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

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A B S T R A C T

We estimate the relationship between temperature and energy spending for both low and higher-income U.S. 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.

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 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. U.S. households receive monthly bills that vary with energy use. We estimate the causal effect of additional hot or cold days on energy spending, allowing for heterogeneity by

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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 30 C (86 F) than is typical. We estimate replacing a temperate day (15–20 C/59–68 F) with a very cold day (< – 5 C/<23 F) 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 is statistically significant. We refer to the muted spending response to extreme weather among low-income households relative to higher-income households as a "poverty gap". This aggregate pattern of energy spending is driven by the fuels associated with heating and cooling: electricity spending exhibits a poverty gap at both extremes, while natural gas spending exhibits a poverty gap only for cold weather. Replacing a temperate day with a very hot day (>30 C/>86 F) 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. Nor are they driven by differences in AC availability: we find similar estimates for a sample where all households have AC. 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 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, but not extreme heat; we also provide contemporary estimates of the 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.[2] More recently, Beatty et al. (2014) finds similar poverty gaps in response to unseasonable cold in the United Kingdom.[3] 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] 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).

[3] 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.

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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.[4] 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 *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.[5]

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, 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. Bee et al. (2015) finds the diary survey has more under reporting of expenditures, especially for categories comprised of small, infrequent expenditures. 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.[6]

We use observations of a household in a particular state, month, and year and limit our sample to the 15 most recent years of CEX data available. Household 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.

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4 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.

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

6 Due to data limitations, we use a subset of these nationally-representative data in estimation. The BLS public use data suppress state of residence for observations from Missouri, Montana, New Mexico, North Dakota, South Dakota, and Wyoming for both CEX surveys, so we omit these states from our analysis. We also exclude Alaska and Hawaii for lack of weather data. According to the 2010 U.S. Census, the states included in our sample account for 96 percent of the U.S. population.

Table 1
Summary statistics.

A: Interview Survey (IS)				
Statistic	Mean	Median	St. Dev.	N
Days under −5 C	1.08	0.00	3.41	925,021
Days over 30 C	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 (DS)				
Statistic	Mean	Median	St. Dev.	N
Days under −5 C	1.07	0.00	3.37	171,336
Days over 30 C	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 −5 C are counts of days each month with an average daily temperature under −5 C; Days over 30 C is the same for >30 C. Energy expenditures (total, natural gas, and electricity) are monthly spending in Jan. 2018 dollars. Over 1.5 FPL is the subset of households with income over 1.5 times the Federal Poverty Line, given their family size. 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.

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). Our income measure is gross income, exclusive of transfers, which is collected quarterly in the CEX. This is a simple, meaningful indicator of relative household poverty, because multiples of this threshold are used to determine eligibility for assistance programs, including LIHEAP, SNAP, and Medicaid. For our primary specification, we allow the effect of weather on spending to differ for households above and below 150 percent of the FPL. We choose this cutoff because it is commonly used for LIHEAP, the federal energy assistance program. Throughout, we refer to households under 150 percent of the FPL as "low income", and households above 150 percent of the FPL as "higher income".

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. These households are spread throughout the U.S., with higher proportions in the South and West; these are also the regions with the most frequent extremely hot days.

Fig. 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. These fluctuations in the aggregate are driven by the dominant billing paradigm in the U.S., where households receive monthly bills for the quantity of energy they consumed last month. In the CEX, where households are observed for up to five quarters, the average within-household standard deviation of monthly fuel spending is $56, which is substantial relative to the average household spending of $193 per month. We note that not all countries use this billing system; for example, some countries bill bi-monthly and others using an account system where households are billed the same amount each month.

