot weather spending gap, possibly because weather in the U.K. is more temperate, and few households have air conditioning.

[3]Extreme temperatures, and especially extreme heat, increase mortality (Deschenes and Moretti, 2009; Deschenes and Greenstone, 2011; Burgess et al., 2017), and Barreca et al. (2016) finds that air conditioner adoption reduces heat-related mortality.

energy burdened describe, respectively, households "unable to adequately meet household energy needs" and that spend a large percentage (typically greater than 10 percent) of their income on energy services (Jessel et al., 2019). In a detailed qualitative study, Hernández (2016) documents substantial hardship among energy-burdened households struggling to pay high utility bills. These hardships include the accumulation of debt, service interruptions, physical discomfort, and the mental load of managing consumption and costs.[4]

Households that lack emergency savings and access to credit may be more sensitive to atypically high energy bills. These bills strain household finances in a way similar to other unanticipated expenses, such as car repairs or medical bills (Gjertson, 2016). Cullen et al. (2005) studies how households without substantial assets smooth consumption shocks caused by higher energy bills, finding households had sufficient liquidity to accommodate anticipated changes in disposable income, but were unable to buffer even modest unanticipated shocks.

We engage with these themes more formally by developing a theoretical model of household energy consumption (see Appendix A). The model incorporates household preferences over reducing health risks from exposure to extreme weather, emphasizing the distinction between willingness- and ability-to-pay for energy spending. Extensions include weather-dependent household income, energy prices that increase with income, and income-associated differences in energy needs.

Recognizing the risks of energy insecurity, social programs exist to help households with their energy bills. The largest such assistance program is LIHEAP, a federal block grant program that provides over $3 billion annually to states for heating assistance, cooling assistance, crisis assistance, and weatherization (Perl, 2018). Murray and Mills (2014) finds LIHEAP reduces energy insecurity, and Frank et al. (2006) finds a positive association between LIHEAP participation and children's health. States and utilities may also supplement LIHEAP funding with additional energy assistance. Despite these programs' size and apparent benefits, take-up and overall participation are low: only 22 percent of eligible households,

[4]This mental burden of energy insecurity is consistent with the bandwidth costs described in Schilbach et al. (2016).

and less than 5 percent of all households, received energy assistance nationwide in recent years (Falk et al., 2015; U.S. Census, 2018).

3 Data

Our analysis focuses on the period from 2004–2018, and our unit of observation is a household in a state, month, and year. We link consumer expenditures on utilities (energy) and groceries (food), to state-level data on temperature and precipitation.

3.1 BLS Consumer Expenditure Survey

Household data come from the Bureau of Labor Statistics' Consumer Expenditure Survey Public-use Microdata (CEX). The CEX is comprised of two separate, nationally-representative surveys: the Interview Survey and the Diary Survey. The Interview Survey collects information about monthly household spending on major and less-frequent purchases (such as cars, rent, and utilities). It interviews households every three months for four quarters. The Diary Survey better captures frequent or minor purchases, such as food. Households in the diary survey record almost all expenses for two consecutive weeks. Both surveys collect data on utilities and food purchases, and both collect households' income and demographic data. Given the strengths and weaknesses of each survey, we follow the BLS in their choice of survey for summary analysis: we use the Interview Survey to study utility expenditures, and the Diary Survey to study food expenditures. For both surveys, observations are individual consumer units, defined as financially independent households or individuals, and referred to here as households for convenience. Each sample consists of different households and is independently nationally representative with provided sample weights.[5]

We use observations of a household in a particular state, month, and year. Household

[5]In order to protect respondent privacy, the BLS suppresses states of residence for observations from Missouri, Montana, New Mexico, North Dakota, South Dakota, and Wyoming for both CEX surveys, and so they are omitted from our analysis. Alaska and Hawaii are excluded from our weather data. The remainder of states comprise our sample.

energy expenditures are the sum of reported bills across all fuel types (such as electricity, fuel oil, and natural gas). We restrict our energy spending analysis to households with positive fuel purchases. For food expenditures, we focus on food spending for consumption in the home ("food in"), but also consider all food spending, which includes fast food and restaurants, including take-out and delivery. We extrapolate from the weekly expenses recorded in the Diary Survey to monthly expenses by multiplying by the number of weeks in each month.

We use annual income and the number of individuals in the household to categorize a household's status with respect to the federal poverty line (FPL). This is a simple, meaningful indicator of relative household poverty, because various thresholds correspond to eligibility for assistance programs, including LIHEAP, SNAP, and Medicaid.

Summary statistics for these data over our study period (2004–2018) are shown in Table 1. The median household spends about 166 dollars per month on fuel for the home and 457 dollars per month on food for consumption in the home. About one quarter of households have incomes and family sizes that put them under the FPL, and about one third are classified as under 150 percent of the FPL. Figure 1 shows how mean energy spending differs over the year for households above and below 150 percent of the FPL. Households above 1.5 FPL spend more on energy, and the difference in spending between the two groups is noticeably larger in the winter and summer months.

3.2 Weather and other controls

We use daily, gridded weather data from Schlenker (2020), which are based on the PRISM weather data for the contiguous United States, and derived from a fixed set of weather stations. Because our household data is only geographically precise to the state level, we create a state-level variable that is a weighted average of grid cell observations. Specifically, we match grid cells to their county and aggregate up, weighting by both inverse squared distances to county population centers and county populations.[6] Daily mean temperatures are the average of the reported minimum and maximum at the grid cell-level before aggregation.

We characterize exposure to weather using counts of the number of days in each state, month, and year during which the mean temperature fell in a particular five-degree Celsius window (bin). This approach follows a large literature and allows for non-linear relationships between temperature and our outcome variables. Our preferred specification uses eight of these bins: under –5 degrees, –5–0 degrees, and so on, up to over 30 degrees. We also estimate and include results for alternate bin choices.

We also report in Table 1 the average number of days in the extreme temperature bins from 2004–2018. We define extremes as average temperatures below –5C and above 30C, and show the full distribution of mean daily temperatures over our study period in Figure B.1. Additional summary statistics are provided in Table B.1.

4 Empirical Framework

We first estimate the relationship between weather and monthly energy spending. We then test whether responses are the same for low-income and higher-income households, and conduct a similar analysis for food spending.

We use temperature bins to flexibly estimate the response to extreme weather, as is common in the climate change literature (Deschenes and Greenstone, 2011; Barreca et al., 2016; Hsiang, 2016; Mullins and White, 2019b). While our spending data is at the household level, we only observe the state where households live, not their exact location. A temperature bin $Temp_{j,smy}$ is the number of days in month m where the average temperature in state s fell within the j^{th} 5C-degree bin. Because we include state-by-month fixed effects in all specifications, results capture responses to deviations from average weather. Our main

[6] County populations are from the Census and vary annually; county population center coordinates are from the Census and 2010 values are used.

specification is

$$\text{ihs}(Spend_{imy}) = \sum_{j=1}^{J} \beta_j Temp_{j,smy} + X_{ismy}\gamma + \delta_{sm} + \mu_{my} + \epsilon_{imy} \tag{1}$$

where $\text{ihs}(Spend_{imy})$ is the inverse hyperbolic sine (IHS) of spending by household i in month m in year y. We include state-by-month fixed effects, δ_{sm}, and month-by-year fixed effects, μ_{my}. The set of temperature bins J omits one reference bin, the 15-20C degree bin. We cluster standard errors at the state level and weight by the CEX sampling weights.

We also control for other determinants of household spending, X_{ismy}. We control for the age, sex, race, and education of the reference individual. We also control flexibly for total household size, the number of children, and the number of elderly. While month-year fixed effects capture the aggregate business cycle, we include the monthly state-level unemployment rate from the BLS to capture local economic conditions. Finally, we control for precipitation and its square.

To allow for differential effects of weather on spending for low-income households, we interact the temperature bins with an indicator variable for the household's poverty status:

$$\begin{aligned} \text{ihs}(Spend_{imy}) = \sum_{j=1}^{J} \beta_j Temp_{j,smy} + \sum_{j=1}^{J} \alpha_j Temp_{j,smy} \times 1[1.5\, FPL_{isy}] \\ + 1[1.5\, FPL_{isy}] + X_{ismy}\gamma + \delta_{sm} + \mu_{my} + \epsilon_{imy} \end{aligned} \tag{2}$$

where $1[1.5\, FPL_{iy}]$ is an indicator for whether household i is under 150 percent of the federal poverty line (FPL). This cutoff is often used to determine eligibility for energy assistance. Throughout, we refer to households under 150 percent of the FPL as "low income."

5 Results

We present results for energy and then food spending. We assess the two using separate survey data, but hypothesize that energy spending due to weather shocks may constrain food spending for low-income households.

5.1 Energy Spending

Figure 2a documents the expected U-shaped pattern in the energy spending response to temperature: households spend more when weather is extreme. When a day in the 15–20C bin is replaced with a day in the under −5C bin, monthly energy spending increases by 1 percent. Similarly, when a day in the 15–20C bin is replaced with a day in the over 30C bin, energy spending increases by 0.4 percent.

We find meaningful differences in the response to extreme weather by household poverty status. Lower-income households' fuel spending matches all other households' spending except at the extremes of the temperature distribution, where it is substantially lower. Table 2 reports regression results using our baseline specification with interactions (Equation 2), for all energy spending and by fuel type, and this relationship is visualized in Figure 2b. For cold weather, when a day in the 15–20C bin is replaced with a day in the under −5C bin, low-income households increase spending by 0.7 percent, or $1.23, less than higher income households. This effect is driven by spending on natural gas. When a day in the 15–20C bin is replaced with a very hot day (one in the over 30C bin), low-income households increase spending by 0.3 percent, or $0.91, less than higher income households. The effect is larger and more precisely estimated for electricity, which is consistent with this spending being driven by air conditioner use. Appendix Table B.2 shows estimates vary as expected when we change the cutoffs for the most extreme bins.

5.2 Food Spending

Food spending is not very responsive to extreme weather for the average household: the effects on food spending of replacing a 15–20C day with a day below –5C or a day above 30C are not statistically different from zero.

