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

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Abstract

We find energy spending disparities that indicate extreme weather causes hardship for low-income households. Using the 2004–2018 U.S. Consumer Expenditure Survey, we estimate the relationship between temperature and energy spending separately for low-income and all other households. Both groups respond similarly – in percentage terms – to moderate temperatures, but low-income households' energy spending is half as responsive to extreme temperatures. We find similar disparities in the food spending response to extreme temperature, consistent with a credit constraints mechanism. These results suggest adaptation to extreme weather, such as air conditioning use, is prohibitively costly for low-income households.

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1 Introduction

Many U.S. households report struggling to pay their energy bills. Eleven percent of households reported keeping their dwelling at an unhealthy or unsafe temperature for at least one month in 2015. Over 20 percent said they 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 insecurity particularly 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), and diminished learning (Park et al., 2020). 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 July 2011, Oklahoma experienced 23 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 0.7 percent but does not increase electricity spending for low-income households.

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. More recently, Beatty et al. (2014) finds similar poverty gaps in response to unseasonable cold in the United Kingdom.[1] 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. These papers highlight the protective role of income and social programs in responding to extreme temperature, and imply low-income households are distinctly vulnerable to temperature shocks. Mullins and White (2019a) finds access to health care mitigates the effect of heat on mortality, and Garg et al. (Forthcoming) 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.[2] On average, people increase energy use in response to extreme temperatures (Deschenes and Greenstone, 2011; Davis and Gertler, 2015; Hsiang et al., 2017).

[1] 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.

[2] 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.

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 *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.[3]

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.

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, 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

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

(food), to monthly 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 a nationally representative survey designed to provide a complete picture of U.S. households' finances and demographics. The Interview Survey (IS) collects information about household spending on major and less-frequent purchases (such as cars, rent, and utilities), and the Diary Survey (DS) better captures frequent or minor purchases, such as food.[4] 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]

For our analysis we use observations of a household in a particular state, month, and year. Household energy expenditures (from the IS) are the sum of reported bills across all fuel types (such as electricity, fuel oil, and natural gas).[6] We restrict the IS panel to households with positive fuel purchases. For food expenditures (from the DS), 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 weekly 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 indicator of relative household poverty, and also meaningful because various thresholds correspond to eligibility for numerous 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

[4]Both survey components 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, and use the IS to study utility expenditures, and the DS to study food expenditures.

[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.

[6]Of course, not all home energy consumption goes towards heating and cooling—other uses include cooking, appliances, lighting, and heating water—but we are unable to differentiate these.

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.

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 aggregate the gridded data by matching cells to their county (using the included crosswalk) and creating a county population-weighted average for each state.[7] 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 A.1. Additional summary statistics are provided in Table A.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,

[7] County populations are from the Census and vary annually.

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 specification is

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

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, γ_{my}. We also include household size by year FE, ϕ_{iy}. 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_{imy}. We control for the age, sex, race, and education of the reference individual. We also control flexibly for both 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:

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

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. Though we assess the two separately, we hypothesize that high energy spending due to weather shocks may constrain food spending for low-income households.

5.1 Energy Spending

Figure 1a 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 0.5 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 1b. 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 \$1.05, 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 0.4 percent, or \$0.33, 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 A.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. The point estimates are also small, implying a decrease in food spending of 0.2 percent for extreme cold and an increase of 0.3 percent for extreme heat.

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: any food spending, 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 1.9 percent less on all food than higher income households. In levels, this gap is \$2.35 for groceries and \$3.12 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 again 0.3 percent less likely to buy any food than higher income households. The corresponding gaps in spending are 2.2 percent for groceries and 2.0 percent for all food spending, or \$3.88 and \$4.14 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. Finding lagged effects would suggest these gaps are due to budget constraints rather than other behavioral changes 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 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. However, point estimates for the poverty interactions are consistently large and negative, and contemporaneous interactions are statistically significant. We find a similar pattern for specifications with energy and food spending in levels.