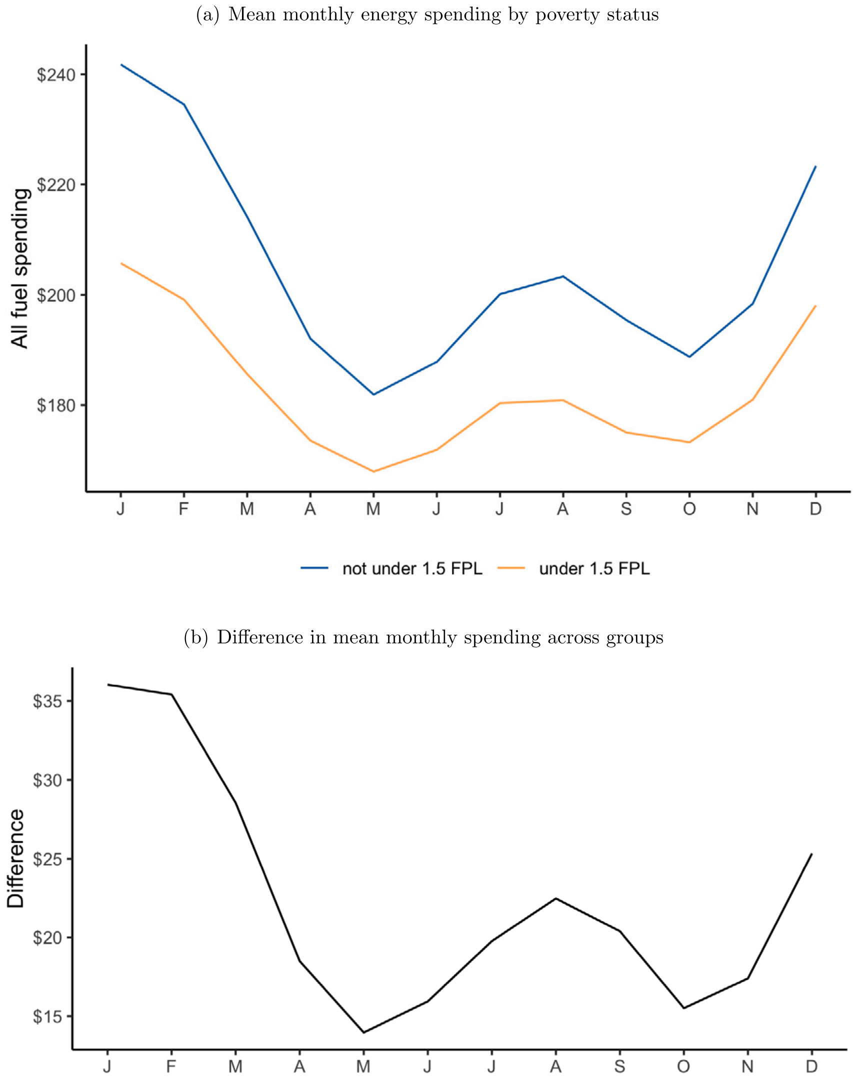

Fig. 1. Seasonal energy spending by poverty status.
Note: Average monthly fuel spending (using sample weights) is plotted separately for households above and below 1.5 times the FPL in Panel (a). Panel (b) plots the difference between the two group means in Panel (a).

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 first aggregate to the county level, weighting each cell by inverse distance to the county population centroid. We then aggregate up to the state level, weighting by county population.[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.

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

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 −5 C and above 30 C, 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 jth 5 C-degree bin. Because we include state-by-month fixed effects in all specifications, results capture responses to deviations from average weather. Because variation in weather is plausibly exogenous, we can causally identify the spending response to weather (Dell et al., 2014). Our main specification is

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

where $Spend_{imy}$ is 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 15–20 C 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.

We next estimate a model that allows for differential effects of weather on spending by income. Specifically, we interact the temperature bins with whether a household falls below 1.5 times the federal poverty line (FPL), a cutoff often used to determine eligibility for energy assistance:

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

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".

This specification is sufficient for describing differential spending responses for low- and higher-income households. However, this specification is insufficient for identifying whether or not income is the cause of a subpopulation's vulnerability to extreme weather (Hsiang et al., 2019). Causal identification of low-income as the source of a weaker spending response would require exogenous changes in both temperature and poverty status (Hsiang et al., 2013). We note that while we do not claim income differences drive our effect, it is highly likely to be the underlying cause, and the relevant policy takeaways – income-targeted heating and cooling assistance – are unchanged.

Using logged spending as the dependent variable drops households with zero spending in a month. For energy spending we observe very few zeros. These zeros may be due to either a disconnection or errors in the data. We also estimate this model separately for spending on natural gas, and the logged specification drops many households that never use natural gas. Finally, to avoid dropping meaningful zeros for food spending, we use the inverse hyperbolic sine (IHS) transformation rather than the log for the dependent variable in food spending regressions.

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

Fig. 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 15–20 C bin is replaced with a day in the under −5 C bin, monthly energy spending increases by 1 percent. Similarly, when a day in the 15–20 C bin is replaced with a day in the over 30 C 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 (Eq. (2)), and this relationship is visualized in Fig. 2b. For cold weather, when a day in the 15–20 C bin is replaced with a day under −5 C, low-income households increase

Table 2
Poverty gap in energy spending response.