As with energy, however, we find food spending poverty gaps for both extreme cold and extreme heat. Table 3 presents estimates for three measures of spending: an indicator for any food spending, total grocery spending, and total food spending. When a day in the 15–20C bin is replaced with a day in the < -5C bin, low-income households are 0.3 percent less likely to buy any food in the survey week than higher income households. Low-income households also respond by spending 1.2 percent less on groceries and 1.7 percent less on all food than higher income households. In levels, this gap is \$1.63 for groceries and \$1.98 (estimated imprecisely) for all food. At the other extreme, when a day in the 15–20C bin is replaced with a day in the > 30C bin, low-income households are 0.2 percent less likely to buy any food than higher income households. The corresponding gaps in spending are 1.8 percent for groceries and 1.6 percent for all food spending, or \$2.88 and \$2.48 in levels.

5.3 Lagged effects

We next turn to models with lagged weather variables. If these poverty gaps are due to liquidity constraints, they may appear in the month following unseasonable weather when the household pays its energy bill. Lingering spending gaps are also more consistent with budget constraints than other behavioral changes in spending related to weather. For diary survey weeks that occur early in a given month, the previous month's weather may also better reflect recent conditions.

We find the effects of last month's weather on spending are similar in magnitude to contemporaneous effects (Table 4). For energy spending, the coefficients on last month's < -5C bin and its interaction with poverty status are nearly identical to this month's coefficients. For hot days, lagged and contemporaneous effects are similar, but only the lagged poverty interaction is statistically significant. In both cases, point estimates for contemporaneous effects are slightly smaller when lags are included. Estimates for the effects of weather on food spending are less precisely estimated when we include lags, but generally consistent with persistent decreases in spending.

6 Discussion

We find a novel poverty gap for energy spending in response to very hot days. This effect is driven by electricity spending, and its magnitude is consistent with disparate air conditioner use: the additional increase in electricity use among non-low income households for an unseasonably hot day would power a typical window air conditioning unit for 4 hours (see Appendix C).

To return to the example of the August 2011 heat wave, our estimates (combined with the shift in each temperature bin relative to the study average) imply a typical higher income household in Oklahoma increased monthly energy spending by about 7 percent, relative to a typical August, while for a low-income household this increase was only 1 percent. Like Bhattacharya et al. (2003), we find that low-income households increase their spending by less in response to extreme cold. During the January 2018 cold wave, our estimates imply energy spending in North Carolina rose by about 4 percent for higher-income households, but less than 1 percent for low-income households.

We next provide evidence these differences in spending are indicative of differences in consumption and differences in dwelling temperatures. We then discuss the implications of inadequate indoor heating and cooling for health and policy.

6.1 Differences in consumption

It is possible differences in energy prices are driving our findings, rather than underlying differences in consumption. We rule this out by comparing energy usage and spending in the Residential Energy Consumption Survey (RECS).

In particular, if low-income households face lower marginal energy prices than higher-income households, then the same increase in energy use would result in a smaller increase in energy spending for low-income households. Marginal energy prices can vary with location or with use, especially for electricity. Borenstein and Bushnell (2019) find almost 60 percent of households face marginal electricity prices that vary with consumption.[7] Of these households, about two-thirds face marginal prices that increase with use, while one-third face marginal prices that decrease with use.

We use the RECS, which collects annual data on energy billing and use directly from respondents' utilities, to find that low and higher-income households face similar prices.[8] For electricity, we find a one kWh increase in use is associated with a $0.105 increase in spending for low-income households, compared to a $0.111 increase for higher-income households. For natural gas, the increase in spending for a one therm increase in use is $1.11 for both groups. Appendix C provides a more thorough discussion of these results. It also shows that our CEX electricity spending results are robust to dropping households with the highest electricity spending, and also the state of California (that is, households most likely to pay high marginal prices under increasing block pricing).

The design of the CEX also makes it unlikely our results reflect bill non-payment or under-payment by low-income households. The CEX questions solicit the amount billed, not the amount paid, for utilities. We cannot rule out the possibility that households misinterpret the question and report the amount actually spent (low-income households may spend less on energy because they are receiving energy assistance), so we test whether results extend to households unlikely to receive energy assistance. Energy subsidies from LIHEAP, the federal assistance program, are limited to households below either 150 percent of the FPL or 60

[7]Using data from 2014-2016 they find 58 percent of households are served by utilities whose primary residential tariff has marginal prices that vary with consumption (p.6).

[8]We cannot use these data to estimate our main specification for three reasons: we only observe household location at the Census division level, the RECS data is annual rather than monthly, and the RECS sample is much smaller than the CEX sample.

percent of state median income (Perl, 2018). If energy assistance were driving our findings, we might expect the energy poverty gaps to disappear as we raise the poverty threshold. This is not the case: the spending disparities remain with a higher threshold of 200 percent of the FPL (Table B.3).

The differences in energy spending we document do not appear to be a product of differences in prices or billing associated with poverty status, but instead evidence of differences in household energy consumption during extreme weather.

6.2 Differences in indoor temperature

It is possible our estimates reflect differences in housing characteristics but not disparities in indoor temperatures. We rule this out by showing spending gaps exist conditional on housing types and sizes.

Smaller homes and apartments require less energy to maintain ambient temperature. In the CEX, low-income households' homes have on average fewer rooms (5.4 versus 6) and are more likely to be apartments (23 versus 15 percent), and these differences could result in energy consumption gaps without indoor temperature differences.

We find little evidence home sizes or types explain these energy spending gaps. First, our preferred specification uses the inverse hyperbolic sine (IHS) of energy spending, which avoids scale effects. Thus, to explain the gap, smaller dwellings would need to require less of an increase in energy spending in *percentage* terms to maintain ambient temperature. Second, our estimates are robust to comparisons within size and type of home. While we do not observe square footage in the CEX, we do observe the number of rooms. For the IHS specifications, we estimate similar poverty gaps if we subset the data by the number of rooms and estimate the model separately for each subset (Table B.4). The point estimates on the extreme bins for higher-income households are also alike across these subsets, suggesting the percentage increase in spending in response to extreme weather is similar across homes of different sizes. Estimating poverty gaps within housing types in the CEX (such as apartments, or single family homes) also yields results consistent with our main estimates (though with less precision, see Table B.5), suggesting our findings are not driven by systematic differences in housing type by poverty status.

Conversely, differences in dwelling characteristics may cause consumption differences to understate differences in indoor temperature. This could be the case if lower-income households' homes are systematically less well insulated or served by less efficient heating and cooling systems. There is survey evidence for just these efficiency disparities: in the 2015 RECS, 25 percent of households below 1.5 times the FPL live in homes with poor or no insulation, compared with only 15 percent of households above that threshold. Frequent draftiness is reported in 19 percent of low-income households, versus 8 percent of other households. In the 2011 American Housing Survey, about twice as many households below the 1.5 FPL threshold as above it report inadequate heating capacity or inadequate insulation in their unit. Low-income households are also 50 percent more likely to report their dwelling has holes in the roof or walls. Thus, lower quality housing could lead to disparities in indoor temperatures even absent observed differences in consumption: the same amount of energy towards cooling will leave a less efficient home warmer on a hot day than a more efficient home.

Finally, while indoor temperature differences may reflect hardship, they are also consistent with low-income households consuming "just enough" heating or cooling. To test for this, we re-estimate equation 2 omitting the most affluent households, that is, those least likely to be concerned about utility bills and monitoring or rationing energy use. Table B.6 shows results are robust to dropping households above five and ten times the FPL, so the gap is not due to excess energy spending by affluent households. Corroborating this interpretation, both qualitative and survey evidence find that low-income households are more likely to keep their homes uncomfortably hot or cold (Hernández, 2016; Energy Information Administration, 2018).

6.3 Implications for health and policy

We conclude these energy spending gaps reflect differences in energy use that result in disparities in indoor temperature. Experiencing too-hot or too-cold temperatures may have serious health consequences. Extreme cold and heat cause a wide range of health ailments, including respiratory illness, heart attacks, and death. Compounding this, lower-income individuals are more likely to have underlying health conditions that increase the danger of exposure to extreme weather.

Low-income households consuming less energy during hot weather is likely not due to lack of access to air conditioning. Air conditioning is prevalent in the U.S.—nearly 90 percent of households had it in their home in 2015 (Energy Information Administration, 2018)—and when we re-estimate our main specification using only households with air conditioning, we find similar poverty gaps (Table B.7).[9] This suggests affordability, not availability, limits U.S. households' consumption of air conditioning over the period we study. Barreca et al. (2016) use data from 1960-2004 to find the relationship between heat and mortality was lower in areas where more households owned air conditioning—but to receive the health benefits of air conditioning, households must be able to afford to run their units.

The food spending results further support the explanation that low-income households consume less energy during extreme weather. If households cannot smooth budget shocks caused by high energy bills, we would expect them to cut back on all variable expenses. We find statistically significant food spending poverty gaps, consistent with low-income households cutting back on necessities, such as maintaining a comfortable indoor temperature, in order to afford energy bills.[10] This suggests a broader pattern of cutting back spending on other healthful expenses, such as medicine, in order to afford energy.

[9] The CEX does not differentiate between households that do not have air conditioning and those that do not respond to the question. Thus, the households we exclude from this analysis may or may not have air conditioning.

[10] It is possible low-income households have different food shopping responses to extreme temperature. Yet, if low-income households are more likely to delay shopping trips, we should find a corresponding rebound in food spending the next month. Instead, we find persistent poverty gaps (Table 4).

Our findings point to a failure of current U.S. assistance programs to adequately buffer households from energy bill shocks. This may be because take-up of these programs is limited: many households eligible for benefits are not enrolled (incomplete take-up of both SNAP and LIHEAP are documented in Currie (2006) and Graff and Pirog (2019), respectively). Benefits may also be inadequate. Twenty-six states did not offer any LIHEAP cooling assistance in 2015.[11] In our sample, low-income households in these states reported average fuel expenditures of $157 for June, July, and August; similar to the $168 low-income households spent in states that did offer cooling assistance. Average summer fuel expenditures for low-income households in states without cooling assistance ($157) are also comparable to their average winter (December, January, February) fuel expenditures of $194. Eligibility thresholds may also be too low. While the LIHEAP eligibility cutoff is 150 percent of the FPL, poverty gap estimates for specifications with a cutoff of 200 percent of the FPL are very similar to those for 150 percent of the FPL (see Appendix Table B.3).