6 Discussion

We first contribute to, and extend to more recent data, the literature documenting U.S. households' U-shaped energy spending response to less-temperate weather. Our household-level estimates of energy spending are smaller in magnitude, but comparable to, the state-level energy use estimates from Deschenes and Greenstone (2011).[8]

However, the U-shaped relationship does not accurately describe energy spending by low-income households. We find a novel poverty gap for energy spending in response to very hot days. This effect is driven mostly by electricity spending, which is consistent with disparate air conditioner use. We also follow Bhattacharya et al. (2003) in documenting heterogeneity in energy spending during cold weather by household poverty status. Thus, low-income households' energy spending response is more of an M-shape than a U-shape (shown in Figure 1b), with smaller increases in spending at the extremes of the temperature distribution. To return to the example of the July 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 nearly 10 percent, while the change for low-income households was not meaningfully different from zero. Similarly, during the January 2018 cold wave, our estimates imply energy spending in North Carolina rose by about 4 percent for higher-income households, but only about half a percent for low-income households. These findings are consistent with qualitative and survey evidence showing lower-income respondents are more likely to keep their homes uncomfortably hot or cold, possibly to manage utility bills (Hernández, 2016; Energy Information Administration, 2018).

Consistent with a credit constraints explanation, we find similar poverty gaps for food spending. 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 in response to extreme weather.[9] These also reflect channel through which ex-

[8] Deschenes and Greenstone (2011)'s most extreme bins are <-12.2C and >32.2C. That paper finds replacing a temperate day with a day from one of these bins increases *annual*, state-level energy use by 0.32 and 0.37 percent. For bins <-5 C and >30 C, we find an additional extreme day increases monthly household-level energy spending by 0.5 and 0.7 percent. If energy spending is uniform throughout the year, the implied annual effects would be 0.04 and 0.06, whereas seasonal demand driving effects yields estimates closer to Deschenes and Greenstone (2011).

[9] It is possible low-income households have different food shopping responses to extreme temperature. We do not think this is supported by the data: 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).

treme weather may affect health: low-income households going hungry or receiving inadequate nutrition.

6.1 Alternative explanations

We next investigate two alternative explanations for these energy spending poverty gaps: housing differences and changes in spending without changes in use. We also discuss the possibility that spending differences reflect excess by higher-income households rather than hardship for low-income households.

We first find evidence that differences in dwelling characteristics are not driving these energy poverty gaps. Smaller dwellings and apartments may require less energy spending to maintain ambient temperature, and, in the CEX, low-income household dwellings have fewer rooms and are more likely to be apartments.[10] We address these concerns by using the inverse hyperbolic sine (IHS) of energy spending, which avoids scale effects, as our preferred specification. Thus, to explain the gap, smaller dwellings would need to require less energy spending in percentage terms to maintain ambient temperature. While we do not observe square footage in the CEX, we do observe the number of rooms. Results for the IHS specifications are similar if we control for the number of rooms, or if we subset the data by the number of rooms and estimate the model separately for each subset (Table A.3). Dwellings of low-income households may also be systematically lower quality, with worse insulation and less efficient heating and air conditioning units. In this case, the gaps in energy spending we find would understate the disparities in indoor temperatures experienced.

The design of the CEX also makes it unlikely our results reflect low-income households reducing energy spending but not energy use. Low-income households may spend less on energy because they are receiving energy assistance or delaying bill payments; however, 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, 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

[10] In the CEX data, the average number of rooms in the dwelling is 5.4 for low-income households and 6 for higher income households. The share of households that live in apartment is 23% for low-income households and 15% for higher income households.

150% of the FPL or 60% of state median income (Perl, 2018). If energy assistance were driving our findings, we might expect the energy poverty gap to disappear as we raise the poverty threshold. This is not the case: the spending disparity remains with a higher threshold of 200% of the FPL (Table A.4).