	Dependent variable:					
	log(All energy) (1)	log(Natural gas) (2)	log(Electricity) (3)	All energy (4)	Natural gas (5)	Electricity (6)
Under −5	0.012***	0.018***	0.005**	2.365***	1.555***	0.668**
	(0.002)	(0.002)	(0.002)	(0.372)	(0.332)	(0.272)
... ×under 1.5 FPL	−0.007***	−0.004***	−0.004***	−1.216***	−0.517***	−0.245**
	(0.001)	(0.001)	(0.001)	(0.181)	(0.134)	(0.114)
Over 30	0.005***	−0.002*	0.005***	1.214***	0.084	1.078***
	(0.001)	(0.001)	(0.002)	(0.266)	(0.167)	(0.261)
... ×under 1.5 FPL	−0.003*	0.003**	−0.004**	−0.886**	0.110	−1.065***
	(0.002)	(0.001)	(0.002)	(0.379)	(0.100)	(0.347)
FE	SxM+YxM	SxM+YxM	SxM+YxM	SxM+YxM	SxM+YxM	SxM+YxM
Subset	IS	IS	IS	IS	IS	IS
Observations	925,021	516,874	912,438	925,021	516,874	912,438
R^2	0.269	0.352	0.269	0.181	0.271	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 with income under 1.5 times the federal poverty line, given their family size. 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) (1)	ihs(Food in) (2)	ihs(All food) (3)	Food in (4)	All food (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.

spending by 0.7 percent, or $1.22, less than higher income households. When a day in the 15–20 C bin is replaced with a very hot day (over 30 C), low-income households increase spending by 0.3 percent, or $0.89, less than higher income households. Appendix Table B.2 shows estimates vary as expected when we change the cutoffs for the most extreme bins.

These differences in energy spending are driven by differences in electricity spending for hot days, and both natural gas and electricity spending for cold days. This is intuitive: electricity alone is used for cooling, while both electricity and natural gas are used for home heating. Table 2 also reports results for spending broken down by fuel type. The hot day spending effect is larger and