Climate change could exacerbate these weather-driven spending disparities. By 2065, the frequency of days with mean temperatures over 30C is expected to rise by about 24 days per year under a business as usual scenario, while the frequency of days below –5C is expected to fall by only 7 days.[12] More frequent heat shocks may exacerbate the unaffordability of air conditioner use for lower-income households. And while less frequent extreme cold may generate savings in winter energy spending (implying reduced energy insecurity during those months), the gains and losses at each end of the temperature distribution may not cancel out, but represent a further source of inequality. For example, low-income households in the Southern U.S. may be especially harmed by an increase in very hot days while households in the Northeast benefit the most from a reduction in extremely cold weather.

[11] Full table of benefits from HHS available at https://liheapch.acf.hhs.gov/tables/FY2015/heatbenefit.htm.

[12] This projection is for the typical household in the U.S. It comes from average changes in each bin of our temperature distribution from 2004–2018 to 2050–2065 under the RCP 8.5 scenario, across the CMIP5 ensemble models from Hsiang et al. (2017) and Rasmussen and Kopp (2017), combined with a middle-of-the-road county population forecast from Hauer (2019).

7 Conclusion

We find a novel poverty gap in the energy spending response to very hot weather, and a corresponding disparity for very cold weather. This muted spending response by lower-income households may indicate homes are insufficiently heated and cooled to prevent adverse health effects. We also find poverty gaps in the food spending response to temperature, corroborating the concern that lower-income households cut back on necessities to afford energy bills. While we propose liquidity constraints as the mechanism for these effects, the policy implications are much the same for alternative mechanisms.

This research has implications for existing social programs, and the design of policies to address climate change. It suggests low-income households are especially vulnerable to exposure to weather shocks. Cooling technologies like air conditioning have a key role to play in adaptation to climate change, but so does energy assistance: the affordability of adaptation is likely to affect the distribution of climate damages.

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8 Figures and Tables

Table 1: Summary statistics

A: Interview Survey (IS)

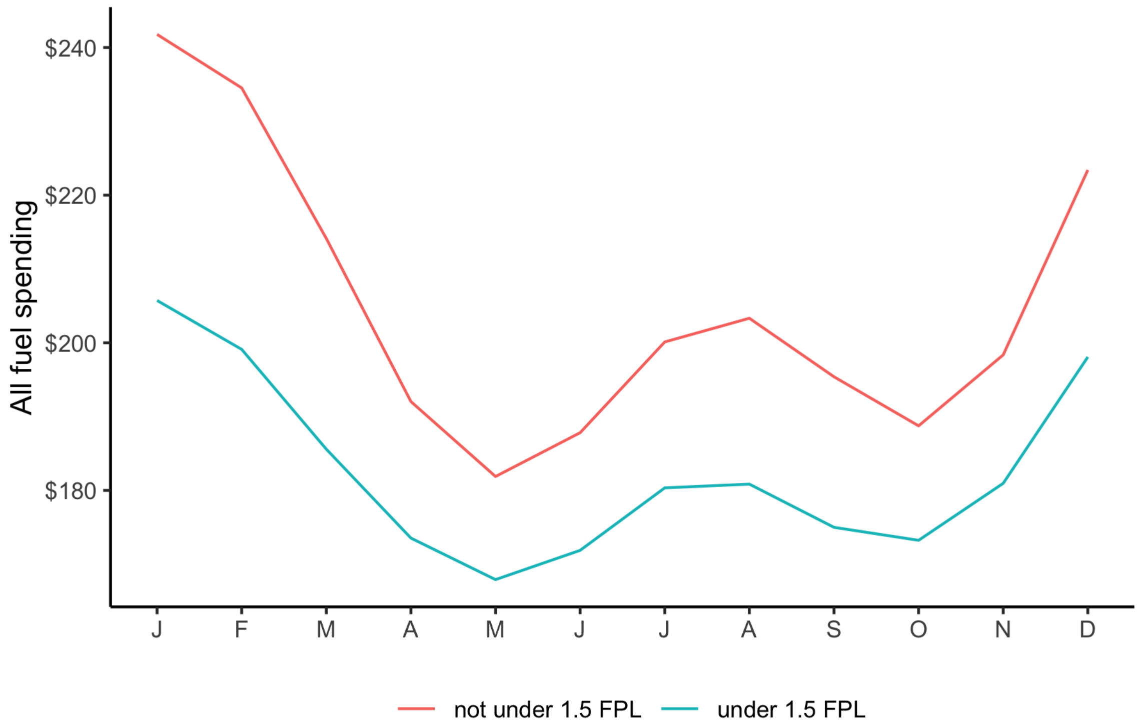
Statistic	Mean	Median	St. Dev.	N
Days under –5C	1.08	0.00	3.41	925,021
Days over 30C	0.54	0	2.64	925,021
Energy expenditures	199.81	165.75	157.99	925,021
... Over 1.5 FPL	207.69	172.67	162.13	628,087
... Under 1.5 FPL	183.12	151.63	147.45	296,934
Natural gas expenditures	49.28	21.22	78.54	925,021
... Over 1.5 FPL	52.64	25.71	80.22	628,087
... Under 1.5 FPL	42.15	3.44	74.37	296,934
Electricity expenditures	138.23	115.1	101.62	925,021
... Over 1.5 FPL	141.19	117.47	102.17	628,087
... Under 1.5 FPL	131.99	109.88	100.15	296,934
Any air conditioning (0/1)	0.74	1	0.44	925,021
... Over 1.5 FPL	0.77	1.00	0.42	628,087
... Under 1.5 FPL	0.67	1.00	0.47	296,934
Rooms in home	6.02	6.00	2.22	917,888
... Over 1.5 FPL	6.27	6.00	2.23	625,186
... Under 1.5 FPL	5.48	5.00	2.11	292,702

B: Diary Survey (IS)

Statistic	Mean	Median	St. Dev.	N
Days under –5C	1.07	0.00	3.37	171,336
Days over 30C	0.51	0	2.56	171,336
Any food expenditures (0/1)	0.90	1	0.30	171,336
... Over 1.5 FPL	0.95	1.00	0.21	109,105
... Under 1.5 FPL	0.80	1.00	0.40	62,231
In home food expenditures	363.92	261.45	396.34	171,336
... Over 1.5 FPL	408.28	311.49	403.91	109,105
... Under 1.5 FPL	286.13	172.63	370.09	62,231
All food expenditures	599.45	456.66	655.71	171,336
... Over 1.5 FPL	701.91	564.27	706.24	109,105
... Under 1.5 FPL	419.81	275.11	508.56	62,231

Note: Statistics constructed from the CEX for 2004-2018. N is the no. of household-months. Days under -5C are counts of days each month with an average daily temperature under -5C; Days over 30 C is the same for > 30C. Energy expenditures (total, natural gas, and electricity) are monthly spending in Jan. 2018 dollars. Over 1.5 FPL is the subset of households over 1.5 times the Federal Poverty Line. Any air conditioning is an indicator for whether a household reported having A.C. that year; it is 0 for both households without A.C. and those that did not respond. Rooms in home is the number of rooms in the households' dwelling. In home food spending is monthly expenditures on food for consumption at home. Table B.1 presents additional statistics.

(a) Mean monthly energy spending by poverty status



(b) Difference in mean monthly spending across groups

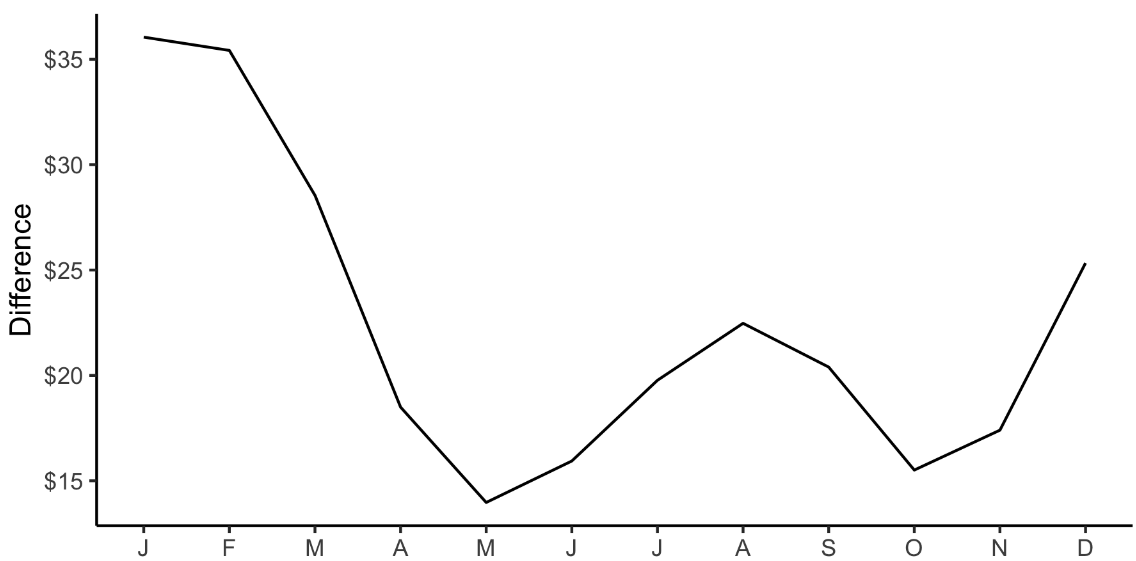
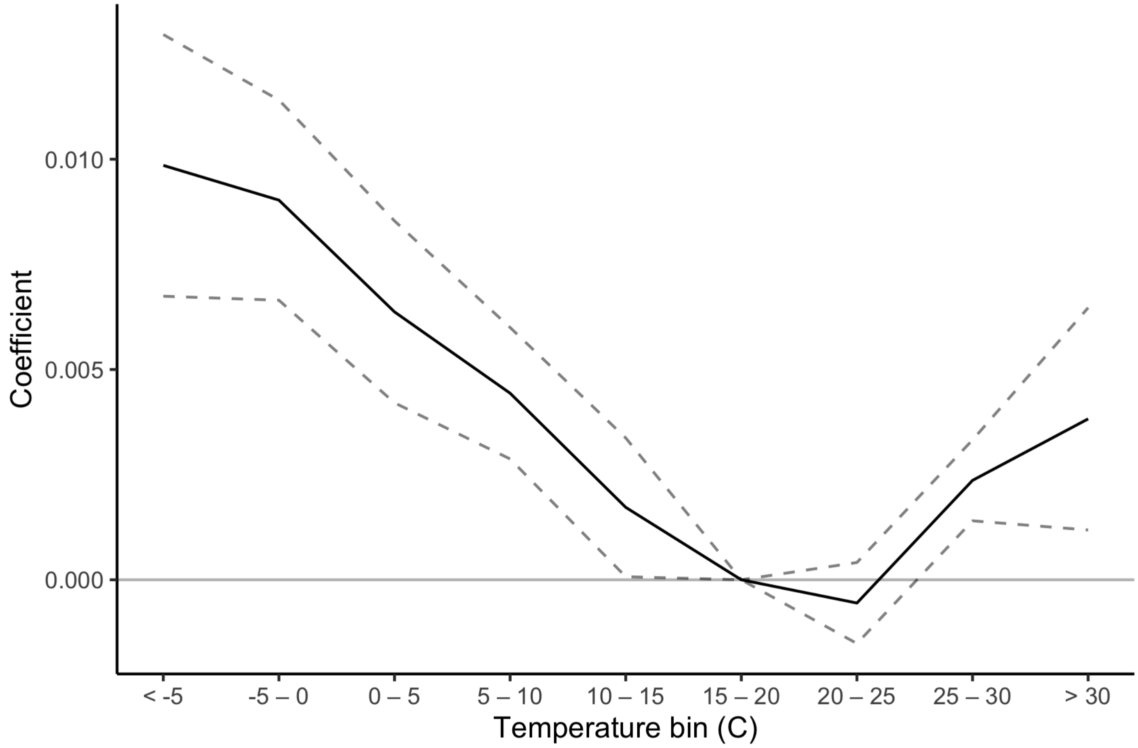