We interpret the difference in energy spending during extreme weather as hardship: compared to other households, low-income households do not get sufficient energy services (heating or cooling) to avoid exposure to unsafe indoor temperatures. However, the spending gap is also consistent with lower-income households consuming “just enough” energy during extreme weather, and other households spending to excess, or wasting energy. While this alternate story could generate the pattern we find in the data, we think it is unlikely. We demonstrate this by omitting the most affluent households (that is, those least likely to be concerned about utility bills and monitoring or rationing energy use) from our sample and re-estimating equation 2. Table A.5 shows our results are robust drop households above five and ten times the FPL (even when the omitted observations comprise a quarter of the sample) suggesting the gap is not due to excess energy spending among affluent households.

6.2 Policy implications

Our findings suggest current U.S. assistance programs fail to adequately buffer households from energy bill shocks. This may be because take-up of these programs is limited, so 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. These large summer bills reflect air conditioning use: nearly 90 percent of U.S. households used air conditioning in their home in 2015 (Energy Information Administration, 2018). Finally, eligibility thresholds may be too low. While the

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

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 A.4).

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.

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 temperature 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, suggesting lower-income households are cutting back on necessities to afford their energy bills. While we propose liquidity constraints as the mechanism for these effects, the policy implications are much the same for alternative mechanisms.