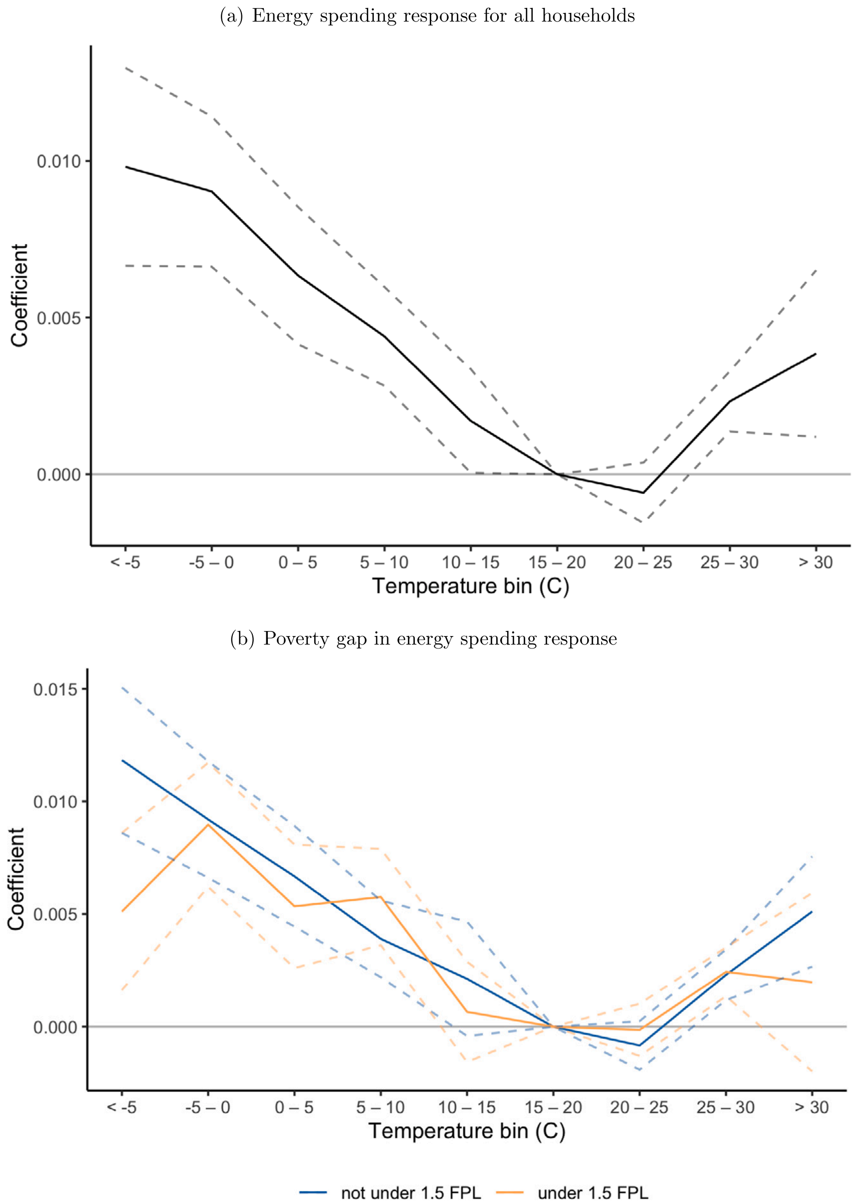

Fig. 2. Energy spending response to temperature.
Note: Coefficients show the effect of one additional day per month in each 5 C-temperature bin on log-transformed monthly home energy spending. Panel (a) corresponds to Eq. (1) in the text, and Panel (b) to Eq. (2), which allows for heterogeneity in household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

more precisely estimated for electricity. Surprisingly, we find also find a statistically significant positive spending gap for natural gas spending on hot days, though overall spending on natural gas on hot days is low. For the response to cold weather, we find poverty gaps for both natural gas and electricity spending contribute to our overall energy spending result.

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 15–20 C day with a day below −5 C or a day above 30 C 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 15–20 C bin is replaced with a day in the < – 5 C bin, low-income households are 0.3 percent less likely to buy any food in the

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

	Dependent variable:			
	ihs(All energy) (1)	ihs(Food in) (2)	All energy (3)	Food in (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 with income under 1.5 times the federal poverty line, given their family size. 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.

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 15–20 C bin is replaced with a day in the >30 C 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 < − 5 C 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 four 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 rule out that the differences we document are driven by measurement error in temperature exposure. Weather is assigned at the state level, which implies mismatch between assigned and experienced weather at the household level. This concern is mitigated by population-weighting the underlying weather data when we aggregate it to the state level. The most likely effect of measurement error on our estimates is attenuation towards zero. Measurement error correlated with household income would also be cause for concern. As a robustness check, we estimate specification (2) omitting the five states with the greatest within-month variability in temperature across counties, i.e., the states where measurement error is likely the largest.[8] Our main results are robust to this sample restriction (see Appendix Table B.3).

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.[9] 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.[10] 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 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.4).

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 log 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 log 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.5). The point estimates on the extreme bins for higher-income households are also alike across these subsets, suggesting

[8] These are Arizona, California, Colorado, Nevada, and New Mexico.

[9] 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).

[10] 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.

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 Eq. (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.7 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.

The energy spending gap 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.8).[11] 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 keep their homes at less comfortable temperatures during extreme weather. If households cannot smooth budget shocks caused by high energy bills, we would expect them to decrease other 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.[12] We cannot test for these monthly budget constraints directly because the CEX only reports income and total expenditures at the quarterly level. Using these quarterly data, we do find that low-income households are much more likely to be spending exactly what they take in each quarter (see Appendix Figure B.2). Overall, these results raise the possibility of a pattern of cutting back spending on healthful categories, such as medicine, in order to afford energy.

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.[13] 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.4).

Climate change could exacerbate these weather-driven spending disparities. By 2065, the frequency of days with mean temperatures over 30 C is expected to rise by about 24 days per year under a business as usual scenario, while the frequency of days below −5 C is expected to fall by only 7 days.[14] More frequent heat shocks may exacerbate the unaffordability of air conditioner

[11] 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.

[12] 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).

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

[14] 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).

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

This paper estimates how energy and food spending responds to unexpectedly hot or cold weather, with a focus on estimating the difference in the response for low and higher-income households. Our data come from the U.S. Consumer Expenditure Survey for 2004–2018. We pair these household-level data with distributions of daily temperatures at the state-month level. We exploit variation in the frequency of unseasonably hot or cold weather to identify how spending on energy and food changes for low- and higher-income households.