Figure 1: Seasonal energy spending by poverty status

Note: Average monthly fuel spending (using sample weights) is plotted separately for households above and below 1.5 times the FPL in Panel (a). Panel (b) plots difference between the two group means in Panel (a).

(a) Energy spending response for all households



(b) Poverty gap in energy spending response

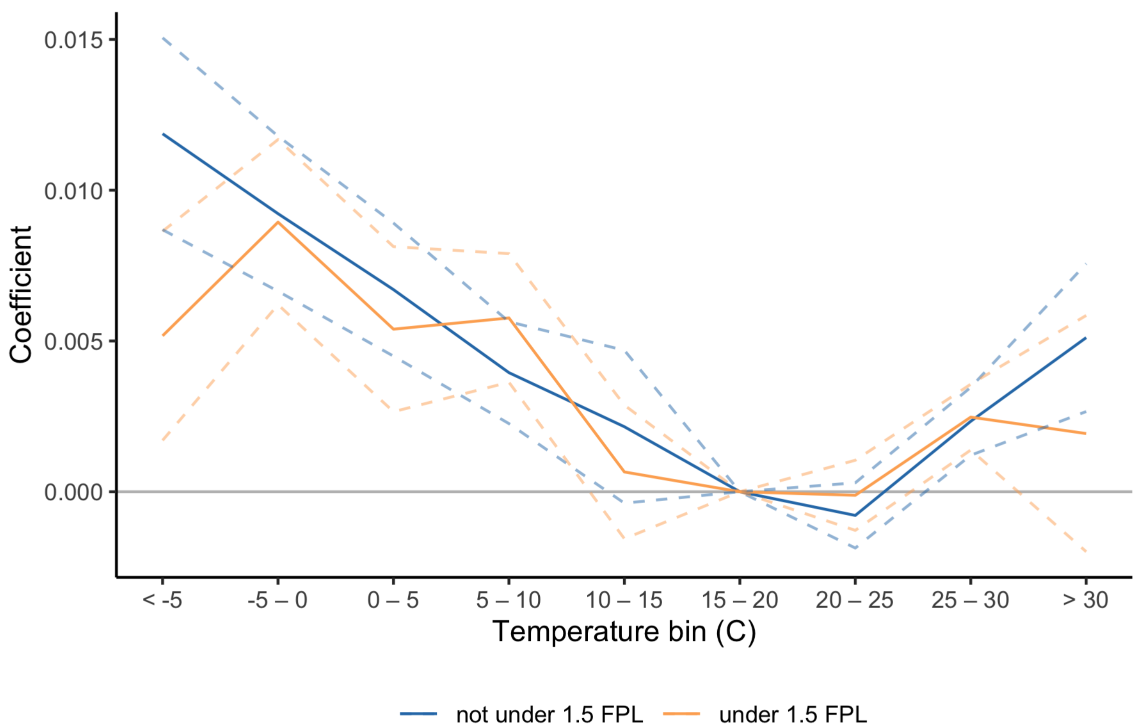


Figure 2: Energy spending response to temperature

Note: Coefficients show the effect of one additional day per month in each 5C-temperature bin on IHS-transformed monthly home energy spending. Panel (a) corresponds to Equation 1 in the text, and Panel (b) to Equation 2, which allows for heterogeneity in household spending by poverty status. Confidence intervals are 95%.

Table 2: Poverty gap in energy spending response

	Dependent variable:					
	ihs(All energy)	ihs(Natural gas)	ihs(Electricity)	All energy	Natural gas	Electricity
	(1)	(2)	(3)	(4)	(5)	(6)
Under –5	0.012***	0.020***	0.005**	2.388***	1.318***	0.667**
	(0.002)	(0.006)	(0.002)	(0.367)	(0.235)	(0.268)
... × under 1.5 FPL	−0.007***	−0.012**	−0.001	−1.228***	−0.658***	−0.200*
	(0.001)	(0.005)	(0.002)	(0.175)	(0.159)	(0.112)
Over 30	0.005***	0.005	0.005***	1.218***	0.231	1.100***
	(0.001)	(0.005)	(0.002)	(0.270)	(0.156)	(0.258)
... × under 1.5 FPL	−0.003*	−0.002	−0.005**	−0.913**	0.107	−1.121***
	(0.002)	(0.008)	(0.002)	(0.379)	(0.104)	(0.329)
Subset	IS	IS	IS	IS	IS	IS
Observations	925,021	925,021	925,021	925,021	925,021	925,021
R^2	0.268	0.210	0.185	0.178	0.186	0.190

Note: Dependent variables are at the household-month level. Data from the CEX Interview Survey (IS). All energy is total HH energy expenditures; Natural gas and Electricity are expenditures for each fuel type. Under -5 is the no. of days in that month with an average temp. < -5 C for the state the HH resides in; Over 30 is the same for days >30 C. Under 1.5 FPL is an indicator for HHs under 1.5 times the federal poverty line. All specifications include temperature bins for < -5 C, -5-0 C, . . ., 25-30 C, >30 C and their interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights.*p<0.1; **p<0.05; ***p<0.01.

Table 3: Poverty gap in food spending response

	Dependent variable:				
	Any food (0/1)	ihs(Food in)	ihs(All food)	Food in	All food
	(1)	(2)	(3)	(4)	(5)
Under –5	-0.001^{*}	0.002	-0.007	1.331	1.472
	(0.001)	(0.006)	(0.005)	(1.127)	(1.772)
... × under 1.5 FPL	-0.003^{**}	-0.012^{*}	-0.017^{**}	-1.632^{*}	-1.977
	(0.001)	(0.006)	(0.008)	(0.825)	(1.830)
Over 30	0.001	0.011	0.008	1.558	2.578
	(0.001)	(0.009)	(0.010)	(1.486)	(3.532)
... × under 1.5 FPL	-0.002^{***}	-0.018^{***}	-0.016^{***}	-2.876^{***}	-2.478
	(0.001)	(0.004)	(0.005)	(0.817)	(1.684)
Subset	DS	DS	DS	DS	DS
Observations	171,336	171,336	171,336	171,336	171,336
R^2	0.082	0.126	0.152	0.158	0.162

Note: Dependent variables are at the household-month level. Data from the CEX Diary Survey (DS). Any food is an indicator for non-zero HH food expenditures during the two week DS. Food in is expenditures on food for consumption at home. Expenditures during the two week DS are scaled up to construct the monthly measure. All Food is the same for total food expenditures. Under -5 is the no. of days in that month with an average temp. < -5 C for the state the HH resides in; Over 30 is the same for days >30 C. Under 1.5 FPL is an indicator for HHs under 1.5 times the federal poverty line. All specifications include temperature bins for < -5 C, -5-0 C, ..., 25-30 C, >30 C and their interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Poverty gap in spending response with previous month's weather

	Dependent variable:			
	ihs(All energy)	ihs(Food in)	All energy	Food in
	(1)	(2)	(3)	(4)
Under –5	0.010***	0.002	1.881***	1.423
	(0.001)	(0.007)	(0.323)	(1.165)
... × under 1.5 FPL	−0.005***	−0.010	−0.866***	−1.950**
	(0.001)	(0.006)	(0.196)	(0.880)
Under –5 (t-1)	0.010***	0.002	1.965***	0.518
	(0.001)	(0.005)	(0.294)	(0.994)
... × under 1.5 FPL	−0.004***	−0.009	−0.688***	0.616
	(0.001)	(0.008)	(0.174)	(0.808)
Over 30	0.004***	0.015	0.855***	1.482
	(0.001)	(0.011)	(0.231)	(1.593)
... × under 1.5 FPL	−0.002	−0.016**	−0.591*	−1.948*
	(0.001)	(0.007)	(0.315)	(0.993)
Over 30 (t-1)	0.005***	−0.014	1.029***	−0.774
	(0.001)	(0.015)	(0.225)	(1.479)
... × under 1.5 FPL	−0.003**	−0.006	−0.621***	−0.982
	(0.001)	(0.007)	(0.217)	(0.808)
Subset	IS	DS	IS	DS
Observations	925,021	171,336	925,021	171,336
R^2	0.269	0.126	0.179	0.158

Note: Dependent variables are at the household-month level. Data from the CEX Interview Survey (IS) and Diary Survey (DS). All energy is total energy expenditures in month t; Food in is expenditures on food for consumption at home in month t. Under -5 is the no. of days in month t with an average temp. < -5 C for the state the HH resides in; Over 30 is the same for days >30 C. Under 1.5 FPL is an indicator for HHs under 1.5 times the federal poverty line. Under -5 (t-1) is the no. of days last month $(t-1)$ with an average temp. < -5 C for the state the HH resides in; Over 30 (t-1) is the same for days >30 C. All specifications include temperature bins for < -5 C, –5-0 C, . . ., 25-30 C, >30 C in t and $t-1$ and their interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights. *p<0.1; **p<0.05; ***p<0.01.