The results in this article have implications for existing social programs, as well as policies to address climate change. They suggest existing programs fail to fully insulate low-income households from weather shocks. They also raise the possibility that many households that would benefit from cooling assistance do not receive it. While about half of the U.S. states offered cooling assistance in 2015, we find poverty gaps for energy spending in response to

[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).

hot days as well as cold days. Cooling technologies like air conditioning have a key role to play in adaptation to climate change. Yet, increasing access to these technologies is only the first step: households must have the resources to deploy them. Our results highlight how the variable costs of operating these technologies are also likely to affect the distribution of climate damages.

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8 Figures and Tables

Table 1: Summary statistics

A: Interview Survey (IS)

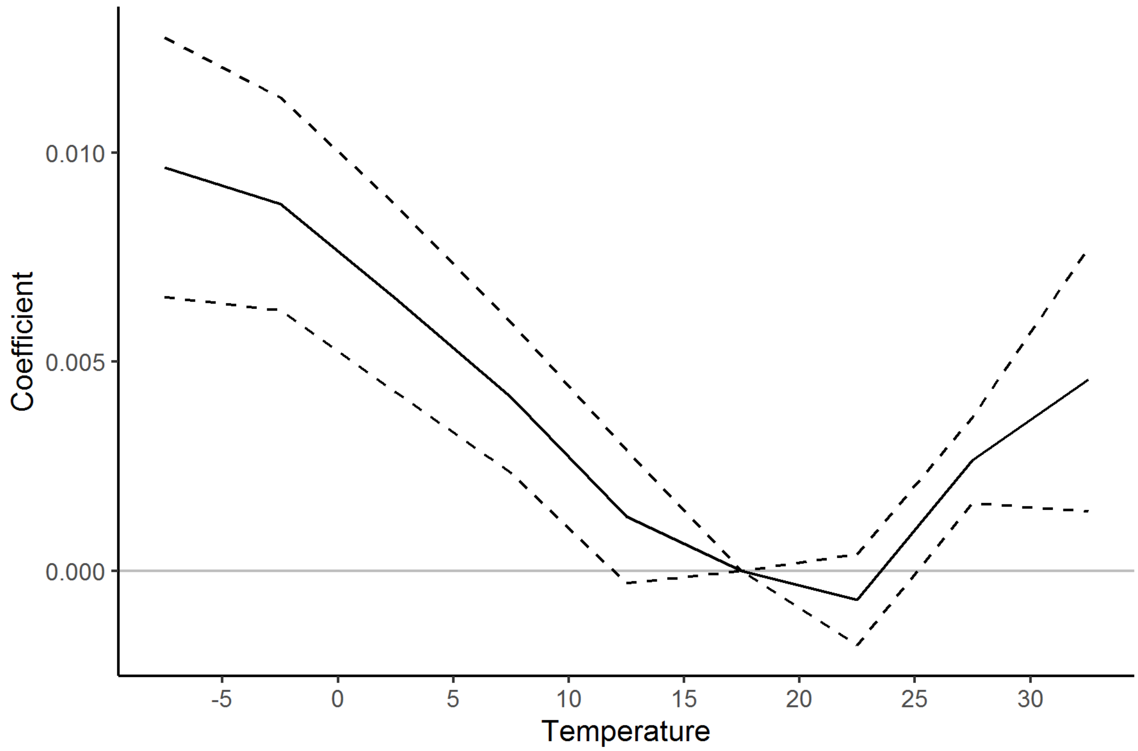
Statistic	Mean	Median	St. Dev.	N
Days under –5C	1.16	0.00	3.53	914,765
Days over 30C	0.52	0	2.33	914,765
Energy expenditures	199.96	165.89	158.14	914,765
... Over 1.5 FPL	207.87	172.79	162.32	620,873
... Under 1.5 FPL	183.25	151.70	147.52	293,892
Natural gas expenditures	49.32	21.22	78.66	914,765
... Over 1.5 FPL.1	52.70	25.68	80.33	620,873
... Under 1.5 FPL.1	42.20	3.51	74.51	293,892
Electricity expenditures	138.35	115.2	101.74	914,765
... Over 1.5 FPL.2	141.31	117.50	102.28	620,873
... Under 1.5 FPL.2	132.09	109.97	100.28	293,892
Any air conditioning (0/1)	0.74	1	0.44	914,765
... Over 1.5 FPL.3	0.77	1.00	0.42	620,873
... Under 1.5 FPL.3	0.67	1.00	0.47	293,892
Rooms in home	6.02	6.00	2.22	907,653
... Over 1.5 FPL.4	6.27	6.00	2.23	617,976
... Under 1.5 FPL.4	5.48	5.00	2.11	289,677