We find a novel poverty gap in the energy spending response to very hot weather, and a corresponding disparity for very cold weather. Higher-income households increase monthly spending by 0.5 percent when faced with an additional very hot day (>30 C/>86 F) relative to a temperate day (15–20 C/59–68 F), whereas low-income households increase their energy spending by only 0.2 percent. The implied difference in electricity use could power a window air conditioner for about four hours. We also find poverty gaps in the food spending response to temperature: food spending by low-income households falls in response to unexpected days with extreme temperature, hot or cold, whereas higher-income food spending is unaffected. This corroborates the concern that lower-income households cut back on necessities to afford energy bills.

This research has implications for existing social programs. It suggests low-income households are especially vulnerable to exposure to weather shocks. Currently, many U.S. states provide heating assistance but not cooling assistance. The hotter, Southern U.S. already has the highest rates of energy insecurity and the lowest fraction of households receiving energy assistance (Energy Information Administration, 2018). Many households that do not receive cooling assistance might benefit from it, particularly as the frequency and intensity of heatwaves rises.

We note several open questions that merit greater study. Differences in spending are particularly concerning if they result in health disparities. Our findings highlight the unaffordability of energy as a potential mechanism behind income-associated effects of extreme weather on health. We cannot assess these health effects directly, but future work could pair a study of energy affordability with direct measures of health outcomes. Next, research could explore how extreme weather affects spending composition. Our findings suggest extreme weather crowds out other spending, but the types of spending crowded out (e.g., soda versus fruits and vegetables or medicine) matters for the health consequences of these shocks. Finally, research to better understand the effects of energy assistance programs on health and financial well-being could help policymakers serve vulnerable households. 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.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2022.102609.

References

Anderson, Soren, Marinescu, Ioana, Shor, Boris, 2019. Can pigou at the polls stop us melting the poles? Working Paper.

Barreca, Alan, Clay, Karen, Deschenes, Olivier, Greenstone, Michael, Shapiro, Joseph S., 2016. Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. J. Political Econ. 124 (1), 105–159.

Beatty, Timothy K.M., Blow, Laura, Crossley, Thomas F., 2014. Is there a 'heat-or-eat' trade-off in the UK? J. Royal Stat. Soc. Ser. A (Statistics In Society) 177 (1), 281–294.

Bee, Adam, Meyer, Bruce D., Sullivan, James X., 2015. The validity of consumption data: Are the consumer expenditure interview and diary surveys informative? In: Carroll, Christopher D., Crossley, Thomas F., Sabelhaus, John (Eds.), Improving the Measurement of Consumer Expenditures. In: Studies in Income and Wealth, vol. 74, University of Chicago Press, pp. 204–240.

Bhattacharya, Jayanta, DeLeire, Thomas, Haider, Steven, Currie, Janet, 2003. Heat or eat? Cold weather shocks and nutrition in poor American families. Am. J. Public Health 93 (7), 1149–1154.

Bhattacharya, Jayanta, DeLeire, Thomas, Haider, Steven, Currie, Janet, 2004. Heat or eat? Cold weather shocks and nutrition in poor American families. NBER Working Paper No. 9004.

Borenstein, Severin, Bushnell, James, 2019. Do two electricity pricing wrongs make a right? Cost recovery, externalities, and efficiency. Hass Energy Institute WP 294R.

Bureau of Labor Statistics, 2019. Average annual expenditures and characteristics of all consumer units, consumer expenditure survey, 2013–2018. https://www.bls.gov/cex/2018/standard/multiyr.pdf.

Burgess, Robin, Deschenes, Olivier, Donaldson, Dave, Greenstone, Michael, 2017. Weather, climate change and death in India, Working Paper.

Chirakijja, Janjala, Jayachandran, Seema, Ong, Pinchuan, 2019. Inexpensive heating reduces mortality. NBER Working Paper No. 25681.

Cullen, Julie Berry, Friedberg, Leora, Wolfram, Catherine, 2005. Do households smooth small consumption shocks? Evidence from anticipated and unanticipated variation in home energy costs. Center for the Study of Energy Markets Working Paper No. 141.

Currie, Janet, 2006. The take-up of social benefits. In: Auerbach, Alan, Card, David, Quigley, John (Eds.), Public Policy And The Distribution Of Income.

Davis, Lucas W., Gertler, Paul J., 2015. Contribution of air conditioning adoption to future energy use under global warming. Proc. Natl. Acad. Sci. 201423558.

Dell, Melissa, Jones, Benjamin F., Olken, Benjamin A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52 (3), 740–798.

Deschenes, Olivier, Greenstone, Michael, 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. Am. Econ. J. Appl. Econ. 3 (4), 152–185.

Deschenes, Olivier, Moretti, Enrico, 2009. Extreme weather events, mortality, and migration. Rev. Econ. Stat. 91 (4), 659–681.