Appendices

A Theoretical model

This section first presents results for a simple, static model of the decision to spend more on energy in response to a weather shock. Though the model applies to extreme hot and cold, our main focus is on the response to hot days. Using a framework anchored by Carleton et al. (2020), we make a distinction between willingness-to-pay and ability-to-pay inspired by Grassi (2010) to predict how energy spending may vary with income. Next, we consider reasonable extensions of the model that allow for greater realism and explore whether our main result still holds.

A.1 Energy Spending and Weather with Liquidity Constraints

Consumers derive utility as $u(x, c, e) = u(x)(1 - f(c, e))$, which is continuously differentiable. Here, $0 < f(c, e) < 1$ is a health variable interpreted as mortality risk, and $(1 - f(c, e))$ is the probability of living to enjoy consumption.[13] Utility also depends on consumption of the numeraire good x, $u(x)$, which is continuously differentiable with $u'(x) > 0$ and $u''(x) < 0$ and x has a positive support. Extreme weather also affects utility: define weather as a random draw c from a climate distribution C which has a positive support.[14] Absent adaptation, extreme weather affects a consumer's utility by reducing health. Consumers may adapt by purchasing extra energy e, which has a positive support, at a cost of p.

Energy spending e reduces the health costs of exposure to extreme temperature, increasing utility derived from the numeraire.[15] The share of utility lost from exposure to extreme

[13]Mortality from exposure to extreme weather is well-documented (Deschenes and Greenstone, 2011).

[14]This random draw is realized at the start of the period, thus there is no uncertainty. The interpretation for c is that it is a deviation, in absolute value, away from a bliss point temperature. This would be excess heat in the summer and excess cold in the winter.

[15]Note in Carleton et al. (2020) health costs are restricted to mortality and adaptation is a composite $\boldsymbol{b} = (b1; \cdots ; b_k)$, where b_k describe all adaptive behaviors, including energy spending. We restrict short-term adaptation to focus on energy spending only and we broaden the risks from extreme temperature to include all health effects.

weather due to health effects is a function of realized weather and household energy spending, $f = f(e, c)$.[16] We begin with the assumption that changes in health risk from energy spending are identical across consumers.[17] The health risk function is continuously differentiable and is increasing and convex in weather, $f_c(e, c) > 0$ and $f_{cc}(e, c) > 0$. This means health risks increase and grow more extreme with more extreme weather. In contrast, health risk is decreasing and concave in energy spending, $f_e(e, c) < 0$ and $f_{ee}(e, c) < 0$, meaning energy spending is protective; however, there are diminishing returns to spending on health. Increased energy spending decreases the severity of more extreme climate, $f_{ec}(e, c) < 0$.

Given a random weather realization c, agents simultaneously choose their consumption of the numeraire x and extra energy spending e to maximize utility subject to an exogenous budget constraint. Consumers' budget constraint is their disposable income Y, which has a positive support. There is no access to credit or borrowing; budgets must balance each period.

$$\begin{aligned} \max_{e,\,x} \quad & u(x)\,[1 - f(e, c)] \\ \text{s.t.} \quad & Y \geq x + pe \end{aligned} \tag{3}$$

Consumers fall into two types: those that increase their energy spending to adapt to weather, making their dwelling temperature more comfortable, and those that do not. Whether or not households consume extra energy depends on their income, their *ability-to-pay*. Households that do not increase energy spending despite their willingness to do so are *energy insecure*.

For those that adapt and purchase extra energy, their utility is

$$u(Y - pe)(1 - f(e, c)) \tag{4}$$

[16] Note, given $f(e, c)$ is the share of utility lost, its range is from 0 to 1.

[17] Given that many health conditions are co-morbid with poverty, it is more likely that energy spending by low-income households brings greater reductions in health costs than energy spending by high-income households. We relax this restriction in our model extensions.

For those that do not adapt, utility is

$$u(Y)(1 - f(0, c)) \tag{5}$$

Following Grassi (2010), we deviate from a traditional neoclassical approach, where within a utility maximization problem the consumers' income (ability-to-pay) determines their willingness-to-pay. In the context of health, consumers may derive large benefits from consumption but not purchase a good if it is unaffordable (Grassi and Ma, 2011; Eames et al., 2017; Kanniainen et al., 2019). In these contexts, separating ability-to-pay and willingness-to-pay is vital to understanding the consequences of policy intervention.

Instead, we follow Kanniainen et al. (2019) and define willingness-to-pay θ implicitly for income Y using the moment when a consumer is indifferent between utility from increasing energy spending and utility from not increasing energy spending

$$u(Y - \theta)(1 - f(e, c)) = u(Y)(1 - f(0, c)) \tag{6}$$

This indifference conditions implies that the health benefit from energy spending equals the utility from foregone consumption of the numeraire.

Proposition 1. *There exists a threshold income, Y_M, such that $Y \geq Y_M$ implies $e > 0$ and $Y < Y_M$ implies $e = 0$.*

Proof. Tautology. Define Y_M as the income-level such that Equation (6) holds.
Given concave utility, $u''(x) < 0$, $u(Y - \theta)(1 - f(e, c)) < u(Y)(1 - f(0, c))$ for all $Y < Y_M$.
Give $u'(x) > 0$ and $f_e(e, c) < 0$, $u(Y - \theta)(1 - f(e, c)) > u(Y)(1 - f(0, c))$ for all $Y > Y_M$. □

This Proposition highlights that, for low-income households, utility from spending on other goods x such as basic needs outweighs utility from lower health risk from energy spending in response to extreme temperature.

Equation (6) also leads to the following remark, which relates willingness-to-pay to ability-to-pay and weather.

Lemma 1. *Willingness-to-pay is increasing in ability-to-pay (income) and weather.*

Proof. Direct calculation. Implicit differentiation gives

$$\frac{\partial\theta}{\partial Y} = 1 - \left(\frac{u'(Y)}{u'(Y-\theta)}\right)\left(\frac{1-f(0,c)}{1-f(e,c)}\right) > 0 \tag{7}$$

and

$$\frac{\partial\theta}{\partial c} = \frac{u(Y)f_c(0,c) - u(Y-\theta)f_c(e,c)}{u'(Y-\theta)\,(1-f(e,c))} > 0 \tag{8}$$

where $f_c(0,c) > f_c(e,c)$ due to $f_{ec}(e,c) < 0$. $\square$

Lemma (1) clarifies how ability-to-pay (income) affects willingness-to-pay, with implications for welfare (Grassi, 2010). Clearly, households with low income benefit from energy spending through reduced mortality risk. However, their willingness-to-pay is limited by their ability-to-pay. Put another way, this model would interpret differences in energy spending between high- and low-income households as reflecting differences in ability-to-pay, not differences across households in the private benefits from energy spending (captured in $f(e,c)$). This stands in contrast to a standard neo-classical model, where differences in willingness-to-pay reflect preferences and are not explicitly tied to ability-to-pay.

A.2 Extensions

The model framing greatly simplifies consumer decision-making to focus on the main tensions for how energy spending in response to weather changes with household income. Our main result is that there is a threshold income below which households fail to consume extra energy in response to weather shocks. Here we explore extensions to the model that recognize different ways that income may affect other objects of the optimization problem to see how they affect our main result.

A.2.1 Income and Weather

In our static model, income is exogenous and does not vary with weather. However, we know that economic activity, and thus income, is affected by weather (Graff Zivin and Neidell, 2014; Burke et al., 2015). Our baseline model abstracts from this link because the magnitude of the changes in income from weather shocks are somewhat small.[18] The simplest way to model how income responds to weather is to make income decreasing and convex in extreme temperature, $\tilde{Y}(c), \tilde{Y}'(c) > 0, \tilde{Y}''(c) > 0$.[19]

Remark 1. *If income is decreasing and convex in extreme temperature, $\tilde{Y}(c), \tilde{Y}'(c) > 0, \tilde{Y}''(c) > 0$, there exists a threshold income for energy spending in response to extreme weather, $\tilde{Y}^c_M$, where consumers with $\tilde{Y} \geq \tilde{Y}^c_M$ increase energy spending and all others do not. Moreover, $\dfrac{\partial \tilde{Y}^c_M(c)}{\partial c} > 0$.*

Proof. For the threshold value $\tilde{Y}^c_M$, proof by tautology identical to Proposition (1).

For $\dfrac{\partial \tilde{Y}^c_M(c)}{\partial c} < 0$, direct calculation using Lemma (1). $\square$

We conclude that allowing income to depend on weather, $\tilde{Y}(c)$, fails to change our main result, that there is a critical value of income for non-zero energy spending. Moreover, we see that allowing for feedback between weather and income increases the set of households that are energy insecure, e.g. those that do not purchase energy despite avoided mortality benefits from doing so.

A.2.2 Income and Energy Pricing

High income households tend to use greater energy, regardless of weather. Given increasing block pricing in some electricity markets, this implies the marginal price of electricity may be

[18] For example, Burke et al. (2015) find an additional day with an average temperature of 30C decreases labor performance by 10%.

[19] Note, this simplification does not address that productivity of cold areas may actually increase with warmer average temperatures in winter (Schlenker and Roberts, 2009). We instead emphasize the negative impacts from extreme heat in summer since this paper documents a new energy spending poverty gap at that time.

monotonically increasing in income. This could make the cost of extra energy e in response to a weather shock vary with income if higher income households tend to be in a higher pricing block.