B: Diary Survey (DS)

Statistic	Mean	Median	St. Dev.	N
Days under –5C	1.15	0.00	3.48	171,336
Days over 30C	0.49	0	2.25	171,336
Any food expenditures (0/1)	0.90	1.00	0.30	169,855
... Over 1.5 FPL	0.95	1.00	0.21	108,109
... Under 1.5 FPL	0.80	1.00	0.40	61,746
In home food expenditures	363.71	261.46	395.94	169,855
... Over 1.5 FPL.1	408.09	311.47	403.33	108,109
... Under 1.5 FPL.1	286.01	172.62	370.06	61,746
All food expenditures	598.84	456.54	648.71	169,855
... Over 1.5 FPL.2	701.27	564.32	696.33	108,109
... Under 1.5 FPL.2	419.51	274.90	508.08	61,746

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 in the households' dwelling. In home food spending is monthly expenditures on food for consumption at home. Table A.1 presents additional statistics.

(a) Energy spending response for all households



(b) Poverty gap in energy spending response

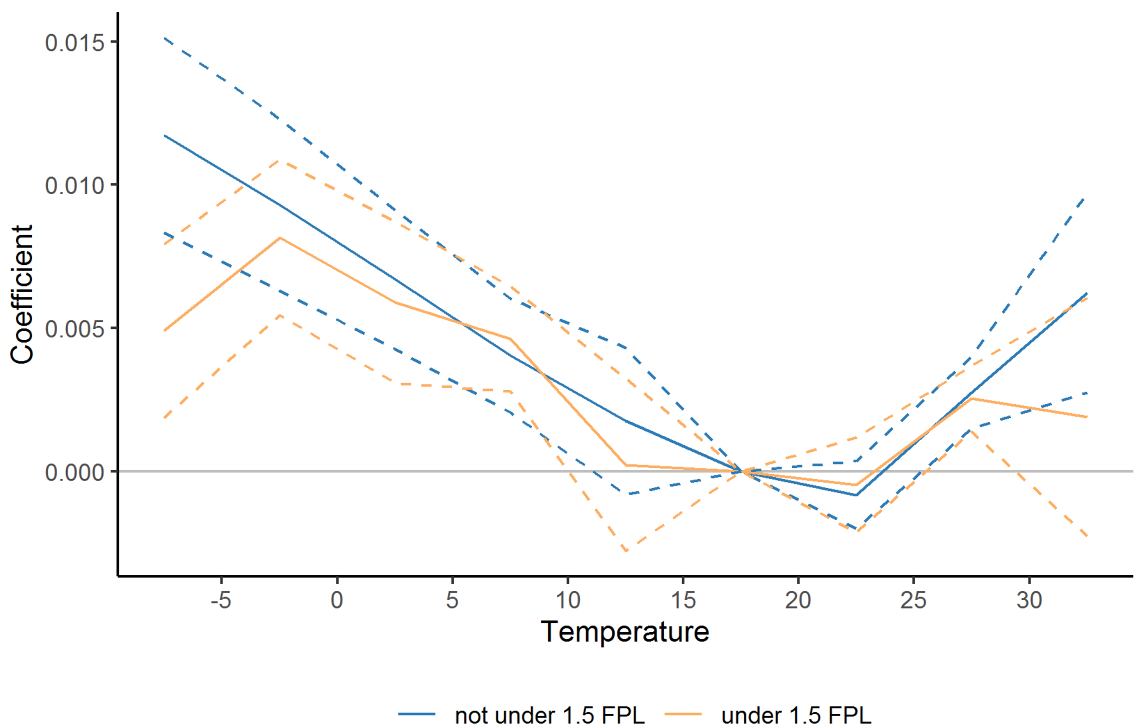


Figure 1: Energy spending response to temperature

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***	0.019***	0.006**	2.276***	1.249***	0.658**
	(0.002)	(0.006)	(0.003)	(0.379)	(0.233)	(0.275)
... × under 1.5 FPL	−0.007***	−0.011*	−0.002	−1.229***	−0.620***	−0.249*
	(0.001)	(0.006)	(0.002)	(0.206)	(0.166)	(0.141)
Over 30	0.006***	0.002	0.007***	1.367***	0.214	1.303***
	(0.002)	(0.004)	(0.002)	(0.325)	(0.153)	(0.326)
... × under 1.5 FPL	−0.004*	0.0004	−0.007***	−1.036**	0.121	−1.281***
	(0.002)	(0.008)	(0.003)	(0.440)	(0.103)	(0.381)
Subset	IS	IS	IS	IS	IS	IS
Observations	914,765	914,765	914,765	914,765	914,765	914,765
R^2	0.270	0.211	0.186	0.182	0.188	0.194

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, month-year FE, and HH-size by year FE; the age, sex, race, and education of the reference individual; HH 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	0.003	-0.005	1.393	1.893
	(0.001)	(0.007)	(0.006)	(1.190)	(1.714)
... × under 1.5 FPL	-0.003^{**}	-0.013^{*}	-0.019^{**}	-2.353^{***}	-3.119^{*}
	(0.001)	(0.007)	(0.008)	(0.835)	(1.613)
Over 30	0.002	0.017	0.014	2.346	3.813
	(0.001)	(0.011)	(0.012)	(1.497)	(3.652)
... × under 1.5 FPL	-0.003^{***}	-0.022^{***}	-0.020^{***}	-3.883^{***}	-4.143^{**}
	(0.001)	(0.004)	(0.005)	(0.901)	(1.670)
Subset	DS	DS	DS	DS	DS
Observations	169,855	169,855	169,855	169,855	169,855
R^2	0.084	0.127	0.154	0.160	0.169