Energy Information Administration, 2018. 2015 RECS Survey data. https://www.eia.gov/consumption/residential/data/2015/..

Falk, Gene, Mitchell, Alison, Lynch, Karen E., Mccarty, Maggie, Morton, William R., Crandall-Hollick, Margot L., 2015. Need-Tested Benefits: Estimated Eligibility and Benefit Receipt by Families and Individuals (R44327). Technical Report, U.S. Congressional Research Service.

Frank, Deborah A., Neault, Nicole B., Skalicky, Anne, Cook, John T., Wilson, Jacqueline D., Levenson, Suzette, Meyers, Alan F., Heeren, Timothy, Cutts, Diana B., Casey, Patrick H., et al., 2006. Heat or eat: the low income home energy assistance program and nutritional and health risks among children less than 3 years of age. Pediatrics 118 (5), e1293–e1302.

Garg, Teevrat, Jagnani, Maulik, Taraz, Vis, 2020. Temperature and human capital in India. J. Assoc. Environ. Resour. Econ. 7 (6), 1113–1150.

Gjertson, Leah, 2016. Emergency saving and household hardship. J. Fam. Econ. Issues 37 (1), 1–17.

Graff, Michelle, Pirog, Maureen, 2019. Red tape is not so hot: Asset tests impact participation in the low-income home energy assistance program. Energy Policy 129, 749–764.

Hauer, Mathew, 2019. Population projections for all U.S. counties by age, sex, and race controlled to the shared socioeconomic pathways. OSF.

Hernández, Diana, 2016. Understanding 'energy insecurity' and why it matters to health. Soc. Sci. Med. 167, 1–10.

Hsiang, Solomon, 2016. Climate econometrics. Annu. Rev. Resour. Econ. 8, 43–75.

Hsiang, Solomon M., Burke, Marshall, Miguel, Edward, 2013. Quantifying the influence of climate on human conflict. Science 341 (6151).

Hsiang, Solomon, Kopp, Robert, Jina, Amir, Rising, James, Delgado, Michael, Mohan, Shashank, Rasmussen, D.J., Muir-Wood, Robert, Wilson, Paul, Oppenheimer, Michael, et al., 2017. Estimating economic damage from climate change in the United States. Science 356 (6345), 1362–1369.

Hsiang, Solomon, Oliva, Paulina, Walker, Reed, 2019. The distribution of environmental damages. Rev. Environ. Econ. Policy 13 (1), 83–103.

Jessel, Sonal, Sawyer, Samantha, Hernández, Diana, 2019. Energy, poverty, and health in climate change: A comprehensive review of an emerging literature. Front. Public Health 7, 357.

Mullins, Jamie, White, Corey, 2019a. Does Access to Health Care Mitigate Environmental Damages? IZA Discussion Paper Series.

Mullins, Jamie T., White, Corey, 2019b. Temperature and mental health: evidence from the spectrum of mental health outcomes. J. Health Econ. 68, 102240.

Murray, Anthony G., Mills, Bradford F., 2014. The impact of low-income home energy assistance program participation on household energy insecurity. Contemp. Econ. Policy 32 (4), 811–825.

Nord, Mark, Kantor, Linda S., 2006. Seasonal variation in food insecurity is associated with heating and cooling costs among low-income elderly Americans. J. Nutr. 136 (11), 2939–2944.

Park, R. Jisung, Goodman, Joshua, Hurwitz, Michael, Smith, Jonathan, 2020. Heat and learning. Am. Econ. J. Econ. Policy 12 (2), 306–339.

Perl, Libby, 2018. LIHEAP: Program and Funding. Congressional Research Service Report.

Rasmussen, D.J., Kopp, Robert E., 2017. Probability-weighted ensembles of U.S. county- level climate projections for climate impact modeling. zenodo.

Schilbach, Frank, Schofield, Heather, Mullainathan, Sendhil, 2016. The psychological lives of the poor. Amer. Econ. Rev. 106 (5), 435–440.

Schlenker, Wolfram, 2020. Daily weather data for contiguous United States (1950–2019) - version march 2020.

U.S. Census, 2018. Survey of income and program participation: 2014 panel wave 1 (Version 1.2). https://www.census.gov/programs-surveys/sipp/data/datasets/2014-panel/wave-1.html.

White, Corey, 2017. The dynamic relationship between temperature and morbidity. J. Assoc. Environ. Resour. Econ. 4 (4), 1155–1198.