Lemma 2. *Suppose the price of energy is increasing in income, e.g.* $p(Y)$*, where* $p'(Y) > 0$ *for all* Y *and* $p(\underline{Y}) = p$*. There exists a critical income level* Y_M^p *such that* $Y > Y_M^p$ *purchase energy and* $Y < Y_M^p$ *do not. Moreover,* $Y_M^p > Y_M$

Proof. For the critical threshold, we use Proposition (1).

To compare the critical income levels with and without prices that increase in income, note that for the marginal household that purchases energy,

$$\theta(Y, e) = p(Y)e \tag{9}$$

Given $p(\underline{Y}) = p$, $\theta(Y, e) > \theta$, if Equation (6) holds, then $Y_M^p > Y_M$. □

Allowing for energy prices to increase in income reduces the return on energy spending for higher income households. This broadens the set of households that fail to increase energy spending in response to weather.

A.2.3 Income and Health Response to Energy Spending

Differences in home energy efficiency could affect the functional relationship between energy spending and health. On average, low-income households have draftier homes and lower quality insulation (Energy Information Administration, 2018)), and this implies the effectiveness of energy spending at protecting health may increase with income. Here, we can incorporate a smaller marginal change in dwelling temperature, given an increase in energy spending, for low-income households in our mortality risk function, $\tilde{f}(e, c, Y)$.

Lemma 3. *Suppose there is a direct relationship between willingness-to-pay and income,* $\tilde{f}(e, c, Y)$*, where* $\tilde{f}_Y(e, c, Y) < 0$*. In this case, there exists a threshold for energy spending in* *response to extreme weather, Y_M^f, where consumers with $Y \geq Y_M^f$ increase energy spending and all others do not. Moreover, if $\tilde{f}(e, c, \underline{Y}) = f(e, c)$, then $Y_M^f > Y_M$.*

Proof. For the threshold value y_M^f, proof by tautology identical to Proposition (1).

$Y_M^f > Y_M$ implied by $\tilde{f}_Y(e, c, Y) < 0$ and $\tilde{f}(e, c, \underline{Y}) = f(e, c)$. □

Like for other model extensions, building in the relationship between income and the function that relates energy spending to health risk amplifies existing tensions in the model. It broadens the set of households that fail to increase energy spending and are energy insecure, e.g. cannot afford energy spending due to their ability-to-pay.

A.3 Conclusions from Model and Extensions

Our model finds a threshold for energy spending in response to extreme temperature. This threshold is robust to several reasonable extensions, including income as a function of weather, increasing block pricing for electricity, and differences in willingness-to-pay due to housing quality. All of these extensions either fail to change the income threshold or increase it, meaning a greater share of households are energy insecure.

Our model limits the behavior we consider in response to extreme temperature. Four limitations deserve note. First, energy spending may have consumption value in its own right, $u(x, e)$.[20] This could be the case if other energy use complements energy spending to change dwelling temperature, e.g. increased television or gaming console use. Our model fails to address these types of energy spending because we suspect they are second-order, in terms of their effect on energy spending.[21]

The second limitation of our model is that it does not address other forms of adaptation, such as averting behaviors like traveling to a more temperate climate or a more comfortable

[20]The physiological evidence suggests that there are measurable health effects from deviations from preferred temperature (Madaniyazi et al., 2016). This suggests that much of the consumption value of energy spending, perceived as comfort, are rooted in physiological health benefits.

[21]An additional six hours of use of a gaming computer with monitor, assuming 300 watts per hour when in use and a price of ten cents/kWh, would cost an additional $0.18.

place, be it public (library) or private (movie theater). Given low-income households tend to have less geographic mobility, we suspect this channel would operate in a way similar to other extensions we consider.

The third limitation of our model is that we do not allow households to borrow. First, our paper focuses on immediate adaptive behaviors, e.g. changes in variable costs in response to weather shocks and not investment in durable assets, which fits well with a static model. Second, empirical evidence shows that low-income households in the U.S. households have very little liquidity (Gelman et al., 2018).

Finally, our model fails to formally consider how these extensions and others interact. Income seems to affect the utility maximization in a consistent way, essentially increasing resilience to weather shocks. Recent work in climate economics emphasizes the protective nature of income, unpacking whether income itself may be a form of adaptation or is correlated with unobserved, protective factors (Hsiang et al., 2019). If we were to consider interactions of model extensions, we would expect our main result of a threshold income to hold.

B Additional figures and tables

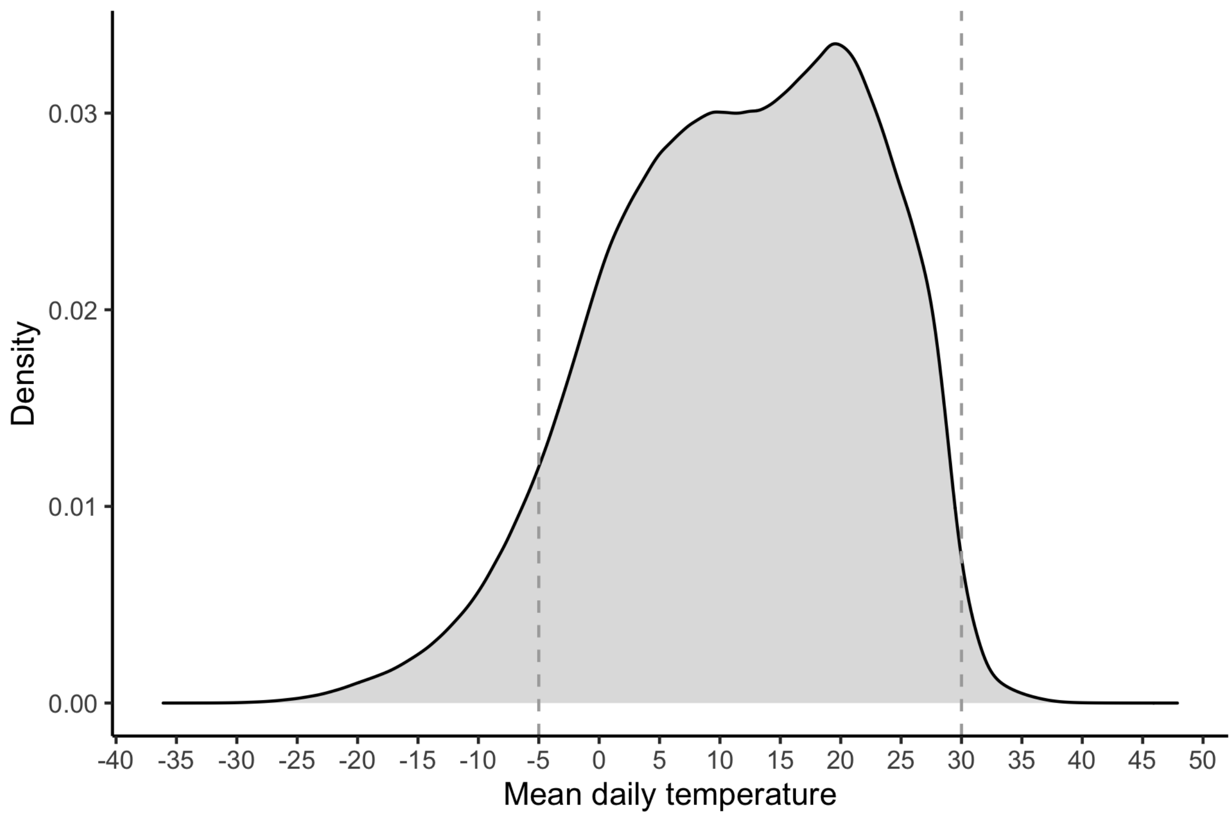


Figure B.1: Temperature distribution over sample period

Note: The distribution of mean daily temperatures is shown over the study period (2004–2018). Dashed vertical lines at –5C and 30C illustrate the cutoffs we use for the most extreme temperature bins. Note, the temperature bins we use in our analysis are counts of daily mean temperatures falling into each range.

Table B.1: Additional summary statistics

Statistic	Mean	Median	St. Dev.	N
Diary/Interview (0/1)	0.84	1	0.36	1,096,357
Days under –5C	1.08	0.00	3.40	1,096,357
... –5–0C	1.66	0.0002	3.46	1,096,357
... 0–5C	2.86	0.10	4.47	1,096,357
... 5–10C	3.87	1.31	4.78	1,096,357
... 10–15C	4.71	2.51	5.21	1,096,357
... 15–20C	5.54	4.21	5.44	1,096,357
... 20–25C	6.04	2.44	6.92	1,096,357
... 25–30C	4.16	0.03	7.44	1,096,357
Days over 30C	0.53	0	2.63	1,096,357
Precipitation	2.78	2.59	1.84	1,096,357
Unemployment	6.33	5.70	2.27	1,096,357
Age (reference person)	50.41	50	16.93	1,096,357
Female (reference person) (0/1)	0.53	1	0.50	1,096,357
Income	60,116.61	41,000	70,697.04	1,096,357
Under FPL (0/1)	0.24	0	0.43	1,096,357
Under 1.5 FPL (0/1)	0.33	0	0.47	1,096,357
Under 2 FPL (0/1)	0.41	0	0.49	1,096,357
HH size (truncated)	2.55	2	1.47	1,096,357
Any children under 18	0.34	0	0.47	1,096,357
Number of children	0.64	0	1.07	1,096,357
Any elderly over 64	0.26	0	0.44	1,096,357
Number of elderly	0.35	0	0.64	1,096,357

Note: Statistics constructed from the CEX for 2004-2018. Unweighted statistics from combined Interview and Diary Survey data (statistics are similar across the two survey products). N is the no. of household-months. Days under –5C are the no. of days in that month with an average daily temperature under -5C. Other weather variables are similar. Unemployment is the state unemployment rate for that month. Income is household income in Jan. 2018 dollars (approximated from binned responses). FPL is the Federal Poverty Line.