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, month-year FE, and HH-size by year FE; the age, sex, race, and education of the reference individual; HH 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	0.009***	0.003	1.736***	1.438
	(0.001)	(0.008)	(0.343)	(1.243)
... × under 1.5 FPL	−0.005***	−0.012*	−0.860***	−2.635***
	(0.001)	(0.006)	(0.227)	(0.888)
Under –5 (t-1)	0.010***	0.004	1.963***	0.587
	(0.001)	(0.006)	(0.309)	(1.095)
... × under 1.5 FPL	−0.005***	−0.011	−0.804***	0.539
	(0.001)	(0.008)	(0.194)	(0.919)
Over 30	0.004***	0.020	0.978***	1.933
	(0.001)	(0.013)	(0.269)	(1.573)
... × under 1.5 FPL	−0.003	−0.018***	−0.686*	−2.473**
	(0.002)	(0.006)	(0.391)	(0.955)
Over 30 (t-1)	0.006***	−0.008	1.176***	0.073
	(0.001)	(0.015)	(0.266)	(1.579)
... × under 1.5 FPL	−0.004***	−0.011	−0.791***	−1.695*
	(0.001)	(0.008)	(0.215)	(0.919)
Subset	IS	DS	IS	DS
Observations	913,082	169,574	913,082	169,574
R^2	0.270	0.128	0.182	0.160

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, month-year FE, and HH-size by year FE; the age, sex, race, and education of the reference individual; HH 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 Additional figures and tables

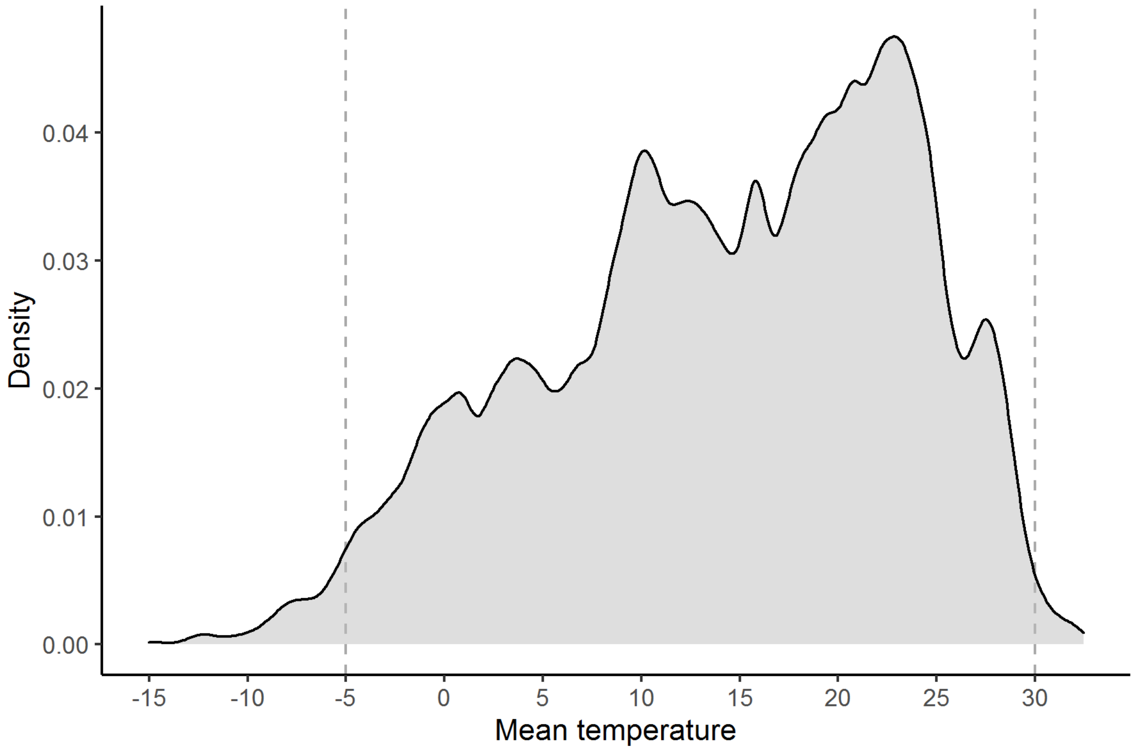


Figure A.1: Temperature distribution over sample period

Note: The distribution of mean daily temperatures is shown for observations in the CEX IS and DS over the study period (2004–2018). Dashed vertical lines at –5C and 30C illustrate the frequency of extreme monthly mean temperatures. Note, the temperature bins used in our analysis are counts of daily mean temperatures falling into each range.

Table A.1: Additional summary statistics

Statistic	Mean	Median	St. Dev.	N
Diary/Interview (0/1)	0.84	1	0.36	1,086,101
Days under –5C	1.16	0.00	3.53	1,086,101
... –5–0C	1.75	0.001	3.50	1,086,101
... 0–5C	2.99	0.25	4.42	1,086,101
... 5–10C	3.98	1.73	4.68	1,086,101
... 10–15C	4.69	2.73	4.97	1,086,101
... 15–20C	5.36	4.07	5.17	1,086,101
... 20–25C	5.89	2.45	6.76	1,086,101
... 25–30C	4.11	0.03	7.41	1,086,101
Days over 30C	0.52	0	2.31	1,086,101
Precipitation	2.82	2.60	1.88	1,086,101
Unemployment	6.35	5.70	2.26	1,086,101
Age (reference person)	50.38	50	16.92	1,086,101
Female (reference person) (0/1)	0.53	1	0.50	1,086,101
Income	59,973	40,967	70,461	1,086,101
Under FPL (0/1)	0.24	0	0.43	1,086,101
Under 1.5 FPL (0/1)	0.33	0	0.47	1,086,101
Under 2 FPL (0/1)	0.41	0	0.49	1,086,101
HH size (truncated)	2.55	2	1.47	1,086,101
Any children under 18	0.34	0	0.47	1,086,101
Number of children	0.64	0	1.07	1,086,101
Any elderly over 64	0.26	0	0.44	1,086,101
Number of elderly	0.35	0	0.64	1,086,101

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 A.2: Poverty gap in spending response by temperature cutoffs

	Dependent variable:					
	ihs(All energy)			All energy		
	(1)	(2)	(3)	(4)	(5)	(6)
Under −10	0.014***			2.298***		
	(0.002)			(0.447)		
... × under 1.5 FPL	−0.010***			−1.407***		
	(0.001)			(0.307)		
Under −5		0.012***	0.012***		2.258***	2.276***
		(0.002)	(0.002)		(0.381)	(0.379)
... × under 1.5 FPL		−0.007***	−0.007***		−1.193***	−1.229***
		(0.001)	(0.001)		(0.210)	(0.206)
Over 25		0.003***			0.608***	
		(0.001)			(0.136)	
... × under 1.5 FPL		−0.001			−0.340*	
		(0.001)			(0.170)	
Over 30	0.006***		0.006***	1.367***		1.367***
	(0.002)		(0.002)	(0.325)		(0.325)
... × under 1.5 FPL	−0.004*		−0.004*	−1.036**		−1.036**
	(0.002)		(0.002)	(0.440)		(0.440)
Subset	IS	IS	IS	IS	IS	IS
Observations	914,765	914,765	914,765	914,765	914,765	914,765
R^2	0.270	0.270	0.270	0.182	0.182	0.182