Table B.2: Poverty gap in spending response by temperature cutoffs

	Dependent variable:					
	ihs(All energy)			All energy		
	(1)	(2)	(3)	(4)	(5)	(6)
Under −10	0.013***			2.298***		
	(0.002)			(0.460)		
... × under 1.5 FPL	−0.010***			−1.343***		
	(0.001)			(0.331)		
Under −5		0.012***	0.012***		2.374***	2.388***
		(0.002)	(0.002)		(0.370)	(0.367)
... × under 1.5 FPL		−0.007***	−0.007***		−1.196***	−1.228***
		(0.001)	(0.001)		(0.178)	(0.175)
Over 25		0.003***			0.590***	
		(0.001)			(0.125)	
... × under 1.5 FPL		−0.0003			−0.319**	
		(0.001)			(0.145)	
Over 30	0.005***		0.005***	1.219***		1.218***
	(0.001)		(0.001)	(0.270)		(0.270)
... × under 1.5 FPL	−0.003*		−0.003*	−0.913**		−0.913**
	(0.002)		(0.002)	(0.379)		(0.379)
Subset	IS	IS	IS	IS	IS	IS
Observations	925,021	925,021	925,021	925,021	925,021	925,021
R^2	0.268	0.268	0.268	0.178	0.178	0.178

Note: Dependent variables are at the household-month level. Data from the CEX Interview Survey (IS). All energy is total energy expenditures. Under −10 is the no. of days in that month with an average temp. < −10 C for the state the HH resides in; Under −5 is the same for days < −5; Over 25 is the same for days >25 C; and Over 30 is the same for days >30 C. Under 1.5 FPL is an indicator for HHs under 1.5 times the federal poverty line. Each specification includes all intermediate temperature bins in 5 degree increments and their interaction with Under 1.5 FPL; the omitted bin is 15–20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights.

Table B.3: Poverty gap in spending response by FPL status

	Dependent variable:					
	ihs(All energy)			All energy		
	(1)	(2)	(3)	(4)	(5)	(6)
Under –5	0.011***	0.012***	0.012***	2.276***	2.388***	2.415***
	(0.002)	(0.002)	(0.002)	(0.371)	(0.367)	(0.371)
... × under 1 FPL	−0.007***			−1.194***		
	(0.001)			(0.204)		
... × under 1.5 FPL		−0.007***			−1.228***	
		(0.001)			(0.175)	
... × under 2 FPL			−0.006***			−1.016***
			(0.001)			(0.181)
Over 30	0.004***	0.005***	0.006***	0.999***	1.218***	1.385***
	(0.001)	(0.001)	(0.001)	(0.253)	(0.270)	(0.289)
... × under 1 FPL	−0.002			−0.440		
	(0.002)			(0.372)		
... × under 1.5 FPL		−0.003*			−0.913**	
		(0.002)			(0.379)	
... × under 2 FPL			−0.004**			−1.085**
			(0.002)			(0.442)
Subset	IS	IS	IS	IS	IS	IS
Observations	925,021	925,021	925,021	925,021	925,021	925,021
R^2	0.266	0.268	0.271	0.177	0.178	0.180

Note: Dependent variables are at the household-month level. Data from the CEX Interview Survey (IS). All energy is total energy expenditures. Under −5 is the no. of days in that month with an average temp. < −5 C for the state the HH resides in; and Over 30 is the same for days >30 C. Under 1, 1.5, and 2 FPL are indicators for HHs under 1, 1.5, and 2 times the federal poverty line. Each specification includes all intermediate temperature bins in 5 degree increments and their interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights. *p<0.1; **p<0.05; ***p<0.01.

Table B.4: Poverty gap in spending response by number of rooms in home

	Dependent variable:							
	ihs(All energy)				All energy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Under −5	0.011***	0.010***	0.012***	0.010***	2.281***	1.273***	2.100***	2.843***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.362)	(0.456)	(0.367)	(0.600)
... × under 1.5 FPL	−0.007***	−0.004***	−0.007***	−0.005***	−1.203***	−0.546***	−0.976**	−1.104***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.194)	(0.199)	(0.365)	(0.343)
Over 30	0.005***	0.003	0.006***	0.004***	1.146***	0.439	1.239***	1.072***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.263)	(0.340)	(0.270)	(0.397)
... × under 1.5 FPL	−0.003*	−0.004	−0.002**	−0.004***	−0.820**	−0.549	−0.283	−1.093***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.316)	(0.539)	(0.255)	(0.222)
Number of rooms	0.104***				20.739***			
	(0.005)				(1.323)			
Subset	All rooms	0–4 rms	5–6 rms	7+ rms	All rooms	0–4 rms	5–6 rms	7+ rms
Observations	917,888	221,499	359,113	337,276	917,888	221,499	359,113	337,276
R^2	0.342	0.211	0.188	0.206	0.238	0.128	0.141	0.152

Note: Dependent variables are at the household-month level. Data from the CEX Interview Survey (IS). All energy is total energy expenditures. Under −5 is the no. of days in that month with an average temp. < −5 C for the state the HH resides in; and Over 30 is the same for days >30 C. Under 1.5 FPL is an indicator for HHs under 1.5 times the federal poverty line. Each specification includes all intermediate temperature bins in 5 degree increments and their interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights.

Table B.5: Poverty gap by house type

	Dependent variable:		
	ihs(All energy)	ihs(Natural gas)	ihs(Electricity)
	(1)	(2)	(3)
Under –5 and apartment	0.002	−0.014	0.005
	(0.005)	(0.015)	(0.005)
... × under 1.5 FPL	−0.006***	−0.015**	−0.002
	(0.002)	(0.006)	(0.004)
Under –5 and house	0.014***	0.026***	0.005**
	(0.001)	(0.007)	(0.002)
... × under 1.5 FPL	−0.003**	0.001	−0.001
	(0.001)	(0.004)	(0.002)
Under –5 and townhouse	0.010***	0.027***	0.005
	(0.003)	(0.009)	(0.004)
... × under 1.5 FPL	−0.003	−0.012	0.003
	(0.003)	(0.012)	(0.003)
Under –5 and other	0.010**	−0.025	0.008**
	(0.004)	(0.016)	(0.004)
... × under 1.5 FPL	−0.005**	−0.014	−0.004*
	(0.002)	(0.012)	(0.002)
Over 30 and apartment	0.004***	0.007	0.005***
	(0.001)	(0.007)	(0.002)
... × under 1.5 FPL	−0.002	0.012**	−0.004**
	(0.001)	(0.004)	(0.002)
Over 30 and house	0.004**	−0.015	0.006***
	(0.002)	(0.015)	(0.002)
... × under 1.5 FPL	−0.001	−0.010	−0.002
	(0.004)	(0.022)	(0.005)
Over 30 and townhouse	0.004	0.017	−0.005
	(0.004)	(0.016)	(0.005)
... × under 1.5 FPL	−0.007***	−0.011	−0.010***
	(0.002)	(0.007)	(0.003)
Over 30 and other	0.015***	0.033***	0.008*
	(0.002)	(0.010)	(0.004)
... × under 1.5 FPL	−0.003	0.018	−0.003
	(0.005)	(0.020)	(0.006)
Subset	IS	IS	IS
Observations	924,865	924,865	924,865
R^2	0.349	0.243	0.206
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: Data from the CEX Interview Survey (IS). About 16% of households live in an apartment, 66% in a single family home, 14% in a townhouse or duplex, and 4% in some other type of housing. All energy is total energy expenditures. Under −5 is the no. of days in that month with an average temp. < -5 C for the state the HH resides in; and Over 30 is the same for days >30 C. Under 1.5 FPL is an indicator for HHs under 1.5 times the federal poverty line. Each specification includes all intermediate temperature bins in 5 degree increments and their interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights. *p<0.1; **p<0.05; ***p<0.01.

Table B.6: Poverty gap, dropping higher income households

	Dependent variable:					
	ihs(All energy)			All energy		
	(1)	(2)	(3)	(4)	(5)	(6)
Under −5	0.012***	0.012***	0.011***	2.388***	2.207***	2.001***
	(0.002)	(0.002)	(0.002)	(0.367)	(0.351)	(0.344)
... × under 1.5 FPL	−0.007***	−0.007***	−0.006***	−1.228***	−1.220***	−1.025***
	(0.001)	(0.001)	(0.001)	(0.175)	(0.161)	(0.147)
Over 30	0.005***	0.006***	0.006***	1.218***	1.305***	1.262***
	(0.001)	(0.001)	(0.001)	(0.270)	(0.265)	(0.240)
... × under 1.5 FPL	−0.003*	−0.003**	−0.003**	−0.913**	−0.842**	−0.653***
	(0.002)	(0.001)	(0.001)	(0.379)	(0.322)	(0.190)
Subset	IS	< 10 FPL	< 5 FPL	IS	< 10 FPL	< 5 FPL
Observations	925,021	869,678	698,597	925,021	869,678	698,597
R^2	0.268	0.268	0.264	0.178	0.182	0.178

Note: Dependent variables are at the household-month level. Data from the CEX Interview Survey (IS). All energy is total energy expenditures. Under −5 is the no. of days in that month with an average temp. < −5 C for the state the HH resides in; and Over 30 is the same for days >30 C. Under 1.5 FPL is an indicator for HHs under 1.5 times the federal poverty line. Each specification includes all intermediate temperature bins in 5 degree increments and their interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights. *p<0.1; **p<0.05; ***p<0.01.

Table B.7: Poverty gap for households with air conditioning

	Dependent variable:			
	ihs(All energy)	ihs(Electricity)	All energy	Electricity
	(1)	(2)	(3)	(4)
Over 30 and central AC	0.005^{***}	0.006^{***}	1.217^{***}	1.180^{***}
	(0.002)	(0.002)	(0.319)	(0.318)
... × under 1.5 FPL	-0.004^{**}	-0.006^{***}	-0.867^{**}	-0.989^{***}
	(0.002)	(0.002)	(0.409)	(0.333)
Over 30 and window AC	0.003	0.001	0.458	0.018
	(0.004)	(0.005)	(0.715)	(0.594)
... × under 1.5 FPL	−0.005	−0.006	−1.234	−1.226
	(0.005)	(0.005)	(0.997)	(0.982)
Subset	Any AC	Any AC	Any AC	Any AC
Observations	683,653	683,653	683,653	683,653
R^2	0.242	0.175	0.169	0.185

Note: Data from the CEX Interview Survey (IS). All energy is total energy expenditures. Under −5 is the no. of days in that month with an average temp. < -5 C for the state the HH resides in; and Over 30 is the same for days >30 C. Under 1.5 FPL is an indicator for HHs under 1.5 times the federal poverty line. Each specification includes all intermediate temperature bins in 5 degree increments and their interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights. *p<0.1; **p<0.05; ***p<0.01.