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; Food in is expenditures on food for consumption at home. 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 < 25; 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 heir interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE, month-year FE, and HH-size by year FE; the age, sex, race, and education of the reference individual; HH 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 A.3: 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***	2.180***	1.211**	2.044***	2.616***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.372)	(0.451)	(0.378)	(0.603)
... × under 1.5 FPL	−0.007***	−0.004***	−0.007***	−0.005***	−1.213***	−0.525**	−0.994***	−1.045***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.208)	(0.215)	(0.368)	(0.367)
Over 30	0.006***	0.004	0.007***	0.004**	1.272***	0.559	1.460***	0.985**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.313)	(0.362)	(0.328)	(0.433)
... × under 1.5 FPL	−0.004*	−0.005	−0.003**	−0.004***	−0.932**	−0.630	−0.348	−1.055***
	(0.002)	(0.004)	(0.001)	(0.001)	(0.378)	(0.588)	(0.252)	(0.243)
Number of rooms	0.104***				20.729***			
	(0.005)				(1.312)			
Subset	All rooms	0–4 rms	5–6 rms	7+ rms	All rooms	0–4 rms	5–6 rms	7+ rms
Observations	907,653	218,890	355,312	333,451	907,653	218,890	355,312	333,451
R^2	0.344	0.214	0.190	0.208	0.241	0.130	0.143	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; Food in is expenditures on food for consumption at home. 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 < 25; 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 heir interaction with Under 1.5 FPL; the omitted bin is 15-20 C. All specifications include state-by-month FE, month-year FE, and HH-size by year FE; the age, sex, race, and education of the reference individual; HH 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 A.4: 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***	2.158***	2.276***	2.303***
	(0.002)	(0.002)	(0.002)	(0.375)	(0.379)	(0.386)
... × under 1 FPL	−0.007***			−1.170***		
	(0.001)			(0.216)		
... × under 1.5 FPL		−0.007***			−1.229***	
		(0.001)			(0.206)	
... × under 2 FPL			−0.006***			−1.017***
			(0.001)			(0.203)
Over 30	0.005***	0.006***	0.007***	1.124***	1.367***	1.558***
	(0.002)	(0.002)	(0.002)	(0.296)	(0.325)	(0.350)
... × under 1 FPL	−0.003			−0.513		
	(0.002)			(0.428)		
... × under 1.5 FPL		−0.004*			−1.036**	
		(0.002)			(0.440)	
... × under 2 FPL			−0.005**			−1.240**
			(0.002)			(0.503)
Subset	IS	IS	IS	IS	IS	IS
Observations	914,765	914,765	914,765	914,765	914,765	914,765
R^2	0.267	0.270	0.272	0.180	0.182	0.183

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; Food in is expenditures on food for consumption at home. 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, 1.5, and 2 FPL are indicators for HHs under 1, 1.5, and 2 times the federal poverty line. All specifications include temperature bins for <-5 C, -5-0 C, . . ., 25-30 C, >30 C and the relevant FPL indicator; the omitted bin is 15-20 C. All specifications include state-by-month FE, month-year FE, and HH-size by year FE; the age, sex, race, and education of the reference individual; HH 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 A.5: Poverty gap, dropping higher income households

	Dependent variable:					
	ihs(All energy)			All energy		
	(1)	(2)	(3)	(4)	(5)	(6)
Under −5	0.012***	0.011***	0.011***	2.276***	2.105***	1.909***
	(0.002)	(0.002)	(0.002)	(0.379)	(0.367)	(0.367)
... × under 1.5 FPL	−0.007***	−0.007***	−0.006***	−1.229***	−1.213***	−1.018***
	(0.001)	(0.001)	(0.001)	(0.206)	(0.194)	(0.183)
Over 30	0.006***	0.007***	0.007***	1.367***	1.465***	1.407***
	(0.002)	(0.002)	(0.002)	(0.325)	(0.335)	(0.326)
... × under 1.5 FPL	−0.004*	−0.004**	−0.004**	−1.036**	−0.950**	−0.708***
	(0.002)	(0.002)	(0.001)	(0.440)	(0.372)	(0.224)
Subset	IS	Drop > 10 FPL	Drop > 5 FPL	IS	Drop > 10 FPL	Drop > 5 FPL
Observations	914,765	860,187	691,156	914,765	860,187	691,156
R^2	0.270	0.269	0.266	0.182	0.185	0.183

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; Food in is expenditures on food for consumption at home. 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, 1.5, and 2 FPL are indicators for HHs under 1, 1.5, and 2 times the federal poverty line. All specifications include temperature bins for <-5 C, -5-0 C, . . ., 25-30 C, >30 C and the relevant FPL indicator; the omitted bin is 15-20 C. All specifications include state-by-month FE, month-year FE, and HH-size by year FE; the age, sex, race, and education of the reference individual; HH 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.