C Energy spending and use in the RECS

Annual data on household energy spending and consumption are available in the Residential Energy Consumption Survey (RECS). The RECS is a nationally-representative survey administered by the Energy Information Administration. It surveys households about their energy use, housing characteristics, and appliances, and it collects data from these respondents' utilities. We cannot replicate our main analysis using the RECS data because they are annual, rather than monthly, and we only observe household location at the Census division level. Instead, we use data from the five most recent waves of the RECS (1997, 2001, 2005, 2009, and 2015) to see how closely energy spending maps to energy use.

We first examine the distributions of energy spending and use for low and higher-income households. Figure C.1 shows these distributions for electricity and natural gas. For each of the four sub panels, the two distributions largely overlap each other. While higher-income households tend to have higher levels of use and spending, some of the highest usage households are low-income. For both fuels, the shape of the spending distributions are similar to those of the use distributions.

Using these data, we regress energy use on energy spending for both electricity and natural gas. In all cases, we interact spending with an indicator for being under 1.5 times the poverty line. The most basic specification includes only spending and this interaction. It thus constrains the constant, which captures fixed costs, to be the same across the two groups. We also estimate a specification which allows for different constants and one with year and Census division fixed effects.

Table C.1 shows that the relationship between spending and use is similar across the two groups, especially for natural gas spending. The same increase in electricity spending is associated with a smaller increase in electricity use for higher-income households. Yet, this difference is relatively small: a one kWh increase in electricity use is associated with a \$0.105 increase in spending for low-income households and a \$0.111 increase for higher-income households. For natural gas, the point estimates imply that a one MBTU increase in use results in the same increase in spending for both groups.

The estimates from Table C.1 allow us to translate our energy spending gap estimates into electricity consumption. Our main specification implies that higher-income households increase their daily electricity spending by 16.1 percent if a temperate day is replaced with a day over 30C, while low-income households increase their daily spending by only 0.8 percent. Assuming these groups face the marginal prices implied by column (3), these estimates imply a difference of 6.5 kWh. For perspective, 6.5 kWh could power a typical window air conditioning unit for 4.4 hours.[22]

Because marginal electricity prices sometimes increase with consumption, the similar relationship between electricity spending and use in Table C.1 may mask larger differences at higher ranges of consumption. High consumption levels might be especially relevant for our analysis since it is associated with both extreme weather and the likelihood of marginal prices in the highest block. Table C.2 shows our electricity spending results are not sensitive to the exclusion of households with the highest spending by dropping households in the top 1 or 5 percent of average electricity spending. It also shows results are robust to dropping California, a state known for its aggressive use of increasing block pricing.

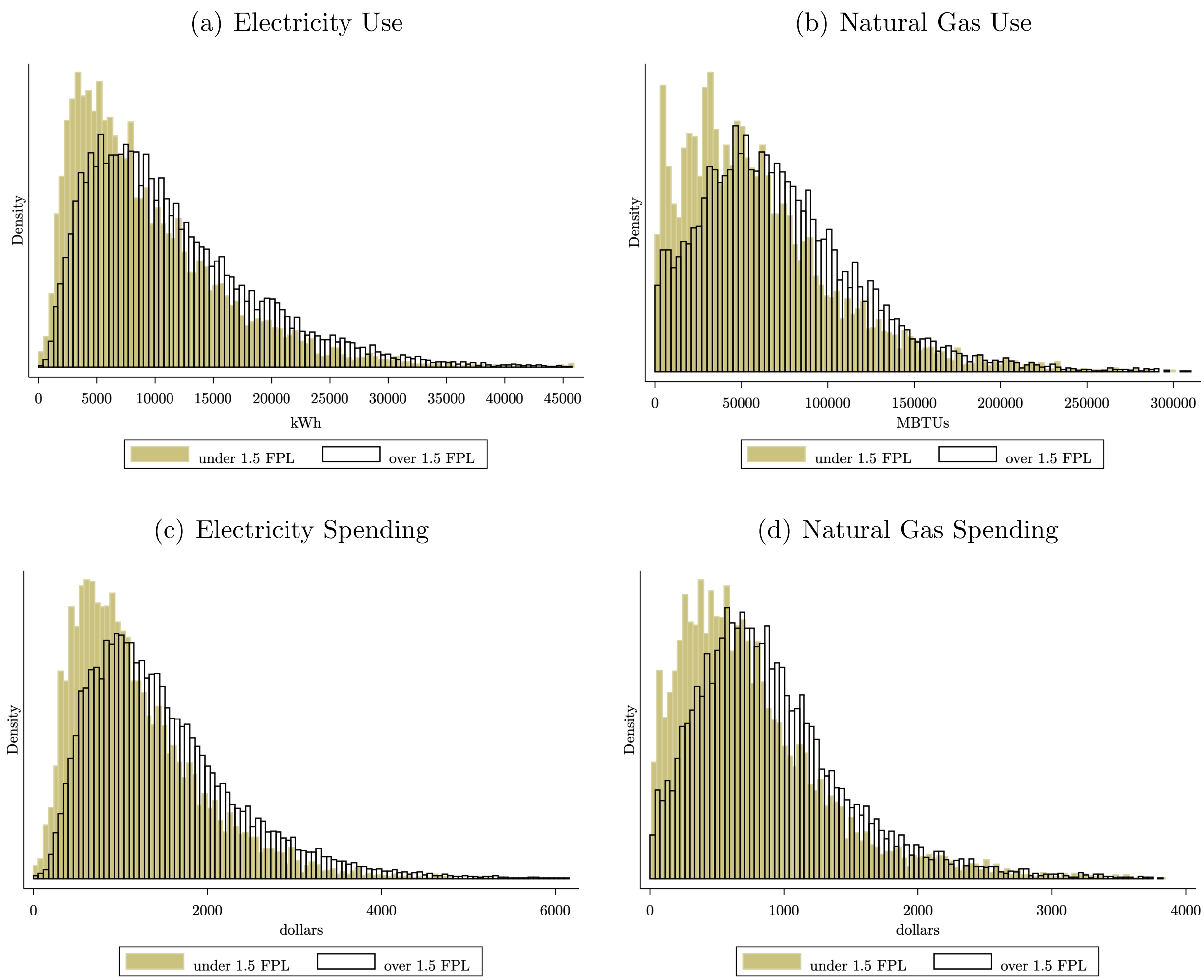
[22] This calculation uses the estimated coefficients on the over 30 bins from column (3) of Table 2 (0.00536 and -0.00509) and assumes 30 days per month. We evaluate the percent increase in spending at the mean of monthly electricity spending for each group ($132 for low-income households, $140 for higher-income households), and assume a typical air conditioning unit is 5,000 BTU/hr, or 1465 W.

Table C.1: Energy Spending vs. Energy Use

	Dependent variable:					
	Electricity Spending			Natural Gas Spending		
	(1)	(2)	(3)	(4)	(5)	(6)
Use (kWh or MBTU)	0.106***	0.105***	0.111***	0.0108***	0.0107***	0.0111***
	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.0001)
UseXUnder 1.5 FPL	-0.007***	-0.003**	-0.006***	-0.0000	0.0005***	-0.0000
	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0002)	(0.0001)
Poverty Indicator		X			X	
Year, Census Division FE			X			X
Observations	32,693	32,693	32,693	19,778	19,778	19,778
R-squared	0.78	0.78	0.81	0.77	0.77	0.85

Note: Dependent variables are at the household-year level. Regressions with natural gas spending as the dependent variable condition in non-zero natural gas spending. Spending is annual spending on each fuel in 2018 dollars. Robust SE in parentheses. Observations weighted by RECS sampling weights. Observations with annual spending or use greater than 5 times the median for either fuel are dropped (0.005 percent of obs.). *p<0.1; **p<0.05; ***p<0.01.

Figure C.1: Energy Use and Spending by Poverty Status



Note: Filled bars show the distribution for households under 1.5 times the federal poverty line; unfilled bars the distribution for all other households. All values are annual. Natural gas spending conditional on non-zero spending. Natural gas measured in 1000 BTUs, electricity in kWhs, and spending in real 2018 $.

Table C.2: Poverty gap in spending omitting highest electricity spenders

	Dependent variable:							
	ihs(Electricity)				Electricity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Under −5	0.005**	0.005**	0.005*	0.003	0.667**	0.610**	0.533**	0.548*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.268)	(0.229)	(0.216)	(0.290)
... × under 1.5 FPL	−0.001	−0.001	−0.002	−0.003**	−0.200*	−0.191*	−0.285***	−0.220
	(0.002)	(0.002)	(0.002)	(0.002)	(0.112)	(0.106)	(0.098)	(0.131)
Over 30	0.005***	0.005***	0.005***	0.005***	1.100***	1.065***	0.988***	0.926***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.258)	(0.237)	(0.200)	(0.206)
... × under 1.5 FPL	−0.005**	−0.005***	−0.005**	−0.007***	−1.121***	−0.936***	−0.837***	−1.137***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.329)	(0.263)	(0.248)	(0.318)
Subset	IS	Drop 1%	Drop 5%	Drop CA	IS	Drop 1%	Drop 5%	Drop CA
Observations	925,021	915,769	878,759	811,913	925,021	915,769	878,759	811,913
R^2	0.185	0.182	0.168	0.184	0.190	0.207	0.200	0.196

Note: Dependent variables are at the household-month level. Data from the CEX Interview Survey (IS). "Drop 1%" and "Drop 5%" refer to subsamples that omit households with average monthly electricity use greater than the 99th and 95th percentiles, respectively. "Drop CA" omits the state of California from the sample. Under −5 is the no. of days in that month with an average temp. < −5 C for the state the HH resides in; and Over 30 is the same for days >30 C. Under 1.5 FPL is an indicator for HHs under 1.5 times the federal poverty line. Each specification includes all intermediate temperature bins in 5 degree increments and their interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE and month-year FE; the age, sex, race, and education of the reference individual; HH size, no. of children, and no. of elderly; the state-level unemployment rate for that month; and state-level precipitation and its square. SE clustered by state. Observations weighted by CEX sampling weights. *p<0.1; **p<0.05; ***p<0.01.